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Investment Anomalies: Investing in falling and rising stocks

Evidence from Finland

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ABSTRACT:
Momentum and contrarian trading strategies have been extensively studied worldwide. These two trading strategies highlight the relevance of timing and challenge empirical financial theories, such as the efficient market hypothesis and the random walk theory. Despite extensive study in many markets, there is a visible research gap in the Finnish context. Utilizing a long, 23-year panel of daily adjusted stock price data, added with event study-type methodology and appropriate robustness tests, two hypotheses regarding the momentum versus contrarian style are tested. The chosen methodology follows event study style, with some adjustments for better suitability for this framework. Data includes all stocks listed in the main list of the Helsinki Stock Exchange over the included years. The events are constructed from price shocks themselves and categorized according to price shock direction and magnitude. Both momentum and contrarian profits are calculated for each category with different metrics to improve the validity of the results.

The findings of this study provide diversified and detailed results of the profitability of momentum and contrarian trading strategies in four different periods of 3, 6, 12, and 24 months from the event. The results show that the shortest 3-month period returns are mixed, especially from a statistical perspective. Most clearly, momentum tends to yield significantly better results over 6- to 12-month horizons after the event. The longest examined period is the most controversial, providing more level results. Most of the original findings are also held after statistical testing and more robustness checks. Nevertheless, the results clearly support the momentum strategy over contrarian trading, especially with a medium horizon.

The results of this study are partly consistent with previous literature, still providing unique findings from Finnish stock markets. The main outcome of this study provides every investor with a practical answer to the question of how to act during heavy stock price movements. In addition, this study contributes to the existing literature on investment decisions during stock price shocks in the Finnish context. The findings are especially relevant for investors with relatively short investment horizons, such as traders, but also for investors as a general group.

KEYWORDS: momentum, contrarian, anomalies, event study, profitability

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TIIVISTELMÄ:
Momentum- ja kontrasijoitusstrategioita on tutkittu kattavasti maailmanlaajuisesti. Nämä kaksi sijoitusstrategiaa korostavat ajoituksen merkitystä ja haastavat empiirisiä rahoitusteorioita, kuten tehokkaiden markkinoiden hypoteesia (efficient market hypothesis) ja satunnaisen kulun teoriaa (random walk theory). Vaikka aihetta on laajalti tutkittu usealla markkinapaikalla, on Suomen ympäristössä tunnistettavissa tutkimusrako. Hyödyntämällä 23 vuoden ajanjaksolta päivittäistä oikaistua osakekurssidataa, yhdistettynä tapahtumatutkimus-menetelmään, bootstrapattuun versioon vinouskorjatusta t-statistiikasta sekä soveltuviin robustisuustesteihin, kahta hypoteesia testataan liittyen momentum- ja kontrastrategioihin. Valittu metodologia seuraa tapahtumatutkimus-menetelmää, kuitenkin joillain tarkennuksilla, sopien paremmin tämän tutkimuksen viitekehykseen. Data sisältää kaikki Helsingin pörssin päälistalla noteeratut osakkeet valitun ajanjakson sisällä. Tapahtumat muodostetaan osakekurssien hintamuutoksista itsestään, ja kategorisoidaan perustuen hintamuutoksen suuntaan ja voimakkuuteen. Sekä momentum- että kontrastrategialle lasketaan tuotot kategorioittain hyödyntäen useaa eri tapaa, parantaakseen tuloksien luotettavuutta ja laatua.

Tämän tutkimuksen löydökset tarjoavat monipuolisia ja kattavia tuloksia momentum- ja kontrastrategioiden kannattavuuksista neljällä eri ajanjaksolla, 3, 6, 12 ja 24 kuukauden ajanjaksoilla tapahtumahetkestä. Tulokset osoittavat kolmen kuukauden tuottojen olevan hajautuneita, etenkin tilastollisesta näkökulmasta. Selkeimmät havainnot liittyvät 6 ja 12 kuukauden tuottoihin, joiden ajalla momentum-strategia tuottaa selvästi paremmat tuotot. Pisimmän 24 kuukauden ajalla tuotot ovat jälleen hajaantuneempia ja tasoittuvat selvästi. Useimmat alkuperäisistä havainnoista pitää myös tilastollisen testauksen ja robustisuustestausten jälkeen. Joka tapauksessa tulokset selvästi tukevat momentum-strategiaa yli kontrastrategiaa, erityisesti keskimmäisillä ajanjaksoilla.

Tämän tutkimuksen tulokset ovat osittain linjassa aiemman kirjallisuuden kanssa, mutta kuitenkin tarjoten uniikit löydökset Suomen osakemarkkinoilta. Tutkimuksen päätulos tarjoaa kaikille sijoittajille vastauksia kysymykseen, kuinka toimia merkittävien osakekurssien muutosten keskellä. Lisäksi tämä tutkimus kontribuoi aiempaan kirjallisuuteen liittyen sijoituspäätöksiin osakkeiden hintashokkien aikana Suomen viitekehyksessä. Löydökset ovat tärkeitä etenkin lyhyen aikavälin sijoittajille, kuten treidaajille, mutta myös sijoittajille ylipäänsä.

AVAINSANAT: momentum, kontrasijoittaminen, anomaliat, tapahtumatutkimus, kannattavuus

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Abbreviations

CAPM	Capital Asset Pricing Model
EBIT	Earnings Before Interest and Taxes
EMH	Efficient Market Hypothesis
EUT	Expected Utility Theory
GEM	SZSE Growth Enterprise Market

HSE	Helsinki Stock Exchange
OMXHCAP	OMX Helsinki CAP Total Return Index
PT	Prospect Theory
RWT	Random Walk Theory
SSE	Shanghai Stock Exchange
SZSE	Shenzhen Stock Exchange

1 Introduction

The efficiency of financial markets and the informative power of past price movements are widely studied topics in the financial literature. The theoretical view of market efficiency is the efficient market hypothesis (EMH) by Fama (1970), which holds that capital markets are efficient when security prices always fully reflect all available information. According to the EMH, the past price movements should not have predictive or informative power for future returns. However, there are several examples of stock price predictiveness (De Bondt & Thaler, 1985; Jegadeesh, 1990; Jegadeesh & Titman, 1993). Yet, the results of many norm-deviating findings, including those of Jegadeesh (1990) and Jegadeesh and Titman (1993), were substantially weaker under different empirical conditions (Hou et al., 2020).

In this research, the profitability of two opposing trading categories, momentum and contrarian strategies, is compared. Momentum trading is based on return continuation, where investors buy assets that have recently performed well and sell or short instruments that have recently performed poorly. Clear momentum profits are presented in previous research (Asness, 2013; Jegadeesh & Titman, 1993; Rouwenhorst, 1998). In turn, the contrarian strategy is based on the expectation that recent price movements may reverse. Previous literature also supports momentum profits (Chen et al., 2018; De Bondt & Thaler, 1985; Yu et al., 2019). Both strategies are based on past price movements, thereby testing the predictive power of past stock price movements.

Stock prices occasionally face large positive or negative movements. Significant stock price movements play a main role in this thesis, as price movement thresholds are used in event identification. Also, major price movements provide a basis for momentum and contrarian strategies, depending on whether the stock price continues in the same direction or reverses. Significant short-term stock price movements and profitability afterward are previously studied by Cox and Peterson (1994) and Jiang and Zhu (2017)

The profitability of momentum and contrarian strategies is also dependent on the length of the holding period. Even if another strategy yields good returns in a 3-month period, returns may reverse in the next 3 months. Previous literature includes examples of return reversal between the strategies over different periods (Barberis et al., 1998; Hong & Stein, 1999). In this study, four different periods are examined to test whether there are mixed results between the two strategies and periods.

Possible inverse findings between the strategy returns may be explained by existing theories. For example, the overreaction hypothesis (De Bondt & Thaler, 1985) presents systematic overreaction in stock markets. The authors further report that overreaction is one notable element behind the stock price movements during turbulent periods. Therefore, initial overreactions in stock pricing may yield good momentum returns or, in turn, lead to a reversal effect in future periods.

1.1 Purpose of the Study

This study provides Finnish evidence on the profitability of momentum and contrarian trading strategies after significant stock price movements. As the intention is to conduct general research where observations from all companies are pooled, this study provides somewhat categorized results. Yet, the purpose is to provide supportive evidence on short-term stock profitability for any investor in the Finnish stock market.

The motivation for this study stems from significant stock price movements in individual stocks. Many Finnish investors remember the rise and collapse of Nokia Oyj, which turned out to be a costly phenomenon for many investors. A recent example is Neste Oyj, whose already very popular stock plummeted almost 90% in April 2025 from its all-time high in January 2021, as the company was in the middle of restructuring its business. At the same time, analysts recommended buying the stock (Inderes, 2024). At the end of 2025, Neste Oyj's stock is still being traded about 70 % below its highest price. Even though this event is a singular example, the research purpose holds after extending the framework to include all the stocks from the market.

Even though there is a wide range of previous research on the same topic, there is a gap in Finnish stock market research from the 21st century. Despite HSE including major stocks, such as Nokia, Kone, and Nordea, there is a lack of recent research on the topic. Statistical data show that Finnish investors heavily prefer domestic stocks over foreign stocks (Bank of Finland, 2025). The statistics show that 85 % of Finnish investors' equity investments are Finnish listed stocks, yet the latest trend is towards foreign stocks, according to the same statistics. Also, the number of Finnish household investors is continuously increasing (Statistics Finland, 2025). The aforementioned further highlight the relevance of this study and the research gap in Finnish markets.

This study provides evidence of the profitability of momentum and contrarian trading strategies in Finland. Although strategy-level comparison is the main focus of this thesis, the market-adjusted returns of each strategy are presented to further describe the strategy returns relative to market performance. Together, these calculations provide a solid understanding for the reader of the profitability of trading and index-level long-term investing.

The first hypothesis is based on the assumption that a contrarian strategy would provide better outcomes during the observation period. In practice, this would follow the process of a contrarian investor, who decides to buy (sell) a stock after significant negative (positive) stock price development. As the existing literature and theories include support for both contrarian (Chen et al., 2018; De Bondt & Thaler, 1985; Yu et al., 2019) and momentum (Asness, 2013; Chan et al., 1996; George & Hwang, 2004; Jegadeesh & Titman, 1993; Rouwenhorst, 1998) trading strategies, the first hypothesis mostly lies in EMH (Fama, 1970) and the overreaction hypothesis (De Bondt & Thaler, 1985). Conclusively, the central hypothesis can be defined as follows:

H1: It is more profitable to buy (sell) a stock after a short and significant stock price decline (increase) than after a short and significant stock price increase (decline), over holding periods of 3–24 months.

Since several profit calculation periods are examined, it is necessary to assess the profitability of each return calculation period separately. As there are two opposing investment strategies, it is interesting to see if the findings differ across different holding periods. The second hypothesis is strongly supported by previous literature. Inverse findings between the different time spans and profitability of contrarian and momentum strategies have been reported in various research (Barberis et al., 1998; Galariotis et al., 2007; Hong & Stein, 1999). Additionally, De Bondt and Thaler (1985) identify overreaction as a notable factor behind stock price movements during volatile periods, which may support short-term momentum profits. However, according to the overreaction hypothesis (De Bondt & Thaler, 1985) and EMH (Fama, 1970), stock price momentum should turn to contrarian profits over longer periods if fundamentals do not similarly change with stock prices. Thus, it is reasonable to believe that momentum dominates in the short period, but the contrarian strategy yields better results over longer periods, leading to the second hypothesis.

H2: Momentum strategy provides better returns in the short term, while the contrarian strategy is more profitable over longer periods.

1.2 Structure of the Study

This paper is structured as follows. The next chapter covers theoretical topics, such as stock market anomalies, both meaningful investing strategies described, and suitable financial theories. The third chapter includes a literature review. The fourth chapter presents the empirical framework, including data, descriptive statistics, and the research methodology. Chapter five presents the study results, the momentum versus contrarian trading comparison, and the main findings. The sixth section includes conclusions and a summary of the research conducted, as well as implications for future research. Finally, there are references at the end of this text.

About the use of artificial intelligence tools, Grammarly was used during the writing process for language editing and proofreading purposes, including grammar, spelling, and clarity improvements. The author is, however, responsible for the final content, analysis, and conclusions presented in this study.

2 Theoretical framework

This chapter includes theories related to stock market anomalies and behavioral finance. In addition, investment strategies relevant to this study and the most relevant financial theories are reviewed.

2.1 Stock market anomalies and behavioral attitude

In financial literature, theories and models exist to explain patterns. Because many theories and models describe continuous and repeated actions, some phenomena are not explained by existing models. In the stock return context, some notable examples are called anomalies because they are not captured by CAPM (Fama & French, 2008).

According to Frankfurter and McGoun (2001), the use of the term "anomaly" in financial literature is very different from other sciences. They argue that the term has been misused in finance, more like a rhetorical device than a way of denoting empirical irregularities. The authors also highlight, with the same view, that EMH and CAPM enjoy a very steady position in financial literature, without relevant empirical proof. Combined with this paper, the aim of this study is to challenge the theoretical side with empirical research and use existing financial anomalies to support the study.

In existing financial literature, several noted anomalies have been examined. One of them is herding behavior, in which people act similarly to a larger group without critical thinking (Hwang & Salmon, 2004). Although it is more of a psychological phenomenon, herding behavior applies in stock markets, especially during shocks. An extreme example of herding behavior occurred in January 2021 when the prices of so-called meme stocks surged rapidly and significantly (Klein, 2022). This provides a concrete example of how herding behavior and irrational acts can cause severe overreactions in stock markets. Thus, herding behavior could be one of the meaningful factors behind overreactions and violations of the EMH in stock markets. Therefore, it may also support the hypothesis H2 of this study, where reversal is expected in longer holding periods.

The opposing view of anomalies proposed by Hou et al. (2020) reviews a total of 452 anomalies. They find that most of the anomalies cannot be replicated, and the ones that can be replicated were done so with lower economic magnitude than previously reported. Their conclusion is that markets are more efficient than earlier recognized. However, as noted earlier, anomalies are considered to be deviations from norms, mostly from EMH and CAPM. In this study, if any profitable patterns are found, they should be explained by risk factors or anomalies.

According to Jegadeesh and Titman (1993), a common view throughout the different professions is that individuals overreact to information. Considering the structure and functionalities of stock markets, there is continuous potential for new, surprising information regarding a specific stock or other important information, for example, macroeconomic changes. According to EMH (Fama, 1970), market prices should reflect all publicly available information, even in its weakest form. However, theoretically, under EMH, when new information reaches investors, price movements of underlying assets should occur immediately, or the markets are not efficient. On the other hand, it might take a relatively long time for the information to reach all investors, which, by itself, should support underreaction in the price.

Previous literature on behavioral finance assumes that beliefs are formed according to the laws of probability (Sandroni, 2005). Additionally, EUT, PT, and Bayes' rule assume agents maximize expected utility and act rationally. Despite this, some financial anomalies have been documented. Wen et al. (2024) described that investor decision-making is heavily linked to stock price movements. Stock price reactions have been approached with different mathematical models and theories. One original view was that Bayes' rule could prescribe correct reactions to new information (De Bondt & Thaler, 1985). By definition, Bayes' rule supports mathematically rational decisions (Sandroni, 2005), which, in the stock price context, would be the opposite of the overreaction hypothesis. The most problematic aspect of using Bayes' rule in explaining agent behavior in stock markets is inconsistency. Even though a major part of agents would act by Bayes’ rule, non-rational investors cause over- or underreactions by definition (Sandroni, 2005). Russell and Thaler (1985) argued that even though there are rational agents in the markets, this does not guarantee a rational expectations equilibrium.

Hong and Stein (1999) find that up to 91% of investors were categorized as momentum-traders, leaving only 9% of investors to be newswatchers or contrarian traders within this framework. In other words, over 90% of investors behave psychologically rather than fundamentally. This easily leads to overreactions and longer-term reversals. Barber and Odean (2000) find that households significantly underperform the benchmark index. Combined with the finding that 91% of investors act psychologically (Hong & Stein, 1999), and that Bayesian agents would force behavioral agents out of the market (Sandroni, 2005), this finding seems coherent. In conclusion, anomalous and irrational actions in financial markets seem to lead to a weak outcome.

2.2 Investment strategies

In the world of investments, there is a wide range of portfolios, strategies, and aims. Yet, there are some typical and recognizable styles of investing. If an investor at least partially believes EMH and considers stock markets to be efficient, timing should not affect the outcome of long-term investment. However, the timing of transactions might make the difference when the investment period is relatively short. This is especially true for stock traders, as their strategy is completely based on short-term stock movements. As this study focuses on short-term investment periods, sentiment-based trading strategies of momentum and contrarian trading are subject to comparison.

2.2.1 Momentum trading

Momentum trading strategy is an investment strategy based on return continuation, where investors buy assets that have recently performed well and sell or short instruments that have recently performed poorly. In the traditional formulation by Jegadeesh and Titman (1993), momentum strategies are constructed by buying past winners and selling past losers, with the expectation that recent return patterns continue over subsequent months. Similarly, Chan et al. (1996) describe a momentum strategy as one that exploits the tendency of stocks with strong past performance to continue outperforming stocks with weak past performance. Asness et al. (2013) further show that momentum can be understood as a broad return pattern in which assets with relatively high recent returns tend to outperform assets with relatively low recent returns across different markets and asset classes.

The existence of momentum is theoretically important because it challenges the traditional view of efficient markets. According to the EMH, stock prices should reflect available information, and historical price movements should not systematically predict future returns (Fama, 1965; 1970). If investors can earn superior returns by relying on past price performance, then recent stock returns appear to contain information that is not immediately or fully incorporated into prices. Momentum can therefore be interpreted as a market anomaly, since it suggests that price history may have predictive power for future returns.

The empirical foundation of momentum trading is strongly associated with Jegadeesh and Titman (1993), who find that strategies buying past winners and selling past losers generate significant positive returns over intermediate holding periods. Their results imply that stock returns may continue in the same direction after portfolio formation, at least for a limited period. This finding is central to the present thesis because the empirical design is based on identifying stocks that have experienced short and significant price increases or decreases and then examining their subsequent performance.

One common explanation for momentum is gradual information diffusion. Chan et al. (1996) and Hong and Stein (1999) argue that momentum profits may arise because markets react gradually to information. Furthermore, Jiang and Zhu (2017) report that underreaction is significant during stock price shocks, and that there is a clear underreaction in short periods. If investors initially underreact to news, earnings information, or other firm-specific signals, stock prices may adjust gradually rather than immediately. A recent price increase may therefore reflect positive information that has not yet been fully incorporated into the stock price, while a recent decline may reflect negative information whose full impact is revealed only over time. This explanation supports the idea that short-term price movements may continue in the same direction before any potential reversal occurs.

Behavioral finance provides an additional explanation for momentum. Barberis et al. (1998) present a model in which investor sentiment and cognitive biases can lead to both underreaction and overreaction in financial markets. Hong and Stein (1999) similarly argue that gradual information diffusion and the interaction of different investor groups may create initial momentum followed by later reversal. These explanations are particularly relevant for this paper because they support the possibility that momentum and contrarian effects may dominate at different horizons. If investors initially underreact, momentum may be stronger over shorter holding periods. However, if prices later overshoot fundamental values, the same initial price movement may eventually be followed by reversal.

2.2.2 Contrarian trading

In contrast with momentum trading, a contrarian investment strategy is based on the expectation that recent price movements may reverse. Unlike momentum trading, where investors buy recent winners and sell recent losers, contrarian investors typically buy stocks that have recently performed poorly and sell or short strongly performing stocks. The traditional empirical foundation for contrarian trading is provided by De Bondt and Thaler (1985), who examine whether the stock market systematically overreacts. Their findings suggest that stocks with poor past performance may later outperform stocks with strong past performance, indicating long-term return reversal. This result is central to the contrarian view because it implies that past losers can become future winners, and vice versa. In this paper, this logic supports the possibility that buying after short and significant stock price declines and selling after short and significant stock price increases may be profitable if the initial price movements are excessive and later corrected.

In addition to momentum, contrarian trading also challenges the traditional efficient market view. According to the EMH, stock prices should reflect available information, and it should not be possible to predict future returns with past performance (Fama, 1965; 1970). If investors can earn superior returns by following a contrarian strategy, it clearly violates the basic principles of EMH. One central explanation for contrarian profits is investor overreaction. Kahneman and Tversky's (1979) prospect theory shows that decision-making under risk may deviate from fully rational expectations. In turn, Barberis et al. (1998) present a model in which investor sentiment can produce both underreaction and overreaction in financial markets. Hong and Stein (1999) show how gradual information diffusion may first generate momentum and later lead to overreaction and reversal. This is especially relevant for hypothesis H2.

Empirical evidence on sharp price movements also supports the relevance of contrarian trading. Cox and Peterson (1994) study stock returns following large one-day declines and provide evidence of short-term reversals and a longer-term weakening of reversals. Even though their profit calculation periods are very short, their findings are relevant since this research examines short and significant price movements as investment signals. A large decline may reflect temporary selling pressure or excessive pessimism, creating a buying opportunity, but it may also reflect genuine negative information. Similarly, a large increase may either signal continuing strength or temporary overvaluation. This uncertainty makes the comparison between momentum and contrarian strategies empirically important.

Contrarian strategies have been studied in various international contexts. De Haan and Kakes (2011) examine momentum and contrarian strategies among Dutch institutional investors. Yu et al. (2019) compare the performance of momentum and contrarian strategies in the Chinese stock market. Chen et al. (2018) link contrarian strategies to herding behavior, and that investor interaction may influence whether price movements continue or reverse. Nagel (2012) finds short-term reversals highly profitable in the U.S, and with high correlation with the VIX index, which measures the implied volatility of S&P 500 index options. These studies indicate that the relative success of contrarian trading may vary across markets, investor groups, and market conditions.

The Finnish stock market offers a relevant setting for testing contrarian effects. Grinblatt and Keloharju (2000) show that different investor types in Finland display different trading behavior and investment performance. This matters because contrarian opportunities may arise when some investors sell recent losers too aggressively or chase recent winners too strongly. If these reactions cause temporary mispricing, subsequent reversals may create profitable opportunities for investors to take the opposite position.

2.3 Applicable theories

Financial literature recognizes many valid theories for asset pricing and behavioral models. As the core of this study is variations in stock pricing and recognizable price movement patterns, the chosen theories cover all these factors.

2.3.1 Overreaction Hypothesis

Originally proposed by De Bondt and Thaler (1985), the overreaction hypothesis refers to systematic overreaction in stock markets. In the context of the overreaction hypothesis, Bayes’ rule was used to define stages of reactions.

De Bondt and Thaler (1985) suggest that individuals overweight past news and, in turn, underweight past data. In their research, the authors conduct an empirical test to determine whether possible overreaction movements follow a predictable formula. They start with a conditional statement that if stock prices systematically overreact, the reverse movement should be predictable from past data alone, and there is no need for any additional data. Conclusively, they form two hypotheses. First, extreme stock price movements are followed by subsequent opposite-direction stock price movements. Second, the higher the initial price movements, the higher the subsequent adjustment.

In their study, De Bondt and Thaler (1985) find that the overreaction hypothesis is not symmetric and it is much larger for losers than for winners. Additionally, their research finds evidence consistent with the overreaction hypothesis, where recent loser stocks outperformed recent winners by a significant margin. According to their study, overreaction seems to be a notable element behind stock price movements during turbulent periods.

Studying the stock price returns after strong movements, over- or underreactions can explain abnormalities in stock returns. Hong and Stein (1999) find psychological factors and different investor types to be very relevant to under- and overreactions. They find that different agent groups behave differently, and the actions of each group do not fully eliminate other groups' actions. This could lead to both over- and underreactions, especially with stocks with lower coverage. Additionally, since psychological factors are mostly universal, the overreaction hypothesis should also be applicable to Finnish investor sentiment and thus for this research.

2.3.2 Efficient Market Hypothesis

While studying market behavior, the efficient market hypothesis provides an attractive framework for the study. According to Fama (1970), there are three different forms of market efficiency. The first is called the weak form, in which markets reflect only historical prices and returns. The second form, called the semi-strong form, reflects all publicly available information. The most efficient type, called the strong form, reflects all possible information, including inside information.

Capital markets are efficient when security prices fully reflect all available information at all times (Fama, 1970). In other words, and according to the strongest form of EMH, stock prices should change only when new information is published. At the time when the EMH was tested, the narrative of efficiency was reversed (Fama, 1970). The weakest form of EMH was examined by testing whether it was possible to make profitable predictions for the future with past returns. Back then, the random walk theory (RWT) by Eugene Fama (1965) was already statistically proven, concluding that it is impossible to make reliable predictions with historical returns.

The semi-strong form of EMH is studied by adjustments of stock price to any information-generating event (Fama, 1970). Each test is then accumulated, and the validity of the model is evaluated. While the evidence remains somewhat limited, the findings are all consistent with the EMH. The findings are mostly expressed in cumulative average residuals before and after information-generating events. Cumulative average residuals rise prior to such events and are mostly random afterward, indicating that the stock prices included all information when published.

The most efficient form of EMH, called the strong form, includes all available information to be priced in, and thus no investor would have higher expected trading profits than others (Fama, 1970). As the model is defined very strictly, it is not considered an exact representation of reality. For that reason, the strong form is described as a benchmark against which the deviations from market efficiency can be compared. However, there is no evidence that continuous abnormal returns would be due to insider information or a similar edge to other investors. Therefore, the strong form holds until otherwise proved. With these findings and specifications, it would be naïve to expect perfect market efficiency.

Although this research does not extensively study stock market efficiency in Finland, EMH is closely related to potential financial gains from momentum or contrarian strategies. If at least the semi-strong form of EMH holds, it should not be possible to gain with any trading strategy, since all the available information should be priced in. Thus, any systematic gains with momentum or contrarian strategies could be viewed as a violation of the EMH.

2.3.3 Random Walk Theory

Considering the mathematical side of applicable theories, random walk theory is one of the most suitable for stock price movements. The random walk theory was developed in recent decades but was first presented by Louis Bachelier in 1900. Afterward, RWT was further developed. Eugene Fama (1965) systematically clarified and formalized the RWT and empirically validated it for stock prices. According to Fama, the random walk theory assumes stock price movements to be independent. Furthermore, RWT expects price changes to be normally distributed within a specific interval. With these assumptions, short-term price movements should be random and thus impossible to predict consistently over long periods.

Fama (1965) defines the random walk model with two hypotheses. The first was independence of successive price changes, and the second was the probability distribution of stock price changes. With these hypotheses, Fama emphasizes independence as a crucial element in stock price movements. The author also separates market efficiency from assumptions about normality. By doing that, common misunderstandings in previous discussions are corrected. Additionally, Fama distinguishes between statistical dependence and economically meaningful dependence. From the perspective of a random walk model, minor statistical dependence is acceptable if past stock prices cannot be used to boost future expected returns. Furthermore, empirical studies strongly and consistently support extensions of the random walk model.

As RWT is empirically validated for stock price movements, it should not be possible to gain an advantage by looking at past stock price movements. There can always be exceptions and outliers, but RWT is expected to hold especially when the sample increases. In this research, the sample group is relatively large. According to RWT, predicting past movements should not provide a systematic edge for investors. Therefore, finding any statistically significant trading pattern violates either RWT, EMH, or both.

2.3.4 Prospect Theory

For decades, expected utility theory (EUT) dominated the theoretical field of risky decision-making. EUT assumes that individuals prefer the highest expected utility in choices, including any risk. It is based on rational choices, and thus reasonable people are expected to act according to EUT. Because it focuses on the mathematical outcomes of different options, it does not consider different preferences or risk willingness of each person.

Kahneman and Tversky (1979) present an alternative model for risky decisions, called prospect theory (PT). Compared with the more normative EUT, prospect theory more accurately describes why some individuals behave in ways that would not be rational under EUT. This is done by identifying systematic patterns of behavior that do not support the maximum expected utility. One key example of such patterns is the reflection effect. Its core idea is that people tend to be risk-willing in negative prospects and risk-averse with positive ones (Kahneman & Tversky, 1979). By the definition of EUT, there should not be any variation between similar positive and negative tradeoffs, since the expected utility would be the same in both cases.

From the perspective of this study, prospect theory could explain why investors behave differently in changing sentiments. In fact, loss aversion is one of the key implications of PT. Thinking from investors' perspective, loss aversion could lead to cutting losses in downward-trend stocks. Furthermore, PT could support momentum behavior among investors.

3 Literature Review

On momentum and contrarian trading, there is previous literature from different time periods and geographic regions. While momentum and contrarian trading are well-studied topics, especially in the largest stock markets, there is no Finnish study on a similar topic. In fact, there is at least one previous study from the Finnish market, but it focuses more on different investor types than market-level behavior-type returns (Grinblatt & Keloharju, 2000). In addition, their study includes a much older sample and a shorter time span and is therefore hardly comparable with this research. However, existing literature provides a good backbone for this research.

Several studies have been conducted within the area of momentum versus contrarian investing. De Bondt and Thaler (1985) study possible systematic overreaction in stock markets. Data from their study consist of monthly returns of NYSE stocks throughout the years 1926 to 1982. They find that loser stocks in the long term outperform winner stocks over several years. According to their study, for the 3-year or 36-month examination period, the loser stocks yield almost 25% more than the past winner stocks. Additionally, they find that during months 1 to 12, the overreaction is not as strong as in months 13 to 36. In any case, their finding violates the EMH and heavily supports contrarian trading strategies, especially with longer periods.

There is also previous literature on other results. For example, Jegadeesh and Titman (1993) find a continuing momentum effect over 3-12 months. The sample period of their study is from 1965 to 1989 and includes U.S. stocks. Stocks are classified by forming winner and loser portfolios for the last 3-12 months of performance. The best strategy in terms of monthly profits is selecting stocks by 12 months' performance and holding the portfolio for a 3-month period. They find this strategy to yield 1,31% per month. As their strategy includes both selling losers and buying winners, it stands for general short-term profitability. However, they also find longer-term reversals in abnormal returns. In comparison, and consistent with the results of De Bondt and Thaler (1985), a short-term momentum but longer-term contrarian trading strategy is found to be profitable among U.S. stocks several decades ago.

In their text, Jegadeesh and Titman (1993) show that the reasons behind the profitability of these strategies are not related to slow stock price reactions or systematic risk. In turn, their evidence shows that the abnormal profits are due to delayed or slow reactions to firm-specific news. They also find longer-term reversals, concluding that the momentum effect is not permanent and reflects temporary inefficiency in markets. In contrast with EMH and the financial point of view, this type of inefficiency should not be repetitive and is possible even if markets are efficient.

Similarly to Jegadeesh and Titman, Rouwenhorst (1998) presents strong relative momentum profits in several European stock markets. The study includes 12 European stock markets, and the examination period is between 1980 and 1995. The methods used include internationally diversified portfolios of both recent winners and losers. The author finds that the momentum strategy dominates up to 12 months after event identification. Also, the finding is not restricted to a specific market, as it is present in all included markets.

Galariotis et al. (2007) study contrarian and momentum profitability with a long sample period of 1975-2005, from the London Stock Exchange. They find that contrarian profits cannot be explained by a single-factor risk model or company size. Regarding profitability, momentum profits are mostly present in shorter holding periods, whereas the contrarian strategy performs better in longer holding periods.

Profitability of momentum and contrarian strategies is studied in the Finnish stock market. Grinblatt and Keloharju (2000) examine the relation of investor type performance and investment behavior. Their study includes only two years of stock data, from the end of 1994 to the end of 1996. Also, they include only the 16 largest stocks on the Helsinki Stock Exchange (HSE), covering about 52% of the market cap of HSE at the time. Their decision is justified by the need to ensure liquidity within the stocks studied. Furthermore, they analyze stocks based on past returns with four different holding periods, which were approximately 1 week, 1 month, 6 months without prior month, and a full half year. These periods are primarily used to evaluate whether investors were contrarian or momentum-minded throughout the period.

Grinblatt and Keloharju (2000) find that individuals are contrarians in every period, which is consistent with prior studies worldwide. Their research for a half-year period highlights the phenomenon with individuals being contrarian on 84% of trading days. However, they find that when households' investment portfolio increases, contrarian behavior starts to diminish. For the biggest individual investors by portfolio size, the net percentage of contrarian behavior is 66% within the same period. However, individual investors are not the only ones who present signs of contrarian behavior. For example, non-financial corporations and financial institutions show contrarian signs, though more marginally (Grinblatt & Keloharju, 2000). Their contrarian behavior is not statistically significant in shorter periods, but for a half-year examination period the institutions are clearly contrarian, according to the authors.

One of the core messages of Grinblatt and Keloharju (2000) is that with every trade, there is both a seller and a buyer at the same execution price. Additionally, and partially derived from that, if someone benefits from a specific trade, another party will face a similar loss. As stock prices increase or decrease, the net effect is always an equilibrium between the buyer and seller, if trading costs and taxes are excluded from consideration. However, the difficulty is that nobody can predict the future with certainty, and the winner and loser of a trade are determined in the future.

Asness et al. (2013) study whether value and momentum investment strategies generate consistent excess returns not only with equities but across different asset classes. Their study includes stock market data from the U.S., the U.K., Europe, and Japan, making the findings geographically widespread. Additionally, they examine if these strategies shared common global drivers and risk exposures, which could explain such returns. The authors find both strategies profitable in every asset class but also a negative correlation between strategies, which indicates higher risk-adjusted returns when combining the strategies.

Chan et al. (1996) examine the profitability of momentum strategies and whether the profits are explained by compensation for the risk or market inefficiencies. Their data include U.S. stock market data from the years 1977 to 1993. The authors focus on stock price movements before and after earnings announcements, and the quality of earnings announcements. Their conclusions are that momentum strategies yielded excess returns over 3 to 12 months with both long and short strategies. However, risk-adjusted models do not completely explain the profitability of each strategy. Since they examine the relation between price movements and earnings announcements, they found that momentum profits are more likely to be linked to underreactions than to risk compensation.

With different geographic evidence, de Haan and Kakes (2011) study momentum and contrarian investment strategies in Dutch markets. More specifically, they analyze strategies used by institutional investors such as pension funds, life insurers, and non-life insurers. The data set in their research is relatively short, including quarterly data from the years 1999 to 2005. They find that institutional investors are showing contrarian behavior. The authors find that only pension funds are systematically contrarian investors, whereas life and non-life insurers were only showing contrarian elements. In particular, contrarian behavior is found during market turbulence. The authors conclude that pension funds stabilize the markets. In general, they also found that the contrarian findings are mostly driven by sales, which are due to realizing capital gains. While their study does not similarly categorize contrarian and momentum behavior by different time spans, the findings still provide necessary evidence from another interesting market and timing.

Notably, the study by de Haan and Kakes excludes individual investors, who may act differently because of non-binding guidelines and restrictions, as well as investment strategies. However, the major role of institutional investors in global financial markets may significantly affect financial market sentiment (de Haan & Kakes, 2011). Even if individual investors act differently in markets, general stock market movements are the decisive factor in this research, and therefore the actions of institutional investors are important to acknowledge.

A few suitable and recent studies cover Chinese stock markets. Chen et al. (2018) study contrarian strategy in two major Chinese stock markets, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). Their study includes stock price values within 1994-2013. One of their main findings is that the momentum strategy is not profitable. Out of contrarian strategies, they find the method ranking by weekly frequency most profitable, especially during the financial crisis between 2008 and 2012. Another very similar study by Yu et al. (2019) compares momentum and contrarian strategies in three Chinese stock markets, SSE, SZSE, and SZSE Growth Enterprise Market (GEM). Their timeframe is more recent, covering roughly from April 2010 to the end of 2017. Their findings are similar to those of Chen et al. (2018), indicating that a contrarian strategy yields better results than momentum. Also, the authors find weekly returns of the loser-minus-winner strategy to be significantly positive, which is the opposite of findings from U.S. and other developed stock markets. These findings highlight differences in market structure and investor composition between developed and emerging markets.

Because previous studies focus on Chinese stock markets, they have a few major structural limitations. Chen et al. (2018) highlight that individual investors did not have realistic opportunities to sell a single stock short, and even institutional investors had very limited opportunities to do so. Yu et al. (2019) also note a fundamental change in stock market structure and effectiveness around 2010. According to the authors, before that, short selling and margin trading were prohibited, which restricted investors from acting in the most efficient way. In the context of this study, disabling short selling would eliminate the ability to profit from a downside movement of a stock. As in Finnish and other Western stock markets, where short selling is allowed, it provides a relevant option to take a position and profit from it. Thus, any research including a market and period with such limitations should be analyzed with proper understanding.

George and Hwang (2004) study publicly observable measurements, stock price nearness to its 52-week high price, and its explanatory power for future stock price movement. Their core idea is that the close-to-52-week-high (low) price captures a high fraction of past good (bad) news, which proxies using fixed-window past returns may not perfectly capture. The sample includes all CRSP stocks, and the period included 1963-2001, indicating a long and thorough sample. They find that the 52-week high/low signal dominates other common momentum measures. Furthermore, the 52-week high winner-minus-loser effect is very strong and even twice as large as, for example, the momentum measure used by Jegadeesh and Titman (1993). In addition, previous financial research, including Jegadeesh and Titman (1993), reports longer-term reversals, but for the 52-week high strategy, there is no evidence of it (George & Hwang, 2004). More specifically, George and Hwang describe short-term momentum and long-term reversals as most likely not to be components of the same phenomenon. Their findings heavily support momentum profits in both the short and longer term. Additionally, their results, as well as the findings of Jegadeesh and Titman (1993), severely challenge the semi-strong efficiency of EMH.

To conclude the previous literature on momentum and contrarian styles, there certainly is a wide range of studies from different areas and markets. Given the age of many previous studies, some results should be evaluated with respect but also with care in today's context. However, there is a lot of support in previous literature for short-term momentum profits and a bit less for longer-term reversal movement.

4 Empirical Framework

This chapter describes the empirical methods used to test the hypotheses, and the data that comprises the sample studied.

4.1 Data source and sample selection

This research uses adjusted daily stock price data for all stocks on the Helsinki Stock Exchange over the period 2003-2025. Specifically, stocks listed in the First North marketplace are excluded from that period. However, if a company's stock has a history from both lists, its history from the main list of HSE is used in this study. The empirical sample consists of companies that have been listed on the main list of the HSE for more than two years during the sample period. Applying this minimum listing requirement, the final raw data universe includes 225 stock identifiers and 6 001 possible daily trading observations per identifier. The panel is therefore structured as a stock-day data set, where there is one daily adjusted closing price for each available trading day for each company identifier. All referred adjusted price data are retrieved from the Datastream database.

The use of daily data is appropriate for the purpose of this study because the research question concerns short and significant price movements. Since the event definitions used in this study are based on 5-, 15-, and 45-trading-day maximum windows, daily observations are necessary to identify the event date as accurately as possible. Daily data also provides substantially more power than weekly or monthly data (Brown & Warner, 1985; MacKinlay, 1997). This is especially important because the study does not define events based on fixed-window returns but instead identifies the first date on which a price-change threshold is reached within the allowed maximum days.

In this study, the adjusted closing price is used as the price variable. Adjusted prices are preferred over unadjusted closing prices because they account for corporate actions that affect the comparability of price observations over time, such as dividends and stock splits. Since the objective of the study is to evaluate the profitability of trading strategies after significant price movements, the price series should approximate the total return experience of an investor as closely as possible. Thus, adjusted closing prices provide a more suitable basis for calculating both event-period price changes and subsequent holding-period returns.

The chosen sample includes a period from 2003 to 2025. This long sample period is useful because momentum and contrarian effects may vary across market conditions. A short sample could produce results that are strongly influenced by one specific market regime. Thus, a longer sample provides a more reliable setting for examining whether return continuation or reversal patterns are observable in the Finnish stock market regardless of market or economic conditions. The long sample also implies that stocks in the sample vary over time, since not all companies were listed for the full period.

The rule of requiring more than two years on the main list of HSE is applied to ensure sufficient price history for meaningful event identification and future return calculation. Since the longest future return horizon in this research is 528 trading days, approximately corresponding to 24 months, very short listing histories would not allow the calculation of all holding-period returns after an event. The two-year minimum listing requirement thus improves the reliability of this analysis by excluding companies with insufficient trading history. At the same time, the study retains both currently listed and historically listed firms when data are available, reducing the risk that the sample reflects only surviving firms.

For empirical analysis, the dataset of daily adjusted stock prices is conceptually modified into an event-level structure. The first phase of the event study structure is event definition (MacKinlay, 1997). The original stock price panel is first used to identify price-movement events for each company. Each detected event is then stored as one observation in a separate event dataset. This event-level transformation is crucial because the unit of analysis in this paper is not the company-year or stock-day observation, but the stock-specific price-movement event. Each event represents a case where a company's stock price has crossed one of the predefined price-change thresholds.

Another task in event study is to determine the selection criteria for the firms and events in the study (MacKinlay, 1997). One key aspect is that this study does not require companies to have stock history for the full period 2003-2025. Instead, events are identified only when the required price data is available. The method is suitable for a long-horizon equity dataset because firms have different listing histories. However, as future returns from each holding period are calculated, events are included only if all four future return horizons are available. This means that an event must have valid adjusted price observations at the event date and at 66, 132, 264, and 528 trading days after the event.

Eventually, this requirement leads to a sample period of 2003-2023 and an additional return observation period of 2024-2025. Events close to the end of a company's available price history are excluded from the final processed sample if one or more of these future return observations are missing. These factors lead to one observation with either upward or downward prior performance, and four different profit calculations for each observation. As all the requirement-filling observations with profit calculations are retrieved, the observations are pooled into two groups depending on the upward or downward performance before the event date t_0.

4.2 Event identification

The traditional approach for event study includes stages of event definition (MacKinlay, 1997). In this study, three independent event definitions are used. The first event type is a 10 percent price change within a maximum of 5 trading days. The other two types follow a similar style with 20 and 30 percent marks within a maximum of 15 and 45 trading days, respectively. These three percentage limits and periods are predetermined and not readjusted after retrieving and analyzing the data. Chosen thresholds allow the analysis to distinguish between moderate but rapid price movements and larger price movements that may develop over a longer interval. The threshold-based event study method is also used in previous financial literature (Kudryavtsev, 2018; Yu & Huarng, 2020). All three definitions are applied separately to each company's adjusted daily price series. If several thresholds are reached on the same day, the event is counted for the highest-percentage threshold.

All the event definitions identify both upward and downward price movements. An upward event occurs when the adjusted price increases by at least the required threshold inside the relevant maximum window. A downward event occurs when the negative-side threshold is passed inside the same time window. The event identification procedure is not based on a simple fixed-window return. For example, the 10 percent event definition does not require that the return from exactly the last five trading days is at least 10 percent. Instead, the method tracks whether the price movement reaches 10 percent at any point during the last five trading days. The subsequent returns after these events are used to evaluate whether the evidence is more consistent with momentum or contrarian trading.

For upward events, the event detection procedure compares the current adjusted price to previous prices within the maximum window. If the current price is at least the required percentage above a prior price within the window, an upward event is found. The starting point of the movement is the most recent prior price observation within the window that allows the threshold to be met with the fewest trading days. In contrast, downward events follow the same logic in the other direction.

The event date is the first date when the threshold is passed. This is an important definition, as stock prices are subject to daily movement. Also, a stock that continues to rise or fall after crossing the threshold could otherwise generate repeated events on consecutive days. However, the three event criteria are first calculated independently. This means that all three positive and three negative event types are identified separately and stored as separate event types. Thus, a single price movement may produce events under more than one criterion. For example, a rapid positive movement of a stock may first trigger the 10% mark, and a few days later cross the 20% threshold. All the events remain visible in the raw event dataset. For every event, all the relevant information is captured. This catalog includes company name and ticker, event date, event price, event direction, event criterion, event-period price change, starting date, and starting price. Additionally, profit calculations are separately done for each event and each profit observation period. Raw data contain all events that are applicable based on the requirements.

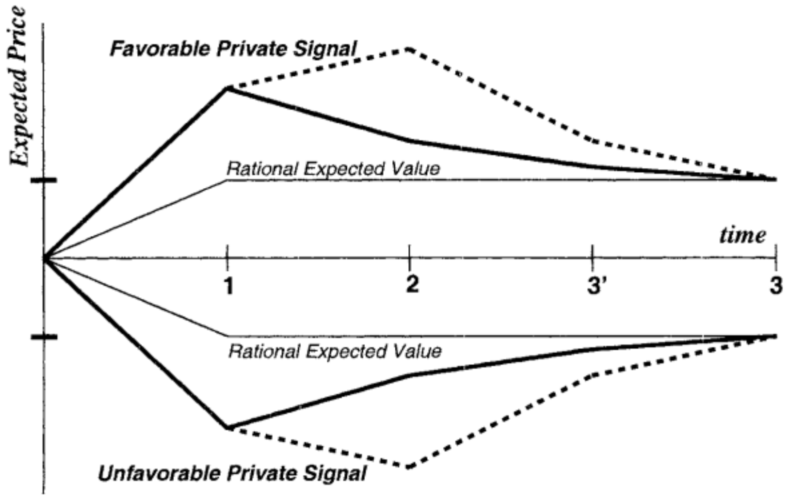

Figure 1. Price movement paths after a stock-related event (Daniel et al., 1998).

As the defined event limits are set to reachable levels, it is inevitable that some events will overlap. The baseline of this study is to follow the full stock price history beginning from 2003, and to provide reliable evidence from the full period. Additionally, any bounce-back movement or longer trend in the same direction is covered with the return calculation period. Thus, excluding continuous events only adds robustness and corrects bias for the results.

Practically, the overlapping events are avoided by using a quarantine period. This type of extension is not usual in event-study methodology. However, Dionysiou (2015) describes the importance of modifying existing models suitable for the chosen study. In this study, the most suitable method to exclude stock-level overlapping events is a quarantine period. The quarantine rule used in this study is 22 trading days. After an event is accepted for a given stock and event criterion, the following 22 price rows are treated as a frozen period for that same stock. The next accepted price movement under any event criterion for that stock must begin only after this period. A key feature of the quarantine rule is that it is based on the starting point of the next price movement, not only on the next event date. Otherwise, for example, a 30% price change and a 45-day event period could use the same price drift for more than one observation, despite the quarantine period. Even though a 22-day quarantine applies for the main study, longer quarantine periods of 132 and 528 trading days are applied to ensure the robustness of this research.

A recognizable fact is that return calculation periods may still overlap, especially with the longest profit calculation periods. However, 22 trading days should be enough for the stock to move independently and to form another starting value for the next profit calculation. For the chosen scope, it is impossible to make events fully independent. If the full 528 trading days after the event date are blocked, there would be only a very limited group of events left, as Table 3 shows. In conclusion, this would weaken the research on its own. Regarding the same topic, market-level co-movements are not excluded or controlled in the main study, leaving some natural correlation and restrictions for this study. However, market-adjusted returns are calculated in the secondary analysis, diminishing the market co-movement effect.

To ensure that the findings are not biased by overlapping timings, an additional, more cautious approach is used. This is consistent with Dionysiou (2015), who adds robustness for longer event studies by repeating the test with different metrics. In a second robust check, the freezing period is set to 132 days, equal to approximately 6 months. In a third, even more careful robust check, the freezing period is set to approximately 24 months, or 528 trading days, which ultimately reduces the number of events. However, with these tests it is possible to evaluate results between more careful approaches and the main test. If the more careful approaches show similar results with the main test, the validity and significance of the results improve.

4.3 Descriptive statistics of raw data

The sample of this research consists of 225 tickers listed on the main list of HSE during the period 2003-2025. The maximum number of possible daily observations for an individual company is 6 001. Since not all the companies were listed for the entire period, the panel is unbalanced. Consequently, the number of available daily observations differs across companies. Some firms have price histories covering the full sample period, while others have shorter histories due to later listings, delistings, and other natural reasons.

Within the described frames, there were 38 432 unique events that met some of the thresholds during the given period. Simultaneously, 34 098 events had appropriate profit calculations for all the metrics. When the 22-day quarantine rule applied, there were 8 723 events left. The same figures for the more robust quarantines of 132- and 528-days were 3 470 and 1 253 events, respectively. From the 225 possible tickers, with a 22-day quarantine rule, there were suitable events from 221 different tickers. The large sample supports the suitability and effectiveness of the event study format (MacKinlay, 1997).

Table 1 presents the descriptive statistics of all approved events with a 22-day quarantine. In other words, Table 1 shows the whole dataset used in the main study of this thesis. In addition, the event identification process statistics are included, with the categorically reported sample sizes, event means, and medians. These include unique event dates, the minimum and maximum number of events in one day, as well as the mean, median, and standard deviation of events for each unique event day. Unique event days are shown to better visualize how the events are distributed throughout the whole period. Furthermore, it provides visibility on whether there is independence between events.

In all three Tables 1, 2, and 3, the event category columns represent a specific event category. All positive and negative events are shown combined in columns All pos. and

All neg., respectively. Positive event categories of +10% – +20%, +20% – +30%, and over +30% price changes are in columns 20% > x ≥ 10%, 30% > x ≥ 20%, and ≥ 30%, respectively. Similarly, the events in each negative event category are shown as -20% < x ≤ -10%, -30% < x ≤ -20%, and ≤ - 30%, respectively.

Table 1. Descriptive statistics of approved events, with 22-day quarantine.

Table 1. Descriptive statistics of approved events, 22-day quarantine

This table presents descriptive statistics of the categorized data points approved after the 22-day quarantine rule and other previously described requirements. ED = event date.

Event category	All pos.	20%> x ≥10%	30%> x ≥20%	≥30%	All neg.	-20%< x ≤ -10%	-30%< x ≤ -20%	≤ - 30%
Sample size / N	5064	4338	440	286	3659	3411	200	48
Price change mean	0,139	0,116	0,221	0,360	-0,123	-0,114	-0,218	-0,329
Price change median	0,113	0,111	0,213	0,313	-0,110	-0,109	-0,209	-0,314
Unique event dates	2678	2449	397	260	1917	1817	173	44
Max events / ED	29	26	3	3	39	37	6	3
Min events / ED	1	1	1	1	1	1	1	1
Mean of events / ED	1,89	1,77	1,11	1,10	1,91	1,88	1,16	1,09
Median of events / ED	1	1	1	1	1	1	1	1
STD of events / ED	1,58	1,46	0,36	0,34	2,26	2,15	0,59	0,36

As the robustness of this study is mostly based on robustness tests with longer quarantine periods, it is reasonable to show similar information to that in Table 1 for the longer quarantine periods of 132 and 528 days. This information is presented in Table 2 for a 132-day quarantine period, and in Table 3 for a 528-day quarantine period.

Table 2. Descriptive statistics of approved events, with 132-day quarantine.

Table 2. Descriptive statistics of approved events, 132-day quarantine

This table presents descriptive statistics of the categorized data points approved after the 132-day quarantine rule and other previously described requirements. ED = event date.

Event category	All pos.	20%> x ≥10%	30%> x ≥20%	≥30%	All neg.	-20%< x ≤ -10%	-30%< x ≤ -20%	≤ - 30%
Sample size / N	2034	1737	162	135	1436	1345	71	20
Price change mean	0,139	0,115	0,217	0,357	-0,121	-0,113	-0,213	-0,325
Price change median	0,112	0,110	0,212	0,311	-0,109	-0,108	-0,207	-0,310
Unique event dates	1464	1299	152	127	947	899	62	19
Max events / ED	15	12	3	2	24	24	4	2
Min events / ED	1	1	1	1	1	1	1	1
Mean of events / ED	1,39	1,34	1,07	1,06	1,52	1,5	1,15	1,05
Median of events / ED	1	1	1	1	1	1	1	1
STD of events / ED	0,82	0,75	0,27	0,24	1,49	1,43	0,57	0,23

While the stock level overlap is lower in the 132-day quarantine and 0 in the 528-day quarantine, relatively lower means of events in Tables 2 and 3 than in Table 1 also visualize higher independence of events at the market level. Even though the sample size is heavily diminished by applying longer quarantine periods, more independent events are necessary to prove the reliability of results.

Table 3. Descriptive statistics of approved events, with 528-day quarantine.

Table 3. Descriptive statistics of approved events, 528-day quarantine

This table presents descriptive statistics of the categorized data points approved after the 528-day quarantine rule and other previously described requirements. ED = event date.

Event category	All pos.	20%> x ≥10%	30%> x ≥20%	≥30%	All neg.	-20%< x ≤ -10%	-30%< x ≤ -20%	≤ - 30%
Sample size / N	724	620	56	48	529	494	32	3
Price change mean	0,137	0,115	0,226	0,323	-0,120	-0,113	0,213	-0,333
Price change median	0,112	0,110	0,211	0,308	-0,110	-0,109	-0,107	-0,333
Unique event dates	588	518	54	45	401	381	28	3
Max events / ED	15	12	2	2	8	8	3	1
Min events / ED	1	1	1	1	1	1	1	1
Mean of events / ED	1,23	1,20	1,04	1,07	1,32	1,30	1,14	1,00
Median of events / ED	1	1	1	1	1	1	1	1
STD of events / ED	0,79	0,70	0,19	0,25	0,85	0,83	0,45	0,00

In Table 3, the sample size in positive and negative events is still sufficient for testing. However, the highest-percentage threshold categories in both positive and negative event types are arguably too thin for reliable research, especially the category of ≤ - 30% with 3 events. Despite these thin categories, the results are later shown for every category, as well as for all positive and negative event types together.

4.4 Research methodology

This research uses an event study-based research design to examine whether short and significant stock price movements are followed by return continuation or return reversal. The threshold-based event format is suitable because the core research question concerns what happens after a stock experiences a clearly defined price shock. Additionally, event study is a widely used research type in financial research when the objective is to measure stock price behavior around identifiable events (MacKinlay, 1997; Yu & Huarng, 2020). Still, this study differs from a traditional event study because it focuses on raw future returns rather than abnormal returns relative to an asset pricing model. In traditional event studies, the event date is typically associated with a corporate announcement or market event, and the researcher examines returns around that date (MacKinlay, 1997). In this study, the event is not an external announcement but an endogenous price movement. The event date is the first trading day on which a stock's adjusted price reaches one of the predefined price thresholds.

One of the key questions in this type of event study is robustness checks. Even though there is approximately one calendar month freezing period from event date t_0, it may still lead to highly overlapping examination periods if another event emerges right after the one-month period. However, robustness checks with longer quarantine periods are conducted to ensure the reliability of the results. These issues are not just firm-level. As shown in Table 1, during the most turbulent conditions, there are up to 39 accepted events on the same date. Therefore, conventional OLS standard errors and simple t-tests that assume independent observations are not appropriate for statistical inference in this type of event study (Kolari & Pynnönen, 2010; Dionysiou, 2015; Cohn et al., 2026).

In turn, a bootstrapped version of the skewness-adjusted t-statistic is used. The chosen method is more suitable for skewed results and is widely used in previous literature (Iqbal et al., 2009; Li & Zhao, 2006; Lyon et al., 1999).

4.4.1 Return measurement

A common approach in the financial literature for comparing and analyzing event returns is to use estimation window profits as a benchmark (MacKinlay, 1997; Dionysiou, 2015; Yu & Huarng, 2020). Another style described is to compare event results to market returns. These strategies describe the event results in relation to stock- or market-level performance. As the aim of this study is not to compare event returns to stock- or market returns, but to compare two opposite strategies, the estimation window is not applicable to this research. However, a benchmark comparison is possible. In a secondary analysis, market-adjusted returns are calculated by comparing individual event returns to market returns from the same period. As in the main study, the market-adjusted event returns are clustered by category, and pooled returns are analyzed afterward. This type of secondary analysis follows the traditional event study form more closely but also adds visibility and robustness to the results (Bessembinder et al., 2019). It also allows the study to examine whether the observed strategy performance is driven by stock-specific continuation or reversal rather than general market movements.

In this study, the main outcome variables are future gross returns after each event. In many previous event studies, the profit calculation window consists of days before and after events (Pandey & Kumari, 2021; Strong, 1992; Yu & Huarng, 2020). This type of surrounding event profit window is not possible in this research, as the aim is to explain the profitability of market actions after significant price movement, before t_0. Once an event date (t_0) is identified, future returns are calculated over four holding periods of 66, 132, 264, and 528 trading days. These horizons correspond to approximately 3-, 6-, 12-, and 24-month periods, respectively. The use of several holding periods is important because the thesis examines whether short-term price continuation and longer-term reversal differ across investment horizons.

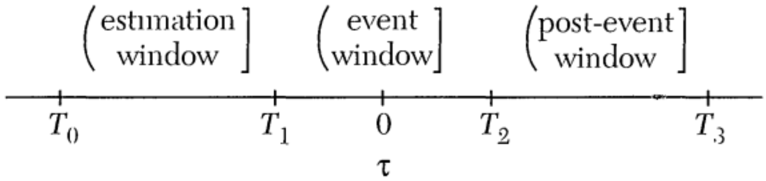

Figure 2. Illustration of traditional event study structure with estimation-, event-, and post-event windows. (MacKinlay, 1997).

The profit calculation method in this study differs from traditional event study methodology, where abnormal returns are usually measured relative to a market model or other benchmark (Brown & Warner, 1985; MacKinlay, 1997; Dionysiou, 2015). In the main study of the thesis, the focus is instead on whether an investor would have earned a positive or negative gross return by taking a specific position after the event. In contrast, and as previously stated, a secondary analysis is conducted to measure returns relative to a market return. Since there are several return calculation periods, it is convenient to report results as log returns. Strong (1992) described log returns as theoretically more suitable when linking together multi-period returns over longer periods. Afterward, several previous event studies have reported results as log returns (Bessembinder et al., 2019; Bessembinder et al., 2025). Future log returns, $R_{i,t_0,h}$, are calculated with the equation

$$R_{i,t_0,h} = \ln(\frac{P_{i,t_0+h}}{P_{i,t_0}}), \qquad (1)$$

where i denotes the stock identifier, t_0 is the event day, and h is the future profit calculation period, practically either 66, 132, 264, or 528 trading days.

The raw holding period returns are first calculated for the stock itself. These returns are then interpreted differently depending on the trading strategy. For a long position, the strategy return equals the raw future stock return. Conversely, for the short position, the total return is the negative of the raw future return figures. This distinction is necessary because the same event implies different actions under momentum and contrarian strategies. Therefore, it is important to distinguish momentum and contrarian trading from long and short positions when calculating profit. Both position types are calculated from every event, illustrating profit calculations of both trading strategies.

For the secondary analysis, the total market log return for the OMX Helsinki CAP Total Return index (OMXHCAP) was used as a proxy for overall market performance in Finland. The market-adjusted long position event returns, MAR^{+} , are calculated with the formula

$$MAR_{i,t_0,h}^{+} = R^{+}{}_{i,t_0,h} - R_{m,t_0,h}, \tag{2}$$

and market-adjusted short position event returns, MAR^{-} , with the formula

$$MAR_{i,t_0,h}^{-} = R^{-}{}_{i,t_0,h} + R_{m,t_0,h}, \tag{3}$$

where $R_{m,t_0,h}$ denotes the OMXHCAP logarithmic return between the period t_0 and h.

Clustered return analysis is conducted separately for each holding period and event category. For each of the six event categories, the mean and median raw future returns over 66, 132, 264, and 528 trading days are calculated. The calculation of mean return of long position event categories $R_{d,c}^{+}$, are described with the formula

$$R_{d,c}^{+} = \frac{1}{N}\sum_{R^{+}=1}^{N} R^{+}{}_{i,t_0,h}, \tag{4}$$

and for the short position event categories, $R_{d,c}^{-}$, with the equation

$$R_{d,c}^{-} = \frac{1}{N}\sum_{R^{-}=1}^{N} R^{-}{}_{i,t_0,h}, \tag{5}$$

where *d* indicates the threshold-passing price movement direction and *c* is the counted threshold category, either 10%, 20% or 30%. Lastly, *N* denotes the sample size for each category. Market-adjusted returns are calculated exactly similarly, but from the market-adjusted returns, $MAR_{i,t_0,h}^{+}$ and $MAR_{i,t_0,h}^{-}$.

Statistical tests in this study are conducted with a bootstrapped version of the skewness-adjusted t-statistic. This method is described and used by Lyon et al. (1999), who present this model to control well for the rebalancing, new listing, and skewness biases. Fama and French (2018) present the issue of increased skewness and increasingly leptokurtic distributions in long-horizon returns. Skewness is a particular issue with longer profit calculation periods, for which this model is well suited. Also, Dionysiou (2015) describes this model as promising for longer-period event studies. Furthermore, the model is used in several previous studies (Iqbal et al., 2009; Li & Zhao, 2006).

4.4.2 Variables

Independent variables of this study consist of the following event characteristics used to explain and group future returns. The first is event thresholds, with three used in this research. The three criteria are 10%, 20%, and 30% stock price movements in a maximum of 5, 15, and 45 trading days, respectively. This variable is used to form the main event categories and to apply the quarantine rule. Several criterion variables also allow the study to examine whether different price movements lead to different end results. In earlier literature, threshold-based methods have been used in event studies to capture applicable events (Kudryavtsev, 2018; Yu & Huarng, 2020).

An event direction variable is used to classify each event as either upward or downward. Yu and Huarng (2020) also classified events based on the event direction. This variable is crucial because it determines how the event is interpreted under momentum and contrarian strategies. These two variables combined define an event category. As a result, there are six event categories, from three thresholds, and two possible event directions for each threshold. The results are calculated separately for each category and for pooled events by event direction. In this way, it is possible to undermine the profitability of momentum and contrarian strategies themselves, as well as the highest-yielding category. Lastly, the momentum and contrarian return variables measure the achievable return by following either strategy. The momentum return equals the raw future return for upward events, and the negative of the raw future return for downward events. As the momentum and contrarian strategies are opposite, the same principle applies in the opposite way for the contrarian return variable.

As this research is conducted as a two-stage event study, there are two types of profit calculations. First is the event-period return, which measures the actual percentage change in price from the start date to the event date t_0. Practically, this calculation describes the magnitude of the initial price shock and can be used to determine the applicable event category. In previous event study literature, the profit calculation window usually consists of days before and after events (Pandey & Kumari, 2021; Strong, 1992; Yu & Huarng, 2020). These papers study the event itself and its return factor. However, this event-period return is completely unrelated to future return outcomes. This is because the future return period starts only from the event date t_0, and the event-period return ends on the same date in all cases.

Another profit calculation in this study is the future return outcomes. These logarithmic returns are also the main dependent variables in this study. As the research is conducted with four different time spans, there are four future return outcomes for every event: R_{66}, R_{132}, R_{264}, and R_{528}. These returns are shown in two different ways, gross log returns and annualized log returns. The latter helps assess comparability across different time spans. Still, both outcomes measure the adjusted logarithmic return between the event date and respective time intervals after the event. Even though event studies typically focus on the price movements near the event date, there are examples of post-event profit calculation periods, such as Ahern (2009).

5 Results

This section presents the results of the empirical analysis of this study. Results and statistics are distributed into several subchapters to maintain the focus on a specific area. First, the results of hypothesis 1 are presented and interpreted. Afterward, the comparison between momentum and contrarian strategies is conducted. The third subchapter adds the robustness tests and implications for previous results. Lastly, the main findings, interpretations, and limitations conclude the chapter.

To ensure simplicity, the return calculation periods of 66, 132, 264, and 528 days are considered to describe 3, 6, 12, and 24 months, respectively. In annualized figures, the year is expected to include 261 trading days. This assumption comes from the study's data set, where the mean trading days per year is 6 001 / 23 = 260,91. Also, log or logarithmic returns are used unless otherwise mentioned.

5.1 Future returns of events

The following tables include the mean and median results of each event category and return periods. The results are presented only for momentum style. This choice is made to avoid repetition since the contrarian profits are equal to the opposing-sign profits for momentum profits. Table 4 presents events with upward movement in the event formation period, whereas Table 5 includes downward movement events. In both Tables 4 and 5, a 22-day quarantine period is applied. These tables also present the statistical tests of the main study.

The structures in Tables 4 and 5 are similar. Both tables include four panels, each of which includes a specific event category. In Table 4, these categories are all three positive or upward threshold categories, and all positive or upward events together. In contrast, categories in Table 5 are all three negative or downward threshold categories, and all negative or downward events together. In all panels of both Tables 4 and 5, the first column from left includes independent variables of different return calculation periods, with momentum profits.

Furthermore, both Tables 4 and 5 describe the profitability of different strategies after each type of event. The dependent variables of both tables are the future returns of events. These are shown in three different figures for each return calculation period. The first is annualized logarithmic mean returns, presenting the mean of annualized percentage gross log returns. This is also the main return variable studied. The next column on the right presents skewness-adjusted t-statistics of the main return variable. The second return variable is an annualized median of logarithmic returns. This is presented to provide additional evidence of the return distribution between the events. The third variable stands for the annualized mean of market-adjusted logarithmic returns, providing a market-adjusted view for the return interpretation. Lastly, the sample size N is presented on the right side of each panel.

Table 4. Descriptive statistics for future returns with a 22-day quarantine, positive event categories

Table 4. Results for future returns, positive event categories

This table presents results of the profitability of long positions for each category and period. The profitability denotes momentum profits. 22-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size.
Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01

Panel A. All events from positive categories.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-1,86 %	-1,533	-0,57 %	-12,21 %	5064
Long, R_{132}	**1,98 %***	2,244	1,72 %	-9,25 %	5064
Long, R_{264}	**1,69 %****	2,605	3,23 %	-9,14 %	5064
Long, R_{528}	-0,15 %	-0,338	1,56 %	-10,07 %	5064

Panel B. Events from category + 20% > N ≥ + 10%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-1,56 %	-1,217	0,00 %	-11,37 %	4338
Long, R_{132}	**1,81 %***	1,925	1,95 %	-9,08 %	4338
Long, R_{264}	**1,54 %***	2,227	3,08 %	-9,12 %	4338
Long, R_{528}	0,03 %	0,072	1,58 %	-9,94 %	4338

Table 4. Results for future returns, positive event categories					
Panel C. Events from category + 30% > N ≥ + 20%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	2,31 %	0,518	-0,41 %	-11,83 %	440
Long, R_{132}	**9,02 %*** **	2,808	1,19 %	-5,27 %	440
Long, R_{264}	**7,46 %*** **	3,104	5,62 %	-5,60 %	440
Long, R_{528}	0,31 %	0,188	3,17 %	-9,84 %	440
Panel D. Events from category ≥ + 30%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	**-12,83 %** **	-2,230	-6,18 %	-25,58 %	286
Long, R_{132}	-6,25 %	-1,628	1,20 %	-17,92 %	286
Long, R_{264}	**-4,90 %* **	-1,823	4,59 %	-14,85 %	286
Long, R_{528}	**-3,64 %** **	-1,986	0,08 %	-12,35 %	286

To begin with, Panel A in Table 4, the findings indicate relatively low profits for either strategy. The results indicate a slight reversal in the first 3 months, turning back to momentum afterward, yet without statistical significance. Best annualized profits starting from the event day are reached with a long strategy and with a 6-month period within annualized mean returns, yielding 1,98% p.a., with 5% statistical significance. The momentum profits are still clear, 1,69% p.a. for a 12-month holding period, with strong statistical significance. Annualized medians show the highest profits, 3,23% p.a., with a 12-month period. However, the momentum profits diminish with median returns and turn negative with mean returns in a 24-month period. The longest period results lack statistical significance.

Panel B shows results very similar to Panel A, partly because most of the positive sample consists of events in Panel B. The statistical significances for the 6- and 12-month periods still hold at the 10% and 5% levels, respectively. In the shortest and longest periods, the results show signs of reversal, but without statistical significance. However, Panel C presents significant profits especially for 6- and 12-month periods, yielding 9,02% p.a. and 7,46% p.a., respectively. More surprisingly, these returns are statistically significant at the 1% level. For a 12-month period, even the annualized median shows positive returns of 5,62% p.a. Only between months 12 and 24 from the event date are the returns heavily negative, almost leveling the profits of the full holding period, still being statistically insignificant. The highest percentage category of over 30% movements shown on Panel

D shows very different results. Contrarian strategies provide clear returns over time, yet the best annualized returns, up to 12,83% p.a. with statistical significance, are reported with the shortest interval of 3 months. This finding also provides very good market-adjusted returns in the short term. Periods of 12 months and 24 months also record statistically significant profits, whereas the 6-month period does not. In conclusion, Table 4 includes various results between the event categories.

Table 5. Descriptive statistics for future returns with a 22-day quarantine, negative event categories

Table 5. Results for future returns, negative event categories					
This table presents results of the profitability of short positions for each category and period. The profitability denotes momentum profits. 22-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size. Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01					
Panel A. All events from negative categories.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	1,70 %	1,148	-3,27 %	12,32 %	3659
Short, R_{132}	**3,29 %*** **	3,071	0,00 %	13,06 %	3659
Short, R_{264}	**2,21 %*** **	2,830	-0,98 %	12,34 %	3659
Short, R_{528}	**1,17 %** **	2,156	-1,60 %	11,74 %	3659
Panel B. Events from category - 20% < N ≤ - 10%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	2,06 %	1,363	-2,97 %	12,40 %	3411
Short, R_{132}	**3,37 %*** **	3,055	0,00 %	13,07 %	3411
Short, R_{264}	**2,16 %*** **	2,723	-0,45 %	12,23 %	3411
Short, R_{528}	**1,10 %** **	1,961	-1,57 %	11,57 %	3411
Panel C. Events from category - 30% < N ≤ - 20%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	0,57 %	0,086	-5,77 %	14,54 %	200
Short, R_{132}	2,66 %	0,579	-4,89 %	13,56 %	200
Short, R_{264}	4,79 %	1,243	-3,31 %	16,18 %	200
Short, R_{528}	2,67 %	1,056	-2,20 %	14,79 %	200
Panel D. Events from category ≤ - 30%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	-18,69 %	-1,057	-6,62 %	-2,33 %	48
Short, R_{132}	0,67 %	0,044	0,00 %	10,05 %	48
Short, R_{264}	-5,41 %	-0,586	-12,23 %	4,27 %	48
Short, R_{528}	0,45 %	0,084	-0,76 %	11,50 %	48

In Table 5, there is strong support for momentum continuation across several panels. In Panels A, B, and C, not a single holding period with a long position yields positive returns in mean terms. Still, in all four panels, annualized median log returns show relatively good returns for the contrarian style during the shortest 3-month period. This would be a sign of heavy negative return events, downward biasing the mean figures. Also, bit surprisingly, despite the mean returns being categorically negative for almost all long positions in Table 5, the median returns show positive nominal returns for the contrarian strategy in all the longest holding periods in every panel. In Panels A and B, the findings are even statistically significant at the 5% level. Furthermore, statistically significant positive results for the momentum strategy are also found in 6- and 12-month periods. The most volatile findings are in Panel D, where switching between the strategies at each return calculation period seems to provide good returns. Although the results show clear support for momentum, neither the gross returns nor annualized returns are very good, and the findings are statistically insignificant. Also, the median returns indicate the opposite outcome, creating a conflict between the findings.

Briefly, the secondary test of market-adjusted returns shows at least one very interesting finding in Table 5. In Panel D, taking the long position after an accepted event seems to outperform the market in the next 3-month period. Although the sample size is limited, both the stock-level and market-adjusted returns seem appealing for contrarian-minded investors. However, the return variable is not statistically significant. Interpreting the positive market-adjusted returns for short position returns should be considered with care. This is especially true because the market-level profits seem to be consistently positive. Thus, the market-adjusted positive returns for short strategies seem to be driven by weaker, barely positive strategy returns.

5.2 Momentum and contrarian strategy comparison

As presented in the previous chapter, there are recognizable patterns and support for both trading styles. This comparison between strategies requires a cohesive analysis of Tables 4 and 5 and the panels within the tables. To begin with Table 4, Panel A (hereinafter, “4A”, similarly with other combinations), the contrarian strategy yielded positive returns in mean and median returns in a 3-month period, yet without statistical significance. In 5A, the contrarian strategy also seems to provide positive returns in a 3-month period according to median returns, whereas mean returns are negative. In turn, the longest 24-month period yields statistically significant profits for the momentum strategy. Support for contrarian profits is weak in statistical terms and also debatable in economic terms.

In turn, the momentum strategy is strongly supported in both Tables 4 and 5 within the 132-day or 6-month period. In 4A, the annualized mean return for the 6-month span is 1,98% p.a., and the similar median return is 1,72% p.a. Also, the momentum strategy in 5A within the same period yields 3,29% p.a. in mean returns and 0,00% in median returns. All the above findings are statistically significant at the 1% level.

The third comparison is within the one-year holding period. In 4A, the findings support the momentum strategy, with annualized mean and median returns of 1,69% p.a. and 3,23% p.a., respectively. Additionally, in 5A, there is additional support for momentum. The annualized mean return is 2,21% p.a., but the median return is -0,98% p.a., indicating that the majority of events support the contrarian strategy, but price changes are greater in momentum-supporting events. Despite the negative median return for the momentum strategy, both the mean returns are again statistically significant, with the strongest level. In addition, the subgroups of +20 – +30 % and -20 – -30 % shown in 4C and 5C provide very strong support for momentum in the 1-year period, at least for the mean returns. In 4C, the annual mean return is 7,46% p.a. with statistical significance, and in 5C, 4,79% p.a. without statistical significance. In conclusion, the momentum strategy is strongly supported in the 12-month period.

The longest examined period, 24 months, is the most complex out of the four periods. The data in 4A carefully point towards a contrarian strategy, without statistical significance. In 5A, the profits are statistically significant and indicate small momentum profits.

Yet again in 5A, median returns are even more towards the contrarian style, being 1,60% p.a. These mixed results for a relatively long period of 2 years partially highlight RWT (Fama, 1965) and lack of predictable patterns.

The most extreme price movement categories should be analyzed once more. In 4D, contrarian style dominates, at least with mean returns with statistical significance over months 3, 12, and 24. In 5D, the sample size is relatively small, and the results are mixed and statistically insignificant. However, both 4D and 5D present quick correlation and solid profits within the next 3 months, supporting the overreaction hypothesis (De Bondt & Thaler, 1985).

5.3 Robustness checks

As described in the research methodology, two robustness checks are implemented to provide additional results with different parameters. These robustness checks extend the length of the quarantine period in the event acceptance process. The first robustness check includes a 132-day quarantine period, and the adjusted event statistics are shown in the following Tables 6 and 7. The results of another robustness check with a 528-day quarantine period are shown in Tables 8 and 9. In all Tables 6-9, the presentation form is identical to that of Tables 4 and 5. To clarify, Tables 4, 6, and 8 are comparable between positive event types, whereas Tables 5, 7, and 9 are also comparable between negative event types. The differences between the mentioned tables are regarding the quarantine period, sample sizes, and return variables.

Since the purpose of robustness tests is to test the main study, these findings will next be compared to the results of the main study. To begin with, Table 6 and Panel A show similar patterns to Table 4. In the shortest period, there is a slight reversal visible, but afterward, especially with 6 and 12 months, the momentum effect seems to yield better. Also, in line with the previous findings, returns within the 24-month period are more controversial but slightly towards contrarian profits. Only the 12-month return is statistically significant at the 10% level. Panel C reveals that a highly statistically significant momentum profit for the 12-month period is documented for the event group of +20 – +30%. This is also linear with the findings in the main test. Lastly, Panel D presents a small statistically insignificant reversal in a 3-month period among the highest threshold category, also linear with the findings of the main test. In conclusion, previous findings in Table 4 hold well after testing with longer quarantine.

Table 6. Descriptive statistics for future returns with a 132-day quarantine, positive event categories

Table 6. Results for future returns, positive event categories, 132-day quarantine

This table presents results of the profitability of long positions for each category and period. The profitability denotes momentum profits. 132-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size. Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Panel A. All events from positive categories.					
Long, R_{66}	-2,09 %	-1,158	-1,27 %	-10,42 %	2034
Long, R_{132}	1,38 %	1,065	0,46 %	-8,50 %	2034
Long, R_{264}	**1,80 %***	1,922	3,08 %	-8,09 %	2034
Long, R_{528}	-0,58 %	-0,868	0,60 %	-9,67 %	2034
Panel B. Events from category + 20% > N ≥ + 10%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-2,31 %	-1,223	-1,39 %	-9,64 %	1737
Long, R_{132}	0,93 %	0,681	0,00 %	-8,50 %	1737
Long, R_{264}	1,23 %	1,248	2,32 %	-8,36 %	1737
Long, R_{528}	-0,48 %	-0,676	0,59 %	-9,54 %	1737
Panel C. Events from category + 30% > N ≥ + 20%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	0,69 %	0,090	2,10 %	-12,92 %	162
Long, R_{132}	6,74 %	1,298	3,63 %	-7,00 %	162
Long, R_{264}	**8,90 %****	2,182	6,76 %	-4,36 %	162
Long, R_{528}	0,20 %	0,061	1,94 %	-10,34 %	162
Panel D. Events from category ≥ + 30%.					
Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-2,65 %	-0,321	-1,14 %	-17,49 %	135
Long, R_{132}	0,63 %	0,112	0,10 %	-10,28 %	135
Long, R_{264}	0,65 %	0,166	7,27 %	-9,15 %	135
Long, R_{528}	-2,83 %	-1,127	-1,68 %	-10,55 %	135

Table 7 includes a more robust approach for Table 5. Panel A of Table 7 follows a relatively similar model to Table 5. Momentum seems to continue after the event, with statistically significant returns in 3-, 6-, and 12-month periods. The best annualized momentum returns are calculated over the 6-month period. Diving deeper into the results, Panel C tends to provide interesting findings across the tables of this study. A clear return reversal is found for the 3-month period with 6,78% p.a. mean return and 6,82% p.a. median return. Even though the mean return reverses again towards the 6-month mark, median returns stay very high with 14,52% p.a. in the half-year period. All the findings on Panel C are statistically insignificant. On Panel D, momentum returns for the 6-month period are exceptionally good, even with statistical significance. Without rejecting the findings, the sample size should be recognized when interpreting findings from Panels C and D. In any case, the findings from Table 7 mainly support the main study results.

Table 7. Descriptive statistics for future returns with a 132-day quarantine, negative event categories

Table 7. Results for future returns, negative event categories, 132-day quarantine

This table presents results of the profitability of short positions for each category and period. The profitability denotes momentum profits. 132-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size. Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Panel A. All events from negative categories.					
Short, R_{66}	**3,71 %***	1,749	0,00 %	14,52 %	1436
Short, R_{132}	**5,10 %*****	3,259	0,93 %	14,83 %	1436
Short, R_{264}	**2,92 %****	2,512	-0,63 %	12,63 %	1436
Short, R_{528}	0,82 %	1,018	-2,20 %	11,21 %	1436
Panel B. Events from category - 20% < N ≤ - 10%.					
Short, R_{66}	**4,06 %***	1,875	0,00 %	14,24 %	1345
Short, R_{132}	**5,23 %*****	3,249	1,59 %	14,58 %	1345
Short, R_{264}	**2,87 %****	2,428	0,00 %	12,35 %	1345
Short, R_{528}	0,88 %	1,083	-2,03 %	11,13 %	1345
Panel C. Events from category - 30% < N ≤ - 20%.					
Short, R_{66}	-6,78 %	-0,689	-6,82 %	17,35 %	71
Short, R_{132}	-3,33 %	-0,473	-14,52 %	17,94 %	71
Short, R_{264}	2,50 %	0,402	-3,19 %	19,16 %	71
Short, R_{528}	-0,76 %	-0,158	-5,27 %	12,53 %	71

Table 7. Results for future returns, negative event categories, 132-day quarantine

Panel D. Events from category ≤ - 30%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	16,95 %	0,677	0,00 %	22,96 %	20
Short, R_{132}	**26,31 %***	1,580	6,13 %	21,05 %	20
Short, R_{264}	7,58 %	0,649	-13,69 %	8,14 %	20
Short, R_{528}	2,05 %	0,400	-6,29 %	12,60 %	20

Moving on to another robustness test with a 528-day quarantine, it is necessary to highlight the significantly smaller sample size, especially in Panels C and D of Tables 8 and 9, compared to the main test results in Tables 4 and 5. Nevertheless, despite the reduced sample size, the following figures are fully independent of stock-level overlap in all profit windows.

Table 8 likewise seems to provide results consistent with earlier results in Tables 4 and 6. The results in Panel A show even more support for momentum investing after increased stock prices. Returns for 6 and 12 months are statistically significant, strengthening the findings. The 12-month strength is partially explained by Panel C, where the returns are even higher than previously found. The statistically significant mean returns are 17,49% p.a. In addition, this category with a momentum strategy seems to outperform the market index by 6,73% p.a. within the same period. Even though the sample size is small, these returns strengthen the overall finding of strong returns in a specific category, even after both robustness tests. Furthermore, even as the profits tend to level towards the 24-month period, the results still indicate slightly positive momentum returns for the longest window. This finding is slightly at odds with previous findings, where the results were unclear or even towards contrarian profits. Finally, Panel D presents further evidence of short-term reversals in the highest threshold categories, with returns of 7,15% p.a. with mean returns and 17,94% p.a. with median returns for the contrarian strategy.

Table 8. Descriptive statistics for future returns with a 528-day quarantine, positive event categories

Table 8. Results for future returns, positive event categories, 528-day quarantine

This table presents results of the profitability of long positions for each category and period. The profitability denotes momentum profits. 528-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size. Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01

Panel A. All events from positive categories.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-2,35 %	-0,831	0,00 %	-11,96 %	724
Long, R_{132}	**3,74 %***	1,805	2,22 %	-8,48 %	724
Long, R_{264}	**4,10 %*****	2,697	5,13 %	-6,99 %	724
Long, R_{528}	0,92 %	0,884	1,46 %	-8,74 %	724

Panel B. Events from category + 20% > N ≥ + 10%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-2,11 %	-0,711	0,00 %	-11,45 %	620
Long, R_{132}	3,03 %	1,361	1,98 %	-9,08 %	620
Long, R_{264}	**2,77 %***	1,705	4,52 %	-8,31 %	620
Long, R_{528}	0,22 %	0,205	0,74 %	-9,57 %	620

Panel C. Events from category + 30% > N ≥ + 20%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-0,89 %	-0,068	-0,31 %	-6,76 %	56
Long, R_{132}	12,64 %	1,383	12,26 %	0,23 %	56
Long, R_{264}	**17,49 %****	2,770	10,84 %	6,73 %	56
Long, R_{528}	6,00 %	1,163	6,64 %	-2,72 %	56

Panel D. Events from category ≥ + 30%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Long, R_{66}	-7,15 %	-0,702	-17,94 %	-24,60 %	48
Long, R_{132}	2,53 %	0,451	0,18 %	-10,79 %	48
Long, R_{264}	5,55 %	1,380	6,33 %	-5,95 %	48
Long, R_{528}	3,96 %	1,262	2,02 %	-5,17 %	48

The final robustness check is presented in Table 9. Due to an exceptionally low sample size in Panel D and partly in Panel C, the focus of this test is mostly on Panels A and B. In earlier results from Tables 5 and 7, the heaviest momentum support was calculated within a 6-month period. Furthermore, the momentum turns to contrarian profits at the end of the time span. As presented in Panel A of Table 9, the findings are somewhat linear with previous results. Even though the results are mixed, the strongest annual mean profit for momentum is found with the 6-month period, whereas the shortest and longest periods tend to skew towards contrarian profits. In Panel B, the 6-month returns are statistically significant, yielding 4,49% p.a. Even as the sample size and distribution are not ideal for further analysis, the robustness test presented in Table 9 supports the core findings of the main study.

Table 9. Descriptive statistics for future returns with a 528-day quarantine, negative event categories

Table 9. Results for future returns, negative event categories, 528-day quarantine

This table presents results of the profitability of short positions for each category and period. The profitability denotes momentum profits. 528-day quarantine rule is applied to these events. Each event category is presented in separate panels to maintain simplicity. Header abbreviations: AGLMR = annualized gross log. mean returns, SA t-stat = skewness-adjusted t-statistics, AMLR = annualized median of log. returns, AMADJR = annualized market-adjusted log. mean returns, N = sample size. Asterisks describe 2-tailed p values of *p<0,10 / **p<0,05 / ***p<0,01

Panel A. All events from negative categories.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	0,77 %	0,234	-4,02 %	13,19 %	529
Short, R_{132}	2,96 %	1,282	-1,00 %	14,27 %	529
Short, R_{264}	1,09 %	0,554	-2,62 %	10,60 %	529
Short, R_{528}	-0,38 %	-0,281	-2,92 %	9,46 %	529

Panel B. Events from category - 20% < N ≤ - 10%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	2,93 %	0,884	-3,91 %	14,94 %	494
Short, R_{132}	**4,49 %***	1,914	-0,53 %	15,38 %	494
Short, R_{264}	2,41 %	1,189	-1,10 %	11,48 %	494
Short, R_{528}	0,26 %	0,193	-2,29 %	9,65 %	494

Panel C. Events from category - 30% < N ≤ - 20%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	-26,17 %	-1,756	-3,96 %	-6,48 %	32
Short, R_{132}	-16,87 %	-1,566	-12,13 %	0,90 %	32
Short, R_{264}	-14,46 %	-1,610	-21,93 %	1,30 %	32
Short, R_{528}	-9,78 %	-1,330	-13,83 %	6,32 %	32

Panel D. Events from category ≤ - 30%.

Return variable	AGLMR	SA t-stat	AMLR	AMADJR	N
Short, R_{66}	-67,60 %	-1,877	-29,04 %	-64,08 %	3
Short, R_{132}	-36,41 %	-0,712	-48,96 %	-26,49 %	3
Short, R_{264}	-48,77 %	-3,854	-35,26 %	-34,36 %	3
Short, R_{528}	-5,14 %	-0,066	-20,82 %	10,83 %	3

5.4 Main findings of the study

After analyzing momentum and contrarian strategies with the main study framework and with additional robustness tests, there are some interesting findings. In this chapter, the aim is to review and collect the findings from earlier interpretations. Also, previous literature is tied into the results as accurately as possible. Limitations for the study and findings are presented separately in the next subchapter.

To begin with the shortest measured period, 66 trading days or approximately 3 months, there seem to be very mixed results. Statistically significant momentum returns are reported in Table 7, Panel A, whereas similar support for the contrarian strategy is presented in Table 4, Panel D. Statistically insignificant mean returns, as well as median returns, mostly support the contrarian style. Although the panels show statistically insignificant support for the contrarian style, the results do not provide statistical answers for the dominance of either momentum or contrarian strategy.

When the time window is extended to 6 months, the results indicate clearly statistically significant support for the momentum strategy. In declined categories, 6-month returns seem to be most clearly towards momentum, as the median returns are also at very neutral levels compared to other periods. Also, within declined events, 6-month momentum returns are clear and robust across the studies conducted. These findings are similar to those of Chan et al. (1996), Jegadeesh and Titman (1993), and Rouwenhorst (1998). In addition, continuing momentum describes long-term underreaction, as reported by Barberis et al. (1998) and Hong and Stein (1999). Thus, momentum returns dominate in a half-year span.

Over a 12-month period, the results again support the momentum category. In negative event categories, momentum's median returns are consistently negative. In turn, mean returns are relatively level with 6-month holding period returns. Still, the 12-month holding period returns clearly favor momentum in negative event categories. Within positive events, momentum dominates across all metrics and delivers robust results. The results match Chan et al. (1996), Jegadeesh and Titman (1993), and Rouwenhorst (1998). Like in the 6-month period, continuing momentum describes long-term underreaction, similar to Barberis et al. (1998) and Hong and Stein (1999). The findings also violate the RWT (Fama, 1965) and EMH (Fama, 1970). Conclusively, momentum is clearly a better choice in the one-year period.

Lastly, the 24-month period provides very mixed results across categories and robustness checks. The only statistically significant support is for momentum, presented in Table 5. However, the statistical significance disappears with the robustness tests. The results in other tables are statistically insignificant and very mixed between contrarian and momentum observations. Therefore, the results of this study do not statistically support either momentum or contrarian strategy.

Regarding the other more detailed findings, the most interesting one is the profitability of +20 – +30% events. This group yields exceptional and statistically significant returns for the 12-month period. Also, the findings are robust with all the applied quarantines. Even the market-adjusted long returns are positive within the robustness test with a 528-day quarantine. This finding is interesting not only because of the strong returns, but also because the phenomenon is much weaker and mostly statistically insignificant in other positive categories. In relation to existing financial theories, this finding challenges the EMH by Fama (1970) and the RWT by Fama (1965), with category-wise predicting power in future returns.

As the results are now presented, it is necessary to review the hypotheses of this study and compare the results with them. As a reminder, the hypothesis H1 was formed as follows.

H1. It is more profitable to buy (sell) a stock after a short and significant stock price decline (increase) than after a short and significant stock price increase (decline), over holding periods of 3–24 months.

The results of this study provide very strong statistical evidence for momentum in 6- and 12-month periods. However, the results for 3- and 24-month periods are not statistically reliable and still provide mixed evidence of the profitability of each strategy. According to these results, the contrarian strategy described in H1 is most likely the least profitable of the two options and thus, the hypothesis H1 is rejected. Another hypothesis, H2, considered the profitability of combining these two trading strategies with different time periods.

H2. Momentum strategy provides better returns in the short term, while the contrarian strategy is more profitable over longer periods.

The profits for momentum are strong and statistically significant, especially in both medium-term windows. Support for contrarian profits is debatable, thin, and not statistically reliable in the shortest and longest periods. Thus, the second hypothesis H2 is not clearly supported by the evidence and is therefore rejected.

Overall, this study provides momentum-dominated evidence on Finnish stock price movements. The 6- and 12-month statistically significant momentum profits are against EMH (Fama, 1970) and RWT (1965), and are similar to those of Chan et al. (1996), Jegadeesh and Titman (1993), and Rouwenhorst (1998). Also, the results highlight the underreaction in Finnish stock markets, matching the findings of Barberis et al. (1998) and Hong and Stein (1999) from other markets. The thorough support for contrarian profits is, bit surprisingly, missing.

Comparing these results to the finding of Grinblatt and Keloharju (2000), that individuals in Finland are strongly contrarian, the results of this study should provide additional insights for most individuals. The results of Grinblatt and Keloharju describe the phenomenon where individuals sell stocks after favorable movements and hold after declines. Further, as prospect theory describes people as risk-willing in negative prospects and risk-averse with positive ones (Kahneman & Tversky, 1979), this combination, combined with the results of this study, leads to a weak outcome. Several important limitations were recognized across the study, which are described in the next chapter in more detail.

5.5 Limitations

This study includes many limitations that should be noted. Overall, the limitations can be roughly distributed into two categories, data and research methods. Of the data-related limitations, several are noted. According to EMH (Fama, 1970), stock prices should reflect a company's fundamental value. Even though market-adjusted returns were calculated and shown, stock-level price movements do not explain the reasons behind an event. Also, the data is clustered, and findings are noted at a general level, which means that there can be outliers. Additionally, previous findings do not provide factual results for future transactions, especially as technical innovations may diminish their effect. Lastly, the data identification process excluded events without price history for the next 528 days. However, the investor cannot be fully sure whether the stock will be on the market for the next two years. This is likely to cause survivorship bias in the results of this study.

Some restrictions and limitations are noted in this type of research methodology. First, the return measurement does not include transaction costs, bid-ask spreads, taxes, short-selling constraints, or liquidity limitations. Thus, the calculated strategy returns should be interpreted as gross theoretical returns rather than fully implementable net trading profits. Nevertheless, gross returns are suitable for the main purpose of the thesis, which is to examine whether return continuation or reversal is present after quick and significant price movements. The second methodology-related restriction is regarding the event identification process. As the daily events were not limited, events were not fully independent marketwise. Different methodologies might provide different or more reliable results in future research. Practical implementation issues can be discussed separately as limitations.

6 Conclusions

This study examined the profitability of momentum and contrarian trading strategies in four different periods of 3, 6, 12, and 24 months. More specifically, the aim of this study was to compare these strategy returns and determine which strategy yields better results within different periods. The dataset consisted of adjusted daily stock prices for each company in HSE between 2003 and 2025. The research was conducted by implementing an event study framework with suitable modifications. Events were identified with six predetermined thresholds: positive and negative price changes of at least 10%, 20%, and 30% on the 5, 15, and 45 trading days, respectively. For each event, the periodic returns were calculated with gross returns and market-adjusted returns. Afterward, the periodic returns were clustered and analyzed within each event category. In the main test, a 22-day stock-level quarantine was applied to ensure more reliable results and to exclude multiple events from consecutive price changes.

The main results of the study were presented with logarithmic annualized returns. Both mean and median results were presented to better understand the distribution and magnitude of price changes. As a statistical test, the bootstrapped skewness-adjusted t-statistics were used for each main return variable. In addition, market-adjusted returns were calculated and shown to evaluate the category returns relative to market returns. To better ensure the reliability of results, two robustness tests were conducted with longer quarantine periods of 132 and 528 days.

Previous literature includes similar studies from around the world and across the history of financial literature. Traditional financial theories were also relevant references for this study, including the overreaction hypothesis (De Bondt & Thaler, 1985), prospect theory (Kahneman & Tversky, 1979), the efficient market hypothesis (Fama, 1970), and the random walk theory (Fama, 1965). Existing literature provided support for both momentum and contrarian strategies, depending on the length of profit calculations and methodological choices. However, there was a notable gap in Finnish studies on the topic. This study was designed to fill that gap and provide answers on the profitability of momentum and contrarian strategies in Finland.

The main findings of this study include a few notable patterns. In the shortest 3-month period, the results between momentum and contrarian strategies varied without statistical reliability. In contrast, momentum is found to be very strong among 6- and 12-month periods. For the longest period, 24 months, the results were mixed between strategies and lacked statistical reliability. In general, this study provides strong evidence of momentum continuation, especially between months 6 and 12 after the price shock. Lastly, groups consisting of +20% – +30% events eventually provide the best returns in the 12-month period, even with statistical significance and after robustness tests.

6.1 Future research

This study provides several insights into future research. First, and possibly the most obvious, is the methodological choice. Excluding all market-level overlapping events, either by pooling same-day events or by otherwise controlling, could provide more certain statistical results. Another possible path would be to combine the strategies using different metrics. This study fully examines holding period returns over a fixed period. A third possible idea would be to repeat the event study with the same metrics but by using a more traditional market model approach to get more reliable event-level results.

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