



Vaasan yliopisto  
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**With or against the trend – Short-term momentum  
and contrarian strategies**

Quantitative study from the Finnish stock market

School of Accounting and Finance  
Master's thesis in Finance  
Master's Degree Programme in Finance

Vaasa 2025

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**UNIVERSITY OF VAASA****School of Accounting and Finance****Author:** Justus Nykänen**Title of the Thesis:** With or against the trend – Short-term momentum and contrarian strategies : Quantitative study from the Finnish stock market**Degree:** Master of Science in Economics and Business Administration**Programme:** Master's Degree Programme in Finance**Supervisor:** Timo Rothovius**Year:** 2025 **Pages:** 72

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**ABSTRACT:**

Momentum and contrarian anomalies have been increasingly examined, especially since De Bondt and Thaler's (1985) and Jegadeesh and Titman's (1993) studies. Momentum and contrarian studies utilize technical analysis to identify specific recurring patterns based on historical data. The short-term return continuity and long-term return reversal of winner and loser stocks have been recognized as one of the strongest market anomalies, existing across industries, firm characteristics, different asset classes, and various geographical regions (Rouwenhorst, 1998; Moskowitz & Grinblatt, 1999; Lewellen, 2002; Moskowitz et al., 2012). According to Fama's (1970) efficient market hypothesis, all information is already reflected in stock prices, and historical data cannot be used to predict future prices. Under the efficient market hypothesis, the efficient market will adjust if any irrationality occurs, ensuring that such inefficiencies eventually disappear in the long run. Momentum and contrarian appear to be exceptions, as they still exist despite drawing significant attention.

This thesis examines the continuation and reversal of returns in the short term within the Finnish stock market from 2009 to 2022. This thesis also seeks to compare the effectiveness of various investment strategies against one another and against the average index return to ascertain their potential for generating excess returns. This thesis tests the performance of four strategies that vary in terms of historical lag, i.e., the period of cumulative returns over which stocks are ranked. All strategies use a uniform holding period of one month, with portfolios rebalanced monthly. The strategies examined include standard momentum, recent past performance, intermediate past performance, and past performance over a single month. This study uses historical stock price data from 81 stocks that have maintained their listing on Nasdaq Helsinki throughout this period.

The findings of this study reveal that short-term continuation and reversal of returns are present in the Finnish stock market. Continuity of returns is evident in the 2 to 12 months before portfolio formation, during which winner stocks outperform loser stocks on average. In contrast, the only instance where loser stocks outperform winner stocks occurs in the short-term reversal strategy (the t-1 lag) and in the t-13 strategy, where loser stocks rebound significantly, outperforming the winner stocks. The most effective strategy identified in this analysis is the standard momentum strategy, which produces an average monthly return of 1.59% and a significant t-statistic of 2.81 at a 5% significance level. Overall, five of the thirteen zero-cost momentum portfolios demonstrate the ability to outperform the average market return, while two contrarian portfolios achieve this as well. It is important to note that this study does not consider transaction costs. Therefore, the practical implementation of these strategies may not necessarily guarantee excess returns.

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**KEYWORDS:** Efficient market hypothesis, stock market anomaly, momentum, contrarian



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## 1 Introduction

Market efficiency has long been the focus of several studies and discussions. However, evidence has emerged that contradicts the concept of market efficiency, with anomalies serving as one example. In finance and economic literature, an anomaly refers to a situation where the actual result deviates from the expected outcome predicted by a model within a given set of assumptions. This indicates that the underlying assumption or model does not effectively align with practical realities. Various market anomalies have been observed, but momentum and contrarian are among the most studied and discussed. Since the 1990s, momentum and contrarian research have gained increased attention, encompassing a wide range of markets and asset classes.

The basis for momentum and contrarian investing lies in exploiting market inefficiencies. Fama's (1970) efficient market hypothesis posits that asset prices incorporate all available information. According to this theory, asset prices should only react to new information, and historical data cannot predict future prices. However, research has identified patterns in asset pricing using historical data. Momentum investing is based on the concept that stocks that have performed well in the past are likely to continue performing well, while those that have performed poorly are likely to continue performing poorly. The momentum strategy aims to capitalize on this trend by buying stocks that have performed well and short-selling stocks that have performed poorly over a specific period.

Like momentum, the contrarian strategy is based on identifying patterns in historical returns. The contrarian strategy involves taking the opposite position to momentum. This means buying the worst-performing stocks in a given period and short-selling the best-performing stocks in the same period. The strategy assumes that the winner stocks will decrease in value while the loser stocks will increase in value. This assumption is grounded in the belief that the loser stocks are undervalued and have growth potential. In contrast, the winner stocks are overvalued and will adjust to a more appropriate price level. Investor psychology and irrational behavior, such as under- and overreaction, have

been said to be at least one of the main causes for excessive price volatility. Investors tend to under- or overreact to stock information, causing excessive price volatility that can result in either a price increase or decrease. Under efficient markets, stock prices should adapt to the equilibrium when the market realizes its irrational behavior. These price patterns and market corrections can create opportunities for momentum and contrarian investors to achieve excess returns.

Edwards (1968) studies cognitive psychology and presents a theory of conservative bias, which is closely related to the existence of momentum and contrarian anomaly. Conservatism bias is the tendency of an individual to make only minor adjustments to their beliefs when new evidence is presented, rather than fully re-evaluating or changing those beliefs. In other words, the theory suggests that individuals underweight new information and often prioritize their existing knowledge. When new information is presented, individuals generally take time to process and adapt to it, which can result in irrational behavior. In finance, conservatism bias is closely associated with other cognitive biases, such as herding and anchoring. In financial markets, this tendency is reflected in the unwillingness of investors to respond adequately to new information, including earnings announcements, dividends, or stock splits. As a result, certain trends may continue longer than what would be rational concerning the company's fundamentals. When the market eventually recognizes its underreaction, price adjustments often lead to corrections (reversals).

In the behavioral finance literature, two differing models address the irrational behavior of investors. The first model argues that investors often overreact to information, leading to a reversal of returns when companies announce corporate news. Conversely, the second model suggests that investors underreact to information, resulting in a continuation pattern of returns. The divide in the literature on these models likely arises because studies measure investor reactions to information from various sources instead of a single, common source (Kadiyala & Rau, 2004). Behavioral models proposed by Daniel et al. (1998) and Hong and Stein (1999) predict that short-term returns tend to continue

while long-term returns may exhibit reversals. Daniel et al. (1998) argue that informed investors can be overconfident about the private signals they receive regarding stock information. This overconfidence is reinforced through biased self-attribution when public information aligns with their private insights. However, when public information conflicts with their private beliefs, investors tend to dismiss it as noise. Daniel et al.'s (1998) model indicates that informed investors put more weight on private information than public information, overreacting to private signals and underreacting to public information.

Hong and Stein (1999) explore the relationship between under- and overreaction in momentum strategies. Their model suggests that overreactions will likely occur in the longer term if a group of investors underreacts to information in the short term. Their findings are consistent with those of Daniel et al. (1998), where the results indicate that the continuity of returns in the short term and the reversals in the long term are more pronounced in smaller stocks, where information spreads more slowly. They propose that using private information may lead to more significant long-term overreactions than initially using public information. Additionally, they propose that there is a connection between time-series momentum and the pattern of return autocorrelations.

If the market significantly underreacts or overreacts to stock market information, adopting the right strategy can create opportunities for excess returns. Technical analysts strive to identify profitable strategies by leveraging these market inefficiencies and biases. A primary focus in technical analysis is determining whether historical stock prices can affect future prices. A primary concept in this field is autocorrelation, which many studies utilize to analyze short-term stock price movements. Autocorrelation assesses the relationship between variables over consecutive time periods, indicating how dependent the current value of a variable is on its past values. In simpler terms, it gauges the interdependence between variables in each lagged time series. For instance, perfect positive autocorrelation implies that an increase in one time series results in a proportional increase in the subsequent time series.

In momentum research, positive autocorrelation is often viewed as an indicator of the momentum effect, whereas negative autocorrelation points to the potential effectiveness of contrarian strategies. Studies have indicated that negative autocorrelation is generally stronger in the short term compared to positive autocorrelation, typically observed in lagged time series over periods ranging from about one week to one month. Moreover, research has discovered that momentum usually operates over lagged time horizons of two to twelve months, yielding average returns of approximately 1% per month, depending on the timing of the measurement and specific market conditions.

### **1.1 Background and previous research**

One of the earliest observations on stock market behavior comes from Keynes (1935), who states that day-to-day fluctuations in the profits of current investments have an excessively influential impact on the market. Later, a seminal study on stock market behavior that questions the efficient market theory is the research conducted by De Bondt and Thaler (1985). They provide evidence of long-term reversal in stock returns, which gained widespread attention and posed one of the early challenges to the efficient market hypothesis. This had a significant impact because it suggested predictable return patterns based on historical performance. This approach was intuitively appealing and consistent with the belief in market overreaction and mean reversion. More specifically, the study investigates how market participants respond to uncertainties in the stock market, such as news events. Their analysis confirms that investors tend to overreact to unexpected events in the market, subsequently influencing stock pricing.

Due to the tendency of markets to underreact or overreact to information, the identification of viable strategies is feasible. In this regard, Jegadeesh and Titman (1993) study the cross-sectional stock returns in the US stock market by buying past winner stocks and selling past loser stocks. They investigate the stock market's efficiency by

analyzing various momentum investment strategies, where the strategies vary in different portfolio ranking and holding periods. At first, stocks are ranked in ascending order based on their returns over a specific period. This allows the creation of portfolios of past winners and past losers from the ends of these deciles. Their findings suggest that strategies involving buying winners and selling losers have resulted in significant returns over holding periods between 3 and 12 months. Specifically, the top decile typically outperforms the bottom decile in the following year. This research gained broad attention and inspired many to investigate the issue further. Fama (1998) delves into the return continuations, highlighting momentum as one of the unexplained anomalies observed in stock markets. Momentum is a widespread phenomenon because it exists not only in cross-sections of individual stocks. Extensive momentum research focuses, for example, on time series, industries, firm characteristics, various asset classes, and international stock markets.

The momentum literature is mainly centered on the cross-sectional performance of stocks, with findings indicating that securities that have recently outperformed their peers over the previous three to twelve months are likely to continue this trend on average over the subsequent month. Time series momentum is regarded as equivalent to, yet distinct from, the concept of "momentum" in financial literature, which primarily emphasizes cross-sectional analysis. Time series momentum focuses exclusively on a stock's historical returns rather than its relative performance within a cross-sectional framework. In a study by Moskowitz et al. (2012), time series momentum is examined across equity index, currency, commodity, and bond futures. The results reveal that returns tend to persist from one to twelve months before experiencing partial reversals over longer periods, supporting sentiment theories related to early market underreaction and delayed overreaction. Furthermore, a portfolio constructed using time series momentum strategies across diverse asset classes is demonstrated to generate abnormal returns with limited exposure to conventional asset pricing variables, performing best in extreme market conditions.

Moskowitz and Grinblatt (1999) investigate the industry momentum and identify an intense and persistent associated effect. Industry momentum is an investment strategy that buys stocks from past winning industries and sells stocks from past losing industries. This effect appears to be unaffected by microstructure factors, individual stock momentum, or the cross-sectional dispersion of average returns. Additionally, industry momentum significantly influences the profitability of individual stock momentum strategies. Except for 12-month individual stock momentum, industry momentum largely accounts for the profits generated by these strategies. The findings indicate that individual stock momentum strategies tend to lack diversification, as both winner and loser stocks typically belong to the same industry. The research also reveals that industry momentum is predominantly driven by long-side stocks, whereas individual stock momentum strategies often capitalize on short-side opportunities. Furthermore, unlike individual stock momentum, industry momentum profits are particularly robust among the largest and most liquid stocks.

Lewellen (2002) extends the research on individual stock and industry momentum by constructing momentum portfolios based on firm characteristics. Specifically, momentum portfolios are created based on firm size and book-to-market value. The results indicate that momentum within these portfolios is as strong and, in some instances, an even stronger phenomenon than momentum observed in individual stock or industry portfolios. This study aligns with previous literature suggesting that momentum is robust and pervasive. Additionally, Lewellen (2002) seeks to identify explanatory factors for momentum. While much of the momentum literature suggests that momentum arises primarily from firm- or industry-specific factors, Lewellen (2002) argues that excess covariance accounts for momentum in size and book-to-market portfolios rather than the market underreaction. One suggestion is that market underreaction and subsequent overreaction to firm-specific factors may explain momentum in individual stocks. Instead, Lewellen (2002) suggests that in size- and book-to-market portfolios, it is macroeconomic factors that drive momentum. Consequently, the effects of size and book-to-market momentum can vary significantly across different

periods. There are instances when large stocks are expected to outperform small stocks, and periods when low book-to-market stocks are anticipated to outperform high book-to-market stocks.

Momentum also exhibits persistence across various asset classes and international markets. Asness et al. (2013) examine value and momentum strategies within eight markets and asset classes. This research design is unique because the existing literature on market anomalies primarily focuses on the U.S. markets, where value and momentum strategies are typically examined separately. In cases where these strategies are studied outside the U.S., they are often studied as distinct phenomena. Specifically, individual stocks from the U.S., U.K., European, and Japanese markets are jointly examined. The asset classes tested jointly include equity index futures, government bonds, currencies, and commodity futures. The findings provide consistent evidence that value and momentum return premia exist across all studied markets. Value and momentum effects are observed in government bonds, with the value effect also noted in currencies and commodities. Another finding highlights the substantial co-movement of value and momentum strategies across asset classes. Value strategies correlate positively with other value strategies in otherwise unrelated markets. A similar correlation appears among momentum strategies, which demonstrate positive co-movement between global markets. However, value and momentum strategies have a negative correlation with each other within and between asset classes.

Further international evidence supporting the existence of momentum is presented in Rouwenhorst's (1998) study, which examines return continuation across twelve different international stock markets. The findings align with those of Jegadeesh and Titman (1993), who focus on US stock markets. Notably, the results indicate that internationally diversified relative strength portfolios, which invest in medium-term winner stocks while shorting medium-term loser stocks, yield an average return of approximately one percent per month. The momentum phenomenon is evident in all the stock markets examined and extends across various size deciles. However, the persistence of returns is

notably stronger in small stocks than in larger ones. The outperformance of winner stocks typically persists for about a year and cannot be adequately explained by conventional risk measures. Interestingly, the study reveals that controlling for market risk or size factor exposure may even enhance the abnormal performance of relative strength strategies. Additionally, Rouwenhorst (1998) provides evidence suggesting that European and US momentum strategies share a common component, indicating that exposure to a common factor may significantly influence the profitability of relative strength strategies.

Contrarian strategies involve assuming an opposing position to momentum strategies, also called return reversals. De Bondt and Thaler (1985) were among the first to argue that return reversals can outperform the market trend in the long term. The study reveals that portfolios comprising underperforming stocks demonstrate higher returns compared to portfolios of outperforming stocks after 36 months following portfolio formation. The loser stocks yielded approximately 25% higher returns than the winner stocks, despite the latter exhibiting a higher level of risk. They propose that positive abnormal returns in reversal strategies are exhibited three to five years after the portfolio formation. In later research, Jegadeesh and Titman (2001) report supportive findings. Their research examines the propositions of contemporary behavioral models, which suggest that momentum profits arise from delayed overreactions that are subsequently reversed. Moreover, the results indicate that there has been no discernible adjustment in market participants' investment actions to eliminate this source of predictable returns.

The findings of Conrad and Yavuz (2017) challenge the assertions made by Jegadeesh and Titman (2001) by demonstrating that momentum and contrarian strategies function independently within the US stock market, and there is no linkage between the two. Their research reveals that certain stocks exhibit short-term momentum without experiencing long-term reversals and vice versa. Specifically, stocks demonstrating momentum in the initial six months do not exhibit significant reversal over the long run.

Conversely, stocks displaying contrarian behavior in the first 6 months tend to show substantial reversals in the 12 to 24-month period. These results align with the conclusions drawn by Rouwenhorst (1998) in the context of European stock markets, where no significant relationship between momentum and contrarian was found. It is noted that stocks demonstrating true momentum do not exhibit long-term reversals after experiencing short-term momentum. Similarly, stocks categorized as contrarian continue to display reversal patterns in the long run after first gaining a short-term reversal. However, some studies argue for and against the connection between momentum and reversal, and it seems there are participants on both sides of the debate (Jegadeesh et al., 2022; Hofmann et al., 2022).

As presented, literature on return reversals has demonstrated the potential for generating abnormal returns over the long term. However, the reversal patterns over the short-term have also been a widely studied subject within market research. Fama (1965) was one of the first to study the predictability of stock market prices, and particularly in the 1990s, the topic has been the subject of extensive study (Jegadeesh, 1990; Lehmann, 1990; Jegadeesh and Titman, 1995b). The core concept of short-term reversal strategies suggests that stocks that performed poorly in the previous month or week are likely to outperform best-performing stocks in the next month or week. Jegadeesh (1990) finds that from 1934 to 1987, a short-term reversal strategy yielded an average return of approximately 2 percent per month.

Furthermore, Lehmann's (1990) study reveals that winners and losers from the past week typically exhibit a reversal of returns in the subsequent week, facilitating the potential for arbitrage opportunities. Lehmann's (1990) findings account for bid-ask spreads and transaction costs, demonstrating the robustness of these abnormal returns. In later research, Novy-Marx (2012) examines monthly stock returns from 1927 to 2010. This study finds that one-month lagged momentum returns yield on average -1.04 percent per month, reinforcing the existing evidence of reversal patterns in past returns.

These insights underscore the complexities of market behavior and the potential for contrarian strategies to capitalize on short-term inefficiencies.

The reasons for short-term reversals have been explored through the perspectives of investor behavior and social movements. One explanation suggests that investors tend to rapidly overreact to information, which may cause later price adjustments when the markets realize their overreaction. Shiller (1984) argues that investing in speculative assets is fundamentally a social activity, implying that investor behavior is often influenced by the social dynamics surrounding them. He states that investors may not always have a comprehensive understanding of the price determinants of speculative assets, so their decisions can be affected by social opinions to a considerable extent. Additionally, Subrahmanyam (2005) suggests that monthly return reversals are primarily influenced by changes in the beliefs and reactions of market participants to these changes. Jegadeesh and Titman (1995a) argue that short-term reversals are due to a delayed reaction to common factors and the tendency of stock prices to overreact to firm-specific information.

Another factor identified contributing to the short-term reversal of stock returns is the potential price pressure associated with stock liquidity. Jegadeesh and Titman (1995b) examine the short-term reversal of stock prices and find that short-term contrarian returns are mainly explained by the bid-ask spreads set by stock dealers. These price pressures and large bid-ask spreads often result from imbalances in liquidity providers' inventories. Jegadeesh and Titman (1995b) conclude that short-term negative serial covariances for stock returns can be primarily attributed to dealer-inventory-related market microstructure effects. These dealer-inventory imbalances can persist for several days. Therefore, liquidity providers are important in managing liquidity and maintaining market efficiency.

Research focusing on the Finnish stock market has been relatively limited compared to larger markets. Grinblatt and Keloharju (2000) study investment behavior around

momentum and contrarian in the Finnish stock market. They examine how previous returns influence investors' buying and selling decisions. It also examines whether the differences in investor knowledge impact their performance. The study uses daily stock return data from the period between the end of 1994 and the end of 1996. The findings reveal that foreign investors, who are mainly institutional, tend to follow momentum investment strategies. On the other hand, retail investors such as households mostly adopt long-term contrarian investment strategies in Finland. The study concludes that the momentum portfolios of foreign investors outperformed the contrarian portfolios during the data period. However, this conclusion can be at least partially explained by the herding behavior of large institutional investors, which can distort markets and drive momentum. According to Pätäri & Vilska (2014), the Finnish stock market is subject to intermittent peripheral syndrome, which means that the market is attributed to the collective behavior of institutional investors. This is reflected, for example, during periods of market turbulence, where these investors typically prioritize divesting their equity holdings from more remote stock markets.

Leivo (2012) examines the stock portfolio performance in the Finnish market between the period of 1993 and 2009. More specifically, he studies the performance of various portfolios in different stock market conditions. These portfolios are formed by using the momentum indicator combined with the value indicator as portfolio formation criteria. In the study, a group of Finnish non-financial stocks are categorized into three quantiles based on valuation multiples and composite value measures. These groups are then further divided based on a price momentum indicator. The study assesses the performance of these groups in terms of both their raw and risk-adjusted returns. Additionally, it examines how the stock market cycle affects the relative performance of these categorized groups.

The results indicate that integrating price momentum with relative valuation criteria enhances the performance of most value-only portfolios over the full sample period from 1993 to 2009. Notably, during bullish market conditions, incorporating a

momentum criterion offers value to investors, while in bearish conditions, this value diminishes. Despite the strong performance of value-winner strategies throughout the full sample and bullish periods, and their outperformance of the stock market average during bearish periods, they are not the most optimal strategies in bearish market conditions. In such scenarios, value-loser portfolios are more effective, particularly for strategies that exhibit strong performance over the entire sample period. Value-loser portfolios experience less decline in their value during bear market conditions and demonstrate lower volatility.

Grobys and Huhta-Halkola (2019) extend Leivo's (2012) study by examining value and momentum strategies within the Nordic stock market context. In addition to Finland, this study examines the stock markets of Norway, Sweden, and Denmark. The objective of the research is to assess the payoffs from value and momentum strategies in the developed Nordic stock markets. Their study includes long and short positions, enabling the formation of zero-investment or zero-cost portfolios. The results indicate that the value anomaly generates excess returns exclusively when the portfolio includes small-cap companies over the sample period. In contrast, when the portfolio consists solely of large-cap companies, the average payoff of the zero-cost strategy declines from 1.25% to 0.44%, failing to maintain statistical significance at the 5% confidence level. Conversely, the zero-cost portfolio derived from the momentum strategy demonstrates a robust average payoff of 1.72% per month when all stocks are included, while the monthly return decreases to 0.86% when the sample is restricted to large-cap stocks. Their findings suggest that the value premium is partially attributable to the size effect in Nordic markets, but it does not fully account for the phenomenon. Finally, they find that combining value and momentum strategies increases the Sharpe ratio, which offers diversification opportunities for investors.

## **1.2 Motivation of the study**

The assessment of risk factors within stock markets is widely recognized as a fundamental aspect of finance. As the markets evolve, identifying and quantifying

emerging risks presents ongoing challenges in modern finance. Debates have emerged regarding the appropriate risk factors for asset pricing and the assessment of the cost of capital. Fama and French (1992) proposed a three-factor model that has undergone refinements, with additional risk factors integrated to enhance asset pricing methodologies. Notably, Carhart (1997) expanded on Fama and French's three-factor model by introducing short-term historical stock returns (momentum) as a fourth risk factor, demonstrating that this enhancement increases the model's explanatory power concerning mutual fund performance. Since then, momentum has become one of the most extensively researched anomalies in financial markets and is frequently employed in asset pricing models and as an investment strategy.

While a large amount of research has been conducted on momentum and contrarian investment, there are still many areas regarding their underlying causes that warrant further exploration. Studies focusing on investor behavior and data snooping have been undertaken to explain market behavior and to identify predictive methods for forecasting future stock price movements. Although trends and productive strategies have been at least theoretically identified, it remains uncertain whether markets will adjust in such a way that these strategies will continue to be viable in the future. One assumption of the efficient market hypothesis suggests that, over time, markets will adapt to eliminate arbitrage opportunities, thereby preventing the consistent achievement of excess returns. Technological advances are expected to facilitate more efficient research, and enhanced access to information is likely to enable the exploration and formulation of new investment strategies. There remains a considerable amount to be explored in the field of finance, with ample opportunities for research into both existing and novel investment strategies. Additionally, understanding market behavior and the root causes of market inefficiencies is deemed essential.

The stock market research primarily focuses on major US and UK exchanges. While some studies examine smaller markets like the Finnish stock market, these markets are not as thoroughly investigated. This thesis aims to determine whether irrational behavior

persists in the Finnish stock market and to evaluate the potential for achieving excess returns in the 2010s through the application of short-term momentum and contrarian strategies, despite the long-standing recognition of these anomalies. Many studies have utilized momentum as a risk factor within asset pricing models. However, the discussion of risk factors and asset pricing models will be reserved for further research in this paper.

### **1.3 Limitations of the study**

Caution should be exercised when reading this work. This document is a final thesis and is not meant to be used as any investment advice. Limitations inherent to this work may result in the documented outcomes differing in practice from their theoretical predictions. A more detailed discussion of some of these limitations and their potential impact on the results presented in the thesis will be provided in this section.

First, while literature often discusses the potential of momentum and contrarian strategies to generate excess returns, the costs associated with implementing these strategies significantly reduce the achievable gains. Specifically, maintaining short-term investment strategies involves frequent buying and selling of stocks, resulting in transaction costs that may render these strategies impractical, especially for individual investors.

Some stocks may occasionally show low trading volumes on the Finnish stock exchange. Such low volumes can lead to liquidity issues that affect stock prices. When trading volumes decrease, larger bid-ask spreads can occur. As a result, sellers may have to lower their asking prices due to a lack of buyers, or buyers may feel compelled to pay overprice because there aren't enough sellers. When the number of buyers and sellers does not match, the actual price of a stock transaction may differ from what is expected in a state of supply and demand equilibrium. Some also argue that an increase in trading volume indicates a strengthening trend, where stock prices can rise excessively, whereas a decline in volume signals a weakening trend. However, this study employs monthly stock returns, as the challenges related to liquidity and volume should not significantly impact

the results. These issues would likely have more relevance if daily or weekly stock price data were used.

Lastly, seasonality biases identified in the market may contribute to some extent to the findings of this study. Jegadeesh (1990) and Jegadeesh and Titman (1993) observe an exceptional trend in momentum returns in January, indicating that momentum returns are influenced by a reversal during this month. This phenomenon is known as the January effect and has gained attention since then. Their studies report that winner stocks typically outperform loser stocks in all calendar months except January, where loser stocks tend to rebound and outperform winner stocks. Similarly, Heston and Sadka (2010) investigate whether past stock returns can predict future performance. Their findings align with those of Jegadeesh (1990) and Jegadeesh and Titman (1993). It is discovered that stocks that perform well in one calendar month are likely to outperform again in the same month one year later. Conversely, stocks that underperform in a specific month tend to continue underperforming in that same month in the following year. Heston and Sadka (2010) report that strategies based on seasonal biases can yield returns of up to 1% more per month compared to some non-seasonal strategies and that this seasonal correlation can persist for up to five years.

Seasonality biases are more widely recognized and have been later examined, for example, by Gong et al. (2015). They investigate seasonality in stock returns, demonstrating that returns from 12 months prior to portfolio formation exhibit a strong positive correlation with returns one year later. Therefore, Gong et al. (2015) recommend that stock returns from 12 months before portfolio formation should be excluded from the intermediate performance analysis due to their overestimation of future performance and tendency to skew the results. Seasonal biases may have a weak but not significant impact on the overall results of this study. However, awareness of this factor should be maintained when interpreting the findings.

## 1.4 Research question and hypothesis

According to the efficient market hypothesis, all available information is already reflected in current stock prices, making it impossible to outperform the market using historical data. However, momentum and contrarian strategies have demonstrated the ability to generate positive excess returns not only in equities but also across various other asset classes and different geographical areas. This study aims to challenge the efficient market hypothesis by using technical analysis to investigate potential patterns in stock returns. The purpose is to determine whether market inefficiencies still exist in the Finnish stock market or if the market has adjusted so that the potential for excess returns through momentum or contrarian strategies has diminished. This thesis examines whether short-term continuity or reversal patterns exist in the post-financial crisis era in the Finnish stock market, despite significant attention given to these anomalies and their potential for generating excess returns. This study also compares momentum and contrarian strategies to establish the most profitable ones.

Jegadeesh and Titman (1993; 2001) state that momentum effects are typically strongest approximately one year from the portfolio formation. This study employs a similar methodology to assess the effectiveness of momentum and contrarian strategies by sorting stocks into winners and losers based on their performance over a specified time horizon. In an efficient market, the potential for any form of excess returns should eventually be eliminated. Therefore, the null hypothesis tests whether short-term strategies based on momentum or contrarian anomalies still have the potential to gain excess returns in the Finnish stock market in the 2010s. The null hypothesis is stated as follows:

*$H_0$  = Any of the tested momentum or contrarian strategies cannot generate positive excess returns, therefore, markets are efficient.*

The alternative hypothesis is accepted if one or more tested strategies based on historical data can generate positive excess returns. This outcome would suggest that

strategies grounded in historical information can be effectively employed to achieve excess returns, indicating a degree of market inefficiency. The alternative hypothesis is stated as follows:

*H<sub>1</sub> = One or more momentum or contrarian strategies can produce positive excess returns, indicating a degree of market inefficiency.*

## **1.5 Structure of the study**

The remainder of the study will be structured as follows: The next main section will present the financial theories and concepts relevant to the research. The third chapter will introduce the data and methodology employed in the empirical study, including the formulas used and the construction of the portfolios. The fourth chapter will present the results of the research on various strategies. Finally, chapter five will draw conclusions based on the findings.

## **2 Concepts of the Study**

### **2.1 The Efficient Market Hypothesis**

Market efficiency is a key topic within financial studies, as it notably influences asset pricing. The underlying expectation is that if markets adequately reflect all available information relevant to asset prices, the prices will align with their true values. One of the seminal contributions to this field was made by Fama (1970), who introduced the Efficient Market Hypothesis, laying the groundwork for understanding the dynamics of market efficiency. Fama (1970) defined efficient markets into three distinct categories: weak-form efficient markets, semi-strong-form efficient markets, and strong-form efficient markets.

#### **2.1.1 Three Forms of Market Efficiency**

The weak form of the efficient market hypothesis asserts that current stock prices reflect all available market information, rendering historical data ineffective in predicting future price movements. This perspective suggests that past price trends and trading volumes do not provide any advantage for forecasting future performance. As a result, the potential for deriving abnormal profits through technical analysis is essentially negated, given that all pertinent information has already been assimilated into current prices.

The semi-strong form of the efficient market hypothesis suggests that all publicly available information is already fully reflected in current stock prices. This concept means that security prices quickly react to new public information. It encompasses market-related data and other relevant public information accessible to investors. Consequently, the semi-strong form implies that investors cannot achieve excess returns through fundamental or technical analysis. For example, the hypothesis assumes that the financial statements of companies are not reliable indicators of future performance since their contents are expected to already be integrated into current stock prices.

Strong-form market efficiency asserts that stock prices fully incorporate all available information, encompassing public and private information. This formulation suggests that security prices reflect every conceivable type of information, such as market insights, publicly accessible data, and insider information. The theory operates under the premise of perfect markets, where all relevant information is freely accessible and uniformly available to all investors. Consequently, the strong-form states that insider information is wholly integrated into stock prices alongside public information. As a result, no group of investors can consistently achieve excess returns, even if they possess exclusive access to information that may affect prices.

In summary, to advance to the next level of the efficient market form, the conditions of the previous level must be met. For instance, to achieve a semi-strong form, the conditions of the weak form must first be satisfied. Similarly, to reach the strong-form of market efficiency, the conditions of the semi-strong form need to be fulfilled. While these concepts are valued in theory and commonly employed as a standard in research, it is crucial to acknowledge that their practical applicability may be limited and that they have faced criticism. Studies have demonstrated that the notion of efficient markets is more of an ideal than a reality, as the conditions necessary for efficient markets are seldom fulfilled. Among others, obstacles to fulfilling these conditions include behavioral anomalies, irrational decision-making, transaction costs, and the unequal distribution of information among market participants.

### **2.1.2 The Random Walk Theory**

The random walk theory gained traction after Malkiel (1973) introduced the theory in his book "A Random Walk Down Wall Street". The term "random walk" refers to the notion that stock price changes occur in a random sequence, where each subsequent price change is an independent deviation from previous prices. This theory posits that when information flows freely and is instantly incorporated into market prices, the price changes observed tomorrow will be influenced solely by news available at that time, making them independent of today's price movements. Since news events are inherently

surprising and unpredictable, the resultant price changes are also unpredictable and random. Under these assumptions, market prices reflect all available information, allowing investors, regardless of their experience level, to achieve similar returns as professional investors by purchasing a diversified portfolio of stocks at current market prices. In conclusion, stock price movements occur randomly, indicating that historical information does not influence future prices. Therefore, price movements are inherently unpredictable, meaning past data offers no reliable indicators for forecasting future prices. According to the theory, neither fundamental nor technical analysis can consistently outperform the market or accurately predict future stock prices in the long run.

Economists and psychologists studying financial behavior have examined models based on the actions of market participants. Many studies have uncovered findings that challenge the random walk theory. For example, Lo et al. (1998) and Lo and MacKinlay (1999) argue that stock markets are at least partially predictable. While Malkiel (2003) supports his theory of random stock price movements, he points out certain phenomena that can disrupt efficient markets temporarily, though not permanently. He explores short-run momentum and identifies the "bandwagon" phenomenon as one of the patterns that may distort financial markets. This phenomenon typically occurs when individuals observe a rising stock price and anticipate that the upward trend will persist, consistent with the underreaction theory. As a result, the stock may become temporarily overpriced, but efficient markets will quickly adapt and fix any temporary inefficiencies that arise. Malkiel (2003) also emphasizes that given transaction costs associated with active portfolio management, it is unlikely for any investor to consistently outperform the market or achieve better profit than using a traditional passive buy-and-hold strategy.

The bandwagon phenomenon is only one of several market biases identified in financial literature. Malkiel (2003) recalls that market efficiency is not always achievable, as demonstrated by historical events such as the internet bubble in the late 1990s. Malkiel (2003) recognizes the possible impact of psychological factors on stock valuation, citing

Graham (1965), who distinguishes between stocks acting as a "voting mechanism" in the short term and as a "weighing mechanism" in the long term. This distinction highlights that short-term stock price movements are often influenced by the emotional states of investors, which can be volatile. In contrast, the "weighing mechanism" suggests that stock values can be measured more accurately and reliably over an extended period. Consequently, long-term analysis is generally less affected by psychological influences, facilitating a more precise assessment of a stock's intrinsic value.

In the discussion of previous studies, we identify the existence of various market inefficiencies in stock markets, particularly over recent and intermediate time horizons. However, Malkiel (2003) argues that investors are unable to reliably exploit these potential market inefficiencies. He expresses skepticism about the durability of any anomaly or predictable pattern that could generate excess returns. According to Malkiel (2003), markets should inherently react and eliminate the possibility of such excess returns once a potential pattern has been identified and published. As a result, he concludes that stock markets are more efficient than suggested in some of the recent academic literature. He highlights that only a small number of professionals have been able to outperform the market over the long term. For the average investor, the costs associated with active portfolio management likely negate the opportunity for exceptional risk-adjusted excess returns. He advocates for a long-term, moderate investment approach rather than short-term trading.

Efficient market theory and the concept of stock price randomness have been the focus of extensive research, particularly over the last two decades. This surge in interest can be attributed to technological advancements that have enhanced the tools available for both technical and fundamental analysis. In the early 2000s, support for efficient market theory began to wane as financial and statistical analysts increasingly argued that stock prices are at least partially predictable. Many highlighted the influence of psychological and behavioral factors in determining stock prices, suggesting that historical price movements and certain valuation measures could be used to identify patterns and

trends. Critics have also pointed out that the theory oversimplifies the complexities of financial markets. A key assumption of the random walk hypothesis is the equal distribution of information among market participants. However, this principle is often undermined in practice, as large institutional investors typically have access to superior information than retail investors. This disparity can lead to an uneven playing field, challenging the notion of market efficiency.

National and international laws and regulations are designed to enhance market efficiency and integrity. A key focus of these laws is to require companies to disseminate information about their activities in a manner that is accessible and available to all stakeholders simultaneously. This commitment to transparency is becoming increasingly vital in today's business landscape, underscoring the importance of ethical business practices. In Finland, the Finnish Securities Market Act governs the stock market, promoting market efficiency and fostering trust among market participants. It has an impact on critical issues such as the agency problem, reinforcing the need for responsible corporate conduct.

While efficient market theory and the random walk hypothesis have faced criticism, many still acknowledge their core principles. The prevailing view suggests that markets may operate efficiently over the long term but can exhibit inefficiencies in the short term. Research has shown that short-term inefficiencies and irrational behavior in markets can occur occasionally and can be influenced by factors such as overconfidence, herding behavior, loss aversion, and various event-driven phenomena, including earnings surprises and geopolitical developments. Additionally, stock market liquidity has been seen to play a role in market efficiency. Typically, large-cap stocks demonstrate more efficient behavior compared to less liquid small-cap stocks and those in emerging markets. Although stock prices may briefly deviate from their fundamental values, they tend to self-correct over time. At least theoretically, efficient markets should eliminate opportunities for excess returns once a continuity pattern or trend is identified and publicized. This study aims to explore these concepts by employing technical analysis to

determine whether the Finnish stock market presented opportunities for excess returns in the 2010s through momentum and contrarian strategies.

## **2.2 Momentum and Contrarian Anomaly**

Many anomalies and patterns discovered in financial markets have gradually disappeared over time. This observation aligns with the assumption of efficient markets, which posits that such distortions and opportunities for excess returns should be eliminated. However, short-term return continuations and reversals continue to persist, indicating the presence of opportunities for excess returns. Investment strategies based on these anomalies have consistently demonstrated the ability to generate excess returns across various stock markets, even though numerous studies have widely recognized their existence. This section explores various momentum and contrarian strategies, which will be further tested with empirical research later in this paper. For momentum strategies, this thesis focuses on standard momentum, recent past performance, and intermediate past performance. Regarding contrarian strategies, this thesis examines the short-term reversal effect. In reviewing the short-term reversal effect, we also study returns based on past performance over a single month. Of particular interest is whether a change in pattern is observed one year after the portfolio formation.

### **2.2.1 Momentum**

Momentum investing is an investment strategy that seeks to take advantage of ongoing trends in stock prices. The fundamental concept of momentum investing posits that securities that have shown strong performance in the past, referred to as "winners", are likely to keep performing well in the near term. Meanwhile, those who have struggled, referred to as "losers", are expected to continue their poor performance. This strategy differs from the conventional view of stock price movements, which assumes that prices fluctuate randomly and do not display consistent trends. Typically, momentum investing focuses on medium-term trends, where investors buy stocks after they have

demonstrated good performance over three to twelve months before a portfolio formation and sell them once they show signs of a downturn. In the financial literature, it is found that momentum has been most profitable during the medium-term horizon. The persistence of momentum can be partially attributed to behavioral finance theories, which highlight factors such as investor psychology and herding behavior. Investors may underreact to new information, allowing prices of winning stocks to trend upward and those of losing stocks to decline. Furthermore, investors often become overly optimistic about stocks that have performed well, which can reinforce these upward trends.

To implement momentum investing, investors commonly use algorithms and technical analysis to identify stocks with strong recent performance and predict the continuation of these trends. Using the past data, stocks are ranked in ascending order based on their returns over a specified period. These stocks are typically categorized into three to ten portfolios depending on the investment strategy. The lowest-ranked portfolio is called the losers portfolio, while the highest-ranked one is known as the winners portfolio. Some strategies also incorporate middle portfolios for additional diversification. In momentum investing, investors generally buy and hold the winner stocks for a predetermined period, based on their strategies, and sell them once their value has increased to a satisfactory level. This investment cycle may be repeated daily, weekly, or monthly, depending on the chosen approach. Momentum investing focuses primarily on buying and selling winner stocks. This method is often utilized by individual investors as a long-only strategy. A more advanced approach might involve creating a "zero-cost portfolio," which includes both buying winner stocks and short-selling loser stocks simultaneously. The idea of short selling is to profit from the decline in the value of underperforming stocks. However, short selling carries significant risks as it, at least theoretically, exposes the investor to unlimited losses.

Research, including the notable study by Jegadeesh and Titman (1993), has shown that momentum strategies historically can provide significant positive returns, even when adjusted for risk. This evidence has established momentum investing as one of the most

widely studied and applied anomalies within financial markets. The research conducted by Jegadeesh and Titman (1993) is regarded as a seminal work in the field of momentum research in finance. They study momentum in the US market from 1965 to 1989, using data from stocks listed on the AMEX and NYSE exchanges. Their study ranks stocks into ten equally weighted portfolios based on their returns over the 12 to 3 months before the portfolio formation. Specifically, stocks are ranked based on returns over three, six, nine, and twelve months before the portfolio formation. The holding periods correspond to these intervals, creating 16 distinct investment strategies. Portfolios are reconstructed monthly, involving overlapping test intervals. The results indicate that winner stocks maintain their positive performance, significantly outperforming loser stocks in the following year. Their 6x6 strategy yields approximately 1% per month, while the most profitable strategy, 12x3, yields an average of 1.49% per month during the data period.

Jegadeesh and Titman (1993) argue that profits from these strategies cannot be adequately accounted for by variations in systematic risk between historical winners and losers, nor by differences in the timeliness of price adjustments to common factors. Instead, they argue that the evidence supports that these profits result from a lagged price response to firm-specific information. Their analysis reveals that, except for the initial month, profits remain positive across each month in the 12 months succeeding a six-month ranking period. Nonetheless, they highlight that over the subsequent two years, the strategy gradually forfeits 50% of its initial profits. It is important to note that the month immediately before portfolio formation is intentionally excluded from the analysis, as it has been demonstrated to exhibit an inverse return behavior. This phenomenon is referred to in the literature as the short-term reversal effect, which will be addressed in more detail later in this section. Momentum research that skips the initial month before portfolio formation and evaluates stock performance over 12 to 2 months is commonly identified in the literature as the standard momentum strategy.

Lui et al. (1999) study price momentum in the UK stock market from 1977 to 1998. They use a method similar to Jegadeesh and Titman (1993), dividing the ranking and holding

periods into quarters, which creates 16 trading strategies. They examine two sets of strategies: one where the holding period starts right after the ranking period and another that includes a one-week break between the ranking and holding period to account for any short-term reversal. To strengthen their findings, Lui et al. (1999) examine momentum profits across different periods, seasonal trends, and company characteristics such as size, price-to-book ratios, and earnings-to-price ratios. They control for various risk factors and use regression analysis to separate the effects of momentum strategies from other return factors. Their results show strong and consistent momentum profits in UK stocks that are not linked to common factors like size, value, or price anomalies. The sub-period analysis reveals that these momentum profits continue over time and are not limited to specific market situations or seasonal changes. Authors show that these returns are not due to delays in price reactions to overall market information or correlations with common risk factors. Instead, the findings indicate that momentum profits result from market underreaction to firm-specific or industry-specific information, similarly documented by Jegadeesh and Titman (1993). This underreaction causes a delay in price adjustment, which creates opportunities for momentum strategies to succeed.

Jegadeesh and Titman (2002) present a comprehensive update to their momentum research nearly a decade after their initial publication. This latter study explores various explanations for the profitability of momentum strategies by constructing portfolios based on stocks' recent past performance, specifically using a ranking criterion based on the stock's performance over the last six months. Notably, they retain the most recent month before portfolio formation, even though this period has been observed to exhibit reverse return patterns in the literature. Following the establishment of these portfolios, they are held for six months. This analysis uses overlapping portfolios to get more observations and strengthen the results. The findings of this study indicate that the market has not experienced significant adjustments that would diminish momentum-based return opportunities, even a decade later. However, momentum returns appear to have strengthened compared to earlier periods. From 1965 to 1989, the winner-loser

portfolio generated an average return of 1.17% per month. Respectively, from 1990 to 1998, winner-loser portfolios produced an average return of 1.39% per month, with t-statistics being significant at both 5% and 1% significance levels. The authors conclude that the persistence of these results over the intervening decade reinforces the conclusion that the observed outcomes are not merely the result of data mining or data snooping biases.

Where recent past performance assesses stock returns primarily based on their performance over the last six months, intermediate past performance considers the period from 12 to 7 months before portfolio formation, skipping the most recent six months. Novy-Marx (2012) examines the momentum returns associated with these two approaches in the US stock market. He contends that the effectiveness of recent past performance has declined, whereas intermediate past performance has shown significantly better predictive power. According to Novy-Marx (2012), strategies based on recent past performance were effective during the 1950s and 1960s, but their efficacy has diminished in subsequent decades. Novy-Marx (2012) points out that over the past 40 years, strategies centered on intermediate past performance have consistently outperformed those that rely on recent past performance. He also emphasizes that intermediate horizon strategies can achieve Sharpe ratios up to twice as high and demonstrate stronger information ratios than strategies based on recent past performance. Ultimately, Novy-Marx (2012) concludes that the momentum is mainly driven by a company's performance during the 12 to 7 months before the portfolio formation rather than by its performance in the past 6 to 2 months. He addresses that the largest and most liquid stocks usually contribute the most to intermediate past momentum profits.

Gong et al. (2015) build upon Novy-Marx's (2012) momentum study by examining intermediate and recent past performance in the US and 26 other international stock markets. They identify biases related to the ranking periods used in common momentum research. First, in the 12-7 ranking period for assessing intermediate past performance,

Gong et al. (2015) find that the returns from the 12th month before portfolio formation can skew the results. This is because that month has been observed to exhibit a strong positive correlation with returns in the same calendar month one year later. Essentially, stocks tend to show similar performance patterns in the same month each year. This phenomenon is known in the financial literature as the "12-month effect," first described by Jegadeesh (1990). In simplest terms, this means that stocks tend to consistently have high or low returns during the same month each year. Second, in the 6-2 ranking period for evaluating recent past performance, authors observe that the returns in the second month before portfolio formation behave similarly to those in the first month before formation. Although the return reversal seen in the second month is not as pronounced as in the first, it still can influence the overall results. To mitigate these biases, Gong et al. (2015) exclude the returns from the 12th month and the 2nd month before portfolio formation in their momentum analysis.

In the study by Gong et al. (2015), they develop intermediate and recent past momentum strategies by dividing stocks into deciles according to their cumulative returns over 12-7, 11-7, 6-2, and 6-3 months before portfolio formation. The top and bottom deciles from each ranking period create zero-cost momentum portfolios. This approach involves purchasing stocks in the top decile while simultaneously selling short those in the bottom decile. The holding period for the stocks is one month, and portfolios are reconstructed every month. The authors then calculate both the equal- and value-weighted average monthly returns for the portfolios, along with t-statistics for all intermediate and recent past momentum portfolios.

It is documented in the financial literature that momentum strategies usually do not perform well in January due to the January effect. Gong et al. (2015) provide evidence for this phenomenon in their research. They find that all four intermediate and recent past momentum strategies have negative returns in January, with all but one being statistically significant at the 5% level. The 12-7 strategy, which includes the returns from the twelfth month before the portfolio formation, had the smallest losses in January.

Outside of January, all four momentum strategies show strong results, generating positive raw and risk-adjusted returns of around 1% per month, each being statistically significant at the 5% level. These results are consistent with the study by Yao (2012), who find that based on raw returns of common stocks from the US stock market, the seasonal effect in January significantly contributes to the better performance of the intermediate past momentum strategy than the recent past momentum strategy.

After controlling for size and constructing quintiles based on a firm's market capitalization, Gong et al. (2015) find that the equal- and value-weighted excess returns in the 12-7 strategy are higher across all size quintiles than in the 11-7 strategy, indicating the 12-month effect. Excluding the 12th month from the ranking period results in a small return reduction in the 11-7 strategy. In contrast to the behavior in the intermediate past performance, omitting the second month before portfolio formation from the stock ranking period increases returns within the recent past performance strategy. The 6-3 strategy yields higher returns than the 6-2 strategy, suggesting that the stocks exhibit short-term reversal movement also in the second month before the portfolio formation.

Afterward, it can be stated that estimation bias concerns Novy-Marx's (2012) research, where he argues that intermediate past performance outperforms recent past performance in the US stock market. Due to seasonality and the 12-month effect, intermediate past momentum is overestimated when the twelfth month before the portfolio formation is included in the portfolio ranking period. Estimation bias also appears in the recent past performance strategy, where the second month before the portfolio formation is included in the ranking period. This underestimation is due to the short-term reversal effect, where returns tend to behave inversely. When those months are excluded from these two momentum strategies, the difference between intermediate past and recent past momentum returns is small and insignificant (Gong et al., 2015). Also, the standard 12-2 momentum strategy can be improved when the second month before the portfolio formation is left out.

### 2.2.2 Contrarian

When discussing market trends, momentum investing typically takes advantage of upward movement in stock prices, while contrarian investing adopts an opposing strategy. Contrarian investors focus on buying underperforming stocks and selling outperforming ones. The idea behind this approach is that underperforming, or “loser” stocks, are often undervalued and have the potential for future growth. In contrast to momentum, contrarian investors believe that outperforming stocks have become overpriced and are likely to decrease in value. Contrarian strategies suggest going against the prevailing market trend, where winner stocks are typically sold, and loser stocks are bought. Research in financial literature indicates that contrarian strategies can yield significant returns over the short- and long-term, but have not been profitable in the medium-horizon, typically between 3 to 24 months before the portfolio formation. Strategies that are based on short-term past performance, typically for performance of less than two months before the portfolio formation, have been able to generate abnormal returns.

Contrarian strategies have been successful in generating positive excess returns one month before portfolio formation by taking advantage of the short-term reversal effect (Jegadeesh, 1990). Additionally, they have shown effectiveness in the long term, achieving excess returns three to five years after the contrarian portfolio is established (De Bondt & Thaler, 1985). However, in this study the emphasis is primarily on short-term reversals.

Jegadeesh (1990) investigates stock predictability using monthly returns on individual stocks from 1934 to 1987. The study finds evidence of short-term return reversals. The results indicate that the monthly returns of individual stocks exhibit a significantly negative first-order serial correlation and a significantly positive higher-order serial correlation. Negative serial correlation suggests that returns exhibit cyclical behavior over time, meaning that high returns are typically followed by lower returns and vice versa. In contrast, a positive serial correlation indicates that the variables tend to move

in the same direction in future periods. The study reveals that extreme decile portfolios, based on past performance, show abnormal returns of up to 2.49% per month during the data period. The difference between abnormal returns from extreme decile portfolios constructed using 1-month and 12-month lagged returns are 1.99% and 0.93% per month, respectively. It is also noteworthy that the pattern of serial correlation in January differs significantly from that observed in other calendar months. Considering these findings, Jegadeesh (1990) rejects the null hypothesis that stocks follow a random walk. He concludes that stock predictability may be linked to market inefficiencies or systematic changes in expected returns, leaving room for future research on the factors that cause predictability in stock markets.

The overreaction theory in the stock market raises important considerations about its impact on the prices of various securities. Consequently, well-diversified equity portfolios comprised of both winner and loser stocks are expected to show some return reversals in stock market conditions. Lehmann (1990) explores the efficient market hypothesis and examines possible arbitrage opportunities by studying historical security prices. He constructs a zero-cost portfolio that buys winners and sells losers. According to the efficient market hypothesis, such zero-cost portfolios should produce zero abnormal returns. However, it has been noted that these portfolios can benefit from a reversal of returns over time when stock prices show signs of overreaction.

Lehmann (1990) examines weekly returns and discovers that stocks classified as winners in one week usually incur negative returns between -0.35% and -0.55% the following week. In contrast, loser stocks from the previous week often produce positive returns in the next week, averaging from 0.86% to 1.24%. This indicates strong and persistent negative serial correlation and reversal in short-term returns. Lehmann (1990) offers a possible explanation for the observed short-term reverse in returns, identifying a liquidity imbalance in securities. He points out that the differing bid-ask spreads between impatient and patient traders might lead to irrational price movements,

especially in illiquid stocks. The findings of this research likely reflect the liquidity inefficiencies present in some stocks.

In a study conducted almost 30 years later, Cheng et al. (2017) also found a relationship between stock liquidity and return reversals. Their study examines cross-sectional variations in monthly contrarian profits within equity markets. The findings indicate that stocks that underperform in the three months before portfolio formation (from  $t-3$  to  $t-1$ ) are likely to experience return reversals two months after (during months  $t$  and  $t+1$ ). The research demonstrates a connection between these findings and fluctuations in the number of active investors in the stock, which in turn affects liquidity provision. The study indicates that drops in stock prices over the past quarter are linked to a reduction in participation from institutional investors during that same period. This decrease is associated with notable increases in reversal-based profits in the subsequent two months.

Cheng et al. (2017) reveal that the decline in the number of active institutional investors over the past is associated with an increase in monthly reversals. This phenomenon, at least partially, results from the law of supply and demand. When large institutions sell great quantities of certain stocks, the supply increases, often leading to a temporary fall in their prices. In other words, short-term reversals tend to be higher when there is a decline in active institutions that provide liquidity to the market. However, the study shows that underperforming stocks in the monthly contrarian strategy do not exhibit higher abnormal profits compared to outperforming ones, and long positions in underperforming stocks do not primarily drive profits from the contrarian strategy. This indicates that the results cannot be solely explained by price pressures resulting from large institutional selloffs in those underperformers. While other explanations might explain some of the findings, the overall evidence supports the idea that changes in the number of active institutions that provide market liquidity influence the dynamic variations, hence affecting the reversal profits.

In addition to liquidity issues, a second possible explanation presented for short-term return reversals is the overreaction to firm-specific information. One of the earliest contributions to the modern financial literature on how social behavior affects asset pricing is by Shiller et al. (1984). They contend that stock prices are particularly vulnerable to social influences due to the absence of a universally accepted framework for assessing their value and the unpredictability associated with altering investment strategies. Many ordinary investors possess either an incomplete model or no model at all for understanding the behaviors of prices, dividends, or earnings related to speculative assets. For instance, it remains often uncertain how the election of a US president or fluctuations in oil prices will affect the earnings of a particular stock or industry. Investors often lack objective criteria to answer these questions. Consequently, the formation of their opinions may be significantly shaped by social dynamics. Extensive research in social psychology has explored the extent to which individual opinions are affected by the views of others, with various experiments illustrating these influences.

Shiller et al. (1984) investigate the relationship and overreaction of dividends to stock prices. They find that news of dividends indicates an overreaction to stock prices, with the forecasting equations for returns aligning with this notion of overreaction. An alternative interpretation of the observed correlation between dividends and prices could be that companies setting dividend policies are also affected by the same social dynamics that shape broader societal behaviors. Additionally, various other interpretations may explain this correlation. The authors present their study as a means of reinforcing the idea of overreaction based on qualitative evidence while acknowledging the complexity of the relationship. Thus, it is reasonable to anticipate that social dynamics play a substantial role in the fluctuations of stock prices, as evidenced by observations of market participants and supported by literature on social psychology.

De Bondt and Thaler (1985) examine the long-term reversals associated with overreaction and stock returns. Their findings indicate that loser portfolios consistently

outperform winner portfolios, particularly over a holding period of three to five years. Specifically, they observe that three years after the portfolio formation, loser stocks generate returns approximately 25% higher than winner stocks during the same interval. Moreover, their study highlights that winner portfolios carry higher risk, as winner stocks are often overvalued, leading to greater potential for downside risk than loser stocks over the long term. De Bondt and Thaler (1985) also emphasize the significant excess returns linked to the loser portfolio, especially in January, which continue to persist even five years after the initial portfolio formation. They conclude that experimental psychology indicates most people often overreact to surprising and dramatic news, which contradicts Bayes' rule.

Studies have demonstrated that overreaction can be a gradual, long-term phenomenon, as illustrated by De Bondt and Thaler (1985). Overreaction has also been examined to impact stock prices in the short-term. Human behavior theories are proposed as at least one explanation for short-term overreaction. Investors often tend to excessively emphasize recent information while neglecting the overall picture. This behavior is closely tied to Kahneman and Tversky's (1973) theory of representative heuristics, which suggests that individuals often make decisions by relying on preexisting stereotypes or courses of action. This theory also highlights that people tend to react to an uncertain event in a similar way to the majority, thereby giving insufficient weight to pertinent information. Consequently, investors influenced by this heuristic may over- or underreact to various market signals.

Further research by Barber and Odean (2008) supports these findings, focusing on attention-driven trading. Their study reveals that investors often face many stocks to choose from, which can lead uninformed investors to make irrational purchases. They often end up choosing stocks that have recently garnered attention, experienced significant trading volume, or featured on best-performing lists. This trend of net buying in attention-grabbing stocks can exert excessive upward pressure on market prices. As a result, short-term price reversals may occur when the market misprices a stock, causing

it to become overbought or oversold. Opportunities for abnormal returns may occur when the stock price realigns with its intrinsic value.

Novy-Marx (2012) investigates the predictability of stock performance by employing ranking criteria based on the stock's past performance over a single month. He ranks stocks into deciles using monthly lagged data from the first month to the fifteenth month before portfolio formation. The findings indicate that the one-month lag ( $t-1$ ) return reversal is strong and highly volatile, signifying a short-term reversal effect. Another observation from the research is that the average returns associated with the strategy demonstrate an upward slope as the lagged period moves further from portfolio formation. Therefore, Novy-Marx (2012) suggests that momentum returns are predominantly influenced by intermediate past performance. Furthermore, an observation regarding the reversal of returns is that precisely one year after portfolio formation, momentum returns experience a substantial reversal. Notably, a zero-cost portfolio composed of winner and loser stocks in the thirteenth month before portfolio formation produces negative momentum returns but positive contrarian returns. This inverse return pattern persists until the fifteenth month of the study. Novy-Marx (2012) concludes that the predictability of returns ceases after one year, at least when controlling for the Fama-French factors.

Interesting in Novy-Marx's (2012) findings is the momentum crash that occurs one year after the portfolio formation. It seems that this is not much discussed in the literature, and an explanation for this phenomenon is not readily available. This phenomenon may be related to investors rebalancing their momentum portfolios. Since the ranking criterion in the stock-picking process of the momentum strategy generally remains within a maximum of one year from the time of portfolio formation, rebalancing of portfolios may have an irrational impact on stock prices after one year. When large institutional investors form their momentum portfolios, this may cause artificial price distortions. Such a phenomenon is referred to in the literature as crowded trades, meaning that it is a position with a high ratio of active institutional investor involvement

relative to the stock's liquidity. This may be reflected in the fact that when investors follow a momentum strategy that divides stocks into winners and losers, these extreme deciles are subject to high buying and selling pressure at the same time. When this pressure settles over time, it can be reflected in a short-term reversal of returns, with loser stocks rebounding better than winners. This result reinforces that momentum primarily operates over a medium-term horizon, typically within a year, and does not function in the 1, 2 or 13 months before portfolio formation. For a short-term contrarian investor, this strategy could be profitable.

### **3 Data and Methodology**

#### **3.1 Data**

The data in this thesis includes 81 stocks that have been publicly listed on the Nasdaq Helsinki stock exchange for the entire sample period. It comprises monthly closing prices for these stocks from January 2009 to December 2022. This data period begins after the financial crisis and extends over the subsequent 14 years. Within this timeframe, a significant instance of market turbulence, COVID-19, occurred at the end of the data period. The stock data is sourced from the Orbis database and cross-verified with Kauppalehti Online. The monthly closing prices are adjusted for dividends and stock splits. Finland's 10-year government bond yield serves as the risk-free rate for this observation period, which is obtained from the Finnish Bank. The OMXH25 index is used as a benchmark to compare the results from the strategies in this study.

It should be noted that the data includes stocks that are less liquid than others (i.e., stocks with lower trading volume). Depending on demand, these stocks may experience price pressure over time, which could lead to potential sales at prices either lower or higher than their intrinsic value. Consequently, bid-ask spreads may have a small but relatively insignificant impact on the findings. The data used in this thesis is collected monthly, making the prices less susceptible to liquidity issues compared to daily prices. Moreover, these issues are more pronounced in the Finnish stock market due to its lower trading volume relative to larger markets like the US.

#### **3.2 Methodology**

Momentum and contrarian strategies involve three main components: a stock formation or ranking period, a holding or investment period, and specific ranking criteria. In this study, all 81 stocks are sorted in increasing order based on their cumulative returns in each ranking period. During a given ranking period, the nine worst-performing stocks end up in the loser's portfolio, while the nine best-performing stocks form the winners'

portfolio. Again, momentum strategies involve purchasing stocks that have outperformed and selling those stocks that have underperformed. In contrast, contrarian strategies take the opposite approach by buying the underperforming stocks and selling those that have performed well. This study employs the two portfolios to construct a zero-cost or zero-investment portfolio, with the return calculated as the difference between the two portfolios, depending on which strategy is tested. In momentum strategies, the return on a zero-cost portfolio is calculated by subtracting the loser portfolio from the winner portfolio (winner-loser). Conversely, the return on a contrarian strategy is determined by subtracting the winner portfolio from the loser portfolio (loser-winner). In addition to the analysis of zero-cost strategies, the individual performance of various winner and loser portfolios is reported.

### 3.2.1 Formulas

This study employs the simple return method, which calculates returns based on the monthly price changes of individual stocks. The returns are expressed as a percentage. The monthly return ( $r$ ) for each stock ( $i$ ) at time ( $t$ ) is calculated as follows:

$$(1) \quad r_{i,t} = \left( \frac{P_t}{P_{t-1}} - 1 \right) * 100$$

**Formula 1.** Monthly return of stock ( $i$ ) at time ( $t$ ).

Where  $P_t$  is the price of a stock ( $i$ ) at time  $t$ .  $P_{t-1}$  is the price of a stock ( $i$ ) in the previous month. To get the percentage return, this monthly price change is subtracted by one and multiplied by a hundred.

After calculating the returns for each stock, the next step is to create the excess return matrix. In the excess return matrix, the risk-free returns are deducted from stock returns at each point in time ( $t$ ). For this study, the risk-free rate of return used is the 10-year Finnish government bond yield. If the risk-free rate is negative at any point in time, the rate is set to zero. The excess return matrix is constructed as follows:

$$(2) \quad \begin{pmatrix} r_1^1 - r_1^{rf}, & r_1^2 - r_1^{rf}, \dots, & r_T^N - r_T^{rf} \\ r_2^1 - r_2^{rf}, & r_2^2 - r_2^{rf}, \dots, & \vdots \\ \vdots & \vdots & \vdots \\ r_T^N - r_T^{rf}, & \dots, & r_{167}^{81} - r_{167}^{rf} \end{pmatrix}$$

**Formula 2.** The excess return matrix (T observations, N stocks).

In the T by N excess return matrix, T is the number of observations in the data sample. The sample consists of 167 monthly observations, so there are 167 row vectors in total. Conversely, each stock forms a single-column vector. Since there are a total of 81 stocks, the excess return matrix contains 81 columns. Therefore, the excess return matrix has a dimension of 167x81.

Using the excess return matrix, portfolios of winners and losers are created. Stocks are ranked in ascending order based on their returns over a specific period, according to the ranking criteria of each tested strategy. The nine worst-performing stocks at a given ranking period form the loser portfolio, while the nine best-performing stocks form the winner portfolio. Stocks outside these two tails are categorized as the middle group, whose performance is not assessed in this study. Portfolios are rebalanced monthly, resulting in a holding period of simply one month in each strategy. This study is conducted in MATLAB software using econometrics and matrix calculus. Once stocks are formed into portfolios based on past information, monthly average return, standard deviation, Sharpe ratio, and t-statistics for each winner, loser, and zero-cost portfolio are reported.

Once the stocks are ranked and categorized into various groups, the monthly average returns for each evaluated portfolio can be calculated. The average monthly return for a portfolio is derived from the arithmetic mean of returns over a designated time frame. This involves summing the returns of the portfolio and then dividing that total by the

count of returns included. The formula to calculate the simple mean return is provided below:

$$3) \quad P_r = \frac{1}{n} \sum_{i=1}^n r_i = \frac{r_1 + r_2 + \dots + r_n}{n}$$

**Formula 3.** Monthly average return of the portfolio.

The riskiness, or volatility of the portfolios examined in this study is estimated using standard deviation. Standard deviation is a statistical measure that indicates how far individual data points deviate from the mean of a set. The formula for standard deviation is as follows:

$$4) \quad S_p = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}}$$

**Formula 4.** The standard deviation of the portfolio.

Where  $x_i$  is the value of the  $i^{\text{th}}$  return in the portfolio,  $\bar{x}$  is the mean value of the portfolio, and  $n$  is the number of returns in the portfolio (i.e., the number of observations).

In this study, the efficiency of portfolios is assessed using the Sharpe ratio. The Sharpe ratio is a commonly used measure that evaluates the relationship between return and risk. A higher Sharpe ratio indicates that an investment has produced a better risk-adjusted return. The Sharpe ratio is calculated by dividing the excess return of the portfolio by the portfolio's volatility. The formula for the Sharpe ratio is as follows:

$$5) \quad \text{Sharpe ratio} = \frac{E(r_i)}{\sigma_i}$$

**Formula 5.** Sharpe ratio.

Where  $E(r_i)$  is the excess return of the portfolio and  $\sigma_i$  is the portfolio volatility. It's essential to recognize that the risk-free return mentioned in the standard formula is already subtracted from the returns when constructing the excess return matrix.

To assess the statistical significance, this study uses a t-test to evaluate the returns of each portfolio examined. The t-test determines if there is a statistically significant difference between the means of the variables being studied. The t-test is also used for testing the hypotheses. The t-test results are assessed at a 5% confidence level, where the critical value is 1.96. The test statistics are formulated as:

$$6) \quad t - value = \frac{mean}{\sqrt{\left(\frac{var}{T - N}\right)}}$$

**Formula 6.** The statistical t-test.

Where the portfolio mean is divided by the square root of portfolio variance, which is divided by the number of observations in the sample. T is the number of observations in the data sample, and N is the rolling time window.

### 3.2.2 Portfolio Formation Process

This section of the methodology presents different strategies used in the empirical study to test the existence of momentum and contrarian anomaly. Strategies vary depending on the historical lag in the stock ranking and the chosen long/short approach. This study will focus on four different strategies. The first strategy tested is a standard momentum strategy commonly used in previous momentum research, such as Jegadeesh and Titman's (1993) study. This standard momentum approach considers the cumulative returns of stocks over the past 12 months, excluding the most recent month (from t-12 to t-2). So, in the standard momentum strategy, stocks are ranked in ascending order based on their cumulative returns over the past twelve to two months and formed into winner and loser portfolios based on this ranking. Once stocks are allocated to their

respective portfolios, they are held for one month after the same procedure is repeated. The purpose of rebalancing portfolios each month is that it is unlikely the same stocks will consistently generate high or low returns from month to month. Usually, by rebalancing at specific intervals, momentum and contrarian strategies can be maximized. This procedure is carried out 155 times throughout the sample period. Thus, the standard momentum strategy evaluates the predictive power of stocks over recent and intermediate time horizons together.

The second strategy tested focuses on stock performance over the recent past horizon. The recent past performance strategy involves buying the stocks that have performed the best over the last six months while shorting the stocks that have performed the worst during the same period. Also, this strategy excludes the most recent month to avoid the return reversal bias, meaning the portfolio formation period considers the cumulative returns of the stocks from time  $t-7$  to  $t-2$ . This strategy examines the predictive power of stocks' recent past performance in the data period. The holding period and rebuilding procedures for portfolios remain the same in all strategies.

The third strategy tested in this thesis is the intermediate past performance, implemented in Novy-Marx's (2012) paper. In this momentum strategy, stocks are ranked into portfolios based on their performance from month 12 to month 7 before the portfolio formation ( $t-12$  to  $t-7$ ). This approach excludes the last six months leading up to portfolio formation, positing that a stock's intermediate past performance has more predictive power of future returns than a stock's recent past performance.

Finally, this study will investigate portfolio returns based on stocks ranked according to their past performance over a single month, following the approach outlined in Novy-Marx's (2012) paper. In this strategy, stocks are ranked in ascending order based on their performance from one month to fifteen months before a portfolio formation. This study focuses on months one, three, five, seven, nine, eleven, twelve, thirteen, fourteen, and fifteen before the portfolio formation. So, the ranking criteria begin from month  $t-1$  and

is reviewed every two months until t-11. Thereafter, this study tests each month up to time t-15. The main goal of this section is to examine whether the performance pattern changes as the portfolio formation period moves further from the time of initial portfolio construction.

Now that the various lags employed in different strategies to rank stocks based on historical returns have been presented, it is essential to clarify another distinction between momentum and contrarian strategies, which is the long/short approach. Both strategies use historical data to identify trends or patterns in stock price performance. Momentum strategies assume that stocks with strong past performance will continue to perform well, while those with weak past performance will continue to underperform. Therefore, winner stocks are bought, and loser stocks are sold short. Conversely, contrarian strategies operate under the belief that stocks that have experienced poor performance in the past will eventually experience a reversal, allowing these previously underperforming stocks to become winners over time. Simultaneously, it is assumed that stocks that have shown strong performance may begin to decline and become losers. Under the contrarian ideology, winner stocks are sold, and loser stocks are bought. In this study, each portfolio is evaluated independently, with all zero-cost portfolios constructed as momentum portfolios. If a momentum portfolio's return is negative, it indicates that the return of the corresponding contrarian portfolio would be positive. The construction of zero-cost portfolios is approached in the following manner:

$$7) \quad r_{zero-cost} = r_{winner} - r_{loser}$$

**Formula 7.** The construction of a zero-cost portfolio.

In each strategy, the return of the zero-cost portfolio is the difference between the winner and loser portfolios, where the winner portfolio takes a long position, and the loser portfolio simultaneously takes a short position.

## 4 Results of the Study

The study's results are presented in this section, focusing first on momentum strategies, comprised of standard momentum, recent past performance, and intermediate past performance. Following this, strategies based on short-term reversal effect and past performance over a single month are presented. For each strategy, the key figures are detailed for the winner, loser, and zero-cost portfolios. The reported figures include the portfolios' average monthly return, standard deviation, Sharpe ratio, and statistical significance (t-statistic). Equal weighting is applied to each stock within the portfolios. It is important to note that transaction costs are not considered in this analysis. The significance level for the t-statistic used in this study is 5%. A more detailed description of the data and methodology can be found in Chapter 3. Table 1 displays the results of all the strategies covered in this paper. After the table, the thesis will discuss the results of each strategy in more detail.

**Table 1.** Summary statistics of strategy results.

	Portfolio		
Panel A: Standard Momentum Strategy	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	0.49%	-1.11%	1.59%
Standard Deviation	6.76%	7.51%	7.10%
Sharpe Ratio	0.07	-0.15	0.23
t-statistic	(0.89)	(-1.84)	(2.81)*
Panel B: Recent Past Performance	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	0.18%	-0.86%	1.04%
Standard Deviation	6.25%	7.01%	6.40%
Sharpe Ratio	0.03	-0.12	0.16
t-statistic	(0.36)	(-1.52)	(2.03)*

Panel C: Intermediate Past Performance	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	0.01%	-1.04%	1.06%
Standard Deviation	6.10%	7.51%	6.41%
Sharpe Ratio	0.002	-0.14	0.16
t-statistic	(0.03)	(-1.73)	(2.05)*
Panel D: Short Term Reversal t-1	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-1.39%	-0.20%	-1.19%
Standard Deviation	6.29%	7.14%	6.23%
Sharpe Ratio	-0.22	-0.03	-0.19
t-statistic	(-2.76)*	(-0.36)	(-2.38)*
Panel E: Single Month t-3	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.21%	-0.89%	0.68%
Standard Deviation	6.42%	7.15%	5.78%
Sharpe Ratio	-0.03	-0.12	0.12
t-statistic	(-0.40)	(-1.55)	(1.47)
Panel F: Single Month t-5	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.16%	-0.28%	0.13%
Standard Deviation	6.99%	7.40%	6.45%
Sharpe Ratio	-0.02	-0.04	0.02
t-statistic	(-0.28)	(-0.47)	(0.24)
Panel G: Single Month t-7	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.30%	-0.70%	0.40%
Standard Deviation	6.63%	6.95%	5.97%
Sharpe Ratio	-0.05	-0.10	0.07
t-statistic	(-0.57)	(-1.25)	(0.83)

Panel H: Single Month t-9	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	0.12%	-0.46%	0.58%
Standard Deviation	6.57%	6.63%	5.47%
Sharpe Ratio	0.02	-0.07	0.11
t-statistic	(0.22)	(-0.86)	(1.31)
Panel I: Single Month t-11	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	0.08%	-0.52%	0.43%
Standard Deviation	6.51%	7.01%	5.82%
Sharpe Ratio	-0.01	-0.07	0.07
t-statistic	(-0.16)	(-0.92)	(0.93)
Panel J: Single Month t-12	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.24%	-1.09%	0.85%
Standard Deviation	6.35%	6.60%	4.93%
Sharpe Ratio	-0.03	-0.16	0.17
t-statistic	(-0.46)	(-2.05)*	(2.15)*
Panel K: Single Month t-13	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.72%	0.48%	-1.20%
Standard Deviation	6.33%	7.10%	5.63%
Sharpe Ratio	-0.11	0.06	-0.21
t-statistic	(-1.41)	(0.84)	(-2.64)*
Panel L: Single Month t-14	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.41%	-0.54%	0.13%
Standard Deviation	6.25%	6.25%	4.87%
Sharpe Ratio	-0.06	-0.08	0.02
t-statistic	(-0.81)	(-1.07)	(0.33)

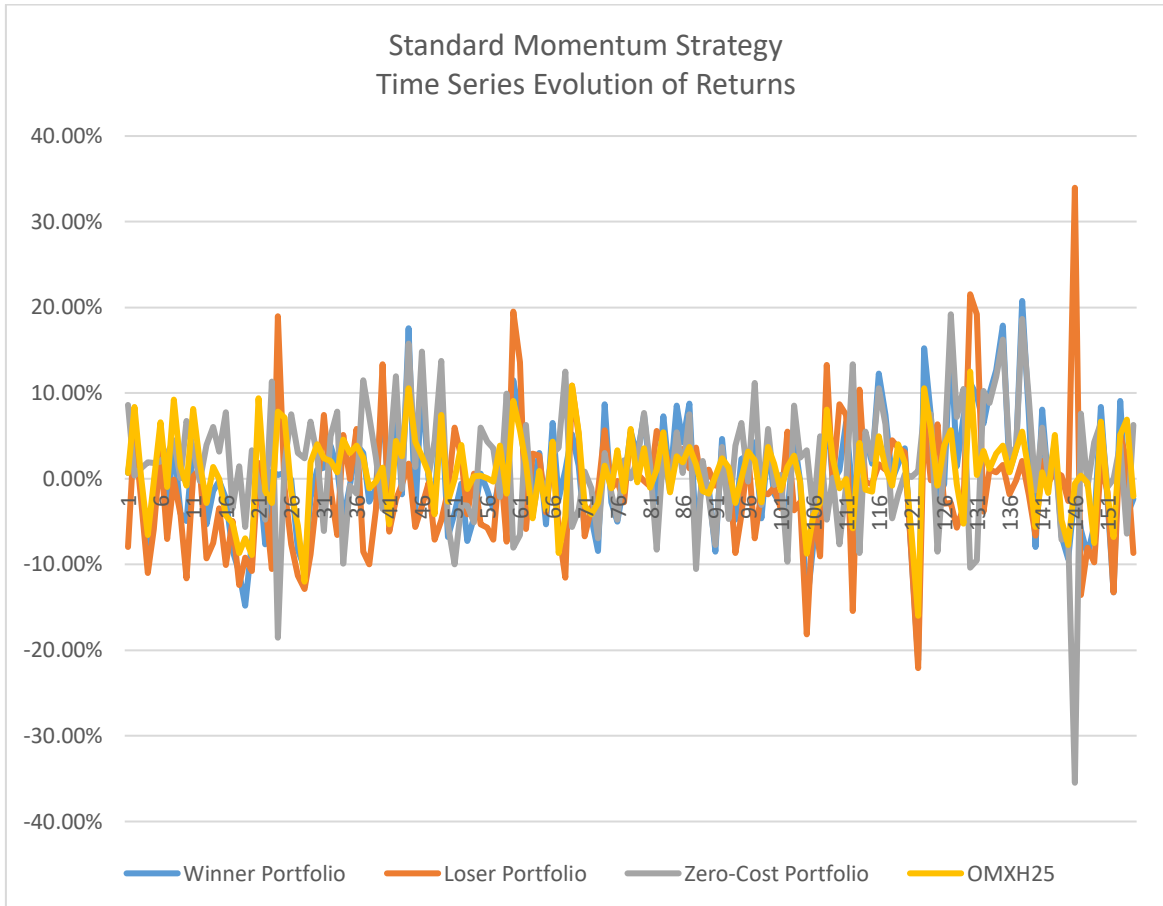
Panel M: Single Month t-15	Winner	Loser	Zero-Cost (W-L)
Average Monthly Return	-0.32%	-0.71%	0.39%
Standard Deviation	6.37%	6.40%	5.10%
Sharpe Ratio	-0.05	-0.11	0.07
t-statistic	(-0.62)	(-1.37)	(0.94)

#### 4.1 Standard Momentum

Panel A in Table 1 presents the statistics for the standard momentum strategy. In the standard momentum strategy, stocks are ranked into winners and losers based on their returns over the last 12 months, excluding the most recent month to avoid short-term return reversal. The results indicate that strong momentum exists in the Finnish stock market. Notably, where the loser portfolio continues to perform poorly, the short-side contributes more to zero-cost portfolio returns than the winner portfolio. Furthermore, the loser portfolio is carrying more risk than the winner portfolio. Due to the profitability of the short-side, where the negative returns of loser portfolios are especially high, the zero-cost portfolio achieves an average monthly return of up to 1.59%. This return is the highest among all strategies examined in this thesis. The Sharpe ratio calculated at 0.23 is also the highest among the strategies examined, indicating that the return-to-risk ratio of standard momentum is the most efficient. These results are significant at the 5% confidence level, supported by a t-statistic of 2.81. Overall, these findings demonstrate a strong continuity of returns in the Finnish stock market, which may be attributed to biases associated with over- or underreaction.

Figure 1 presents the time series evolution of standard momentum strategy returns. The graph illustrates the time series evolution of the winner, loser, and zero-cost portfolios. For comparison, the returns of the OMXH25 index are also included. It is observed that a few momentum crashes have occurred throughout the period, with a smaller crash at the beginning of the time series and a larger crash toward the end. A momentum crash is characterized by the high returns of the loser portfolio, leading to significant negative returns for the momentum or zero-cost portfolio. Consequently, the returns of the loser

portfolio and the zero-cost portfolio behave inversely. It is noted that the short-side of the momentum strategy, which involves short-selling loser stocks at least theoretically, exposes the investor to unlimited losses. As the results show, the standard momentum loser portfolio exhibits the highest volatility among the portfolios examined, together with the intermediate past strategy counterpart.



**Figure 1.** Time series evolution of standard momentum strategy returns.

The standard momentum strategy outperforms the average monthly return of the OMXH25 index during the period, with the OMXH25 yielding a monthly average return of 0.66%. The index has a standard deviation of 4.65% and a Sharpe ratio of 0.14. Due to its higher volatility, the standard momentum strategy has been riskier than the OMXH25 index. However, due to its higher returns, it has a better risk-return ratio than the index. In practice, it should be noted that transaction costs accompany the implementation of

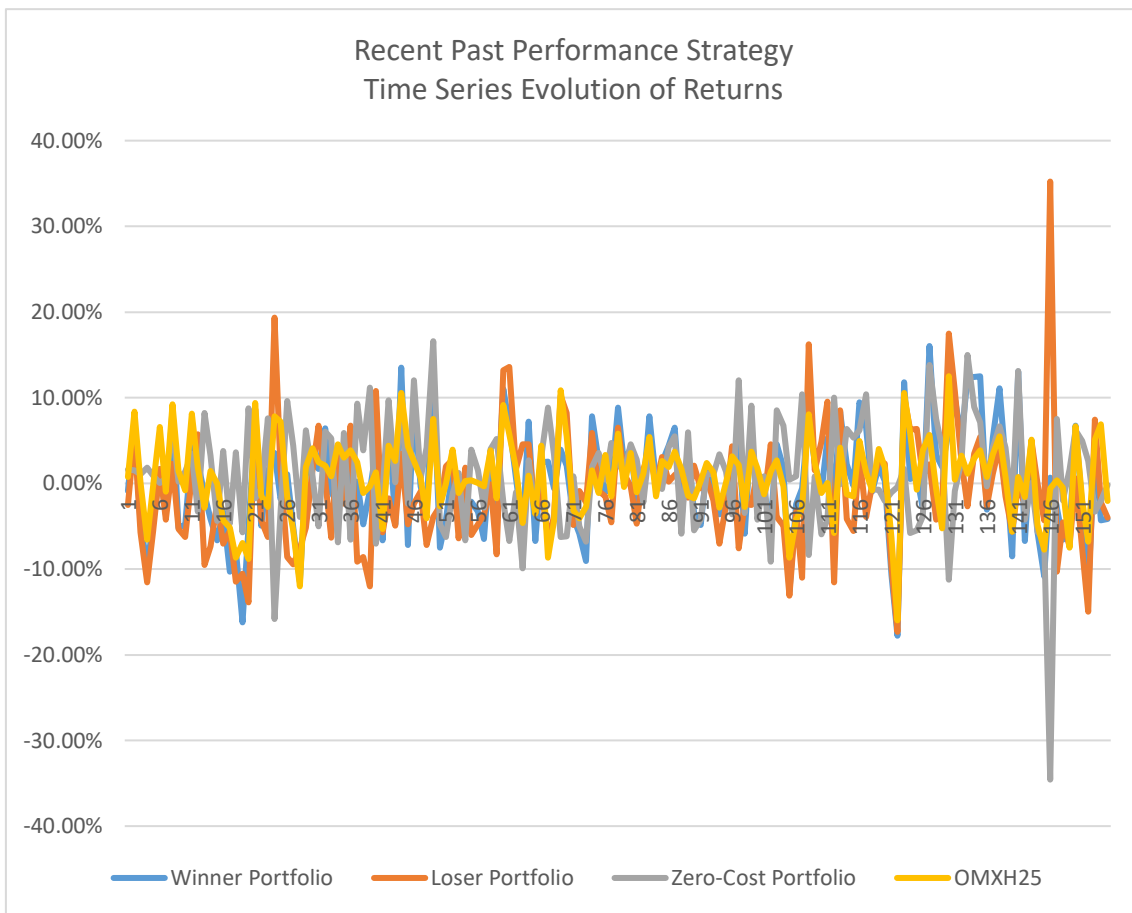
a momentum strategy, suggesting that the actual returns from momentum may not reach the projected levels.

## 4.2 Recent Past Performance

Panel B in Table 1 presents the results of the recent past performance strategy. In this strategy, winner and loser portfolios are formed based on the performance of stocks over the last six months, excluding the most recent month. The observed trend in the recent past performance results mirrors that of the standard momentum. It is observed that losers continue to underperform while the winners generate a small positive monthly average return. In the case of the zero-cost portfolio, the short-side contributes more significantly to momentum returns than the long-side. The average monthly return of the zero-cost portfolio is recorded at 1.04%, supported by a significant t-statistic of 2.03 at the 5% confidence level. Compared to standard momentum, the recent past performance strategy is less risky, as the zero-cost portfolio exhibits a standard deviation of 6.4%. Consequently, the Sharpe ratio is also slightly lower than in the standard momentum, recorded at 0.16.

Figure 2 presents the time series evolution of recent past performance strategy returns. The graph closely resembles the graph of standard momentum returns. It is observed that recent past performance is slightly less volatile than standard momentum. When comparing the returns of zero-cost portfolios during momentum crashes, it is noted that the recent past performance strategy experiences a negative return about one percentage point lower than that of the standard momentum strategy. Conversely, the positive returns of the loser portfolio during momentum crashes are slightly more than one percentage point higher with the recent past performance strategy compared to the standard momentum strategy. This indicates that, on average, the winner portfolio does not generate as large positive returns in the recent past performance strategy as it does in the standard momentum strategy. In contrast, loser portfolios perform better under the recent past performance strategy, resulting in lower negative returns than those experienced in the standard momentum strategy. Therefore, it can be concluded that

when examining the winner and loser portfolios individually, winner portfolios tend to perform worse, while loser portfolios tend to perform better when stock selection is based on the information from the past six months rather than the past year. However, the zero-cost portfolio based on recent past performance does not achieve the same level of return as one based on standard momentum, although it is associated with lower risk.



**Figure 2.** Time series evolution of recent past performance strategy returns.

Based on the results discussed so far, it can be concluded that a stock selection criterion relying solely on recent past information does not outperform a standard momentum strategy that integrates both recent and intermediate past data for stock selection. Therefore, it can be concluded that using this data set, intermediate past performance adds value to the standard momentum strategy because it can achieve better risk-adjusted returns compared to a strategy based solely on recent past information. As

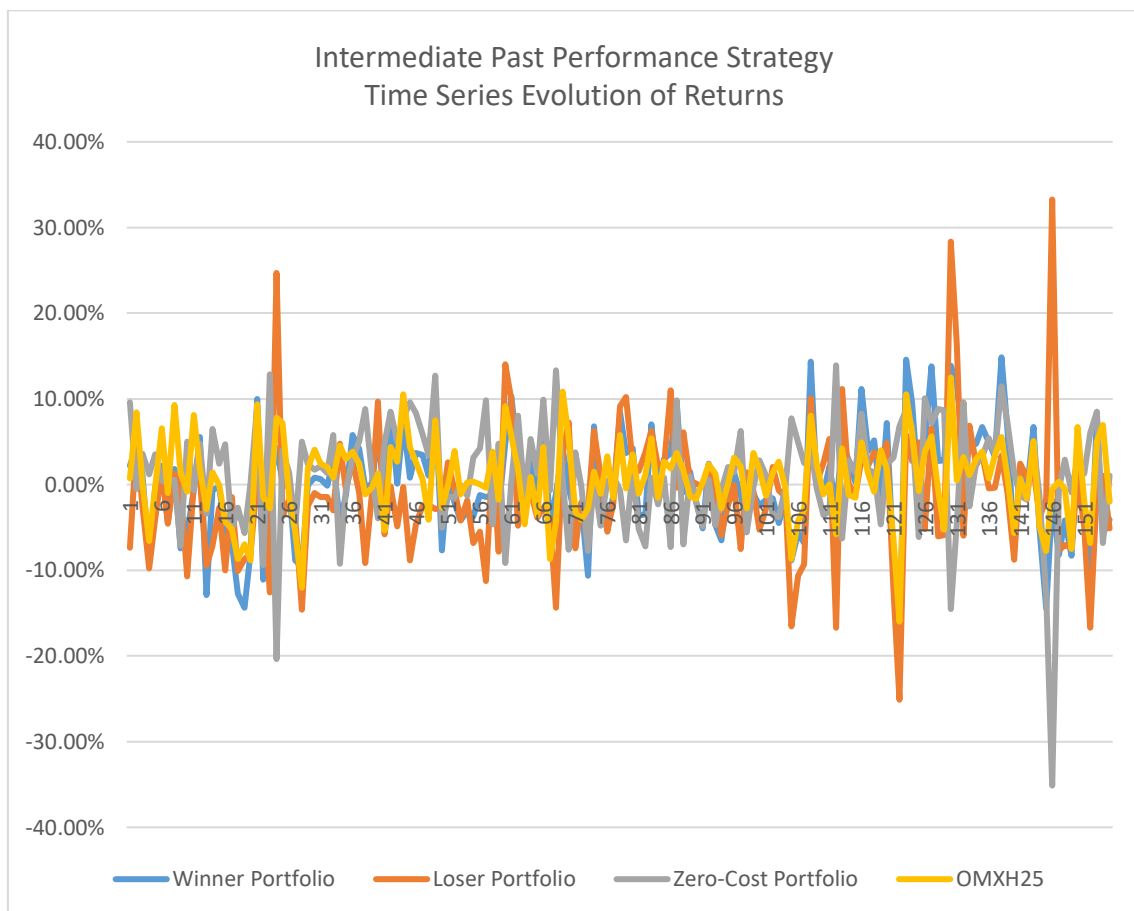
mentioned in chapter two, strategies that account for the 12th month before portfolio formation may be subject to overestimation due to the 12-month effect. Gong et al. (2015) also observe that recent past strategies might encounter a slight short-term reversal in the second month before portfolio formation, potentially leading to an underestimation of the performance of recent past momentum strategies. However, we leave this debate for further research, but these over- and under-estimation biases should be considered when interpreting the results.

### **4.3 Intermediate Past Performance**

The intermediate past performance strategy results are presented in Panel C in Table 1. In this strategy, winner and loser portfolios are formed based on stock performance from 12 to 7 months before portfolio formation, while the most recent six months are excluded. The average monthly return of the winner portfolio is around zero, being slightly positive. Among the strategies discussed so far, the winner portfolio from the intermediate past performance exhibits the smallest standard deviation, indicating that it is the least risky option. However, the return is minimal, resulting in a low Sharpe ratio. The intermediate past performance loser portfolio follows the established trend of losers continuing to lose, with an average monthly return of -1.04%. This portfolio is the riskiest among all portfolios examined in this study, with a standard deviation of 7.51%. Notably, this result is identical to the standard momentum loser portfolio. The zero-cost portfolio continues to yield an average monthly return of approximately 1%, slightly exceeding the profitability of the recent past strategy's zero-cost portfolio. Additionally, the standard deviation of the zero-cost portfolio is nearly identical to that of the recent past performance, producing the same Sharpe ratio of 0.16. The t-statistic for the zero-cost portfolio is significant at the 5% confidence level, with a reported value of 2.05.

Figure 3 illustrates the time series evolution of intermediate past momentum returns. From the graph, it's immediately apparent that the tails of the loser portfolio returns are more extreme than those in other strategies. The disparity in volatility among the loser portfolios, particularly between recent and intermediate past momentum, is evident.

This indicates that stock selection based on intermediate past information for the winner portfolio can produce relatively stable volatility, but the average monthly return is nearly non-existent. For a loser portfolio, using intermediate past information for stock selection leads to greater portfolio volatility, which is why the zero-cost portfolio can achieve statistically significant returns. Compared to the OMXH25 index numbers, the zero-cost portfolio based on the intermediate past performance can deliver a Sharpe ratio of 0.02 basis points higher. Again, transaction costs regarding portfolio management are excluded.



**Figure 3.** Time series evolution of intermediate past performance strategy returns.

A comparison between the recent and intermediate past strategies reveals that in the recent past horizon, the winner portfolio yields higher returns, and the loser portfolio sustains smaller losses compared to its intermediate past counterparts. Over the intermediate horizon, winners perform worse, and losers experience more significant

losses than in the recent past horizon. The numbers show nearly identical figures when evaluating the zero-cost portfolios from recent and intermediate past momentum strategies. The winner-loser portfolio spread is 1.04% for the recent past strategy and 1.06% for the intermediate past. The standard deviations are recorded at 6.40% and 6.41%, respectively, resulting in a risk-return ratio of 0.16 for both strategies.

While Novy-Marx's (2012) argument suggests that intermediate past momentum outperforms and is a better predictor of future returns than recent past performance in the US stock market, this finding does not significantly appear to extend to the Finnish stock market. When comparing zero-cost portfolios, intermediate past momentum slightly outperforms the recent past in average monthly returns, but the difference in the context of this study is small and insignificant. Novy-Marx (2012) emphasizes that this gap is most pronounced among the largest and most liquid stocks. Although this study does not apply cut-offs based on firm size or stock liquidity, accounting for these factors might yield different results, potentially aligning with Novy-Marx's (2012) insights regarding the US stock market.

While Novy-Marx (2012) argues in favor of the intermediate past performance, Gong et al. (2015) find that excluding the twelfth and second month before portfolio formation from the ranking criteria results in no significant difference in the predictability of stock performance between intermediate and recent past performance strategies. The argument suggests that the twelfth month may lead to an overestimation of intermediate past performance, while the second month may lead to an underestimation of recent past performance. However, even with the inclusion of these two months in the stock selection criteria of this study, no significant difference in predictability between these two strategies is observed.

#### **4.4 Short-Term Reversal and Past Performance Over a Single Month**

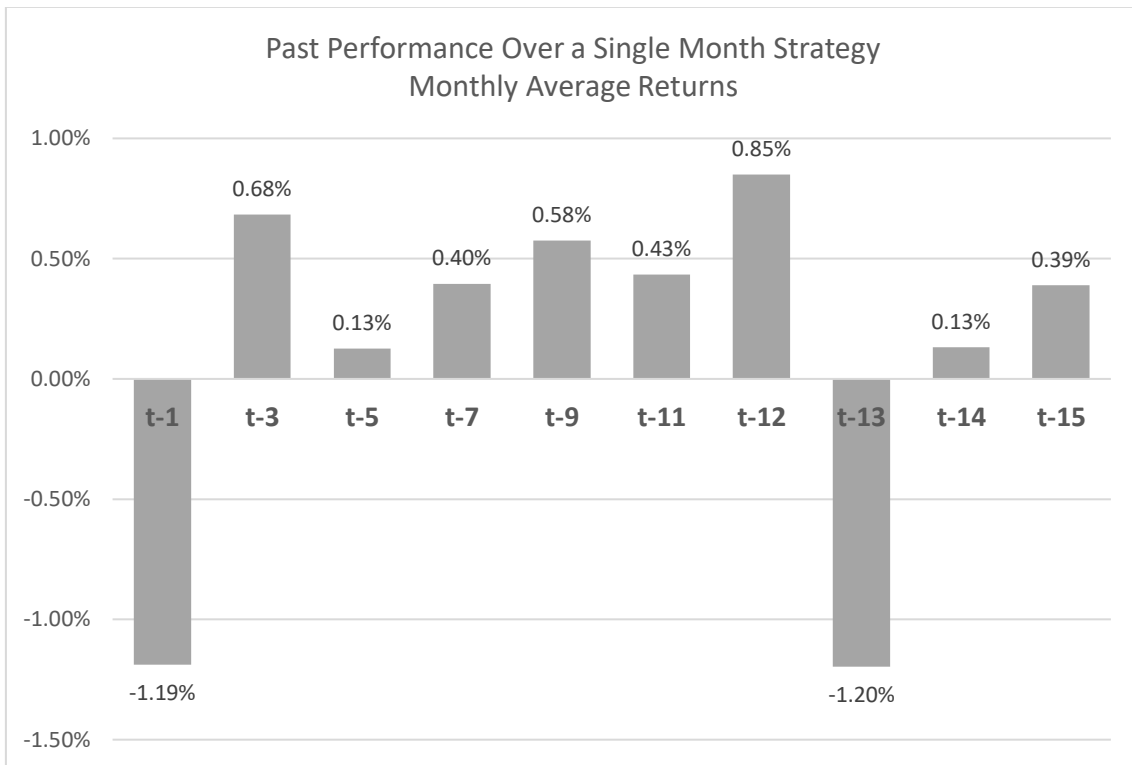
The short-term reversal strategy, which is the first contrarian strategy discussed, seeks to take a position that is contrary to momentum investing. The fundamental assumption

is that the value of winner stocks is expected to fall while the value of loser stocks is expected to rise. In this strategy, loser portfolios are assigned to take long positions, while the winner portfolio simultaneously takes short positions. In the short-term reversal strategy, stocks are categorized as winners or losers based on their performance one month before the portfolio formation. For equal comparison and ensuring the consistency of the results in this study, the zero-cost portfolios in this section are constructed similarly to those in momentum strategies, as the winner-loser portfolio. However, it should be noted that for a contrarian investor, creating a zero-cost portfolio involves an opposite event, wherein the zero-cost portfolio is formed as a loser-winner portfolio.

As shown above in Table 1, the results of the short-term reversal indicate that the phenomenon is evident and statistically significant within the Finnish stock market. The average monthly return for the winner portfolio is -1.39%, while the average for the loser portfolio is -0.20%. The t-statistic for the winner portfolio is significant at the 5% confidence level, reported at -2.76. This implies that stocks that have been the top performers in the previous month tend to drop in value in the following month. Also, the t-statistic for the zero-cost portfolio is significant, producing a value of -2.38. The average monthly return for a zero-cost portfolio established is -1.19%. When interpreting the results, it is essential to understand that the return on a contrarian position is the inverse of the return on a momentum position. In this context, the average monthly return on a contrarian position is 1.19%.

After the short-term reversal, the interpretation of the subsequent portfolios based on one-month performance is continued. The next section discusses additional results from the past performance over a single-month strategy. This study examines every other month for up to one year, followed by each month for up to fifteen months from the time of portfolio formation. To maintain a manageable number of results and tables, months less than one year from portfolio formation are examined on an every-other-month basis. The primary focus is to determine whether any significant changes occur

in the pattern of returns after one year. Results from the past performance over a single-month strategy are presented above in Table 1. Additionally, Figure 4 illustrates the average monthly returns of the strategy in a bar chart format. A discussion of the results and the most relevant findings follows.



**Figure 4.** Past performance over a single-month strategy. The zero-cost portfolio's monthly average returns.

Some of the results are statistically significant, from which it can be inferred that the markets at least partially suffer from inefficiencies and biases. First, negative average monthly returns appear for both the winner and loser portfolios at the strategies t-3, t-5, t-7, t-12, t-14, and t-15. Nevertheless, the winner portfolios perform better in these cases, indicating they have sustained smaller losses than the loser portfolios. The winner portfolios achieve a positive return for the first time at the t-9 strategy. Before this point, the winner portfolios from the single-month strategy had not recorded a positive average monthly return. Two months following the short-term reversal, the zero-cost momentum portfolio shows positive returns, with the t-3 portfolio recovering to yield an

average monthly return of 0.68%. In the t-5 strategy, the returns from both the winner and loser portfolios are close, leading to a small average return for the zero-cost portfolio. Starting from t-5, there is a noticeable upward trend in the returns of the zero-cost portfolios until year-end. This trend implies that returns of the zero-cost portfolios typically increase as time progresses from the initial portfolio formation, a finding also observed in Novy-Marx's (2012) study. The upward-sloping structure is also consistent with the findings of Heston and Sadka (2010), who estimate the slope coefficient of past performance on predicted returns as a function of historical lag. However, the upward-sloping term structure contradicts the widely accepted belief that momentum suggests a short-term autocorrelation of returns.

In the t-12 strategy, a drop in average monthly returns for both winner and loser portfolios is noted when compared to month t-11. The loser portfolio experiences a notable reduction, with its average monthly return decreasing by over 0.5 percentage points from the previous month, resulting in a value of -1.09%. This result is statistically significant at the 5% confidence level, indicated by a t-statistic of -2.05. The substantial increase in negative returns of the loser portfolio contributes to the t-12 zero-cost portfolio returns, which show a monthly average return of 0.85%, supported by a significant t-statistic of 2.15. This return is the highest of any momentum portfolio based on one month's performance. Due to the low standard deviation, the t-12 zero-cost portfolio achieves the second-highest momentum position Sharpe ratio in the study, recorded at 0.17. The 12-month effect is likely to influence the winner-loser portfolio spreads, thereby enhancing the t-12 zero-cost momentum portfolio returns. The 12-month effect implies that stock returns tend to be positively correlated in the same calendar month each year (Jegadeesh, 1990; Heston & Sadka, 2010; Gong et al., 2015). Therefore, the 12-month effect may influence the particularly bad performance of loser stocks at time t-12 in this study.

A notable finding occurs after twelve months from the portfolio formation. The t-13 momentum portfolio shows an even more pronounced reversal compared to the short-

term reversal strategy. The t-13 loser portfolio surprises and is the only loser portfolio within the entire study to record a positive monthly average return, producing a result of 0.48% per month. This pattern is in significant contrast with the returns of the loser portfolio from the month prior. The strong positive performance of the loser portfolio deteriorates the zero-cost momentum portfolio's returns, producing an average monthly return of -1.20%. For a loser-winner contrarian position, the t-13 strategy produces an average monthly return of 1.20% and an impressive Sharpe ratio of 0.21. Furthermore, the t-13 strategy exhibits a significant t-statistic of -2.64 (2.64). After the reversal at t-13, the momentum pattern gradually reverts to an upward-sloping term structure. At t-14, the zero-cost momentum portfolio yields a monthly average return of 0.13%, followed by a slightly higher return of 0.39% at t-15. Finally, the t-14 zero-cost portfolio produces the lowest standard deviation examined in this study.

An inversion of returns after twelve months is also identified in the study by Novy-Marx (2012), but a definitive explanation for this phenomenon remains elusive. Heston and Sadka (2010) also examine the seasonal effect on the cross-section of stock returns and confirm the reversal of momentum returns after one year. Their findings indicate that stocks tend to exhibit either high or low returns consistently in the same calendar month for the long term. The factors that influence the reversibility of t-13 returns remain largely unclear. This phenomenon may suggest that momentum persists for only twelve months before the market undertakes adjustments to rebalance portfolios, or it could be a consequence of seasonal strategies or the anticipation of annual news events. Heston and Sadka (2010) propose that the under- or overreaction to seasonal occurrences, such as earnings announcements, dividends, or fiscal year news, could potentially serve as explanatory factors for the observed seasonal effect. However, they conclude that because the periodic patterns in the cross-section of average returns are present in each calendar month, this explanation may ultimately prove insufficient. These findings imply that the market is to some extent predictable and therefore does not work fully efficiently. Such irrational behavior displayed by markets presents a challenge to contemporary asset pricing theories.

## 5 Conclusions

This thesis employs technical analysis to evaluate the performance of four investment strategies using historical stock prices. The thesis investigates whether stock returns in the Finnish stock market exhibit continuity or reversal patterns in the short term from 2009 to 2022, despite the long-standing recognition of momentum and contrarian anomalies as phenomena. The thesis also tests the efficient market hypothesis, arguing that historical information cannot predict future returns. It also suggests that if any disruptions against market efficiency were to occur, the market should adjust so that the potential for any excess returns over the long term cannot be realized.

The strategies examined are based on historical stock price data. However, the strategies differ in the historical period over which stock price data is used to construct the winner and loser portfolios. In the empirical study, standard momentum portfolios are sorted into winners and losers based on the cumulative stock returns over  $t-12$  to  $t-2$  before the portfolio formation. Recent past performance tests the strategy's performance by sorting stocks into winners and losers based on cumulative stock returns over  $t-7$  to  $t-2$  before portfolio formation. The intermediate past performance strategy similarly tests the performance of a strategy that sorts stocks into winners and losers based on their cumulative returns over  $t-12$  to  $t-7$ . Intermediate past performance thus completely ignores the stock performance over the previous six months before portfolio formation. The fourth strategy tested sorts stocks into winners and losers based on their one-month historical returns, starting with a one-month lag.

The empirical findings indicate that irrational behavior is present in the Finnish stock market, similar to patterns observed in other markets internationally, across various periods, and in different asset classes. Among the strategies examined, the standard momentum strategy has proven to be the most effective during this period, achieving an average monthly return of 1.59% with a statistically significant t-statistic of 2.81. Additionally, a zero-cost portfolio based on the performance of stocks in the recent past yields an average monthly return of just over 1%. It has a statistically significant t-statistic

of 2.03. When examining stock selection based on intermediate past performance, the results for the zero-cost portfolio are nearly similar to those of the recent past strategy. However, the performance of winners and losers is weaker in the intermediate past performance compared to the recent past. Despite this, the underperformance of losers enhances the returns of the intermediate past strategy's zero-cost portfolio, resulting in an average monthly return of 1.06% and a statistically significant t-statistic of 2.05.

Strategies based on one-month historical performance yield interesting results. First, the stock market appears to have a short-term return reversal. The t-1 strategy produces an average monthly return of -1.19%, accompanied by a statistically significant t-statistic of -2.38. The poor performance of winner stocks under this strategy suggests that stocks that have performed well in one month tend to experience a decline in value in the following month. The average monthly return for winner portfolios under the t-1 strategy is recorded at -1.39%, with a t-statistic of -2.76, providing further evidence of the tendency for previously top-performing stocks to lose value in the subsequent month. Interestingly, the magnitude of this reversal appears more pronounced after one year from the portfolio formation, where the t-13 strategy's zero-cost portfolio shows an average return of -1.20% per month, along with a significant t-statistic of -2.64. Similar trends have been identified in Novy-Marx's (2012) and Heston and Sadka's (2010) studies. However, the underlying causes of this reversal after one year remain inadequately explained. Other momentum strategies based on one-month past performance yield moderate positive monthly returns, with the t-12 strategy producing the best monthly average return of 0.85% for the zero-cost portfolio.

The overall findings of this study are consistent with the existing literature. The results indicate that the market has not adequately adjusted to eliminate the possibility of excess returns through momentum and contrarian strategies. Notably, return reversals are observed in the first month before portfolio formation, indicating a pattern of negative serial correlation with the following holding period. Momentum tends to persist for 12 months, after which market activities instigate a correction, leading to dramatic

losses for winner stocks and an outstanding rebound of loser stocks. The underlying causes of these anomalies may be explained by theories related to investor behavior, including tendencies to underreact or overreact to new information. Additionally, the liquidity of specific stocks is believed to influence price dynamics, potentially leading to temporary fluctuations from the stocks' intrinsic values.

Based on the analysis of the results, the null hypothesis is rejected, leading to the acceptance of the alternative hypothesis that one or more momentum or contrarian strategies can generate excess returns. It is important to note that, while these strategies are theoretically positioned to outperform market returns, practical implementation tends to be impacted by transaction costs, which are likely to absorb any excess returns generated. Notably, despite the enduring awareness of momentum and contrarian anomalies in financial markets, they remain strongly present in stocks. Future research should focus on further exploring and understanding factors that affect the continuity and reversibility of returns across asset classes, as efficient markets have not eliminated these phenomena from the market.

## References

- Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance (New York)*, 68(3), 929-985. <https://doi.org/10.1111/jofi.12021>
- 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*, 21(2), 785-818. <https://doi.org/10.1093/rfs/hhm079>
- Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance (New York)*, 52(1), 57-82. <https://doi.org/10.1111/j.1540-6261.1997.tb03808.x>
- Cheng, S., Hameed, A., Subrahmanyam, A., & Titman, S. (2017). Short-Term Reversals: The Effects of Past Returns and Institutional Exits. *Journal of financial and quantitative analysis*, 52(1), 143-173. <https://doi.org/10.1017/S0022109016000958>
- Conrad, J., & Yavuz, M. D. (2017). Momentum and Reversal: Does What Goes Up Always Come Down? *Review of Finance*, 21(2), 555-581. <https://doi.org/10.1093/rof/rfw006>
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance (New York)*, 53(6), 1839-1885. <https://doi.org/10.1111/0022-1082.00077>
- De Bondt, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance (New York)*, 40(3), 793-805. <https://doi.org/10.1111/j.1540-6261.1985.tb05004.x>

- Edwards W. (1968). Conservatism in human information processing. *Formal Representation of Human Judgment*, B. Kleinmuntz, 17–52. New York: Wiley & Sons.
- Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business (Chicago, Ill.)*, 38(1), 34-105.
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417. <https://doi.org/10.2307/2325486>
- Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3), 283-306. [https://doi.org/10.1016/S0304-405X\(98\)00026-9](https://doi.org/10.1016/S0304-405X(98)00026-9)
- Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance (New York)*, 47(2), 427-465. <https://doi.org/10.1111/j.1540-6261.1992.tb04398.x>
- Gong, Q., Liu, M., & Liu, Q. (2015). Momentum is really short-term momentum. *Journal of banking & finance*, 50, 169-182. <https://doi.org/10.1016/j.jbankfin.2014.10.002>
- Graham, B. (1965). *The Intelligent Investor*. New York: Harper & Row
- Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: A study of Finland's unique data set. *Journal of Financial Economics*, 55(1), 43-67. [https://doi.org/10.1016/S0304-405X\(99\)00044-6](https://doi.org/10.1016/S0304-405X(99)00044-6)

- Grobys, K., & Huhta-Halkola, T. (2019). Combining value and momentum: Evidence from the Nordic equity market. *Applied economics*, 51(26), 2872-2884. <https://doi.org/10.1080/00036846.2018.1558364>
- Heston, S. L., & Sadka, R. (2010). Seasonality in the Cross Section of Stock Returns: The International Evidence. *Journal of financial and quantitative analysis*, 45(5), 1133-1160. <https://doi.org/10.1017/S0022109010000451>
- Hofmann, D., Keiber, K. L., & Luczak, A. (2022). Up and down together? On the linkage of momentum and reversal. *Global finance journal*, 54, 100754. <https://doi.org/10.1016/j.gfj.2022.100754>
- Hong, H., & Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance (New York)*, 54(6), 2143-2184. <https://doi.org/10.1111/0022-1082.00184>
- Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance (New York)*, 45(3), 881-898. <https://doi.org/10.1111/j.1540-6261.1990.tb05110.x>
- Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance (New York)*, 48(1), 65-91. <https://doi.org/10.1111/j.1540-6261.1993.tb04702.x>
- Jegadeesh, N., & Titman, S. (1995a). Overreaction, Delayed Reaction, and Contrarian Profits. *The Review of Financial Studies*, 8(4), 973-993. <https://doi.org/10.1093/rfs/8.4.973>

- Jegadeesh, N., & Titman, S. (1995b). Short-Horizon Return Reversals and the Bid-Ask Spread. *Journal of Financial Intermediation*, 4(2), 116-132. <https://doi.org/10.1006/jfin.1995.1006>
- Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance (New York)*, 56(2), 699-720. <https://doi.org/10.1111/0022-1082.00342>
- Jegadeesh, N., & Titman, S. (2002). Cross-Sectional and Time-Series Determinants of Momentum Returns. *The Review of Financial Studies*, 15(1), 143-157. <https://doi.org/10.1093/rfs/15.1.143>
- Jegadeesh, N., Luo, J., Subrahmanyam, A., & Titman, S. (2022). Short-Term Reversals and Longer-Term Momentum Around the World: Theory and Evidence. *Review of financial studies*, Paper No 22-13, Available at SSRN: <https://ssrn.com/abstract=4069575> or <http://dx.doi.org/10.2139/ssrn.4069575>
- Kadiyala, P., & Rau, P. (2004). Investor Reaction to Corporate Event Announcements: Underreaction or Overreaction? *The Journal of Business (Chicago, Ill.)*, 77(2), 357-386. <https://doi.org/10.1086/381273>
- Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, 80(4), 237-251. <https://doi.org/10.1037/h0034747>
- Keynes, J. M. (1935). *The general theory of employment, interest, and money*. New York.
- Lehmann, B. N. (1990). Fads, Martingales, and Market Efficiency. *The Quarterly journal of economics*, 105(1), 1-28. <https://doi.org/10.2307/2937816>

- Leivo, T. H. (2012). Combining value and momentum indicators in varying stock market conditions: The Finnish evidence. *Review of accounting & finance*, 11(4), 400-447. <https://doi.org/10.1108/14757701211279187>
- Lewellen, J. (2002). Momentum and Autocorrelation in Stock Returns. *The Review of Financial Studies*, 15(2), 533-563. <https://doi.org/10.1093/rfs/15.2.533>
- Lo, A. W., & MacKinlay, A. C. (1999). *A non-random walk down Wall Street*. Princeton: Princeton University Press. <https://doi.org/10.1515/9781400829095>
- Lo, A. W., Whitelaw, R. F., Campbell, J. Y., & MacKinlay, A. C. (1998). THE ECONOMETRICS OF FINANCIAL MARKETS. *Macroeconomic Dynamics*, 2(4), 559-562.
- Lui, W., Strong, N., & Xu, X. (1999). The Profitability of Momentum Investing. *Journal of business finance & accounting*, 26(9-10), 1043-1091. <https://doi.org/10.1111/1468-5957.00286>
- Malkiel, B. G. (1973). *A Random Walk Down Wall Street*. W.W. Norton & Company, New York, ISBN: 9781324035435
- Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives*, 17(1), 59-82. <https://doi.org/10.1257/089533003321164958>
- Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance (New York)*, 54(4), 1249-1290. <https://doi.org/10.1111/0022-1082.00146>

- Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228-250. <https://doi.org/10.1016/j.jfineco.2011.11.003>
- Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, 103(3), 429-453. <https://doi.org/10.1016/j.jfineco.2011.05.003>
- Pätäri, E., & Vilksa, M. (2014). Performance of moving average trading strategies over varying stock market conditions: The Finnish evidence. *Applied economics*, 46(24), 2851-2872. <https://doi.org/10.1080/00036846.2014.914145>
- Rouwenhorst, K. G. (1998). International Momentum Strategies. *The Journal of Finance (New York)*, 53(1), 267-284. <https://doi.org/10.1111/0022-1082.95722>
- Shiller, R. J. (1984). Stock Prices and Social Dynamics. *Brookings papers on economic activity*, 1984(2), 457-510. <https://doi.org/10.2307/2534436>
- Subrahmanyam, A. (2005). Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns. *The Financial Review (Buffalo, N.Y.)*, 40(1), 11-35. <https://doi.org/10.1111/j.0732-8516.2005.00091.x>
- Yao, Y. (2012). Momentum, contrarian, and the January seasonality. *Journal of banking & finance*, 36(10), 2757-2769. <https://doi.org/10.1016/j.jbankfin.2011.12.004>