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Mimicking Claimed Alpha Generating Strategies

Master Thesis

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Abstract

This research paper focuses on the implementation and evaluation of Minervini's momentum analysis techniques in an algorithmic approach. The study aimed to assess the limitations and challenges associated with executing Minervini's strategy in an algorithmic trading system. Several technical restrictions, practical application problems, and the exclusion of fundamental and catalyst aspects contribute to the implementation of a primitive variant of Minervini's strategy. The challenges included the subjective nature of base patterns making bases difficult to identify and limitations in risk and position sizing. However, despite the challenges, the algorithmic approach offers advantages such as the ability to analyze a large number of stocks rapidly. It is suggested to use the algorithm as a tool for stock exclusion rather than fully automating the buying and selling decisions.

The research investigates the possibility of generating excess returns in Sweden, Denmark, and Finland using the implemented algorithm over different time periods from 2008 to 2023. Hundreds of stocks were divided up into 18 stock portfolios based on market capitalization size calculations for a given year. These portfolios were traded using both the momentum strategy and an index strategy. The empirical results indicate that small-cap portfolios exhibited consistent excess returns compared to mid-cap and large-cap portfolios, particularly during high volatility periods. However, the research did not account for transaction costs, which are essential to evaluate the strategy's net returns in real-world scenarios. Despite the exclusion of transaction costs in the study, the significant excess returns observed in small-cap portfolios indicate that the implemented momentum strategy performs notably better for small-cap stocks compared to mid-cap and large-cap stocks. This finding contradicts the efficient market hypothesis, assuming equal transaction costs across different market capitalizations. Further research should consider incorporating transaction costs to gain a more comprehensive understanding of the strategy's overall performance and its practical implications for various market segments. Future research should consider incorporating transaction costs and optimizing the stop-loss and profit-taking levels, and exploring a weekly-based approach instead of a daily-based approach. Additionally, volume analysis, data handling improvements, and a more detailed analysis of buy and sell decisions are recommended to optimize the algorithm's performance for future research.

To summarize, while the implemented algorithm does not fully mimic Minervini's strategy, it offers valuable insights and potential value, especially in small-cap stocks. Further research and optimization are required to enhance its effectiveness and address the identified limitations.

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Signature: ______________________

Nomenclature

Basing Period	Base formation time period.
Large Cap	OMX Stockholm Large Cap
Mid Cap	OMX Stockholm Mid Cap
Small Cap	OMX Stockholm Small Cap
First North	Nasdaq First North Growth Market
large-cap	Simulated Large Cap for a given year.
mid-cap	Simulated Mid Cap for a given year.
small-cap	Simulated Small Cap for a given year.

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1 Introduction

1.1 Background

The efficient market hypothesis (EMH) originates from Fama (1963) who stated that markets are rationally priced when taking in consideration all the information that is available. A little further down the road Damodaran (2015) argued that even though equities in markets have random fluctuations, markets could still be efficient. Damodaran's (2015) modified version of the EMH defined the efficient market as one where "the market price of an asset is an unbiased estimate of the true value of the investment". According to Damodaran (2015), a market can therefore still be considered efficient even if the prices of equities deviate from their true value, as long as these deviations are random in nature. If the valuation of assets only differs by randomness from the true value this would imply that no investor can consistently outperform the market. Today there are both believers and non-believers of the EMH. On the believer side, Malkiel (2003) stated in a research report that "a monkey throwing darts with a blindfold could pick stocks as well as a fund manager". On the non-believer side there are still many market participants who believe that there are certain market inefficiencies that can be exploited to achieve market-beating returns. One such group of investors are momentum traders. Momentum traders believe that stock prices tend to continue moving in the same direction for some time after a trend has been established. One theory explaining the existence of momentum in markets is that initial market reactions to new information may be irrational, causing prices to either overreact or underreact (Moskowitz and Daniel 2011. According to Jegadeesh and Titman (1993) the momentum strategy that was implemented in their report managed to generate excess return. In their research report the conclusion was that buying stocks that performed well and selling stocks that performed poor on the selected time period of a year is a strategy that generates excess returns (Jegadeesh and Titman, 1993). The same momentum strategy used by Jegadeesh and Titman (1993) has been replicated and the applied on various markets and time frames and the excess return generated has been confirmed by Rouwenhorst (1998); Moskowitz and Grinblatt (1999). However not all studies find evidence of momentum strategies, Agathee (2012) found that momentum strategies does not generate excess return. To summarize some studies have found evidence of momentum, others have failed to find a significant effect. This has led to a debate in the academic literature about whether momentum trading is a real phenomenon or whether it is simply a statistical artifact.

Aside from the scientific researchers there are notable momentum traders who have achieved significant returns over long periods of time. One notable momentum trader is Mark Minervini. Minervini (2022) won the U.S. Investing Championship in 1997. Pure luck one might say? Which is why Minervini (2022) engaged and won the same championship in 2021 with an annualized return of 155%. Minervini has achieved exceptional returns over a long period of time using Minervini's proprietary momentum trading strategy. Minervini's performance could be based on consistent luck over the last 20 years, but it is improbable which is what makes Minervini's trading strategy interesting to research. This research seeks to investigate the replicability of Minervini's momentum trading strategy in the Swedish, Finnish and Danish equity markets. The purpose of this research is to evaluate whether it is possible to achieve market-beating returns using an algorithmic implementation of Minervini's approach. The study will also examine the potential limitations and delimitations of the strategy, as well as its implications for the EMH. The implementation of Minervini's strategy in an algorithmic approach to research momentum is different from the research by Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Rouwenhorst (1998) and Agathee (2012). In the algorithmic implementation of the momentum strategy used by Minervini, buy and sell decisions will be based on a daily price analysis compared to the aforementioned momentum research were the buy and sell analyses were made on a time span of at least three months.

1.2 Problem Specification

Jegadeesh and Titman (1993), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), and Agathee (2012) conducted extensive research on the momentum effect using historical prices spanning a 3–12-month period and holding periods that varied from 3-12 months as well. However, as the momentum effect is not defined within a specific time frame, it could be studied on a shorter time interval. The momentum effect using a shorter time frame where decision making is made daily has not been extensively explored and warrants further investigation. Minervini is a momentum strategy trader that claims to have a proven method to generate excess returns within the equity market which makes Minervini's (2013) strategy relevant to initiate shorter term momentum research on. Minervini's momentum strategy (2013) primarily relies on daily spot price analysis and volume of a traded stock, which is different from the research mentioned earlier. Minervini (2022) is a full-time equity trader who has released multiple books to explain Minervini's trading strategy. These books create the basis of the momentum strategy that will be implemented by programming a buy and sell algorithm in python. The algorithm analyses stocks on the daily time frame and buys and sells the stock depending on if the conditions from the chosen strategy are achieved.

1.3 Purpose and Research Questions

The purpose of this study is therefore to analyze and examine the technical analysis techniques of Mark Minervini's stock trading strategy and evaluate the effectiveness of implementing the strategy in an algorithmic approach. The study aims to identify the limitations and challenges of executing Minervini's momentum trading strategy using an algorithm and assess the possibility of generating excess returns in the stock markets of Sweden, Denmark, and Finland over different time periods ranging from 2008-2022. To achieve this purpose, the following research questions has been formulated:

1. *What are the limitations and challenges of executing Minervini's momentum analysis techniques in an algorithmic approach?*
2. *Is it possible to generate excess returns in Sweden, Denmark, and Finland by using the implemented algorithm over different time periods ranging from 2008-2022?*

The research questions have been determined through the logical process of understanding if and how it is possible to implement Minervini's trading strategy and determine the effectiveness of the implementation. By answering the research questions, the study aims to provide private investors with valuable insights into the practical implementation of Minervini's momentum techniques and contribute to the existing momentum strategy research.

1.4 Delimitations

The study assumes that all trades can be executed without any restrictions on liquidity or transaction costs. By assuming that trades can be executed without any restrictions on liquidity or transaction costs, the study can provide a more straightforward analysis of the trading strategy's performance without the added complexity of real-world constraints. However, it's important to note that these assumptions may not hold in practice, and the results may differ when real-world limitations are considered.

The analysis is limited to the Swedish, Danish, Finnish stock markets and covers the period from January 2008 to January 2023. This delimitation sets the geographical and temporal boundaries of the study. By focusing on the Nordic region and a specific time period, the study can provide a more focused analysis of the trading strategy's performance in these markets. However, it's important to acknowledge that the results may not be applicable to other markets or time periods, and further research would be necessary to evaluate the strategy's performance in different contexts.

Furthermore, it is difficult to perfectly mimic Minervini's trading strategy in the algorithm due to several reasons. Firstly the research report covers only a part of Minervini's full strategy, the research is therefore not testing Minervini's full trading strategy only the momentum techniques and the momentum analysis in the strategy. This is further discussed in Chapter 6.1.3. Moreover, the momentum technique is not possible to implement with the time frame that was given. The algorithmic implementation is essentially a simplification of Minervini's strategy even when it comes to the momentum analysis aspects. For example the buying point is different in the implemented algorithm compared to how Minervini applies it in real life because of the difficulty of precisely mimicking something in a algorithmic approach. The buying will be delimited from Minervini's strategy primarily in two ways. Firstly Minervini might not buy a share even though it fulfills all Minervini's criteria because the current market sentiment (Minervini, 2013). In this research report the assumption is that a negative market will generate an insignificant amount of buy signals and thus there will be significantly less buy signals during a negative market trend. Secondly, Minervini always identifies a so-called *"base pattern"* of a specific stock before buying. This base pattern is difficult to implement in an algorithm partly because of the complexity of condensing basing patterns into an algorithm and partly due to the subjectivity of basing patterns. Therefore, instead of fully implementing base patterns in the algorithm, a simplified version that mimics the base patterns will be implemented. These are just two examples of implementations that needs to be simplified. This is evaluated and discussed further in Chapter 3.1.

Moreover, the execution of the strategy also involves a lot of discretionary decision-making, which can be difficult to replicate in an algorithm. For instance, Minervini often emphasizes the importance of staying flexible and being able to adjust the strategy as per the market conditions. This requires a high degree of situational awareness and a deep understanding of the market dynamics, which may not be possible to automate using an algorithm. This is further discussed in Chapter 6.1.1.

2 Frame of Reference

2.1 Compilation of Research on the EMH

There are research reports concluding that markets are efficient, a research report by Maxey (2017) concluded that 92% of the actively managed funds were not able to beat their comparative index over a 15-year period making a statement regarding the efficiency of markets. However, other research reports such as Amenc and Le Sourd (2015) and Lo (2004) have a more dynamic view regarding the efficiency of markets in comparison to the EMH by Fama (1963), Damodaran (2015) and Maxey (2017) . Amenc and Le Sourd (2003) concluded in their research that the ability for a portfolio to surpass a market index is associated with the market's assessment of the securities and their inherent value, and the capacity to take advantage of imbalances in the market equilibrium. Whether these imbalances exist is dependent on the speed and effectiveness in which new information is incorporated into the financial market, and the valuation of the securities in the market (Amenc and Le Sourd, 2003). This aligns well with Lo (2004) who takes a more evolutionary perspective. According to Lo (2004), a market's efficiency and the effect of momentum can vary in different contexts. Lo (2004) argues that in a stock market environment where there are plenty of resources, the number of market participants will increase, which in turn will lead to greater consumption of these resources. Fewer resources have a negative impact on the number of market participants (Lo, 2004). Therefore, the researcher concludes that the efficiency of markets depends on the survival of market participants (Lo, 2004). This could mean that momentum strategies are more or less suitable depending on the economic climate in which they are applied (Lo, 2004). To conclude, there is research on both sides of the spectrum regarding market efficiency, the EMH might be more dynamic than what Fama (1963) suggested and Damodaran (2015) later built on to. Markets might be more varying than this as suggested by by Lo (2004) and Amenc and Le Sourd (2003). Markets might be varying in efficieny and this leaves some room to discuss when and why markets could be temporarily less efficient as suggested by Fama (1963) and Damodaran (2015).

2.2 Theoretical Explanations for Momentum Strategies' Success

As was stated earlier in the background section of this report there have been multiple research reports that have found momentum strategies to consistently generate excess return. According to Moskowitz and Daniel (2011) the reason why momentum strategies work is based on the theory of delayed overreactions and initial underreactions. According to Moskowitz and Daniel (2011) equities initially have over- or under reactions meaning prices of equities move either too much or too little when news reaches the market. This is the explanation as to why momentum strategies could work. Similar perspective on the momentum strategy is brought forward by De Bondt and Thaler (1985) who claim that investor emotions is the reason for initial overreactions as well as initial underreactions.

2.3 The Definition of a Momentum Strategy

Traditionally the momentum strategy used by Jegadeesh and Titman (1993) incorporated only one factor, the price of an equity. More specifically the price trend, where prices are expected to keep moving in the current direction they are currently heading, whether that is increasing or decreasing in price. However, according to more modern interpretations (Investopedia 2023), a momentum strategy usually includes both the price and volume analysis of a stock. For this research, the more modern definition of momentum strategies is used, thus including both price and volume analysis of an equity.

2.4 Compilation of Previous Momentum Research

In "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" Jegadeesh and Titman studied the stock market in the USA between 1965-1989 (Jegadeesh and Titman, 1993).

The study concluded that positive significant excess return was generated by buying equities that had a positive momentum and selling equities that had a negative momentum (Jegadeesh and Titman, 1993). Jegadeesh and Titman ranked equities based on their returns from the last 3, 6, 9 and 12 months. For every time interval they picked out the strongest performing 10% of equities and added them to an equally weighted portfolio which they held for 3, 6, 9 or 12 months. In conclusion they studied a total of 16 portfolios. The most significant excess return was generated by using 12 months of input stock price data and holding the stocks for 3 months (Jegadeesh and Titman, 1993). It is also notable that all the portfolios from the research generated excess return (Jegadeesh and Titman, 1993). From the research, Jegadeesh and Titman also estimated the risk for the different portfolios by calculating portfolio betas. It was concluded that the risk of the portfolios could not explain the generated excess return, thus the risk taken, and the returns given were not congruent(Jegadeesh and Titman, 1993). The authors stated that outperformance is unlikely to be inferred from a higher degree of risk because of the "magnitude and persistence" of the results (Jegadeesh and Titman, 1993).

In "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations" (2001) by Jegadeesh and Titman the research from 1993 was repeated in 2001 with the same method. The scientists updated the study for two reasons. Firstly, they wanted to reinforce their prior findings and secondly, they wanted to investigate new explanations for the momentum effect. The Efficient Market Hypothesis proposes that predictable patterns should be immediately capitalized upon, which in this instance would imply that the momentum effect would be neutralized (Fama, 1963). However, the researchers were able to demonstrate that the momentum effect continued to generate excess return and the momentum strategy was established as a profitable strategy on the American market. Jegadeesh and Titman further developed their research by adjusting the returns of portfolio for risk using the Fama-French three-factor model. Despite considering risk, the excess returns remained statistically significant, which was congruent with their earlier research from 1993. Jegadeesh and Titman argue that the persistence of the momentum effect from their study in 1993 still was viable represents a strong argument against the Efficient Market Hypothesis (Jegadeesh and Titman, 2001).

Rouwenhorst (1998) conducted a study of twelve European countries between 1978 and 1995, using a similar investment strategy as Jegadeesh and Titman (1993). The research showed that the momentum effect exists in all European markets examined (Rouwenhorst, 1998). Portfolios that included buying winners and selling losers generated significant outperformance (Rouwenhorst, 1998). The study indicated that the best-performing momentum strategy was to pick the strongest performing stocks on a 12-month historical interval and then hold the stocks for a period of three months. This result is congruent with the conclusions from the research by Jegadeesh and Titman (1993). The optimal portfolio outperformed the market with an average of 1.84% per month. Furthermore Rouwenhorst (1998) concluded that the outperformance could not be explained by an increase in risk and that the momentum strategy had a weaker performance in emerging markets.

Moskowitz and Grinblatt conducted a similar study to Jegadeesh and Titman (1993) on the US market with equities, but with the difference that the study tested industries instead of individual stocks (Moskowitz and Grinblatt, 1999). The research concluded that the reason behind the effectiveness of momentum strategies can be explained by momentum within stock industry groups and not individual stocks themselves(Moskowitz and Grinblatt, 1999). According to Moskowitz and Grinblatt there is no excess return from momentum strategies after controlling the returns from the underlying industry (Moskowitz and Grinblatt, 1999). However, in 1998 the researchers Grundy and Martin indicated that industry performance was not relevant for the performance of a momentum strategy for an individual stock (Grundy and Martin, 1998). The conclusions thereby contradicting the research by Moskowitz and Grinblatt (1999).

In "Momentum Has Its Moments" by (Barroso and Santa-Clara, 2015) the research acknowledges that momentum strategies can be profitable over certain periods, but argues that the effect is not consistent across all markets and time periods, and may be driven by behavioral biases rather than true market inefficiencies. This is similar to De Bondt and Thaler (1985) because emotions are the underlying factor behind momentum strategies.

The paper "Momentum in the UK Stock Market" (Tonks and Hon, 2003) examines momentum strategies in the UK stock market using data from 1965 to 2000. They discovered that momentum strategies generate excess return over the period studied, even after accounting for transaction costs. The authors also found that momentum strategies work better for small stocks than for large stocks. Moreover, they also found that the effectiveness of momentum strategies has weakened in more recent years and varies across different industries. According to Lesmond, Schill and Zhou (2004) the transaction costs perfectly balances out the potential excess return created from momentum investing.

2.5 Summary of Momentum Strategy Research

Several studies have found that buying equities with positive momentum and selling equities with negative momentum generates significant excess returns. Jegadeesh and Titman's research on the US market in 1993 and 2001, as well as Rouwenhorst's study on twelve European countries, demonstrated that the momentum effect exists in all markets and could not be explained by increased risk. Moskowitz and Grinblatt's study on the US market found that the momentum effect can be explained by momentum within stock industry groups. The profitability of momentum strategies has been shown to vary across markets and time periods and may be driven by behavioral biases. A compilation of some relevant results from the discussed momentum studies can be seen in Table 1[1] below:

Publication	**Monthly Excess Return**	**t-value**	**Sample Period**
Jegadeesh and Titman (1993)	1.84%	3.07	1965–1989
Rouwenhorst (1998)	1.63%	3.24	1965–1994
Moskowitz and Grinblatt (1999)	1.03%	4.35	1963–1993
Jegadeesh and Titman (2001)	1.27%	4.51	1970–1996
Tonks and Hon (2003)	0.91%	2.36	1975–2000
Barroso and Santa-Clara (2015)	1.06%	2.73	1990–2011

Table 1: Summary of Momentum Studies

Notable, is that none of the studies in Table 1 above used daily price analysis to buy and sell equities. The momentum strategies in the studies analyzed all involved holding periods of at least one week, which means that the portfolios were typically rebalanced on a weekly or less frequent basis. In other words, the momentum portfolios were not traded on a daily basis but rather held for a minimum of one week before being adjusted based on the chosen momentum criteria.

2.6 Momentum Research in Relation to Market Efficiency

The studies regarding momentum strategy research align well with the research of market efficiency by Lo (2004) and Amenc and Le Sourd (2003) suggesting that markets are more dynamic than Damodaran (2015) and Fama (1963) suggested. However, there are too many cross-sectional variables to reach a unanimous conclusion. Even though the research conducted by Jegadeesh and Titman (1993, 2001), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), and Tonks and Hon (2003) all demonstrate that momentum strategies can generate significant excess returns the conclusions might have been different if the research was done on another market or another time frame. The difficulty to reach a conclusion regarding market efficiency could align well with Lo (2004) that suggests that there are some periods where momentum strategies are profitable and other periods with higher market involvement where momentum strategies might not be making excess returns. The interpretation could be done that the effect of initial under- and over reactions is lessened the more actors there are within a market because the efficieny of a market increases with the number of participans in the market. In this study the scope is of the Swedish, Danish, and Finnish equity markets. All these markets are considered developed markets in Europe and momentum strategies might therefore have a slightly smaller impact than with other less developed equity markets. Another aspect brought forward is that transaction costs from momentum strategies might perfectly balance out the excess return generated as suggested by Lesmond, Schill and Zhou (2004).

[1]A high t-value indicates that the momentum effect is more likely to be real and not due to random variation.

2.7 Momentum Analysis Techniques of Minervini's Stock Trading Strategy

Inspired by Love (1977) and Reinganum (1988) who discussed and researched the commonalities between stocks that performed well on the stock market Minervini came up with a framework to understand when and which stocks to buy. Minervini's strategy (2013) includes the following factors when assessing a stocks potential trading performance:

- Momentum analysis
- Fundamental analysis
- Catalysts

The Momentum analysis aspects of Minervini's trading strategy are contained in the Momentum analysis section and thus the chapters regarding Fundamental analysis and Catalysts will be excluded from the research. In this chapter, the components of Minervini's Momentum analysis techniques will be examined, as they form the core focus of this research. However, this chapter will not discuss the implementation of these techniques, only discuss the strategies brought forward in the book. This chapter creates the framework from which the algorithm will be implemented. In Chapter 3, the algorithmic implementation of the theory from this chapter is discussed and explained.

2.7.1 Stage Analysis

A stock is always in one of four stages (Minervini, 2013). These four stages are:

1. Consolidation (neutral trend)
2. Accumulation (positive trend)
3. Distribution (neutral/negative trend)
4. Capitulation (negative trend)

Minervini (2013) wants to own a stock during stage 2 (accumulation) when the momentum is strong and sell a stock during later stage 2 or in stage 3 (distribution). As an initial guide to conclude whether a stock is in stage 2 or not Minervini does momentum analysis by using a momentum template described in the chapter below.

2.7.2 Initial Momentum Analysis (the momentum template)

To find potential buy candidates Minervini always performs a stock screening process to identify the momentum of a stock (Minervini, 2016). In this stock screening process, a stock must satisfy certain characteristics contained in the momentum template below to be considered for a buy (Minervini, 2016). One could argue that the initial momentum template acts as a hygiene factor for the stock that will be bought. The momentum template consists of the following criteria (Minervini, 2016):

1. The current stock price is above MA150 and MA200.
2. MA150 is above MA200.
3. The MA200 line has been trending up for at least 1 month.
4. MA50 is above MA150 and MA200.
5. The current stock price is above MA50.

6. The current stock price is at least 30% above its 1 year low.
7. The current stock price is within at least 25% of its 1 year high.
8. The relative strength (RS) ranking is at least 70.

Where the moving average (MA) is calculated as follows where n is the number of historical trading days:

$$MA_n = \frac{\sum_{i=1}^{n} P_i}{n} \tag{1}$$

The relative strength (RS) ranking is a measure of a stock's performance over the past 12 months relative to other stocks in the market (Minervini, 2016). The ranking is calculated by comparing a stock's return over this period to the returns of all other stocks in the selected market (Minervini, 2016). RS Ranking is therefore a kind of momentum indicator.

$$RS = \frac{\text{Stock's Price Performance over the last 12 months}}{\text{Price Performance of all other stocks in the market over the same period}} \tag{2}$$

After the relative strength of all the stocks in the index are calculated the relative strength ranking is created by sorting all the RS scores. The ranking ranges from 0 to 100, with a score of 99 indicating that the stock has outperformed 99% of all other stocks in the market (Minervini, 2016). Once a stock fulfills the momentum template, Minervini will consider the stock for a buy. However, fulfilling the momentum template is only the first stage of Minervini's buy analysis. Within a stage 2 phase the stock will form base patterns that will be discussed in the next chapter.

2.7.3 Base Patterns

Within a stage 2 advance of a stock the stock will decline temporarily before accelerating further to continue its stage 2 advance (Minervini, 2016). When a stock temporarily declines during a stage 2 advance phase the stock will form a base pattern. A base pattern can last from anywhere between 5 to 26 weeks. In addition to varying base length the base patterns vary as well. After the stock has fallen more drastically when profit taking has occurred the base pattern is recognized by the volatility in the stock getting smaller and smaller until the end of the base (Minervini, 2013). Essentially, as the base pattern develops and finishes the stock will break out from the base upwards or downwards. If the stock breaks downwards to keep developing the basing area or turn into stage 3 the stock will not be bought. If, however, the stock breaks out from the base upwards to continue its stage 2 move the stock will move through the buy point from the basing area.

2.7.4 The Buy Point

The buy point for a trade is when the price of a stock breaches the "pivot point" from a basing area (Minervini, 2013). According to Minervini, at the pivot point a stock has the highest probability of keeping its momentum upwards therefore the stock should be bought at the pivot point (Minervini, 2013). Minervini states:

> *"Specifically, the point at which you want to buy is when the stock moves above the pivot point on expanding volume."*

So, what then is a pivot point? The Pivot point occurs when the base pattern has finished developing and the stock reaches a new local high from the basing area. Pivot points can occur in connection with a stock reaching a new high or below the stock's high (Minervini, 2013). In conclusion, after a stock has reached a local maximum during a stage 2 advance the stock starts declining and creates a new base pattern that is between 5 to 26 weeks long (during a so called basing period). This means that a stock that is set up correctly should develop a new pivot within every 5 to 26 weeks after the previous high was made. If the stock does not create a new buy point and instead declines in price after the basing period the stock is considered to no longer be in the stage 2 consolidation phase and should therefore not be bought. Moreover, in the quote above there needs to be explanation regarding "expanding volume".

2.7.5 Volume Analysis

Expanding volume in the quote above means that the volume (no. of traded stocks during a day) should show an increase on the day of the buy point occurring compared to historic levels in a decided time frame Minervini (2013). Minervini's comparison of volume varies but one of the common measures seems to be the 50-day average for volume. On the day of the pivot point breakout Minervini states that it is *"not uncommon to see a surge of several hundred percent or even as much as 1,000 percent compared with the average volume"*.

2.7.6 Stop-loss

Before understanding the selling point for a trade, a concept called stop-loss needs to be introduced. Minervini (2013) always defines a sell stop-loss before the trade is entered, this way the stock will be sold if the trade is not showing profits in order to protect against a bigger loss. Minervini (2013) varies where the stop-loss is set depending on several variables. However, Minervini (2013) always sets his stop-loss between 2-8% below the current stock price. The stop-loss % partly depends on whether trades in the near historical time frame have been showing profit or not (Minervini, 2013). Minervini (2013) applies progressive exposure which means that if nearby historical trades have not been working out he sets a stop-loss closer to the buy price, hypothetically between 2-6%. The stop-loss is generally adjusted upwards in price if the trade is showing profit. However, the detailed conditions for moving the stop-loss will be defined later in the report in the chapter of algorithm implementation. The stop-loss function is an essential part of Minervini's momentum strategy. Minervini (2013) argues that the number of successful trades can drop to as low as 30% which infers that cutting the losses using a stop-loss is important to stay profitable.

2.7.7 The Selling Point

Once the stock has been bought there are various scenarios that can occur. As stated previously, the stock should be held for as long as possible until the trade loses its momentum. In practice there are three choices that will affect the size of the gains (Minervini, 2016):

1. When to sell if a trade is not profitable
2. When to raise the stop-loss if the trade is profitable, thus giving the share smaller room for a pullback but locking in some profits.
3. When to sell if the trade is profitable.
4. When to add equity to a position

The selling point therefore has more varying rules and more subjectivity compared to the buy point. Since Minervini uses subjective assessment and hours and hours of trading experience to guide Minervini's decisions it is difficult to dense down his knowledge into rules that are followed without exception. However, no matter how a trade is working out Minervini (2013) always has a pre-defined stop-loss point where the stock is sold. This stop-loss point is set at a maximum of -8% from the initial buy price. The other selling rules vary depending on how long the current trade has been active. When a position initially has been taken and has been active for a short amount of time the following rules are, especially in combination, acting as sell signals:

- Three or four lower lows without supportive action (Minervini, 2016)
- More down days than up days (Minervini, 2016)
- A close below MA20 (Minervini, 2016)
- A close below MA50 on heavy volume (Minervini, 2016)
- Full retracement of a good size gain (Minervini, 2016)

If the trade has not reached the stop-loss or violated any of the initial sell rules Minervini (2013) will give the stock more room to fluctuate and apply primarily other selling rules. For trades that have been active for a longer period of time or for trades that are showing profit some of the other rules applied can be seen below:

- ”Move your stop up when your stock rises by two or three times your risk, especially if that number is above your historical average gain”. For example, if the stop-loss is set at 8% and the stock gains 24% the stop-loss will be raised to at least the buy price. The historical average may vary, Minervini (2013) states that his average gain for an example year was 18.4%.
- A trailing stop can be used to ride out the trend fully (Minervini, 2013). A trailing stop follows the price of the stock upwards with a moving average and when the price crosses the moving average line the stock should be sold (Minervini, 2013). However, Minervini usually uses a back-stop rather than a trailing stop (Minervini, 2013). Minervini likes to use a trailing stop in stocks that increase in price drastically in a short amount of time (Minervini, 2016).
- After the stop-loss has been raised, Minervini (2013) explains “If the stock continues to rise, I start to look for an opportunity to sell on the way up and nail down my profit”.

From this information it can be inferred that Minervini distinguishes between different types of selling signals based on the trade’s duration and the level of gain it has accrued. Initially a trade has stricter rules, but as the trade shows profit Minervini (2013) gives the stock more room to fluctuate in price.

As stated earlier one can see that various rules are sometimes in contradiction to each other. The reason for that is because Minervini analyzes every stock individually to conclude how to handle the every trade. There is no fixed rule that is applied to every trade. This will be discussed further down in the report but it is worth noting..

2.7.8 Position Sizing

According to Minervini (2013) a larger portfolio should consist of no more than 20 stocks at any given time. This implies 5% position sizes in every stock. However, Minervini (2016) adjusts the position sizes depending on several factors such as quality of the stock price movement and current market climate. Minervini’s portfolio can sometimes take positions that are up to 25-50% of the portfolio. Minervini uses the following rule for position sizing: the total risk of a trade cannot exceed 1.25% of the total equity on average. Where the risk is calculated as:

$$\text{Risk (\%)} = \text{Stop-loss (\%)} \times \text{Position size (\%)} \leq 1.25\% \tag{3}$$

Minervini (2013) also applies progressive exposure for the position sizing (same way as progressive exposure is discussed in Chapter 2.7.6 for stop-loss) for his position sizing. Namely, if trades in the near history has been working out Minervini (2013) can take larger positions and scale up those positions in size fast.

2.7.9 Industry Groups

Minervini 2013 puts a lot of emphasis on finding the winning industry groups, however Minervini uses a top-down approach and first finds the stocks performing well to then guide him to the best performing sectors.

3 Replicable Method

3.1 Algorithmic Implementation of Minervini's Momentum Techniques

This chapter will discuss the implementation of Minervini's momentum techniques from Chapter 2.7. Note that the names of the chapters indicate the corresponding chapters from Chapter 2.7.

3.1.1 Stage Analysis

There will be no analysis regarding which stage a stock is in. The subjectivity of the stage analysis makes it difficult to implement in an algorithm. Rather, the stock is assumed to be in stage 2 when the momentum template is true for a stock at a given date.

3.1.2 Initial Momentum Analysis (the momentum template)

The full momentum template (from 2.7.2) is applied with only two modifications. Firstly, the relative strength calculation will not be accounted for. This is discussed further down in the report. Secondly, Minervini urges the trader not to be too strict in the screening process. Minervini explains "Otherwise, you may inadvertently eliminate good candidates that meet all your criteria except for one... and misses by a hair" Minervini (2013). Because the algorithm will apply one screen this is compensated for by using a parameter called the flex factor which makes the momentum template less strict. The flex factor is a multiplier to slightly relax the strict limitations from the momentum template. In the algorithm this flex factor is set to 0,95. To exemplify, let's use condition number 4 in the momentum template that state "the current stock price must be above MA50".

MA50	Flex factor	MA50 (with flex factor)
100	0.95	95

Table 2: Table exemplifying MA50 and MA50 with flex factor.

3.1.3 Base Patterns, Buy Points and Volume Analysis

As stated in Chapter 2.7.3 base patterns can vary both in length and structure. The patterns are complex to program and thus separate base patterns will not be identified by the algorithm. However, in order to establish a buy point there needs to be some estimation of when a stock breaks out of a base since that is where the pivot point occurs. According to Minervini (2013) the base length varies between 5-26 weeks. If the basing period is set to a low number of weeks, the algorithm will recognize more breakouts as compared to if the basing period is set to a higher number of weeks. In the span of 5-26 weeks lays 17 weeks which is the average base length according to Bulkowski (2000) and thus the base length parameter is set to be 17 weeks (85 days). A spot price is therefore considered a pivot point when the stock price reaches a minimum of 17 week maximum in connection with a volume that should exceed 1.5*Volume MA 50.

To conclude the following conditions need to be met on the same date:

- The stock price breaks through the previous high on a minimum of a 17-week time frame.
- The volume of traded stocks increases of at least 50% from the average volume on the 50 day time frame.

In addition to a breakout there also needs to be liquidity available to buy the stock, this liquidity condition is evaluated in detail in Chapter 3.1.7.

3.1.4 Stop-loss

As stated in Chapter 2.7.6 the stop-loss varies between 2-8% where in Minervini's (2013) opinion if a stock declines more than 8% from the buy point the the buy signal is faulty. Therefore, the stop-loss is initially set at 8% below the buy price. As stated in Chapter 2.7.6 the stop-loss is raised when a trade is showing profit. Inferred from the description in Chapter 2.7.6 the stop-loss will be raised the buy point if the trade shows a profit of 3x the initial stop-loss. An example of the outcome is illustrated below:

Date	**Stock Price**	**Buy price**	**Gain (%)**	**Stop-loss price**
Jan-01	100	100	0%	92
Jan-02	124	100	24%	100

Table 3: Table showing example of stock price, buy price, gain percentage, and stop-loss price for two dates.

3.1.5 The Selling Point (short holding time)

As stated in Chapter 2.7.7 initially after a trade has been taken there are several rules that Minervini sees as sell signals. Firstly Minervini applies varying sell signals depending on how long the trade has been active. The short holding period is set to 100 days and there is also one rule regarding a large gain on a small period of time to lock in profits. During the shorter holding periods the following selling rules are applied:

- If the stock price breaks the stop-loss.
- If the trade shows a profit of at least a 30% gain within 7 days from the buy date.
- More down days than up days for the 7 days from the buy date.
- The current stock price is below MA50.

3.1.6 The Selling Point (long holding time)

For trades where the holding period is longer than 100 days Minervini gives more "room" for the stock to fluctuate (Minervini, 2016). If the trade is not stopped out with the stop-loss a trailing stop will be implemented in the algorithm and the longer the trade is active the larger MA measure will be used as the stop-loss to give the stock more room to mimic Minervini's raise of his stop-losses. Additionally, the stock can also be sold as it is increasing in price (referred to as selling into strength) compared to for example a stop-loss which is a sell signal on a price decline (referred to as selling into weakness).The following rules are generally used for longer holding periods ($\leq$100 days):

- If the stock price breaks the stop-loss.
- The current stock price is below MA150.
- If the gain of the trade is $\geq$100% the stock will be sold.

3.1.7 Position Sizing

Various implementations and variations can be applied to mimic Minervini's position sizing strategy. As was stated in Chapter 2.7.8, Minervini never exceeds 20 stocks in a portfolio at any given time. Moreover, the risk exposure very seldom exceeds 1.25% of the total equity available. Table 4 shows how the risk percentage varies with position size when the stop-loss is fixed at 8%

Stop-loss (%)	Position size (%)	Risk (%)
8	1	0.08
8	2	0.16
8	3	0.24
8	4	0.32
8	5	0.40
8	6	0.48
8	7	0.56
8	8	0.64
8	9	0.72
8	10	0.80

Table 4: Table showing how the risk could vary for a trade with a fixed stop-loss of 8% and a varying position size.

As can be seen in Table 4 , when a stop-loss of 8% is set the position size for a traded equity could be even larger than 10% before the risk criterium is no longer upheld. However, the larger position size the more risk for every trade and the less trades can be active simultaneously. For example, with a position size of 10% the number of equities that can be active at any given time cannot exceed 10 since that would create a leveraged portfolio. Minervini 2013 recommends a maximum of 20 holdings for a large portfolio (where large portfolio is referring to the amount of money beeing managed). In this report the position size will vary depending on the amount of active trades on any given date. If the number of active trades for a given date is 20 the position size for that date is set to 100/20 = 5%. This means that when a trade is entered the trade position size will vary on a daily basis. An example of how the position sizing can vary is seen conceptually in Table 5 and an example from an iteration in the algorithm can be seen in appendix D. If the number of active trades drops below or equal to 5 for any given date the maximum position size is still set to 20% in order to make the risk similar to what Minervini would have accepted.

Date	No. active trades	Position size(%)
2018-01-04	0	NaN
2018-01-05	5	20 %
2018-01-08	10	10 %
2018-01-09	20	5 %
2018-01-10	100	1 %
2018-01-11	50	2 %
2018-01-12	25	4 %
2018-01-15	3	20 %

Table 5: Table showing an example of how the position sizing of various equities will vary from one day to another as the number of active trades varies.

Moreover, Minervini (2013) makes a subjective assessment which buy signals are better and transfers the equity to the chosen buy trades. However, the algorithm will not be able to differ between a “strong” and a “weak” breakout which is why it is logical to set weigh all position uniformally.

3.2 Summary of Parameter Values

Below is a summary of all the parameter values set in the algorithm.

- Number of days for a base to be considered completed = 85.
- Flex factor = 0.95.
- Volume increase compared to the Volume MA50 = 50%.
- Stop-loss percentage = 8%.

- Position size = Varies for every date.
- Maximum position size = 10%

3.3 Comprehensive Walkthrough of the Algorithm Iteration Process

In Figure 1 below is an overview on how the algorithm will act for every stock in the selected portfolio when using the momentum strategy:

Once all the stocks have been iterated through the process to calculate the return of the whole portfolio on a daily basis from the start date to the end date is easily obtained. This is explained further down in the report.

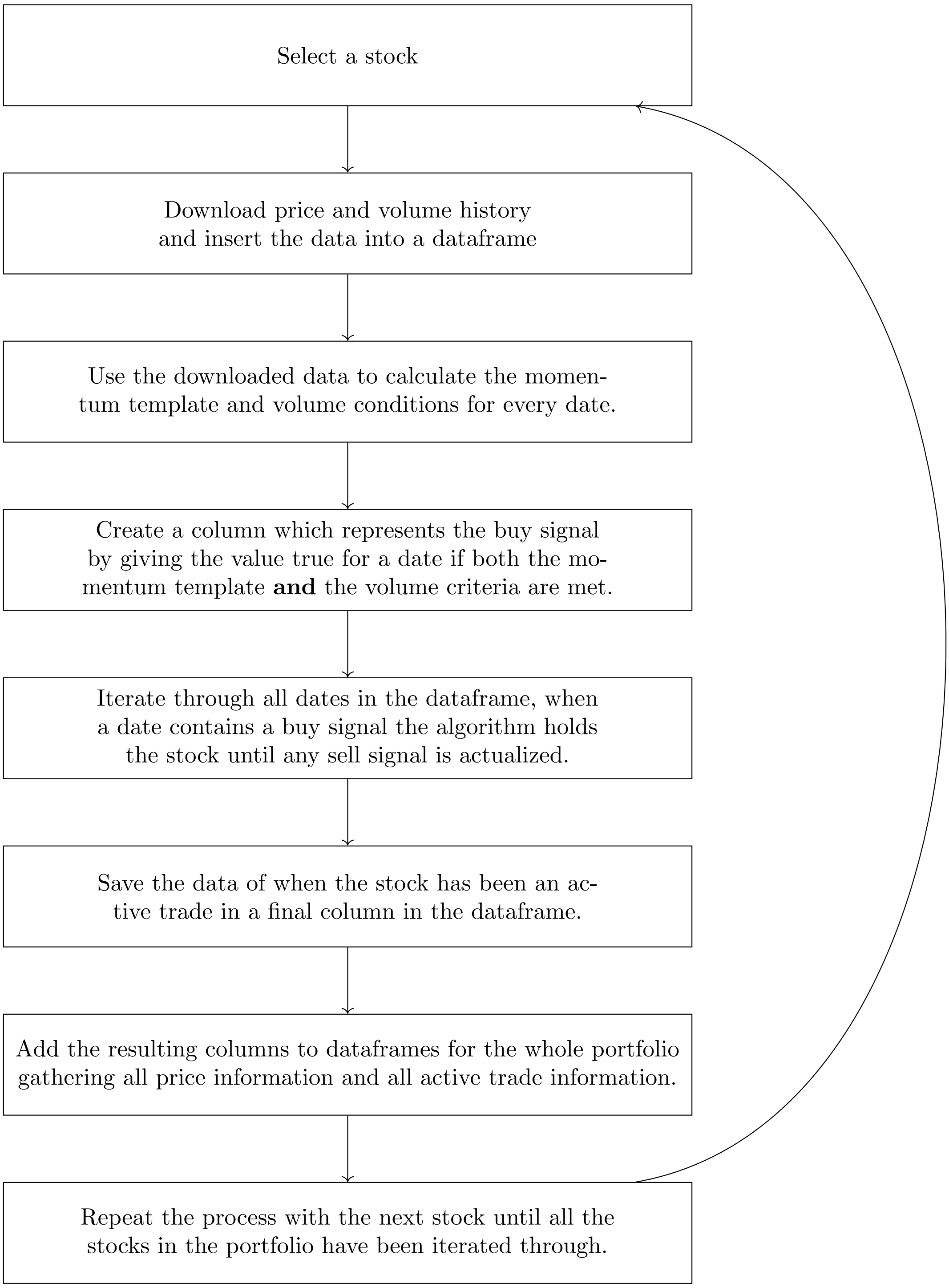


Figure 1: An overview of an iteration over one stock in the algorithm.

4 Method

4.1 Scientific Approach

Bryman and Bell (2011) discusses that there is both both qualitative and quantitative research methods. Qualitative research is a non-numerical approach that aims to understand experiences, perspectives, and feelings of individuals. It often involves using unstructured data sources such as interviews, observations, and open-ended surveys. Meanwhile, quantitative research uses numerical data to analyze and draw conclusions. Quantitative research typically employs structured data sources to gather data in a systematic manner. Both qualitative and quantitative research methods have their strengths and weaknesses, and the authors concludes that it is important to choose the correct approach for the specific research question and situation. (Bryman and Bell, 2011). Bryman and Bell suggest that a quantitative research approach is best suited for studying numerical data and testing theories that have been developed based on previous research findings (Bryman and Bell, 2011). Firstly, this report aims to further investigate the research within momentum strategies and secondly, there is a clear numerical data collection to analyze which makes the decision of using the quantitative research method straight forward. Furthermore the research aims to use deductive reasoning in accordance with the definition by (Bryman and Bell, 2011). The deductive approach is well-suited for testing cause-and-effect relationships, making predictions, and testing the validity of theories which is why it makes a good fit for the current research (Bryman and Bell, 2011).

4.2 Data Collection

4.2.1 Borsdata (Börsdata)

Börsdata is hereby referred to as Borsdata. The data is collected from *börsdata.se* which is one of the largest independent providers of financial data in the Nordic markets (Börsdata, 2023). Borsdata is making financial data available mainly to private investors. Borsdata provides the daily price information for all the stocks and indexes used in this report by giving the researcher access to the Borsdata database via an API key.

4.2.2 API

By using an API key together with a programmed API (Application Programming Interface) in the python programming language the data can be downloaded from Borsdata's database. The database on Borsdata uses the Json-format for all the datafiles. These Json datafiles are converted to a dynamic and usable format using the pandas library in python. The API has a daily restriction of 10,000 API calls every day and recurrence of 100 api calls every 10 seconds. An API called is needed whenever a new url needs to be requested from Borsdata.

4.2.3 Collected Data

The dataset used comprises stock market data collected from three Nordic countries, namely Denmark, Sweden, and Finland. The data covers a period of almost 20 years, stretching from 2003 to 2023, and includes information on various stocks traded on the respective markets. Specifically, the database contains detailed information on each stock including in the current sector, index and list in which it is currently contained.

In Table 6 below is a summary of all selected lists from which countries that were selected from the database for this research:

Sweden	Finland	Denmark
Large Cap	Large Cap	Large Cap
Mid Cap	Mid Cap	Mid Cap
Small Cap	Small Cap	Small Cap
First North	First North	First North

Table 6: Available stock indexes/lists

These lists are referred to as indexes in the research report. A total of around 1500 equities from Sweden, Finland and Denmark will be included in the different portfolios. See appendix B for all equities included in the research.

4.3 Python Libraries

Pandas is a powerful open-source data manipulation library for the Python programming language. It provides an easy-to-use data structure called a DataFrame, which allows users to perform complex data analysis tasks on structured data. A DataFrame looks like a matrix where rows or columns can be added or altered. The key features of pandas include data cleaning, data manipulation, data analysis, and data visualization.

The other frameworks used in the research are Json, Requests and Numpy. The Json and Requests libraries make it possible to communicate with the Borsdata server and Numpy is used for various data calculations.

4.4 Portfolio Construction

Benchmarking a trading strategy against an index is a common approach used in finance to evaluate the effectiveness of investment strategies. To make a comparison, it is essential to use a benchmark index that closely tracks the underlying asset class or market being traded. The portfolio selection is therefore dependent on the available data. In the data available at *börsdata.se* there is no historical data regarding which companies have been in which indexes at a specific point in time. There is only information regarding which companies are included in which index as of today's date. All the companies from Large Cap, Mid Cap, Small Cap and First North as of are included for Sweden, Finland and Denmark. All the lists in Table 6 are included in one of the analyzed portfolios. The indexes Small-cap, Mid-cap and Large-cap will be simulated for a chosen year by applying the calculated market caps for that year and using the rules by Nasdaq to create reasonable "buckets" of market cap sizes that mimics Small Cap, Mid Cap and Large Cap [2]. The portfolios researched in the report are therefore referred to as market cap-based portfolios because they try to mimic how Small Cap, Mid Cap and Large Cap could have looked like during the selected time frame.

4.4.1 Market-cap based Portfolios

As discussed above these portfolios are designed to mirror the performance of a particular index, such as the Small-cap, Mid-cap, or Large-cap index, at any given point in time during the period being researched. The market cap-based portfolio groups stocks that are within a certain market cap size during a set year from the user. The user selects which year the user wants to calculate the market caps for and then selects lower and upper boundaries for the market cap the results in the selection of stocks used in that research iteration. To summarize the inputs needed to create a Market Cap based portfolio and run the program are the following:

[2] As stated in the above paragraph the companies from First north will also be included in one of the simulated market-cap based portfolios depending on the calculated market-cap sizes in stocks from the First north.

- Year to calculate market cap for
- Lower bound of market cap (mEur)
- Upper bound of market cap (mEur)
- Start date
- End date (which is always set to *2023-01-01*)

To calculate the market capitalizations for a given year, the report utilizes the average stock price for that year multiplied by the average number of stocks for each company during that same year. Since the market caps will be estimated in EURO the market caps for Sweden and Denmark are multiplied with the average EUR/SEK or EUR/DKK exchange rate for the selected year. For Finland the market cap calculated will already be in EURO. The market cap boundaries used to construct the different portfolios are discussed in further detail later in this chapter of the report. The number of stocks in the portfolio will therefore vary depending on how the parameters are set for every portfolio simulation. For example, if the lower bound is small and the higher bound is large for the market cap the portfolio will consist of many stocks. Compare that to if the range of market cap is smaller, that would result in a portfolio with fewer stocks.

4.5 Selected Portfolios

The performance of stocks from every portfolio selection will be evaluated over two different time periods: 2008-2023 (15 years) and 2018-2023 (5 years). To get an overall view of the performance of the portfolio a longer time frame is preferred. The time frame of 15 years was choosen to balance the accessibility of data and to get a long time span. The time frame of 5 years was been selected to capture periods of higher market volatility. To conclude the time frames were chosen to provide a comprehensive view of the portfolio's overall performance.

To fully specify the evaluated portfolios, it is necessary to select not only the time frames to be considered, but also the portfolios to be evaluated during those time frames.

4.5.1 Selection of Market-cap based Portfolios

To construct a market cap-based portfolio, stocks are split into three distinct subgroups based on their market capitalization, which is calculated in the local currency (*Sek, Dkk or Eur*) and then converted to *Eur* using the average exchange rate for the starting year. The three subgroups are as follows:

1. Market caps exceeding 1,000 mEur.
2. Market caps between 1,000 mEur and 150 mEur.
3. Market caps less than 150 mEur.

These subgroups are created in accordance with the rules of Nasdaq, which defines a large-cap company as having a market capitalization of over 1,000 mEur, a mid-cap company as having a market cap of between 1,000 mEur and 150 mEur and small-cap company as having market caps less than 150 mEur. These market cap-based portfolios are used as a proxy for historical equity listings when there is no access to actual historical lists. To summarize there will be a total of 18 portfolios spanning over, market caps, countries and time frames. All portfolios are illustrated in appendix A.

The created market-cap based portfolios will be the portfolio used in both the momentum strategy but also in the index portfolio. This is also visualized in Figure 2. The reason why the index varies with every portfolio instead of set as a more official OMXS Small Cap comparison is discussed further down in the report.

4.6 Overview of the the Algorithm Iteration Process

The Market-cap based portfolios generated by the algorithm will be traded two times. Both using the buy and hold strategy and using the momentum strategy. The momentum strategy will use a various position sizing of depending on the number of active trades for a date as discussed in Chapter 3.1.7. The buy and hold strategy will uniformally distribute the position sizes of all the holdings in the Market-cap based portfolio. To exemplify, a portfolio that consists of 50 equities using the buy and hold strategy will therefore have portfolio weights of 2% for every stock.

In Figure 1 from Chapter 3.3 is an overview of how one stock is iterated in the algorithm. Once the columns representing spot prices and date ranges when a stock has been active for all the dates has been created and summarized in two separate dataframes the overall structure that is used in the portfolio return calculation has taken shape. In order to depict how the portfolio is applied to calculate the return of the buy and hold strategy and the momentum strategy it is appropriate to present a diagram depicting the comprehensive workflow of the algorithm using for the portfolio. This is shown in Figure 2 below.

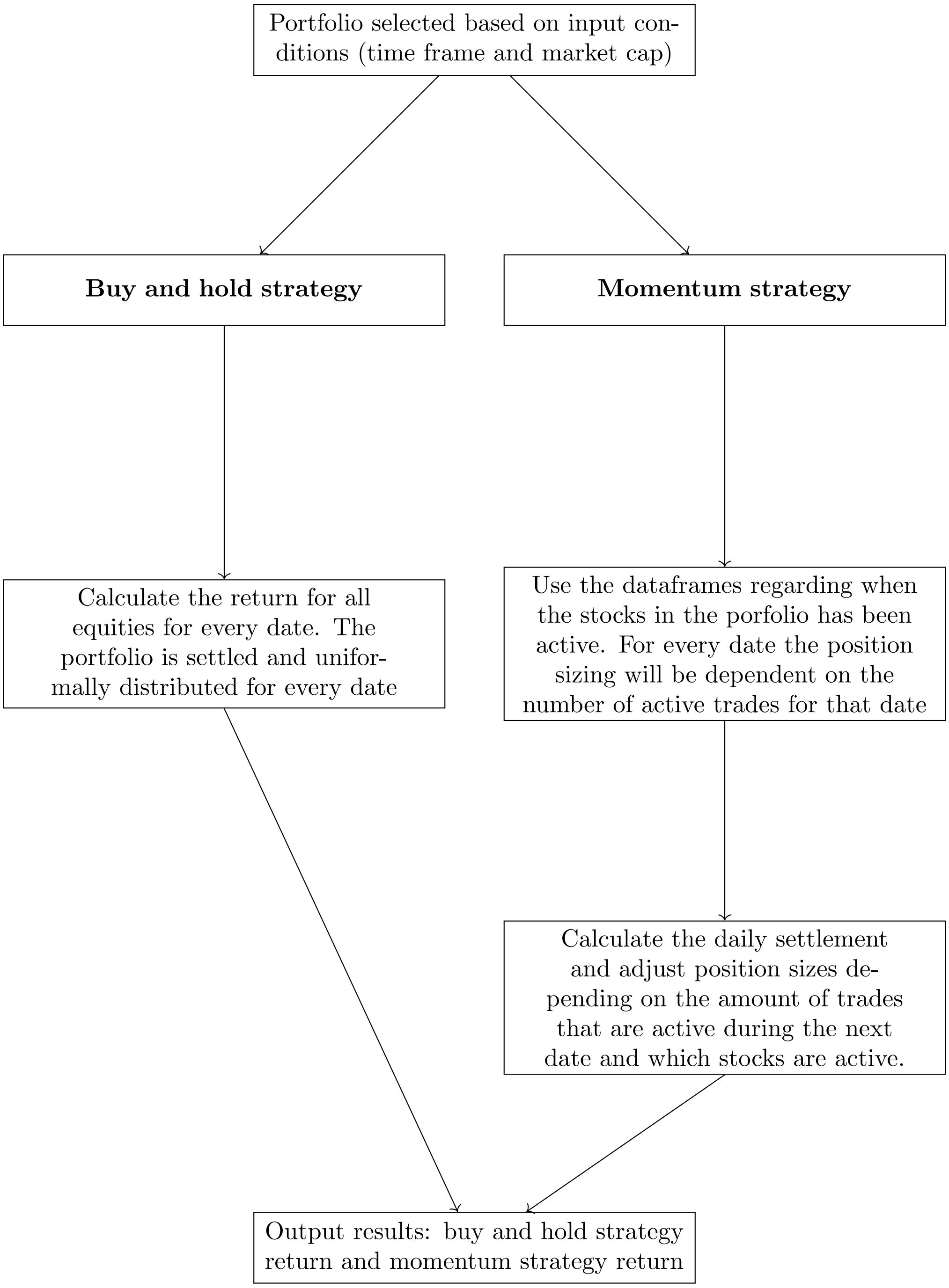


Figure 2: An overview of the implemented algorithm.

See appendix D in order to see an example of the rebalancing of the portfolio during a shorter time frame.

4.7 Algorithm Performance Evaluation

For all the portfolios created the benchmarking is done identically. For all portfolios the start value is 100 (for both the buy and hold strategy and the momentum strategy). For the buy and hold portfolio the return is calculated by using the dataframe consisting of date ranges when stocks are active just as the momentum strategy, however, in the buy and hold portfolio date range dataframe all the stocks are always active. This infers that every day the portfolio will rebalance the portfolio to make it uniformally distributed. For the momentum strategy the algorithm will use the date range dataframe (which was created from Figure 1) that varies for every date depending on which stocks that are active in the dataframe. An extract from a date range dataframe can be seen in appendix E.

This therefore alternates what the daily positon sizes will be and which stocks will be active. The algorithm generates an output for each traded portfolio that illustrates the changes in portfolio value from the initial value of 100 to the final value at the end of the specified time frame, excluding transaction costs. In summary, each of the 18 portfolios executed in the algorithm will produce an output indicating the increase or decrease in value for both strategies. In order to quantify and understand whether the returns are statistically different from each other a hypothesis test is completed. The Sharpe ratio is also used as a complementary tool to visualize how the hypothetical excess return is not inferred from increase standard deviation of the returns.

4.7.1 Hypothesis Test

Hypothesis test for all portfolios were calculated using Welch's t-test. Welch's t-test is a statistical method used to compare the means of two sample groups that have different variances. It is a modification of the standard two-sample t-test that adjusts for unequal variances. Welch's t-test is more appropriate to use since the variances of the momentum portfolio and the index portfolio might be different. In order to use Welch's t-test the samples (in this case the daily returns) are assumed to be normally distributed which is why the returns are converted to logarithmic daily returns before applied in Welch's t-test. The test statistic t and the degrees of freedom df are calculated as seen in (4.7.1) and (4.7.1)

$$t = \frac{\bar{x_1} - \bar{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{s_1^4}{n_1^2(n_1-1)} + \frac{s_2^4}{n_2^2(n_2-1)}} \tag{5}$$

In these formulas, $\bar{x_1}$ and $\bar{x_2}$ are the sample means, s_1^2 and s_2^2 are the sample variances, and n_1 and n_2 are the sample sizes for the two groups being compared. Once the test statistic and degrees of freedom have been calculated, a t-distribution table is used to find the p-value associated with the test statistic and draw conclusions regarding the hypothesis test. The significance level of the hypothesis test will be set to 1%.

4.7.2 Sharpe Ratio

The Sharpe ratio is a widely used measure to evaluate the risk-adjusted return of an investment. It takes into account the total return of an investment and the risk associated with it by measuring the excess return per unit of risk. The formula for the Sharpe ratio is:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

where R_p is the expected portfolio return, R_f is the risk-free rate of return, and σ_p is the standard deviation of the portfolio excess return.

4.8 Ethical Principles

Greenwood and Shleifer's (2014) research sheds light on the potential risks associated with momentum strategies and their potential contribution to market crashes. According to their findings, momentum strategies can create a self-reinforcing cycle where investors chase high returns and bid up the prices of stocks that are already overvalued. When a significant number of investors chase returns through momentum strategies, it can distort market pricing mechanisms and lead to illogical allocation of capital. Such behavior may contribute to market crashes.

4.9 Method Criticism

When conducting momentum strategy research, taking transaction fees, taxes, or contingent costs into consideration is highly relevant. In the absence of such considerations, the findings may not accurately reflect real-world performance. This research method could therefore be seen as an optimistic estimation of how the algorithm would perform in the real world and the results should therefore be seen as only an *indication* of whether the momentum strategy generates excess return.

Moreover, if a stock is of dual-class (having A and a B issue) or more the stock will likely exist in the database twice as many times. This results in more weight being put on those companies that have issued many different stock classes. This probably has an insignificant effect on the research since the vast majority of the shares are not dual-class stock, see appendix B. As previously stated Minervini can sometimes weight the positions of his portfolio as high as 25% and so it is improbable to break any of Minervini's rules.

Borsdata is a third-party provider of equity data, and they are not accountable if there is any incorrectly reported data. The usage of borsdata as a the database for the study is relevant for the target group of the report. However, one could argue that an even larger and more familiar database such as Refinitiv Eikon could be used, but the main argument against this is that the accessibility of Refinitiv Eikon is smaller for a private investor.

4.10 Quality Discussion

The validity of the study concerns the extent to which the research accurately measures what it intends to measure (Bryman and Bell, 2011). In this study, the validity of the algorithmic implementation of Minervini's Momentum Techniques is a critical issue. While the algorithm is designed to replicate Minervini's strategy as closely as possible, it is important to note that the algorithm excludes many parts of the strategy. For instance, the algorithm does not consider economic indicators, earnings reports, or conference calls, which Minervini's strategy relies on. Therefore, the algorithmic implementation of the strategy may not entirely reflect the strategy as used by Minervini.

Another factor regarding validity is the quality of the data collected from Borsdata and the API. If the data is inaccurate or incomplete, the validity of the results may be compromised. To ensure the validity of the data, several steps were taken, including data cleaning and cross-checking with multiple sources. Another factor that could affect the validity of the results is the methodology used to analyze the data. To address this, a scientific approach was taken, and the methodology was based on established momentum strategies used by successful traders.

Moreover, reliability concerns the consistency and stability of the study's findings (Bryman and Bell, 2011). In this study, the reliability of the algorithmic implementation of Minervini's Momentum Techniques is consistent and repeatable, indicating that the same results can be obtained under similar conditions. However, because the algorithm excludes several parts of Minervini's strategy, there is a risk that the results may not be entirely reliable. Therefore, it is important to interpret the results of the study with caution and recognize that there may be limitations due to the algorithm's inability to completely replicate Minervini's strategy.

5 Results

The forthcoming graphs in this chapter follow a specific structure. Each portfolio is represented by two graphs. The upper graph depicts the development of the selected portfolio, which initially has a value of 100, over the designated time period. Conversely, the lower graph illustrates the number of active trades executed by the momentum strategy (and the index portfolio) during the same time frame for each respective portfolio. In this chapter only the most relevant portfolios are shown. Not all portfolios are included graphically in this chapter because of some portfolios having data quality issues and some portfolios being more relevant than other for the end result. All portfolios, their return and the number of active trades during the two time periods can be seen in appendix G.

In total there were 18 portfolios that were created and traded by the momentum algorithm and the index portfolio. Of those 18 portfolios there were 14 of those where the momentum strategy achieved higher returns than the index portfolio. However, only 3 of the 14 portfolios that beat the index portfolio outperformed statistically on the 1% significance level.

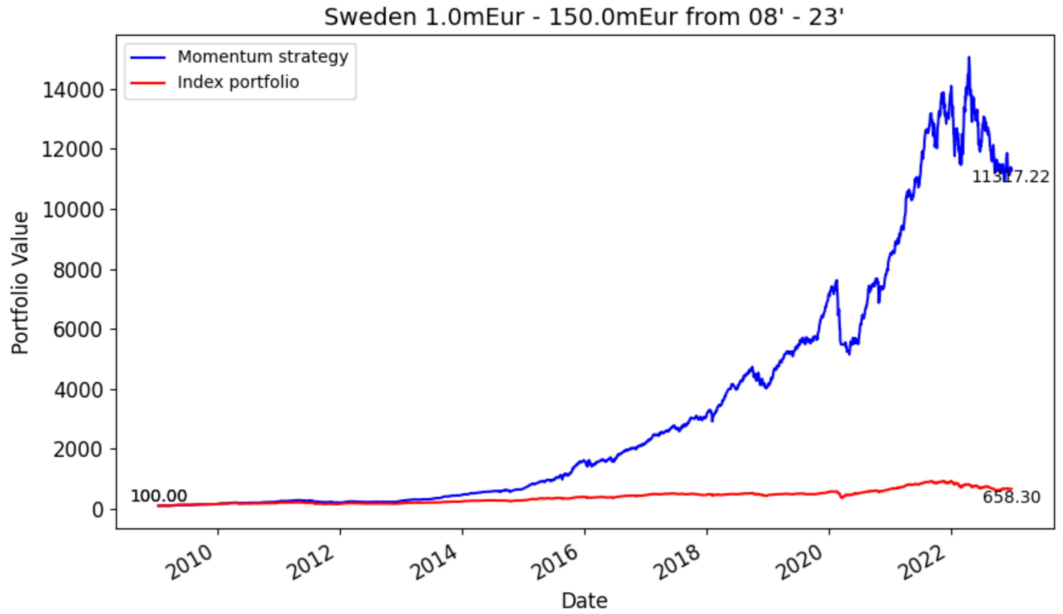
5.1 Statistically Outperforming Portfolios

The portfolios that generated statistically excess return on the 1% significance level were the following:

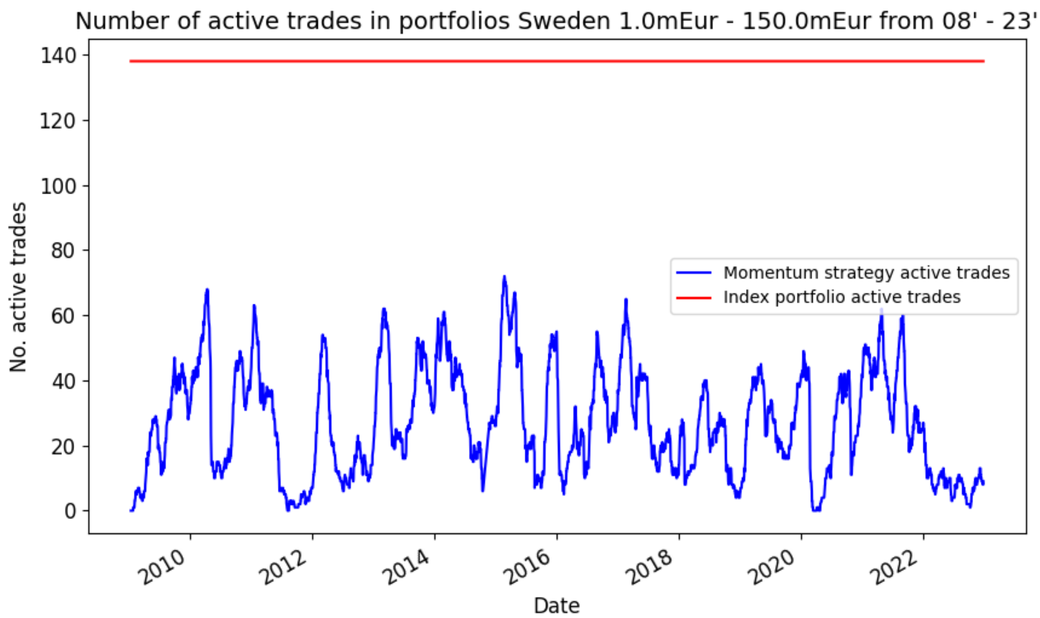
- Sweden small-cap 2008-2023
- Finland small-cap 2008-2023
- Finland small-cap 2018-2023

These performance of the portfolios above is seen in this section. The figures show how the portfolio value increased over the time frame for the momentum strategy compared with the index portfolio and how the number of active trades in the momentum portfolio varies over the portfolio's time frame.

5.1.1 Sweden Small-cap 08-23



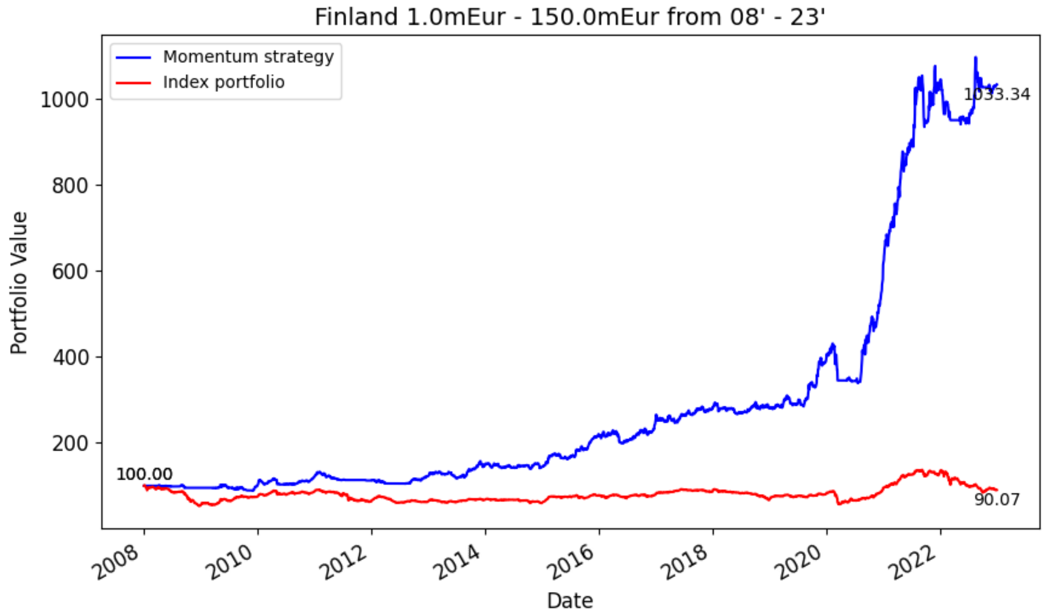
(a) Portfolio value



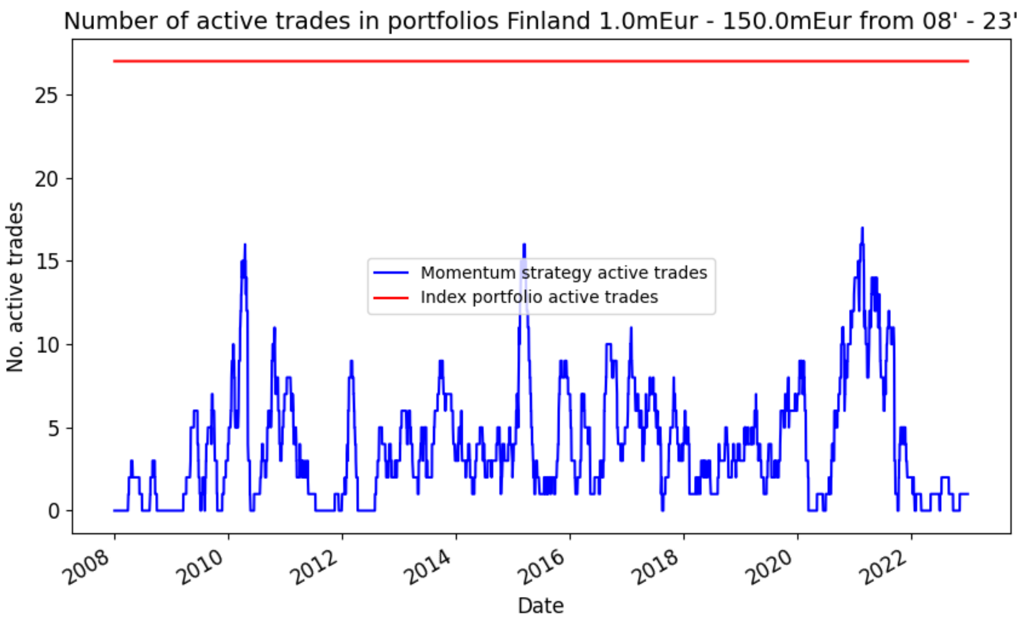
(b) Active trades during the research period.

Figure 3: Return and active trades for the Sweden small-cap portfolio between 2008-2023.

5.1.2 Finland Small-cap 08-23



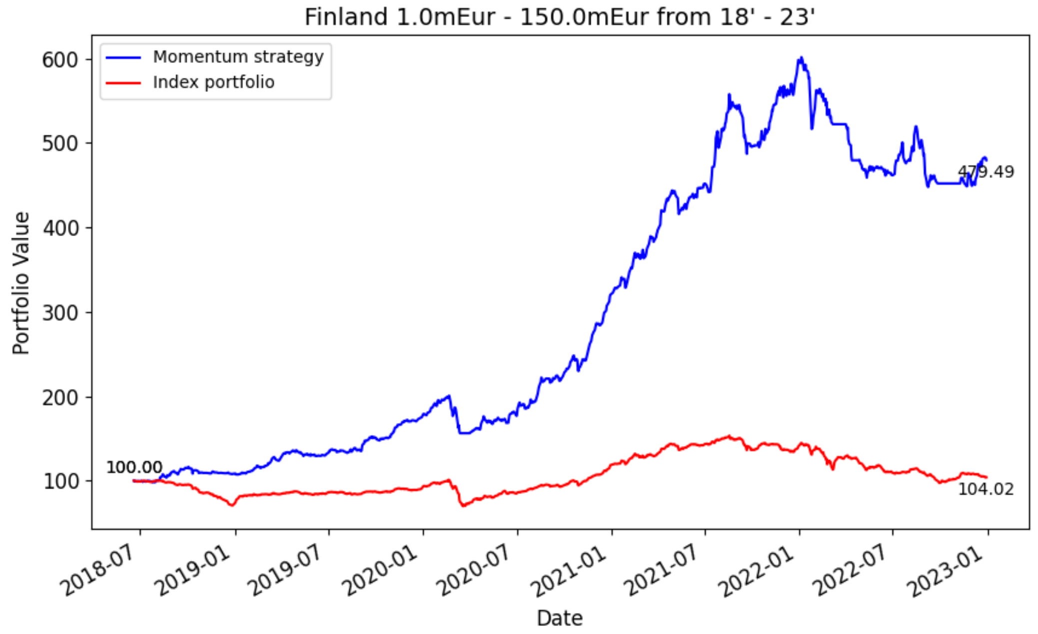
(a) Portfolio value



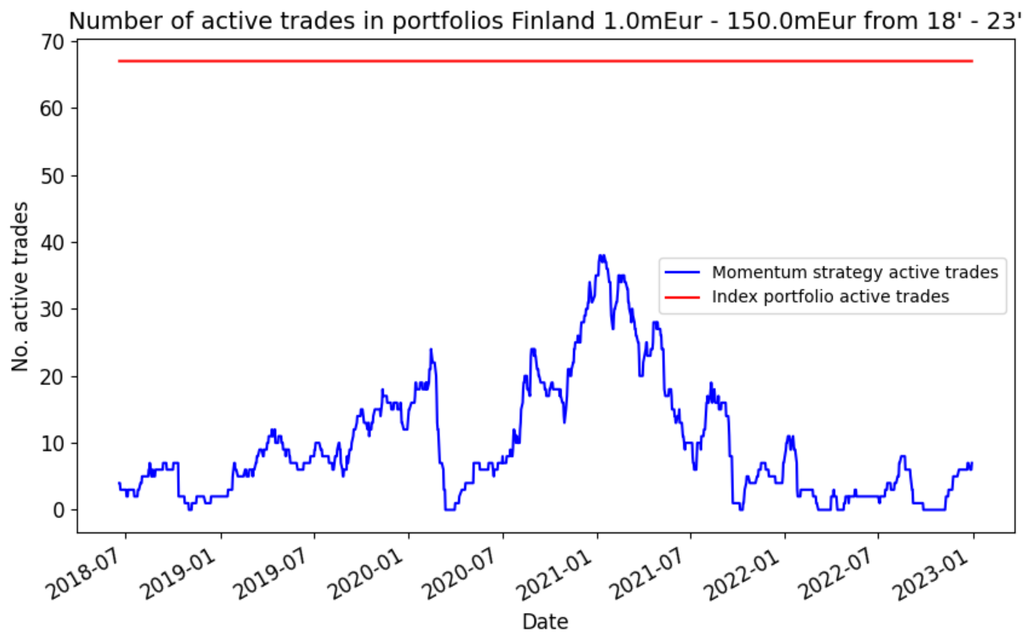
(b) Active trades during the research period.

Figure 4: Return and active trades for the Finland small-cap portfolio between 2008-2023.

5.1.3 Finland Small-cap 18-23



(a) Portfolio value



(b) Active trades during the research period.

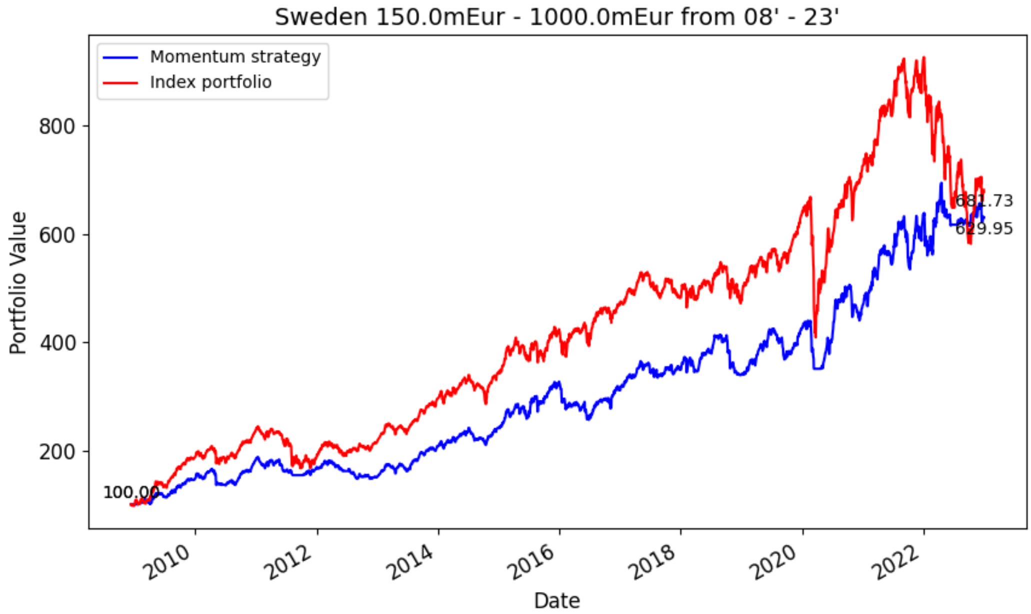
Figure 5: Return and active trades for the Finland small-cap portfolio between 2018-2023.

5.2 Statistically Non-outperforming Portfolios

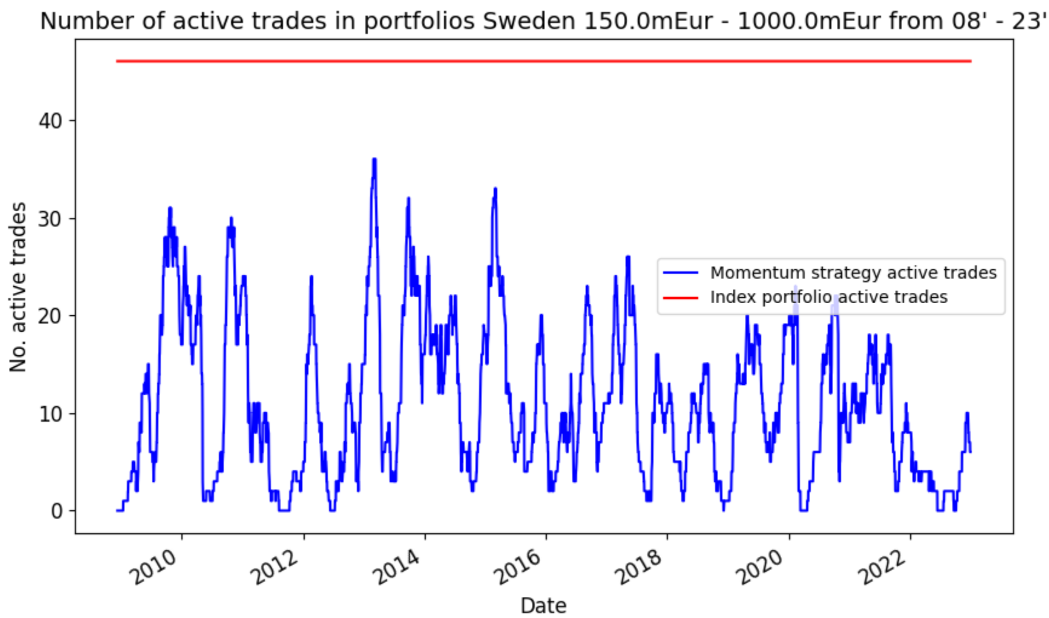
The full performance of the non-outperforming portfolios can be seen in appendix G. For these portfolios the significant test could not say that the returns came from different distributions on a 99% level. These portfolios were:

- Denmark small-cap 08-23
- Sweden small-cap 18-23
- Denmark small-cap 18-23
- Sweden mid-cap 08-23
- Finland mid-cap 08-23
- Denmark mid-cap 08-23
- Sweden mid-cap 18-23
- Finland mid-cap 18-23
- Denmark mid-cap 18-23
- Sweden large-cap 08-23
- Finland large-cap 08-23
- Denmark large-cap 08-23
- Sweden large-cap 18-23
- Finland large-cap 18-23
- Denmark large-cap 18-23

An example of a portfolio that did not statistically outperform the index portfolio is seen in Figure 6 below:



(a) Portfolio value



(b) Active trades during the research period.

Figure 6: Return and active trades for the Sweden mid-cap portfolio between 2008-2023.

5.3 Hypothesis Tests for All Portfolios

Table 7 below summarizes which portfolios generated excess return according to a hypothesis test. The daily average logarithmic return for the momentum portfolio is recognized by rm_d and the daily average logarithmic return for the index portfolio is recognized by ri_d. The standard deviation of the returns can be seen in the columns rm_σ and ri_σ. The α is the significance level of the test performed.

Portfolio	rm_d	ri_d	rm_σ	ri_σ	t-value	p-value	α	Excess rm_d?
Sweden small-cap 08-23	0.00107	0.00029	0.01019	0.00896	2.03	0.004	0.01	Yes
Finland small-cap 08-23	0.00062	-0.00003	0.00744	0.00778	3.69	0.001	0.01	Yes
Denmark small-cap 08-23	0.00102	0.00038	0.01037	0.00691	1.63	0.104	0.01	No
Sweden small-cap 18-23	0.00137	0.00055	0.00920	0.00763	4.05	0.001	0.01	No
Finland small-cap 18-23	0.00138	0.00003	0.00995	0.00848	3.46	0.00055	0.01	Yes
Denmark small-cap 18-23	0.00102	0.00038	0.01037	0.00691	1.63	0.104	0.01	No
Sweden mid-cap 08-23	0.00052	0.00054	0.00795	0.00927	-0.11	0.913	0.01	No
Finland mid-cap 08-23	0.00032	0.00005	0.00726	0.00975	1.35	0.176	0.01	No
Denmark mid-cap 08-23	0.00013	-0.00008	0.00289	0.01273	0.98	0.328	0.01	No
Sweden mid-cap 18-23	0.00048	0.00027	0.00871	0.01065	0.54	0.588	0.01	No
Finland mid-cap 18-23	0.00065	0.00024	0.00960	0.00923	0.97	0.331	0.01	No
Denmark mid-cap 18-23	0.00046	0.00023	0.00787	0.01104	0.61	0.541	0.01	No
Sweden large-cap 08-23	0.00028	0.00021	0.00730	0.01108	0.34	0.733	0.01	No
Finland large-cap 08-23	0.00025	0.00014	0.00581	0.01062	0.52	0.600	0.01	No
Denmark large-cap 08-23	0.00035	0.00031	0.00544	0.01144	0.18	0.855	0.01	No
Sweden large-cap 18-23	0.00005	0.00017	0.00776	0.01021	-0.28	0.783	0.01	No
Finland large-cap 18-23	-0.00000	0.00005	0.00647	0.00969	-0.15	0.881	0.01	No
Denmark large-cap 18-23	0.00053	0.00020	0.00725	0.01001	0.90	0.366	0.01	No

Table 7: Hypothesis tests for all portfolios.

To summarize there were 3 portfolios that, according to the hypothesis test, generated significant excess return on a 1% significance level and therefore 99% confidence level. All of the portfolios that generated excess return according to the hypothesis test were small-cap portfolios.

6 Analysis

Firstly the implementation of Minervini's momentum analysis techniques is discussed, this analysis is referred to as *Analysis of the Replicable Method.* Secondly there is an analysis of the data used and how it was handled, this chapter is referred to as *Data quality and data handling* . Thirdly the analysis of the empirical results from the implemented algorithm is analyzed and is referred to as *Empirical Results and the Efficient Market Hypothesis*

6.1 Analysis of the Replicable Method

The algorithm is seen as a primitive variant of Minervini's strategy. There are primarily three reasons why the algorithmic approach is seen as primitive:

- Technical restrictions (base count, relative strength rank, position sizing)
- Practical application problems (position size, buy orders)
- Exclusion of fundamental and catalyst aspects (see Chapter 2.7)

6.1.1 Technical Restrictions

Base count is one of the key technical restrictions of the momentum strategy. However, the challenge with implementing base count in an algorithmic trading system is that it requires significant computational power and very complex coding patterns to identify bases accurately. As was stated in Chapter 2.7.3 base patterns vary widely (between at least 5-26) weeks. In the algorithmic approach used in this research the base pattern was set to an exact number of 85 days to form a base (can be seen in Chapter 3.1.3) which is a big deviation as to how Minervini would identify a base. In a more complex algorithm using more computing power one could probably come closer to reaching Minervini's approach but the subjective nature of bases, makes it difficult to build a reliable algorithmic system to identify bases. Another example of where subjectivity in the trading strategy poses challenges in the algorithmic approach can be seen among the selling rules. For instance, one of Minervini's initial selling rules states that if a trade experiences *"three or four lower lows without supportive action"* it should be considered to sell the position. However, defining "supportive action" in programming terms becomes subjective, as it is typically discerned visually and on many different parameters. Therefore that selling rule was excluded in the algorithm implementation.

Another important aspect in Minervini's momentum strategy is the relative strength rank. As was stated in Chapter 3.1.2 there was no relative strength ranking implemented in the algorithm. Minervini does not contemplate buying unless the relative strength ranking criteria is upheld. Since the method used various different indexes for all portfolios it would have been more complex to benchmark a stock's return in the approach used in this research. Furthermore, if a relative strength ranking function were to be developed there would have been additional subjective decisions to be made in that implementation.

Moreover, the risk and position sizing aspect in the algorithm needs to be analyzed. As described in Chapter 2.7.6 Minervini uses various stop-losses dependent on many variables which creates the setup of a trade. Firstly the near historical trading results are taken into account, if the trades have not been working out Minervini uses a smaller stop-loss and often also a smaller position sizing. This has two implications, firstly Minervini can with a varying stop-loss also vary his position size. Sometimes Minervini takes positions as large as 25% or 50% of his portfolio when Minervini is confident. However this is not possible with a stop-loss of 8% (as implemented in the algorithm) since that would consistently break the rule of keeping the risk less than 1.25%. See Table 8 below.

Stop-loss (%)	Position size (%)	Risk (%)
8	2	0.16
8	4	0.32
8	6	0.48
8	8	0.64
8	10	0.80
8	20	1.60
8	50	4.00
2	50	1.00

Table 8: Table showing an example of how the risk varies for a trade with a when stop-loss and position size is altered.

Where risk measure is defined as in Chapter 2.7.8 and can also be seen below:

$$\text{Risk (\%)} = \text{Stop-loss (\%)} \times \text{Position size (\%)} \leq 1.25\% \tag{7}$$

Secondly, Minervini does not adjust his position sizes daily as implemented in the algorhithm. The algorithm sets a daily position size depending on how many active positions there are in the portfolio during that trading day. Minervini adjusts the position sizing of stocks in his portfolio but refrains from making daily updates to add more trades to the portfolio. Minervini's approach is to have a limited number of active positions, typically no more than 20, and to closely monitor these trades. In contrast to the implemented momentum strategy, which may involve a larger number of positions with less scrutiny. Minervini's approach is more focused and allows for more in-depth analysis and close attention to active trades. By limiting the number of active positions, Minervini aims to maintain a high level of control and precision in executing trades. Minervini makes subjective decisions of when to add, sell or buy another stock to the portfolio because Minervini sees a better risk reward position than what is currently in Minervini's portfolio. Additionally, there are various buy signals sent out by the algorithm that fulfills all the buy conditions but where Minervini would probably not have bought the stock. The portfolio managed by Minervini will therefore be a lot more complex, an algorithm could probably capture more of Minervini's strategy by also specifying when a certain stock trade is more attractive than another which should transfer the equity in the portfolio to be more tilted towards the better risk/reward trade or when to add more equity to a current open position but all in all Minervini's knowledge is difficult to mimic with an algorithm.

6.1.2 Practical Application Problems

The algorithm outperformed primarily in the small-cap portfolios. Since the lower limitation of market cap sizes were drawn at 1 mEur this could create problems when it comes to liquidity for larger actors in the market. If a private investor has a portfolio of 5mEur and the investor uses the algorithm which sets a buy order of the maximum position size (20%) in a stock with a market cap of 1 mEur. This would imply an absolute position size of 1 mEur in a company currently valued at 1mEur. It is improbable to be able to get that stake of a company and absolutely to that current market price.

The algorithm demonstrated superior performance primarily in the context of small-cap portfolios. However, this approach may be problematic for larger actors in the market due to the lower limitation of market cap sizes at 1 million Euros. This constraint can result in challenges related to liquidity for investors with larger portfolios, as illustrated by the following example:

Consider a private investor with a portfolio of 5 million Euros who utilizes the algorithm to set a buy order with the maximum position size (20%) in a stock with a market cap of 1 million Euros. This implies an absolute position size of 1 million Euros in a company currently valued at the same amount. However, it is highly unlikely that an investor would be able to obtain such a large stake in a company at its current market price. The ability to execute trades at the desired price and quantity may be limited by liquidity constraints. Thus, for investors with larger portfolios the performance for momentum trading using the algorithm in the smaller companies might be misleading.

6.1.3 Exclusion of Fundamental and Catalyst Aspects

As described in Chapter 2.7, momentum analysis is just one component of Minervini's comprehensive trading strategy. The other two components, namely fundamental and catalyst analysis, were not included in the research. If fundamental and catalyst analysis were to be incorporated into the algorithm, it is likely that the number of buy signals would decrease This is because adding more constraints to the buy signal can only make it more selective, thereby reducing the number of qualifying stocks. Consequently, in order to maintain a fully invested portfolio, position sizes for the qualifying stocks would need to increase. This would give greater weight to the stocks that cleared all three aspects of the analysis, thereby increasing their influence on the overall portfolio performance. While this approach may work for portfolios with a larger number of equities, it may not be suitable for portfolios that are already on the brink of being too small. In such cases, the incorporation of additional constraints could result in an excessively concentrated portfolio, with a limited number of positions holding disproportionate weight. This would increase the risk associated with any individual position and could adversely affect overall portfolio performance.

6.2 Data Quality and Data Handling

As can be seen in appendix B there were 851 Swedish stocks that were eligible in the study that came from the Borsdata database. However, in the resulting portfolios that can be seen in appendix a there were much fewer stocks that participated in the study. A significant reduction from the available 851 may be excepted due to companies participating in an IPO after 2018 and thus not having public info for the starting year of the research. The number of Swedish stocks that participated in any portfolio during the research was 329 *(138+137+54)* for the research with the start year 2018. Since the implemented algorithm cannot add a stock to the portfolio if the market cap for a year could not be calculated a certain drop from available companies to companies in the portfolio was expected. It is only logical that many companies were deleted from the data set when market caps were unable to be calculated for a certain year but a decline from 851 available data points down to 329 may be too significant. It is unlikely that all the stocks that did not participate in the study had their IPO after 2018. For further studies there would be more effort spent on data cleaning and understanding were the companies that were not included in any portfolio were lost in the process. Even though the data cleaning process might be entirely correct it has been difficult to back-track which companies were dropped and why.

6.2.1 Excluding Portfolios with Insufficient no. Stocks

Ensuring that the data is reliable when analyzing the data is important. In the research it is therefore important that the portfolios that are used in the algorithm are of high quality. Portfolios containing too few stock are of lower data quality. The are many reasons why the results from the portfolios with too few equities should get less focus in the analysis, some of these reasons include:

1. Minervini's risk preference of keeping the risk lower than 1.25% of the total equity will be overridden often and during longer periods of time (See Table 4). The risk in every trade performed by the algorithm increases when there are few active positions since that increases the position weight.
2. The portfolio will not be fully invested as often since there needs to be at least 5 active positions in a portfolio in order for the portfolio to be fully invested (since maximum position size is 20%).
3. The portfolio is more likely to be subject to significant volatility due to the heavy influence of a few stocks. Randomness will play a bigger role of the performance of the portfolio.

By a qualitative analysis of the performance of the portfolios a line was drawn at 15 stocks for a portfolio. A lower number can be drawn at 4 since if there are only 4 stocks in a portfolio the momentum strategy can never be fully invested with the current risk measures. The upper number is more difficult. Minervini likely has an average position size of between of between 5-15% but in all those positions Minervini oversees the trades daily and makes a lot more effort into how the trades are handled. In this research paper the algorithm is acting on buy signals without ranking the quality of the buy signal and it is therefore difficult to say how large position sizes Minervini would have preferred on average in the algorithm. Likely, Minervini would have preferred smaller position sizes of around 1-5% which would be the case if between 20-100 trades were active in a portfolio. The maximum amount of active trades seems to be around 80 (can be seen in appendix G for the small-cap portfolio of Sweden between 2008-2023). Minervini would therefore probably have preferred a larger number of stocks in almost every portfolio (with exception for the largest portfolios such as Sweden small-cap 2018-2023). It is arguably difficult to draw a line and say that the minimum amount of equities in a portfolio using this strategy should be X but the line is drawn at 20. Therefore, the portfolios that comprise less than 20 stocks are given less or weight in the study and any strong trends or results from these portfolios are not considered relevant for the study.

Therefore, the following portfolios have been excluded from the analysis:

- Denmark small-cap 2008-2023 (3 stocks)
- Denmark mid-cap 2008-2023 (4 stocks)
- Denmark large-cap 2008-2023 (12 stocks)
- Finland large-cap 2008-2023 (17 stocks)

In Figure 7 below the number of active trades for the Denmark small-cap 2008-2023 portfolio is shown. The momentum strategy has been in full cash during many periods in the graph and again, even at full portfolio exposure with the momentum strategy the portfolio will only have been 60% invested.

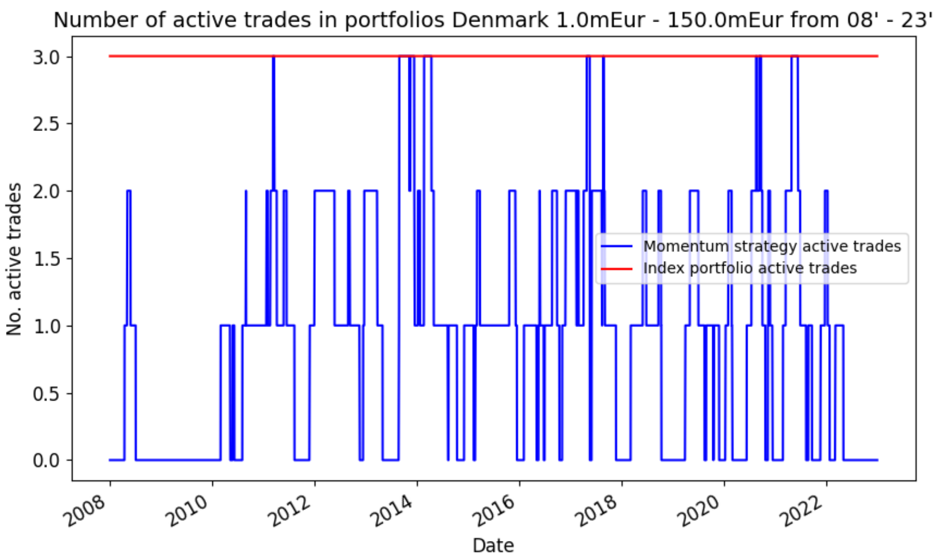


Figure 7: The figure above shows excess return which is defined as the momentum strategy return subtracted by the index portfolio return

6.2.2 Comparison Indexes

Earlier in the report it was stated that the index portfolio will consist of the same stocks as the momentum portfolio. The difference is that all stocks in the portfolio will always be uniformally distributed and held in the index portfolio while in the momentum portfolio the active stocks depends on the buy signals. There is mainly one reason for this choice of comparison index. The data that is available is only which stocks currently are in a selected index (such as Small Cap). There is no historical data regarding which companies has been in which index at what time. Therefore, if a comparison is made between the index history performance and all the current stocks in the index this is comparing apples and oranges. This problem can be clarified by looking at Fortnox, a company that is currently listed in Large Cap, Sweden. Fortnox was initially listed in 2011 on Nordic Growth Market in Sweden and has since then returned $\sim$ 25 000% as of 30th march of 2023 (mfn, 2011). Fortnox switched list to Large Cap Sweden the 13th of April 2022 and hence Fortnox has not been involved in the return for Large Cap Sweden during the absolute majority of it's big return. Another alternative was therefore to compare all the current stocks in the chosen index with the historical return of the current stocks in the index. Even though this alternative will compare apples and apples there is a minor problem with this as well. With logical reasoning one can conclude that stocks that has declined will not stay in the Large Cap index for a long time. If one therefore benchmarks the returns of the current stocks in the Large Cap index with a uniformly distributed portfolio against how well the algorithm performs on portfolio the algorithm will likely underperform the buy and hold strategy from the index-portfolio. The same argument but vice versa is applicable on the small-cap list where the algorithm will likely outperform a uniformally distributed portfolio of the stocks currently in the small-cap index. Even though a comparison with an index is a regular way of benchmark performance the use of an index is not optimal in this research due to the data restrictions.

6.3 Empirical Results in Relation to the Efficient Market Hypothesis

As can be seen in Table 7 was significance excess return in 3 of the 18 portfolios on the 1% significance level. The stock portfolios that generated excess return were small-cap portfolios. The consistent results among the small-cap portfolios is notable even though not all portfolios made the threshold confidence level. Of the 6 small-cap portfolios one of the portfolios (Denmark small-cap 2008-2023) contained only 3 stocks and that was the portfolio that did not beat the index portfolio. Therefore all the small-cap portfolios that had an acceptable amount of stocks in their portfolio did beat the index portfolio. Compare this to the large-cap portfolios were three of the six portfolios had the momentum strategy perform better and three of the portfolios had the index portfolio perform better. Furthermore in the mid-cap portfolio segment five of the six portfolios performed better (not statistically significant) using the momentum strategy compared to the index portfolio. The trend is clear, as the market-cap size of the stocks in the portfolio grew the performance of the momentum algorithm decreased. If not a negative correlation between large market-cap size and algorithm performance the performance at least becomes random or only slightly negative (but could then be because of randomness) performance of the momentum strategy compared to the index portfolio. In Figure 8 the results are plotted which gives a clear illustration of the findings. In Figure 8 the monthly excess return for all portfolios was calculated by first scaling both the index portfolio return and the momentum strategy return from daily returns to monthly returns. Thereafter the momentum strategy monthly returns were subtracted by the index portfolio monthly returns to create *"Monthly excess return (%)"* in the figure.

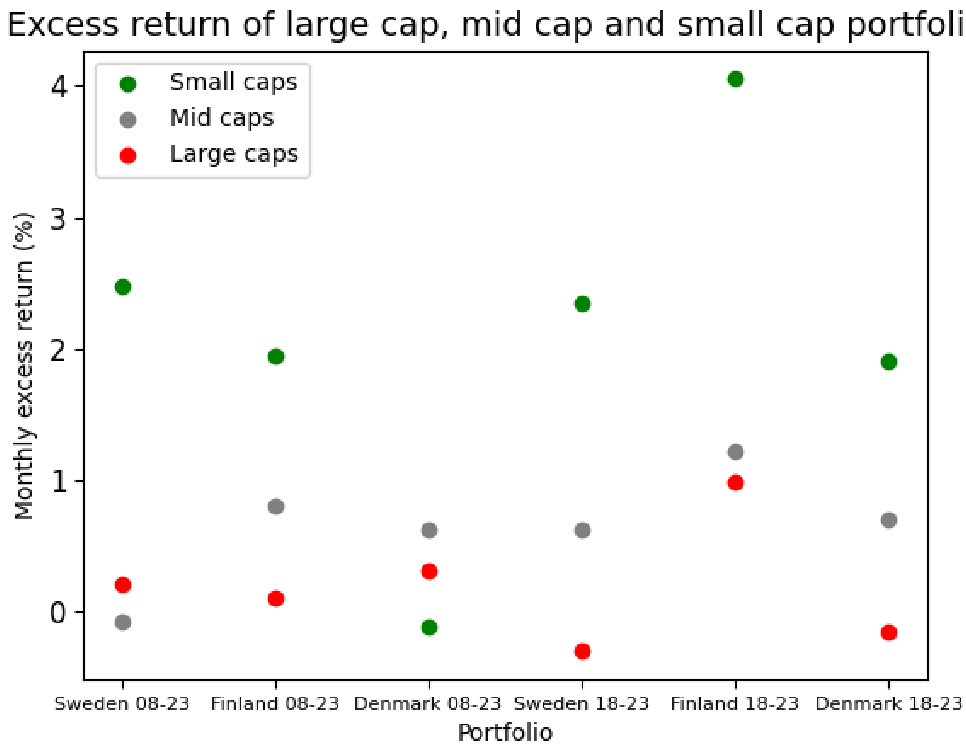


Figure 8: The figure above shows excess return which is defined as the momentum strategy return subtracted by the index portfolio return

Notable in Figure 8 is that in every portfolio except for the low quality portfolio Denmark 08-23 (were the amount of stocks participating too low) and Sweden 08-23 the small-caps outperformed the mid-caps which in turn outperformed the large-caps. The most significant result is the excess performance of the small-cap stocks. Furthermore what is interesting to analyze is when and how the momentum strategy performed the best (and the worst). One of the portfolio developments can be seen in Figure 9 below:

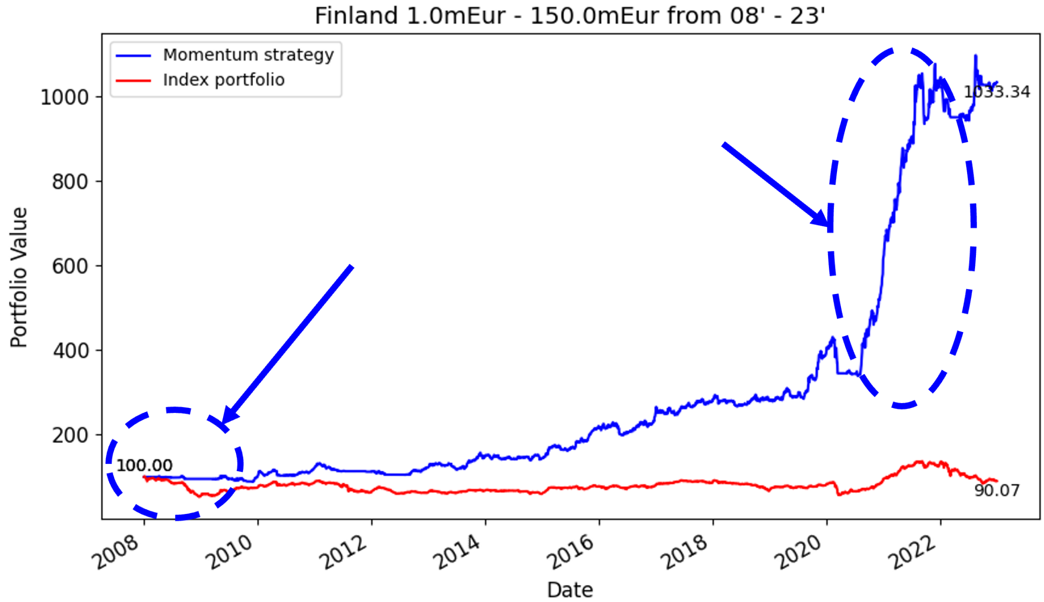


Figure 9: Finland 08-23 portfolio with highlighted volatility zones

A significant portion of the portfolio's return is attributed to a period characterized by high market volatility, which occurred in 2020. The momentum portfolio had a particularly strong performance during this period. Additionally, it is worth noting that the portfolio was almost entirely invested in cash during the negative market sentiment that persisted between 2008-2009, when the index portfolio was declining. This can be seen in both the portfolio performance figure above but also in Figure 10 where the active trades during the time period for the discussed portfolio is shown. The number of active trades between 2008 and middle of 2009 does not exceed three at any time. The portfolio was therefore at most 60% invested and only momentarily as the stocks were sold quickly.

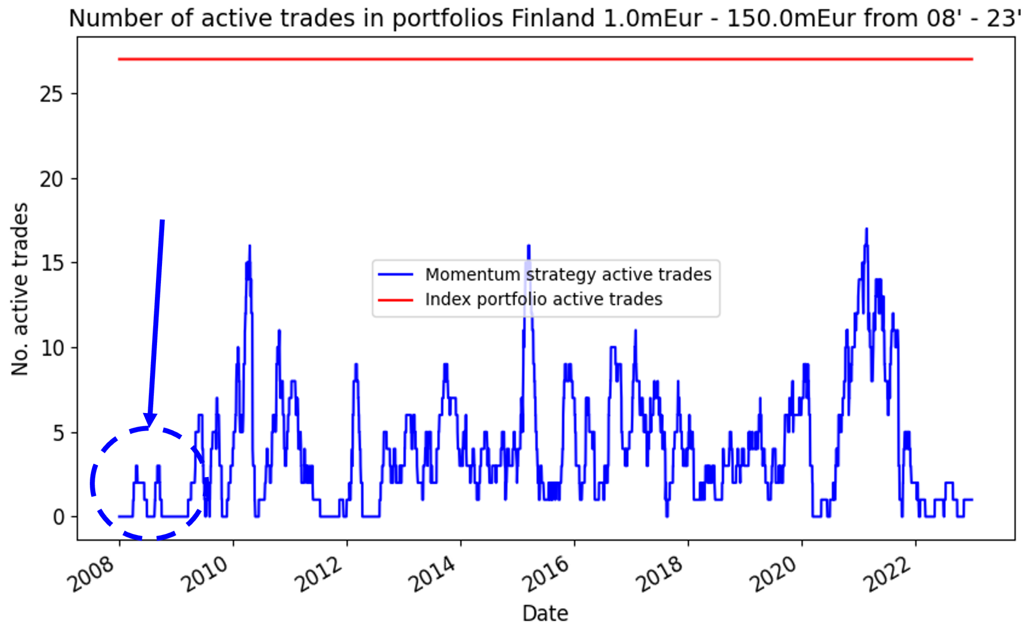


Figure 10: Active trades in Finland 18-23 portfolio

The reason for the liquidity in the portfolio is due to the algorithm not getting any buy signals. The buy signals, as known, depends on the momentum template and volume analysis. The reason for the liquidity in the portfolio in this case is probably that the stocks in the portfolio were in a stage 4 decline, where the momentum template was not fulfilled. When the momentum template is not fulfilled no buy signal will be generated. The portfolio above is only 1 of the 18 portfolios researched but similar patterns can be seen in many but not all of the other small-cap portfolios, even in the portfolios that did not beat the index. For the mid-cap and large-cap stocks the amount of active trades is lower when the index portfolio was declining in 2008-2009 but the excess return seen in the mid-cap and large-cap stocks in periods of of high volatility is not as clear. During period of high market volatility the small-cap portfolios might perform better. How then does these results relate to the EMH?

As was stated by Damodaran (2015) a market could be efficient as long as *"the market price of an asset is an unbiased estimate of the true value of the investment"*. Given that transaction costs are not higher for small-cap stocks than for large-cap stocks the market prices does not seem to be unbiased estimators of the true market values. If the market prices were true unbiased estimators of the true market values it would be unlikely to see such a high inclination towards the small-cap portfolios compared to the larger-cap portfolios. If the underlying assets had a drastically different volatility between small-cap, mid-cap and large-cap one could argue that it is an extreme difference in volatility that has caused market prices to oscillate randomly around the true value in the performance of the small-cap portfolio to differentiate so much from the other portfolios. It is a reasonable assumption to say that smaller-cap stocks is more volatile but the vast difference and consistency in the result is indicating that the reason for higher return is likely not due to higher risk-taking. This claim is also bolstered by looking at the sharpe-ratio [3] of the three portfolios that generated statistically significant excess return. The momentum strategy sharpe-ratio for all three portfolios is higher than the index portfolio sharpe-ratio as can be seen in Table 9. In Table 9, *M Sharpe* is the sharpe ratio for the momentum strategy and *I Sharpe* is the sharpe ratio for the index portfolio. The excess return of the portfolios can therefore not be explained by additional volatility.

[3] Where the sharpe-ratio was calculated using 0 as risk-free rates for both portfolios. The benchmarking is therefore only relevant in this research paper and the sharpe-ratios cannot be compared to external sources.

Portfolio	rm_d	ri_d	rm_σ	ri_σ	M Sharpe (%)	I Sharpe (%)
Sweden small-cap 08-23	0.00107	0.00029	0.01019	0.00896	14.9%	7.1%
Finland small-cap 08-23	0.00062	-0.00003	0.00744	0.00778	8.3%	-0.4%
Finland small-cap 18-23	0.00138	0.00003	0.00995	0.00848	13.9%	0.4%

Table 9: Sharpe ratios for the portfolios where the momentum strategy generated statistical excess return
.

A proponent of the EMH would likely argue that the impact of transaction costs on the performance of the momentum strategy cannot be predicted with certainty using the implemented algorithm, which is true. If the algorithm was implemented to trade one stock at a time to understand how often the stock needs to be bought and sold instead of rebalancing the portfolio every day one could probably make a decent estimate the transaction costs. Therefore, while the findings of the analysis provide some evidence that small-cap stocks outperform larger-cap stocks using the implemented algorithm, it's crucial to consider the potential impact of transaction costs before drawing any conclusions regarding the EMH. To summarize the results suggest that the performance of the momentum strategy varies depending on the size of the market capitalization, even when considering volatility. While these findings are significant, it's important to note that the impact of transaction costs has not been accounted for in the analysis. Nevertheless, the findings provide evidence that small-cap stocks outperform larger-cap stocks using the implemented algorithm. As was pointed out by Lo (2004) the effectiveness of a market could vary on for example the number of participants in a market and for the smaller cap stocks there could hypothetically be less actors interested in the stocks thus making the market less efficient compared to the stocks with larger market capitalizations.

6.3.1 Measurability of Hypothesis Test

One might argue that the significance level of the hypothesis test is too high and with a significance level of 5% more portfolios would have made the threshold. One the other hand that would make the results less reliable and so a significance level of 1% was considered satisfactory. With almost 20 portfolios beeing evaluated, a 5% significance level would make the results from the hypothesis tests less reliable. What is of bigger analysis value if that the hypothesis test is based on normal distributions. The probable outcome of the returns from the algorithm might be more positively skewed than the outcome of returns from the index portfolio, primarily due to the left tail of the normal distribution being *"cut off"* when the stop-loss of 8% is activated. This makes the distribution of the returns be more positively skewed than the normal distribution.

6.4 Discussion

While these restrictions that were summarized brings the algorithm further away from Minervini's implemented strategy the results from the algorithm are still relevant in the studies regarding momentum strategies in the stock market. Relating the empirical results to the Damodaran's interpretation of the EMH, which suggest that *"the market price of an asset is an unbiased estimate of the true value of the investment"* it would be impossible to consistently achieve excess returns without luck. The study's results show that if transaction costs are not higher for small-cap stocks than for large-cap stocks, the market prices do not seem to be unbiased estimators of the true market values, which therefore is inconsistent with Damodaran's interpretation of the EMH. The general conclusion and results of the algorithm points towards that the market might not be entirely efficient unless the transaction costs vary widely depending on the market-cap size of stocks. The study gives an indication that the implemented momentum strategy is more effective on small-cap stocks than on larger cap stocks.

One criticism of the study is the potential survivorship bias effect. The stocks included in the analysis were those that were present in the market as of January 1, 2023, and had already survived until that point. This means that the momentum strategy was tested on a selection of stocks that had already demonstrated their ability to stay afloat in the market. However, when the strategy is applied for future decision-making purposes, it may be used on stocks that could potentially go bankrupt in the near future. This could potentially skew the results of the strategy and may limit its effectiveness in real-world applications.

7 Conclusion and Further Research

7.1 Conclusion

What are the limitations and challenges of executing Minervini's momentum analysis techniques in an algorithmic approach?

The implemented momentum algorithm is seen a primitive variant of Minervini's strategy due to several technical restrictions, practical application problems, and exclusion of fundamental and catalyst aspects. The technical restrictions highlighted in the analysis include the challenge of implementing base count accurately in an algorithmic trading system due to the subjective nature of base patterns, the absence of a relative strength ranking in the algorithm, and the risk and position sizing aspect of the algorithm. The algorithm's fixed stop-loss of 8% does not allow for varying position sizes as Minervini, which makes it difficult to implement Minervini's risk management approach accurately. The algorithm's daily adjustment of position sizes is also identified as a deviation from Minervini's approach, which involves a limited number of active positions and closer monitoring of the active trades where position sizes are not altered daily. Minervini would not mindlessly always keep a uniformally distributed portfolio because the stocks fulfills the buy conditions. Minervini would put careful consideration which stocks that should get a bigger position size and Minervini would always pay more attention to the general market environment when deciding which position size to enter a trade with. Overall the biggest challenges when it comes to mimicking Minervini's momentum strategy in an algorithmic approach is the subjectivity aspects regarding recognising a base and a buy point and also how to adjust the position size.

However, even though it is challenging to implement a partly qualitative analysis in an algorithmic approach the algorithm might add value even though it cannot fully mimick Minervini's strategy. The strengths of using an algorithm is that hundreds of stocks can be analyzed in the blink of an eye compared to the manual scrolling and manual analysis that is done by Minervini. A suggestion is to not let the algorithm fully perform the buy and selling of an equity but rather make suggestions that needs input from the user on whether the stock should be bought. The algorithm could probably speed up the process of excluding stocks that are not of interest.

Is it possible to generate excess returns in Sweden, Denmark, and Finland by using the implemented algorithm over different time periods ranging from 2008-2022?

The empirical results showed that small-cap portfolios of the momentum strategy had the most consistent excess returns generated compared to the mid-cap and large-cap portfolios where the returns did not show a significant difference compared to the index portfolio. The significant excess returns are attributable to high volatility periods. During market declines, the stocks were probably in a stage 4 decline which led to the stocks in the portfolio not fulfilling the momentum criteria which led to no buy signals being generated. As a result, the momentum portfolio maintained high liquidity in negative market conditions. On the other hand in periods of high volatility to the upside the momentum strategy quickly rebalanced to the stocks that were breaking out from bases. The theory is the same for all market caps, but for the mid-cap and large-cap portfolios the effects were not significant or even existing.

Even though this research suggests that excess return was generated for many of the small-cap portfolios (See Figure 8 and Table 9) the research did not account for transaction costs. Since transaction costs were not accounted for in the research it is difficult to say whether excess return was generated after transaction costs. However, given that the transaction costs for the small-cap portfolios are the same as for mid-cap and large-cap portfolios the results indicate that the momentum strategy performs stronger in small-cap stocks compared to mid-cap and large-cap stocks. This in itself is not consistent with Damodaran's interpretation of the EMH. Therefore the conclusion can be drawn that the momentum algorithm seems to perform better for smaller-cap stocks compared to larger-cap stocks but if the momentum technique is generating excess returns after transaction costs are reduced is still to be researched.

7.2 Further Research

Transaction costs are an important factor to consider in any investment strategy, as they can significantly impact the overall returns of the portfolio. In the current study, transaction costs were not taken into account, which may limit the applicability of the results in real-world scenarios. In order to further validate the effectiveness of the implemented algorithm, it is recommended to implement reasonable transaction costs and analyze the performance of the strategy in light of those costs. This would provide more accurate estimates of the net returns that could be achieved with the strategy, and help to identify potential areas for optimization or improvement. This could have adjusted the stop-loss from -8 to -4% or made the algorithm take large profits at +50% instead of 100

Additionally, including transaction costs in the analysis would allow for a more realistic comparison of the strategy against other investment strategies, and provide valuable insights into the practical implications of the strategy for private investors. The methodology could also be adjusted in order to make the strategy not make transactions every day as it is currently implemented. One possible way to improve the current approach is to introduce a ranking system for the buy signals and consistently select the top 20 highest-ranked stocks each week. This modification would shift the momentum analysis to a weekly-based approach, which could help mitigate the transaction costs incurred by daily rebalancing.

The studies referred to in this research paper did not consider volume analysis in their research methodology. However, in the implemented algorithm, the volume aspect is a crucial factor in determining the appropriate time to buy a stock. As a result, future research could involve implementing the same algorithm without the volume condition to examine whether volume has indeed played a significant role in the returns achieved. Furthermore, as discussed in Chapter 6.2, the number of stocks that passed the screening process was lower than expected. Therefore, more attention should be given to the data handling area to investigate the reasons and timing of why some stocks disappeared from the studied dataset. This could help improve the screening process and potentially increase the number of stocks available for analysis.

To optimize the algorithm, it is crucial to conduct a detailed analysis of the reasons behind selling a stock, instead of solely relying on True/False values in matrices (see appendix E) . This approach would facilitate a more comprehensive understanding of the timing and circumstances under which stocks were sold, and enable more precise adjustments and optimizations of the algorithm. The performance of the algorithm could probably be improved with more analysis regarding buy and sell decisions.

Lastly, as discussed in 6.3.1 there needs to be further research regarding the full distribution of the returns and the output data. This can ensure that hypothesis testing is the most suitable approach to use when understanding the performance of the algorithm.

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A Appendix A - Evaluated Portfolios

Country	Market cap	Year	No. of stocks
Sweden	small-cap	2008-2023	138
Sweden	mid-cap	2008-2023	47
Sweden	large-cap	2008-2023	54
Denmark	small-cap	2008-2023	3
Denmark	mid-cap	2008-2023	4
Denmark	large-cap	2008-2023	12
Finland	small-cap	2008-2023	27
Finland	mid-cap	2008-2023	24
Finland	large-cap	2008-2023	17
Sweden	small-cap	2018-2023	138
Sweden	mid-cap	2018 2023	137
Sweden	large-cap	2018-2023	54
Denmark	small-cap	2018-2023	73
Denmark	mid-cap	2018-2023	21
Denmark	large-cap	2018-2023	36
Finland	small-cap	2018-2023	67
Finland	mid-cap	2018-2023	43
Finland	large-cap	2018-2023	33

Table 10: All analyzed portfolios

B Appendix B - All Shares Analyzed in the Report

B.1 Swedish companies

1. AAK
2. ABB
3. Active Biotech
4. Addnode
5. Addtech
6. Alfa Laval
7. Anoto
8. Arise Windpower
9. Assa Abloy
10. AstraZeneca
11. Atlas Copco A
12. Atrium Ljungberg
13. Autoliv
14. Avanza Bank
15. Axfood
16. Bergman & Beving
17. BE Group
18. Beijer Ref
19. Beijer Alma
20. Beijer Electronics
21. Bergs Timber
22. Betsson
23. Bilia
24. Billerud
25. BioGaia
26. Bioinvent
27. Biotage
28. Björn Borg
29. Boliden
30. Bong Ljungdahl
31. Brinova Fastigheter
32. BTS Group
33. Bure Equity
34. Byggmax
35. Castellum
36. Catena
37. Nelly Group
38. CellaVision
39. Clas Ohlson
40. Cloetta
41. Concordia Maritime
42. Concejo B
43. Corem Property A
44. CTT Systems
45. Diamyd Medical
46. Diös Fastigheter
47. Doro
48. Duni
49. Duroc
50. Eastnine
51. Elanders
52. Elon
53. Electrolux B
54. Elekta
55. Elos Medtech
56. Enea
57. Eniro
58. EnQuest
59. Ericsson B
60. eWork
61. Fabege
62. Fagerhult
63. Fastpartner A
64. Fast Balder
65. Fenix Outdoor
66. Fingerprint Cards
67. Formpipe Software
68. Getinge
69. Havsfrun Investment
70. Heba
71. Hennes & Mauritz
72. Hexagon
73. Hexpol
74. HMS Networks
75. Holmen B
76. Hufvudstaden A
77. Husqvarna B
78. I.A.R Systems
79. Image Systems
80. Industrivärden C
81. Indutrade
82. Rolling Optics
83. Intrum
84. Investor B
85. ITAB Shop Concept
86. JM
87. Kabe
88. Kinnevik B
89. KnowIT
90. Lagercrantz
91. Lammhults Design
92. Latour
93. Lindab
94. Loomis
95. Lundbergföretagen
96. Lundin Mining
97. Orrön Energy
98. Malmbergs Elektriska
99. Medivir
100. MEKO
101. Mycronic
102. Midsona B
103. Midway B
104. Millicom
105. Stockwik Förvaltning
106. Empir Group
107. Modern Times Group B
108. NAXS
109. NCC B
110. Nederman
111. Net Insight
112. New Wave
113. NIBE Industrier
114. Nobia
115. Nolato
116. Nordea Bank
117. Nordnet
118. NOTE
119. Strax
120. Novotek
121. Vivesto
122. Logistea A
123. OEM International
124. Orexo
125. Ortivus B
126. Peab
127. PION Group
128. Precise Biometrics
129. Prevas

130. Pricer
131. Proact IT
132. Probi
133. ProfilGruppen
134. Ratos B
135. RaySearch Laboratories
136. Rejlers
137. Coala-life
138. Rottneros
139. Saab
140. Sagax A
141. Sandvik
142. SAS
143. SCA B
144. SEB A
145. Sectra
146. Securitas
147. Sensys Gatso
148. Handelsbanken A
149. SinterCast
150. Skanska
151. SKF B
152. SkiStar
153. Softronic
154. SSAB A
155. Stora Enso R
156. Studsvik
157. Svedbergs
158. Svolder B
159. Sweco B
160. Swedbank
161. Swedish Orphan Biovitrum
162. Systemair
163. Tele2 B
164. Telia Company
165. TietoEVRY
166. Traction
167. TradeDoubler
168. Viking Supply
169. Trelleborg
170. Kindred
171. VBG Group
172. Rizzo Group
173. Vitrolife
174. Volvo B
175. VNV Global
176. Wallenstam
177. Wihlborgs Fastigheter
178. XANO Industri
179. AFRY
180. Öresund
181. Karolinska Development
182. Boule Diagnostics
183. Dedicare
184. Moberg Pharma
185. Concentric
186. Cavotec
187. Nokia
188. Micro Systemation
189. Vitec Software
190. Bulten
191. Moment Group
192. ADDvise Group A
193. Africa Oil
194. Arctic Minerals
195. Avensia
196. Avtech
197. Bredband2
198. C-RAD
199. Catella B
200. Auriant Mining
201. Nordic LEVEL
202. Creades
203. DistIT
204. Diadrom
205. Dignitana
206. Drillcon
207. Ellen
208. Kakel Max
209. Eolus Vind
210. EnergyO Solutions
211. Episurf Medical
212. Firefly
213. Arcario
214. Generic Sweden
215. Genovis
216. Binero Group
217. Götenehus Group
218. Hansa Biopharma
219. Stendörren Fastigheter
220. Hifab
221. Impact Coatings
222. Invisio
223. Northbaze
224. JLT Mobile
225. Kancera
226. Copperstone
227. Kopy Goldfields
228. Lucara Diamond
229. Mackmyra
230. MedCap
231. Modern Ekonomi
232. Misen Energy
233. NetJobs
234. New Nordic Healthbrands
235. Online Brands Nordic
236. Saxlund
237. Egetis Therapeutics
238. Precio Fishbone
239. Precomp Solutions
240. ScandBook
241. ShaMaran
242. Ogunsen
243. Skåne-möllan
244. Stille
245. TagMaster
246. Tethys Oil
247. Unlimited Travel Group
248. Nordic Flanges
249. Vestum
250. Westpay
251. Wise Group
252. ALM Equity
253. Mangold
254. Platzer Fastigheter
255. aXichem
256. Nexam Chemical
257. Xvivo Perfusion
258. Bufab
259. Bactiguard
260. Scandi Standard
261. Arctic Paper
262. Besqab
263. G5 Entertainment
264. Abliva
265. Oscar Properties
266. Starbreeze B
267. Cell Impact
268. BIMobject
269. Mendus
270. Polyplank
271. Fastator
272. Ages Industri

273. Clavister
274. Cortus Energy
275. Reato Group
276. Doxa
277. Hanza
278. Heliospectra
279. Hexatronic
280. Kallebäck Property
281. Kambi
282. Kentima
283. Mavshack
284. Irisity
285. NanoCap
286. Nicoccino
287. Clemondo
288. ScandiDos
289. Scandinavian Enviro
290. Advenica
291. Speqta
292. LIDDS
293. DDM Holding
294. Inwido
295. Gränges
296. Safeture
297. Thule
298. Sprint Bioscience
299. Nexstim
300. Humble Group
301. Bonzun
302. Arcoma
303. PowerCell
304. Christian Berner Tech
305. Absolent Air Care
306. Samhällsbyggnadsbolag B
307. Lifco
308. NP3 Fastigheter
309. Premium Snacks
310. Gabather
311. Scandinavian Real Heart
312. Greater Than
313. Ecoclime
314. Tourn
315. Storytel
316. OptiCept Technologies
317. Ortoma
318. ProstaLund
319. Saniona
320. Serstech
321. RLS Global
322. Guard Therapeutics
323. Enzymatica
324. Spago Nanomedical
325. Sivers Semiconductors
326. AQ Group
327. AroCell
328. Qlosr Group
329. Botnia Exploration
330. Clinical Laserthermia
331. Acroud
332. iZafe
333. NGS Group
334. Railcare
335. QuiaPEG Pharmaceuticals
336. Senzime
337. Sileon
338. Guideline Geo
339. KebNi
340. Hedera
341. Fortnox
342. Zinzino
343. Lundin Gold
344. Eltel
345. Byggmästare AJ Ahlström
346. Freja eID
347. Dustin Group
348. OrganoClick
349. Acrinova A
350. Corem Property Pref
351. ALM Equity Pref
352. Oscar Properties Pref
353. Sdiptech Pref
354. K2A Knaust & Andersson Pref
355. Volati Pref
356. Pandox
357. Alimak
358. Collector Bank
359. Coor Service Management
360. Hoist Finance
361. Tobii
362. Troax Group
363. Cantargia
364. Corline Biomedical
365. Evolution
366. Gaming Corps
367. Heimstaden Pref
368. Inission
369. Kontigo Care
370. Nilörngruppen
371. Pegroco Invest Pref
372. Studentbostäder
373. SavoSolar
374. Scibase
375. SolTech Energy
376. Spiffbet
377. SpectrumOne
378. SaltX Technology
379. Cline Scientific
380. CombiGene
381. Idogen
382. Nanexa
383. Pharmacolog
384. Transtema
385. Bonäsudden
386. Link Prop
387. Insplorion
388. SpectraCure
389. VEF
390. Footway Pref
391. Vimab Group
392. Sinch
393. Bravida
394. Dometic
395. Klaria Pharma
396. Minesto
397. Photocat
398. Waystream
399. Alzinova
400. Nanologica
401. Attendo
402. Camurus
403. Scandic Hotels
404. Immunovia
405. Nilsson Special Vehicles
406. Stillfront
407. Vicore Pharma
408. Toleranzia
409. Xbrane Biopharma
410. Catena Media
411. Humana
412. Garo
413. Polygiene
414. AddLife

415. Xintela
416. Simris Alg
417. Infant Bacterial
418. Litium
419. Nepa
420. Resurs Holding
421. Paradox Interactive
422. Talkpool
423. Lauritz
424. Swedencare
425. B3 Consulting
426. Clean Motion
427. SynAct Pharma
428. Alelion Energy
429. TF Bank
430. Nordic Waterproofing
431. AcadeMedia
432. Bonava B
433. Acuvi
434. Cyxone
435. Oscar Properties Pref B
436. Eagle Filters
437. Enorama Pharma
438. GomSpace
439. Redwood Pharma
440. Quartiers Properties Pref
441. Maha Energy
442. ExpreS2ion Biotech
443. Flowscape
444. Alcadon Group
445. Filo Mining
446. Cyber Security 1
447. Solnaberg
448. Nosa Plugs
449. Gasporox
450. Embracer
451. BICO Group
452. Serneke
453. Volati
454. Byggpartner
455. Crunchfish
456. Gapwaves
457. InDex Pharmaceuticals
458. Alligator Bioscience
459. Swedish Stirling
460. ChemoTech
461. Smart Eye
462. Aino Health
463. AppSpotr
464. Acarix
465. AAC Clyde Space
466. SeaTwirl
467. Svenska Aerogel
468. Vo2 Cap
469. AcouSort
470. Effnetplattformen
471. Oncopeptides
472. Hemcheck Sweden
473. Hoylu
474. IRLAB Therapeutics
475. Initiator Pharma
476. Chordate Medical
477. Ambea
478. Mips
479. ChromoGenics
480. FM Mattsson
481. Actic Group
482. Biovica
483. Unibap
484. Sonetel
485. Isofol Medical
486. Tangiamo Touch
487. Intervacc
488. Instalco
489. Sdiptech
490. Munters
491. SECITS Holding
492. International Petroleum
493. Mantex
494. Annexin
495. Athanase Innovation
496. Bambuser
497. XMReality
498. Integrum
499. ISR Holding
500. Bioservo Technologies
501. Medicover
502. TerraNet
503. Boozt
504. Zaplox
505. Ayima
506. Paxman
507. Essity B
508. Enersize
509. Bonesupport
510. OXE Marine
511. Alligo
512. Agtira
513. Nitro Games
514. Urb-it
515. Netmore
516. NextCell Pharma
517. Promore Pharma
518. Realfiction
519. Sedana Medical
520. Surgical Science
521. Trianon
522. Seamless Distribution Systems
523. Balco Group
524. Quartiers Properties
525. SenzaGen
526. Xspray Pharma
527. BioArctic
528. Fram Skandinavien
529. Climeon
530. Qiiwi Games
531. Ferronordic
532. Goodbye Kansas
533. Artificial Solutions
534. 2cureX
535. Seafire
536. Flexqube
537. Awardit
538. IRRAS
539. Tempest Security
540. DevPort
541. MAG Interactive
542. Scout Gaming
543. Acconeer
544. Lyko
545. Arjo
546. Enad Global 7
547. Bio-Works
548. H&D Wireless
549. ADDvise Group B
550. Atlas Copco B
551. Bonava A
552. Catella A
553. Corem Property B
554. Electrolux A
555. Ericsson A
556. Essity A

557. Handelsbanken B
558. Holmen A
559. Husqvarna A
560. Industrivärden A
561. Investor A
562. Kinnevik A
563. Midsona A
564. Midway A
565. Modern Times Group A
566. NCC A
567. Ortivus A
568. Ratos A
569. Sagax B
570. Sagax D
571. SCA A
572. SEB C
573. SKF A
574. SSAB B
575. Starbreeze A
576. Stora Enso A
577. Svolder A
578. Sweco A
579. Tele2 A
580. Volvo A
581. Leading Edge Materials
582. Cibus Nordic
583. BHG Group
584. Green Landscaping
585. BuildData
586. Iconovo
587. Fluicell
588. Infrea
589. NP3 Fastigheter Pref
590. Better Collective
591. NCAB Group
592. I-Tech
593. Ovzon
594. JonDeTech Sensors
595. Africa Energy
596. Arion Banki
597. Epiroc A
598. Epiroc B
599. Flexion Mobile
600. Projektengagemang
601. Calliditas Therapeutics
602. Midsummer
603. Raketech
604. Ranplan
605. Asarina Pharma
606. Metacon
607. Nordic Iron Ore
608. Ziccum
609. Zordix
610. Nyfosa
611. AlzeCure Pharma
612. Axolot Solutions
613. S2Medical
614. Scandion Oncology
615. Azelio
616. Jetpak
617. Lime Technologies
618. NeoDynamics
619. Q-Linea
620. CAG Group
621. Footway
622. Samhällsbyggnadsbolag D
623. InCoax Networks
624. Clean Industry
625. Ferroamp
626. Teqnion
627. Upsales
628. Ascelia Pharma
629. Viaplay B
630. Viaplay A
631. Karnov
632. Train Alliance
633. Gaming Innovation
634. Triboron
635. FluoGuide
636. Vertiseit
637. OssDsign
638. John Mattson
639. K2A
640. Mentice
641. Traton
642. EQT
643. Lipidor
644. Akelius D
645. ZignSec
646. K-Fast Holding
647. Adventure Box
648. QleanAir
649. MOBA Network
650. Divio Technologies
651. Fastpartner D
652. Kollect on Demand
653. Zwipe
654. Nord Insuretech
655. Veg of Lund
656. QLife
657. Stayble Therapeutics
658. Electrolux Professional B
659. Bioextrax
660. Epti
661. AegirBio
662. Nanoform
663. Magle Chemoswed
664. Genova Property
665. Exsitec
666. Readly
667. Implantica
668. Lifeclean
669. Neola Medical
670. MGI - Media Games
671. Qliro
672. Wästbygg
673. BoMill
674. Klimator
675. Nordic Paper
676. Lohilo Foods
677. Prostatype Genomics
678. Svenska Nyttobostäder
679. Svenska Nyttobostäder Pref
680. CDON
681. Luxbright
682. Fortinova
683. Re:NewCell
684. Thunderful
685. Fasadgruppen
686. Annehem Fastigheter
687. CirChem
688. Stenhus Fastigheter
689. Scandinavian Biogas
690. Aros Bostadsutveckling Pref B
691. ELLWEE
692. Nimbus
693. Fractal Gaming
694. Cint Group
695. OncoZenge
696. Desenio
697. Lipigon Pharmaceuticals
698. CoinShares

699. Spherio Group
700. Ekobot
701. RugVista
702. Acrinova B
703. Embellence
704. Fantasma Games
705. ACQ Bure SPAC
706. Idun Industrier
707. Pierce Group
708. LMK Group
709. Euroafrica Digital Ventures
710. Pharmiva
711. Hemnet
712. Dlaboratory
713. Lipum
714. Plexian
715. Modelon
716. Nilar International
717. Tellusgruppen
718. Goobit Group
719. checkin.com
720. Duearity
721. Safello Group
722. Twiik
723. Aligro Planet SPAC
724. Arla Plast
725. Cedergrenska
726. Tessin Nordic
727. Linc
728. Bokusgruppen
729. Loyal Solutions
730. Mildef Group
731. Permascand
732. SaveLend
733. Sozap
734. Sleep Cycle
735. Ngenic
736. Maven Wireless
737. Elicera Therapeutics
738. Aventura Group
739. Revolutionrace
740. TH1NG
741. Aros Bostadsutveckling
742. Acast
743. CodeMill
744. Hexicon
745. Physitrack
746. Vimian Group
747. Brilliant Future
748. Creaspac SPAC
749. LL Lucky Games
750. OX2
751. tbd30
752. Biosergen
753. Emplicure
754. Intellego Technologies
755. USWE Sports
756. Corem Property D
757. Linkfire
758. First Venture
759. Profoto
760. Wyld Networks
761. Amniotics
762. Freemelt
763. Godsinlösen
764. Diagonal Bio
765. Fragbite
766. Modus Therapeutics
767. Pila Pharma
768. Söder Sportfiske
769. Arlandastad
770. Kjell Group
771. Kiliaro
772. Aprendere Skolor
773. CTEK
774. eEducation Albert
775. FSport
776. Fastighetsbolag Emilshus
777. Storskogen
778. Truecaller
779. Nordisk Bergteknik
780. Haypp Group
781. Netel Holding
782. Byggfakta
783. Flat Capital
784. Pagero Group
785. Hilbert Group
786. Advanced SolTech
787. Volvo Car
788. Synsam
789. Medhelp Care
790. XP Chemistries
791. Bricknode
792. Candles Scandinavia
793. Compodium
794. Norditek
795. Qlucore
796. Bubbleroom
797. Opter
798. SignUp Software
799. Alpcot
800. Resqunit
801. Logistea B
802. Adtraction
803. Careium
804. ChargePanel
805. Devyser Diagnostics
806. KlaraBo
807. Nivika Fastigheter
808. Norva24
809. Solid Försäkring
810. Tobii Dynavox
811. Titania
812. Mestro
813. Viva Wine
814. Case Group
815. Nordic Asia
816. MTI Investment
817. W5 Solutions
818. Dala Energi
819. Learning 2 Sleep
820. Newbury Pharmaceuticals
821. Zazz Energy
822. Smart Valor
823. Purefun
824. Lyckegård
825. Move About
826. RightBridge Ventures
827. BeammWave
828. Northgold
829. Bawat Water
830. CombinedX
831. Swedish Logistic Property
832. Oneflow
833. Momentum Group
834. High Coast Distillery
835. Promimic
836. Västra Hamnen
837. Arctic Blue Beverages
838. 4C Group
839. Job Solution Sweden
840. Skolon
841. Engcon
842. Sweden BuyersClub
843. Fastighetsbolaget Emilshus
844. Alleima
845. Cinis Fertilizer
846. Sampo
847. Gotlandsbolaget A
848. Gotlandsbolaget B
849. LumenRadio
850. Neobo Fastigheter
851. RanLOS

B.2 Finnish companies

1. Cargotec
2. Citycon
3. Elisa
4. Fiskars
5. Fortum
6. Huhtamäki
7. Kemira
8. Kesko B
9. KONE
10. Konecranes
11. Neste
12. Nokia
13. Nokian Renkaat
14. Nordea Bank
15. Orion B
16. Outokumpu
17. Metso Outotec
18. Sampo
19. Sanoma
20. SSAB B
21. Stora Enso R
22. Telia Company
23. TietoEVRY
24. UPM-Kymmene
25. Valmet
26. Wärtsilä
27. YIT Corporation
28. Aktia Bank
29. Caverion
30. Oriola B
31. Atria
32. Aspo
33. Alma Media
34. Bittium
35. Finnair
36. WithSecure
37. Lassila Tikanoja
38. HKScan
39. Metsä Board B
40. Olvi
41. Ponsse 1
42. Rapala
43. SRV Group
44. Stockmann
45. Uponor
46. Vaisala
47. Viking Line
48. Enento
49. Pihlajalinna
50. Endomines Finland
51. Sotkamo Silver
52. Saga Furs
53. Reka Industrial
54. Valoe
55. Apetit
56. Afarak
57. Aspocomp
58. CapMan
59. Componenta
60. Digia
61. Dovre
62. Enedo
63. eQ Oyj
64. Etteplan
65. Suominen
66. Solteq
67. Exel Composites
68. Glaston
69. Innofactor
70. SSH Communications
71. Ålandsbanken B
72. Raute
73. Biohit
74. QPR Software
75. Elecster
76. Honkarakenne
77. Ilkka 2
78. Incap
79. Digitalist Group
80. Ovaro Kiinteistösijoitus
81. Marimekko
82. Martela
83. Nurminen Logistics
84. Keskisuomalainen
85. Kesla
86. PunaMusta Media
87. Revenio
88. Sievi Capital
89. Wetteri
90. Investors House
91. Trainers House
92. Boreo
93. NoHo Partners
94. Panostaja
95. Scanfil
96. Tecnotree
97. Teleste
98. Tulikivi
99. Wulff-Yhtiöt
100. Fellow Pankki
101. Consti
102. Detection
103. Eagle Filters
104. Herantis Pharma
105. Nexstim
106. Nixu
107. Piippo
108. Robit
109. SavoSolar
110. Siili Solutions
111. Taaleri
112. Talenom
113. United Bankers
114. Verkkokauppa.com
115. Tokmanni Group
116. Lehto Group
117. Qt Group
118. NYAB
119. Vincit
120. Heeros
121. Rovio
122. Fondia
123. Kamux
124. Remedy Entertainment
125. Terveystalo
126. Efecte
127. Gofore
128. Titanium
129. Kesko A
130. Metsä Board A
131. Oriola A
132. Orion A
133. SSAB A
134. Stora Enso A
135. Ålandsbanken A
136. BBS-Bioactive Bone
137. Admicom

138. Harvia
139. Enersense
140. Kojamo
141. Eezy
142. Oma Säästöpankki
143. Rush Factory
144. Viafin Service
145. Tallink Grupp
146. LeadDesk
147. Aallon Group
148. Relais Group
149. Fodelia
150. Faron Pharmaceuticals
151. Optomed
152. Musti Group
153. Nanoform
154. Partnera
155. Kreate Group
156. Nightingale Health
157. Orthex
158. Sitowise Group
159. Alexandria Pankkiiriliike
160. Netum
161. Toivo Group
162. Merus Power
163. Solwers
164. Puuilo
165. Spinnova
166. Anora Group
167. Bioretec
168. EcoUp
169. Modulight
170. Loihde
171. Inderes
172. Lifeline SPAC
173. Fifax
174. Lemonsoft
175. Duell
176. Aiforia Technologies
177. Springvest
178. Betolar
179. Digital Workforce
180. Lamor
181. Norrhydro
182. Kempower
183. Administer
184. Purmo Group
185. Evli
186. LapWall
187. Lifa Air
188. Witted Megacorp
189. Asuntosalkku
190. Nordic Lights Group
191. F-Secure
192. Koskisen
193. Tamtron

B.3 Danish Companies

1. A.P. Moller Maersk B
2. Carlsberg B
3. Chr Hansen
4. Coloplast
5. Danske Bank
6. DSV
7. FLSmidth Co.
8. Genmab
9. GN Store Nord
10. Novo Nordisk
11. Pandora
12. Vestas Wind Systems
13. Royal UNIBREW
14. H. Lundbeck B
15. Nordea Bank
16. ISS
17. Jyske Bank
18. Kobenhavns Lufthavne
19. Novozymes
20. Rockwool B
21. Sydbank
22. Topdanmark
23. Tryg
24. Demant
25. Matas
26. FirstFarms
27. Bang Olufsen
28. Flugger
29. Roblon
30. ALK-Abello
31. Alm. Brand
32. Ambu
33. Bavarian Nordic
34. D/S Norden
35. DFDS
36. Jeudan
37. NKT Holding
38. NNIT
39. Per Aarsleff
40. Ringkjobing Landbobank
41. SAS
42. Schouw Co.
43. SimCorp
44. Solar
45. Sparekassen Sjaelland-Fyn
46. Tivoli
47. Spar Nord Bank
48. UIE
49. Zealand Pharma
50. Össur
51. Aalborg Boldspilklub
52. AGF B
53. Atlantic Petroleum
54. BankNordik
55. BioPorto
56. Pharma Equity
57. Brd. Klee
58. Brdr. AO Johansen
59. Brdr. Hartmann
60. Brondbyernes IF
61. cBrain
62. ChemoMetec
63. Columbus
64. Copenhagen Capital
65. Danske Andelskassers
66. Dantax
67. Djurslands Bank
68. Scandinavian Investment
69. Erria
70. Fast Ejendom
71. Fynske Bank
72. Gabriel Holding
73. German High Street
74. Glunz Jensen
75. Grönlandsbanken
76. Gyldendal B
77. HH International
78. Harboes Bryggeri
79. Hvidbjerg Bank
80. MT Hojgaard B
81. InterMail
82. Kreditbanken
83. Lollands Bank
84. Luxor
85. Lån og Spar Bank
86. Mons Bank
87. NTG Nordic Transport
88. NewCap Holding
89. Nordfyns Bank
90. Nordic Shipholding
91. Park Street
92. North Media
93. NTR Holding
94. PARKEN Sport
95. Prime Office
96. Rias
97. RTX
98. EAC Invest
99. Scandinavian Brake
100. Silkeborg IF
101. SKAKO
102. Skjern Bank
103. Ennogie Solar
104. SP Group
105. Rovsing
106. Strategic Investments
107. Agat Ejendomme
108. Cemat
109. TORM
110. Totalbanken
111. Vestjysk Bank
112. EgnsINVEST
113. Enalyzer
114. FastPassCorp
115. Jobindex
116. WIRTEK
117. Orsted
118. Scandinavian Tobacco
119. GreenMobility
120. Conferize
121. Nilfisk
122. Orphazyme
123. TCM Group
124. Copenhagen Capital Praef
125. A.P. Moller Maersk A
126. Carlsberg A
127. Gyldendal A
128. Rockwool A
129. SPENN Technology
130. HRC World
131. Agillic
132. Netcompany Group
133. Happy Helper
134. ViroGates
135. Odico
136. Hypefactors
137. Stenocare

138. Scape Technologies
139. Seluxit
140. Danish Aerospace
141. Konsolidator
142. Astralis
143. Shape Robotics
144. Penneo
145. Monsenso
146. LED iBond
147. Fom Technologies
148. Mdundo.com
149. Alefarm Brewing
150. WindowMaster
151. Dataproces
152. Boozt
153. HusCompagniet
154. DecideAct
155. Nexcom
156. BactiQuant
157. Valuer
158. RISMA Systems
159. Hydract
160. Impero
161. Trophy Games
162. Digizuite
163. NORD.investments
164. DonkeyRepublic
165. Trifork
166. MapsPeople
167. Green Hydrogen
168. Aquaporin
169. OrderYOYO
170. SameSystem
171. Brain+
172. Movinn
173. Scandinavian Medical
174. Q-Interline
175. Hove
176. Relesys
177. Re-Match
178. H. Lundbeck A
179. Swiss Properties Invest
180. Noble Corporation

C Appendix C - Example of a Trade History

Stock	Modern Times Group B
Stock ID	148
buy_date	2020-07-09
sell_date	2020-09-04
sell_price	114.80
buy_price	112.05
pct_return	2.454261
holding_time	42
sell_reason	Sold into weakness crossing MA50
portfolio_value	215.903662
buy_date	2020-09-16
sell_date	2020-10-21
sell_price	121.40
buy_price	129.00
pct_return	-5.891473
holding_time	26
sell_reason	Sold into weakness crossing MA50
portfolio_value	214.951422
buy_date	2020-11-05
sell_date	2020-11-25
sell_price	124.65
buy_price	139.20
pct_return	-10.452586
holding_time	15
sell_reason	Sell Due to Stop Loss
portfolio_value	213.261968
buy_date	2021-09-03
sell_date	2021-09-10
sell_price	118.65
buy_price	129.10
pct_return	-8.094500
holding_time	6
sell_reason	Sell Due to Stop Loss
portfolio_value	211.953652
Buy and Hold Return	-74.04700487245628%

Table 11: Stock Performance: Modern Times Group B (Stock ID: 148)

D Appendix D - Algorithm Run Extract

Date	No. active trades	Portfolio Value	Pos. Sizing (Dec)	Pos. Sizing (Abs)
2018-01-02	3	100	0.2	20
2018-01-03	4	101.6002437	0.2	20.32004874
2018-01-04	7	103.4204037	0.142857143	14.77434338
2018-01-05	7	106.3971092	0.142857143	15.19958703
2018-01-08	13	107.1690857	0.076923077	8.243775822
2018-01-09	14	107.7899447	0.071428571	7.699281766
2018-01-10	15	107.7111497	0.066666667	7.180743314
2018-01-11	16	107.9255904	0.0625	6.745349399
2018-01-12	16	108.1294922	0.0625	6.758093264
2018-01-15	19	107.8686233	0.052631579	5.677295964
2018-01-16	19	108.4062965	0.052631579	5.705594554
2018-01-17	18	110.3198973	0.055555556	6.128883181
2018-01-18	17	110.861069	0.058823529	6.521239356
2018-01-19	19	111.0825071	0.052631579	5.846447744
2018-01-22	20	111.2682134	0.05	5.56341067
2018-01-23	23	111.289525	0.043478261	4.838675001
2018-01-24	22	111.5381519	0.045454545	5.069915994
2018-01-25	22	110.1612704	0.045454545	5.007330471
2018-01-26	22	109.9686093	0.045454545	4.998573151
2018-01-29	22	110.0520162	0.045454545	5.002364372

Table 12: Example table showing how the position sizing of various equities will vary from one day to another.

E Appendix E - Date Range Dataframe Extract

A date range dataframe for the momentum strategy was calculated and can be seen below:

Date	7	33	34	37	47	63	82	83
2018-01-02	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2018-01-03	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-04	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-05	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-08	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-09	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-10	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-11	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-12	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-15	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-16	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-17	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-18	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-19	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE
2018-01-22	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-23	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-24	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2018-01-25	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE

Table 13: The date range dataframe above shows how many active trades there are for a given date. For there was one active trade.

For the buy and hold strategy a date range dataframe extract would look like the below:

Date	7	33	34	37	47	63	82	83
2018-02-19	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-20	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-21	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-22	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-23	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-26	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-27	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-02-28	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-01	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-02	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-05	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-06	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-07	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-08	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-09	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2018-03-12	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

Table 14: The date range dataframe above shows how the date range dataframe looks like for the buy and hold strategy active trades there are for a given date.

F Appendix F - Price Dataframe Extract

Date	Spot Price	MA50	MA150	MA200	Vol50	52W High	52W Low	Trend	Pivot
2015-03-20	18.2	–	–	–	–	–	–	False	False
2015-03-23	17.8	–	–	–	–	–	–	False	False
2015-03-24	17.9	–	–	–	–	–	–	False	False
2015-03-25	18.2	–	–	–	–	–	–	False	False
2015-03-26	18.2	–	–	–	–	–	–	False	False
				...					
2023-03-27	1323.1	1257.5	1069.3	1037.0	499675.4	1335.0	793.6	True	False
2023-03-28	1323.4	1261.4	1072.2	1039.0	496065.2	1335.0	793.6	True	False
2023-03-29	1335.4	1265.0	1075.3	1041.1	492065.7	1335.4	793.6	True	False
2023-03-30	1361.9	1269.3	1078.6	1043.4	494589.5	1361.9	793.6	True	False
2023-03-31	1384.1	1273.9	1082.1	1045.6	495369.5	1384.1	793.6	True	False

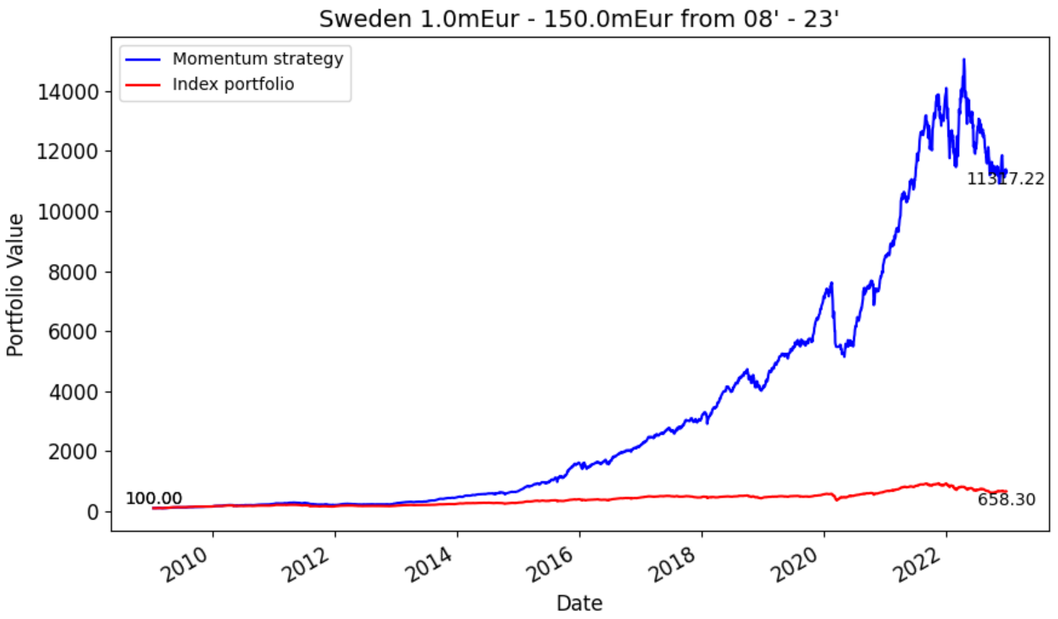
Table 15: A condensed version of a price dataframe used for every stock. The data in the table comes from stock id 750 which is *Evolution*

G Appendix G - Return and Active Trades for All Portfolios

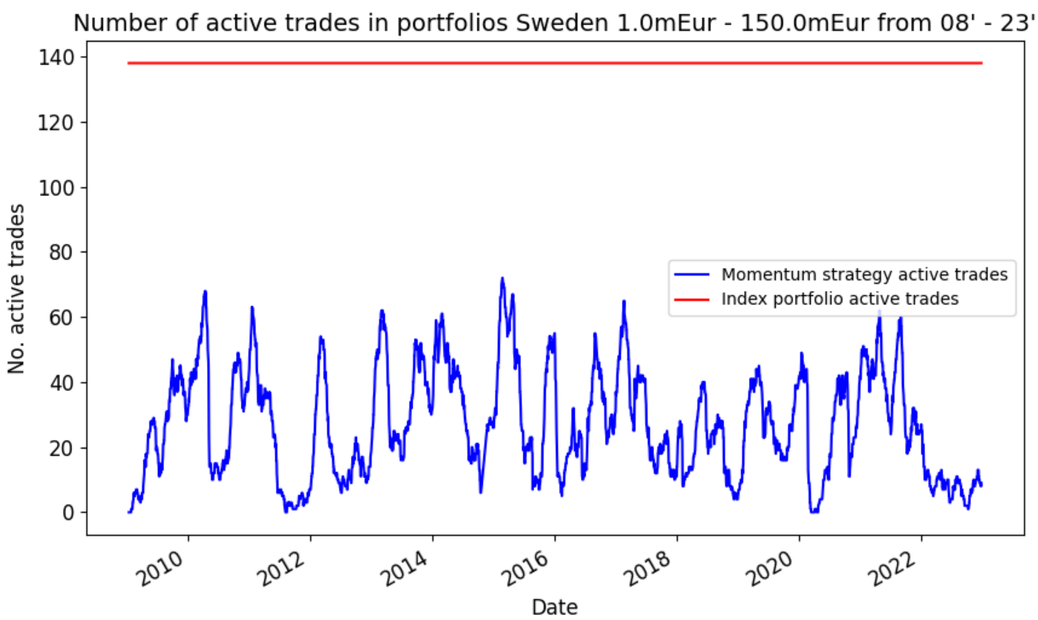
This Appendix is structured so that small-cap results come first followed by mid-cap results and lastly large-cap results. For every section of either small, mid or large-cap the results for Sweden, Finland and Denmark is presented in that order. The presentation order has been set to Sweden, Finland and Denmark for every capitalization size due to the size and quality of the data-sets. Furthermore the 2008-2023 portfolios are presented before the 2018-2023 portfolios are presented.

G.1 Small-cap portfolios

G.1.1 Sweden small-cap 2008-2023



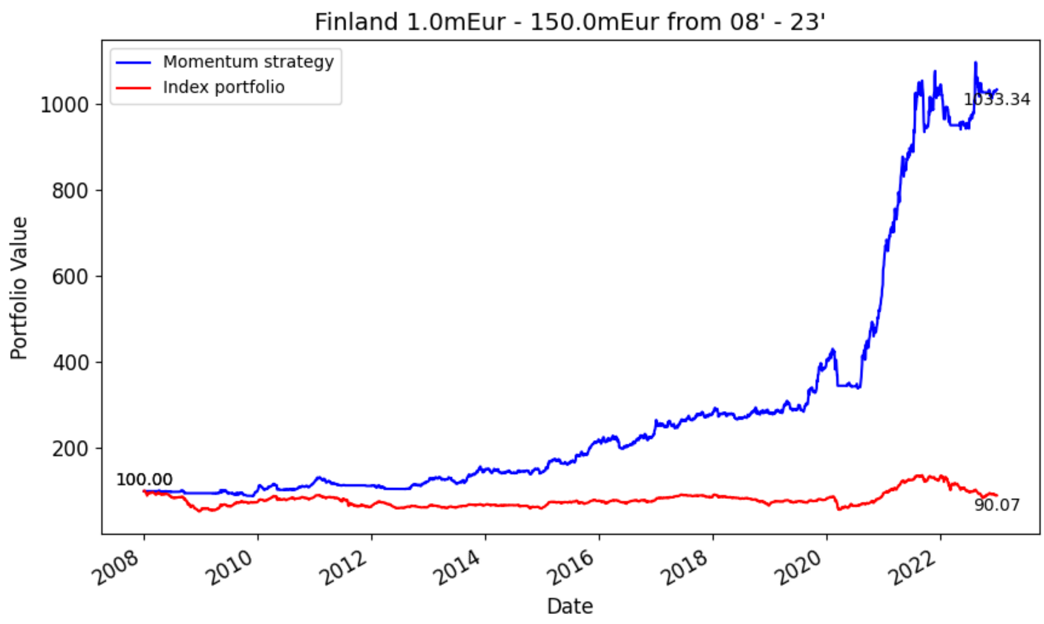
(a) Portfolio value



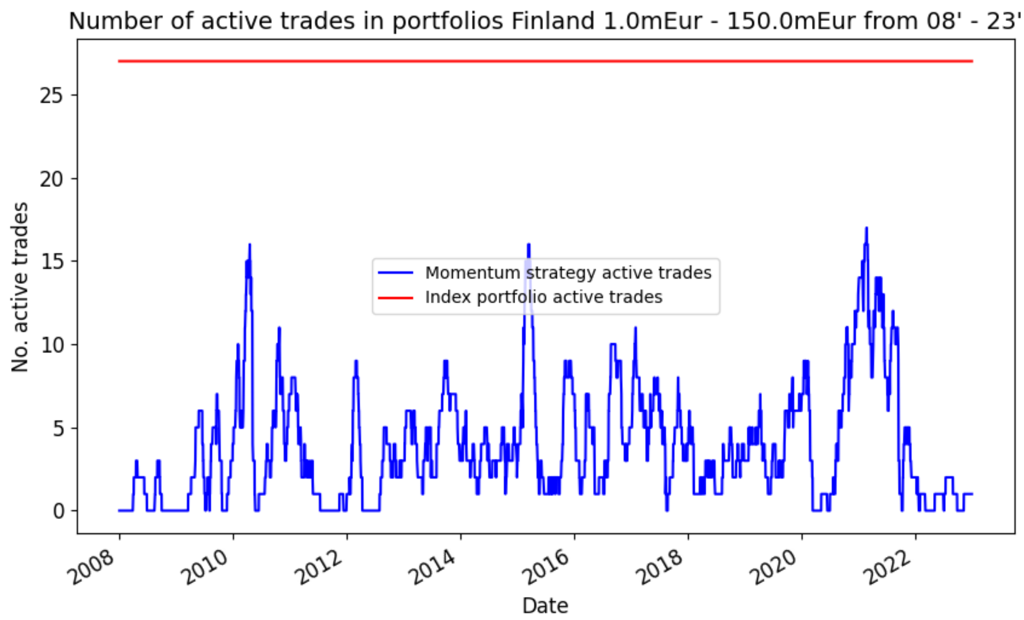
(b) Active trades during the research period.

Figure 11: Return and active trades for the Sweden small-cap portfolio between 2008-2023.

G.1.2 Finland small-cap 2008-2023



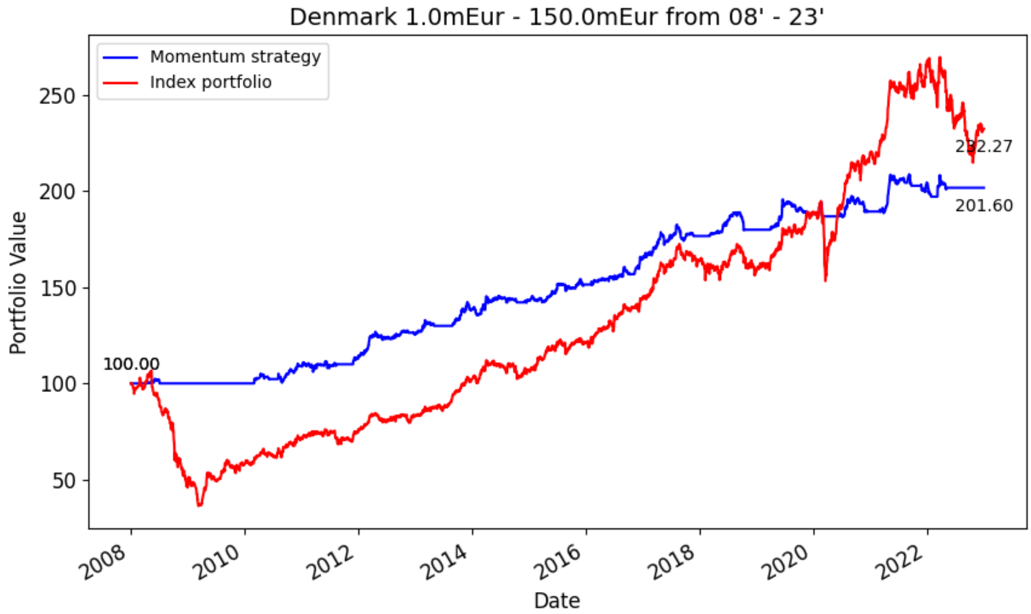
(a) Portfolio value



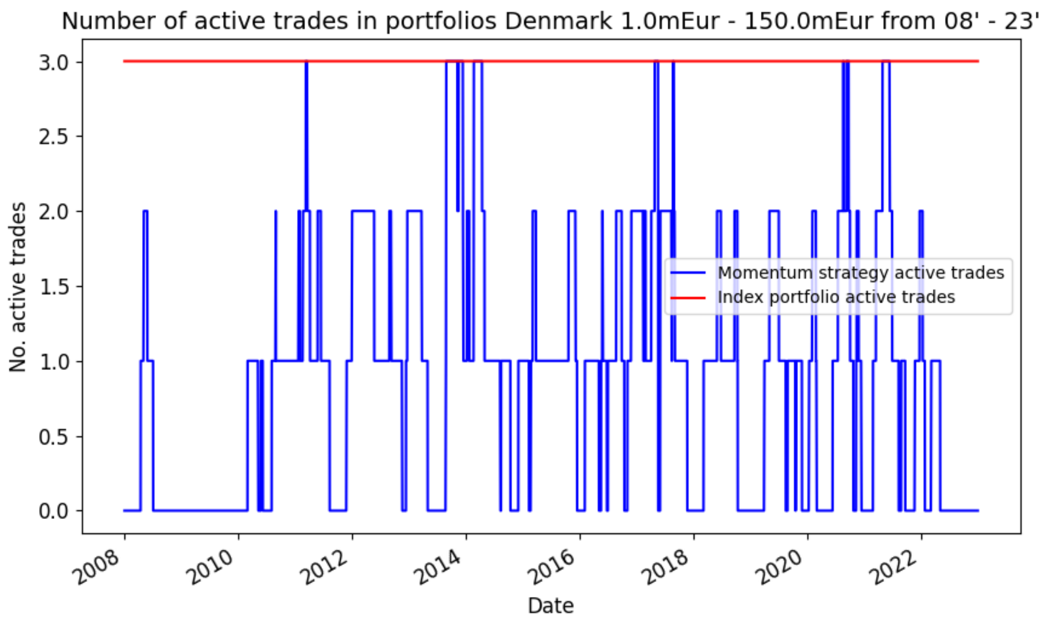
(b) Active trades during the research period.

Figure 12: Return and active trades for the Finland small-cap portfolio between 2008-2023.

G.1.3 Denmark small-cap 2008-2023



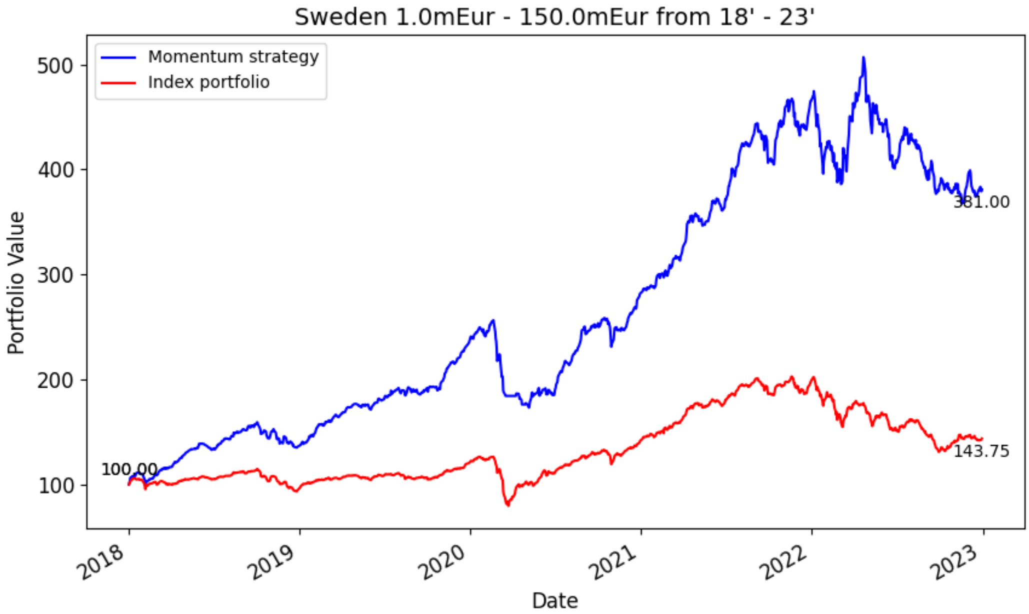
(a) Portfolio value



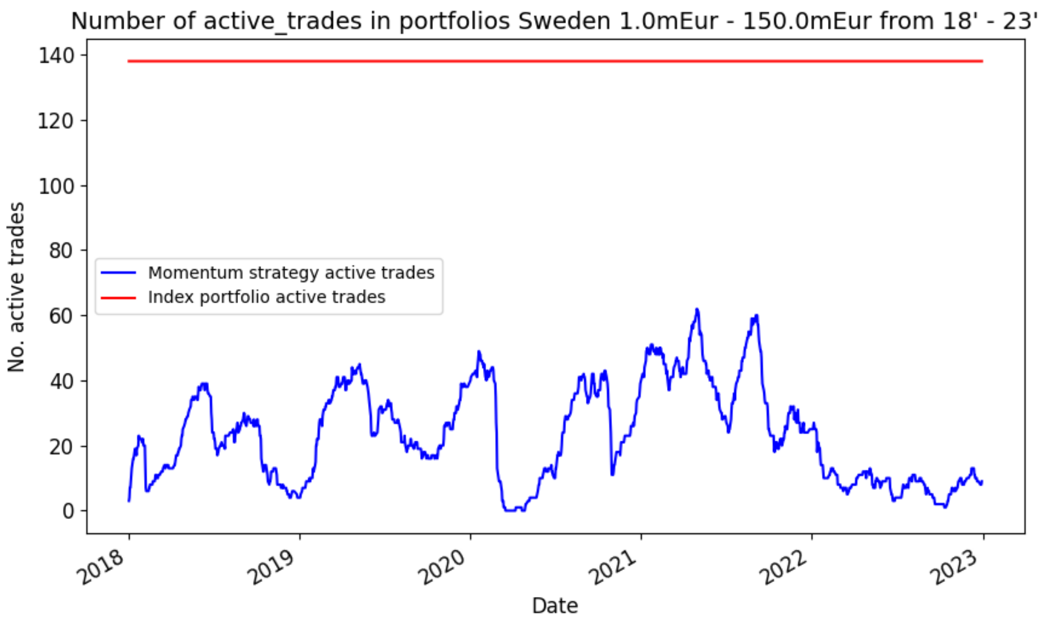
(b) Active trades during the research period.

Figure 13: Return and active trades for the Denmark small-cap portfolio between 2008-2023.

G.1.4 Sweden small-cap 2018-2023



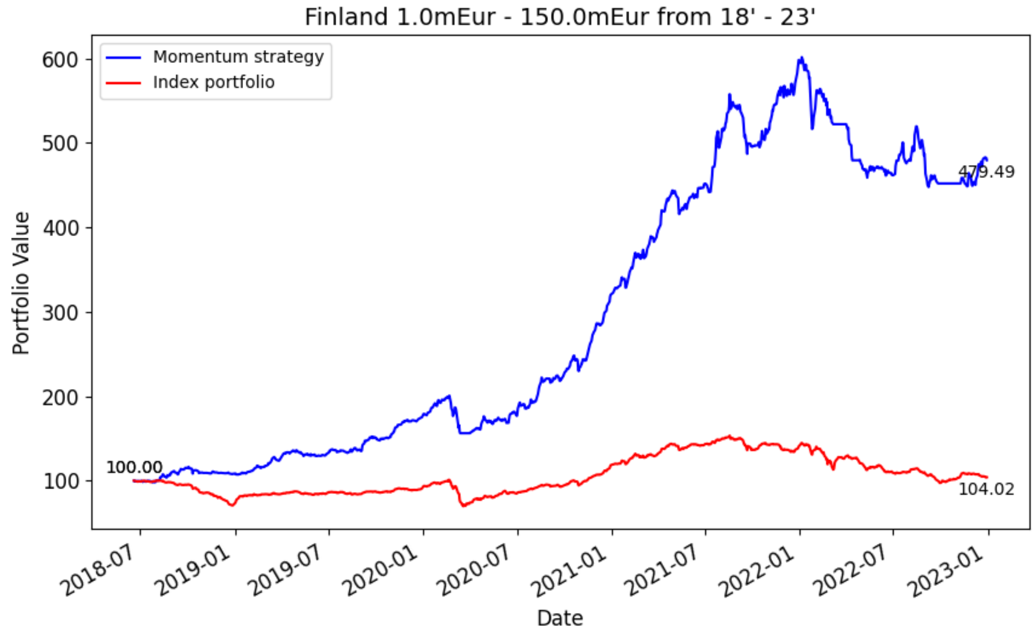
(a) Portfolio value



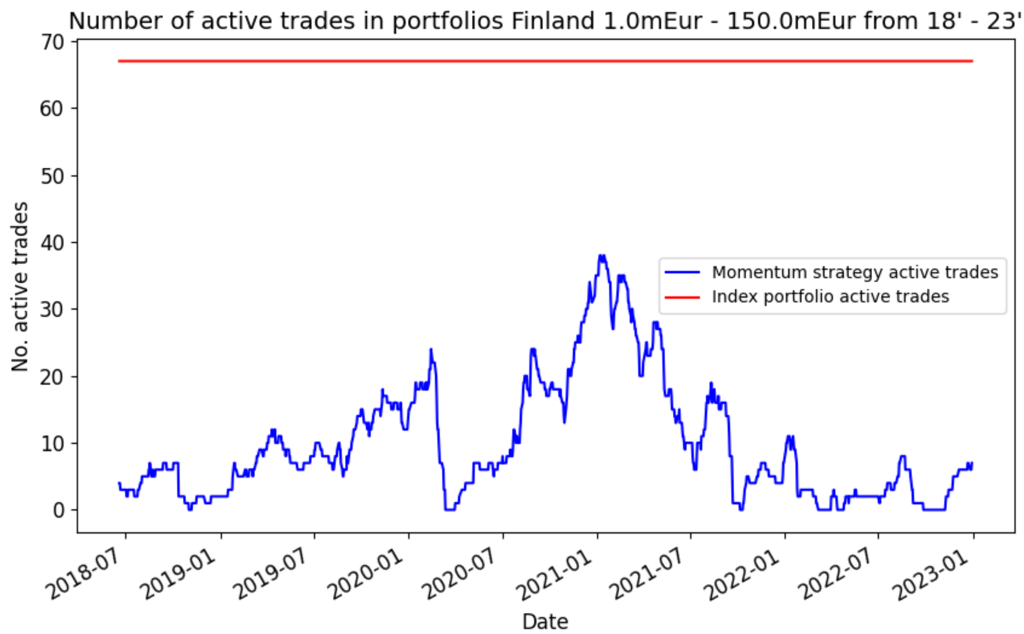
(b) Active trades during the research period.

Figure 14: Return and active trades for the Sweden small-cap portfolio between 2018-2023.

G.1.5 Finland small-cap 2018-2023



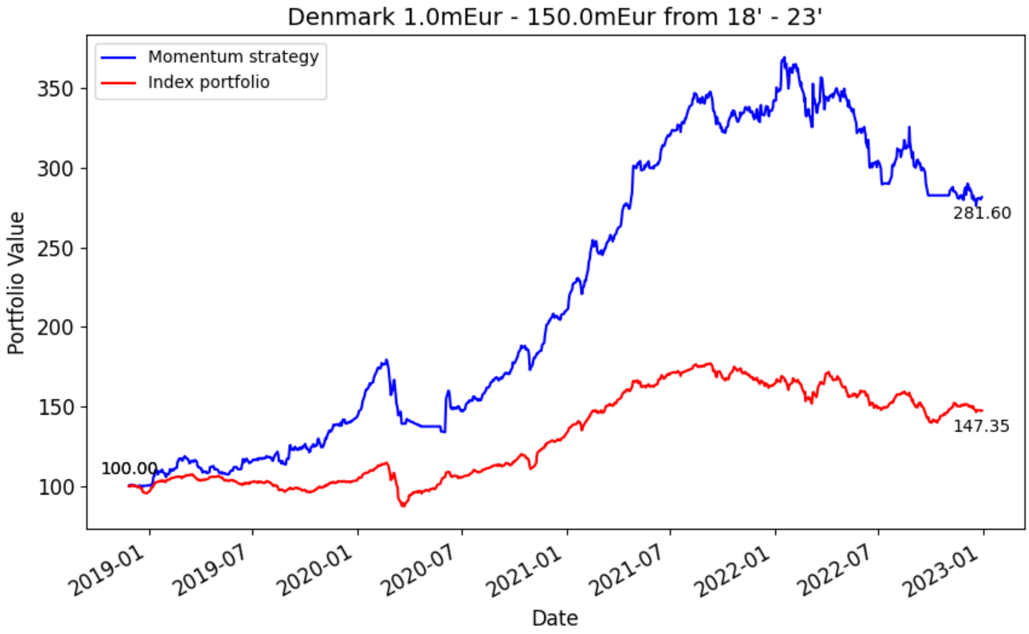
(a) Portfolio value



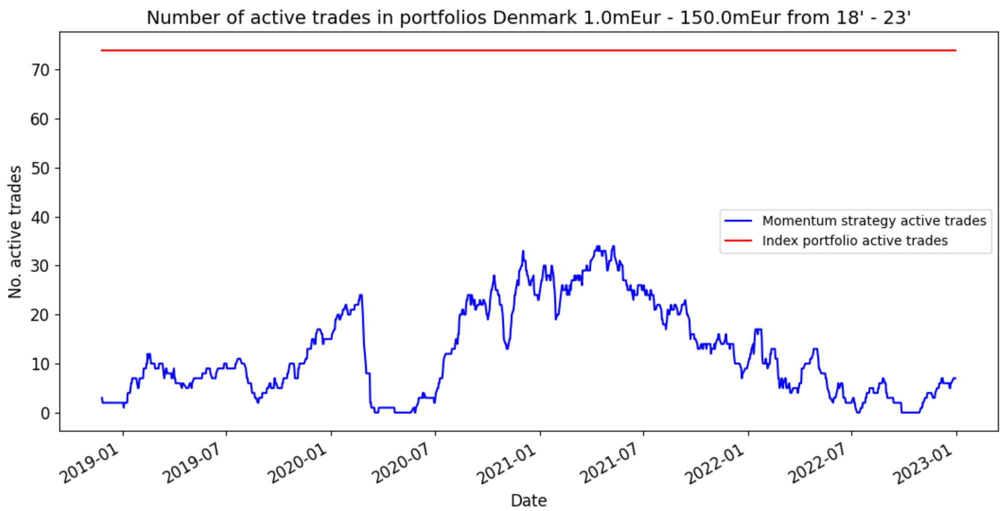
(b) Active trades during the research period.

Figure 15: Return and active trades for the Finland small-cap portfolio between 2018-2023.

G.1.6 Denmark small-cap 2018-2023



(a) Portfolio value

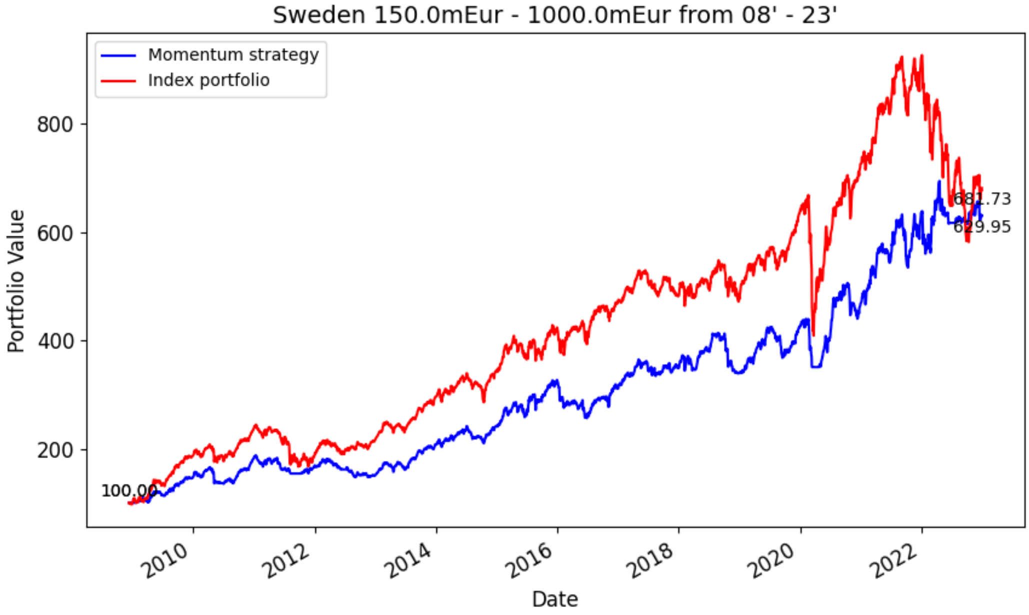


(b) Active trades during the research period.

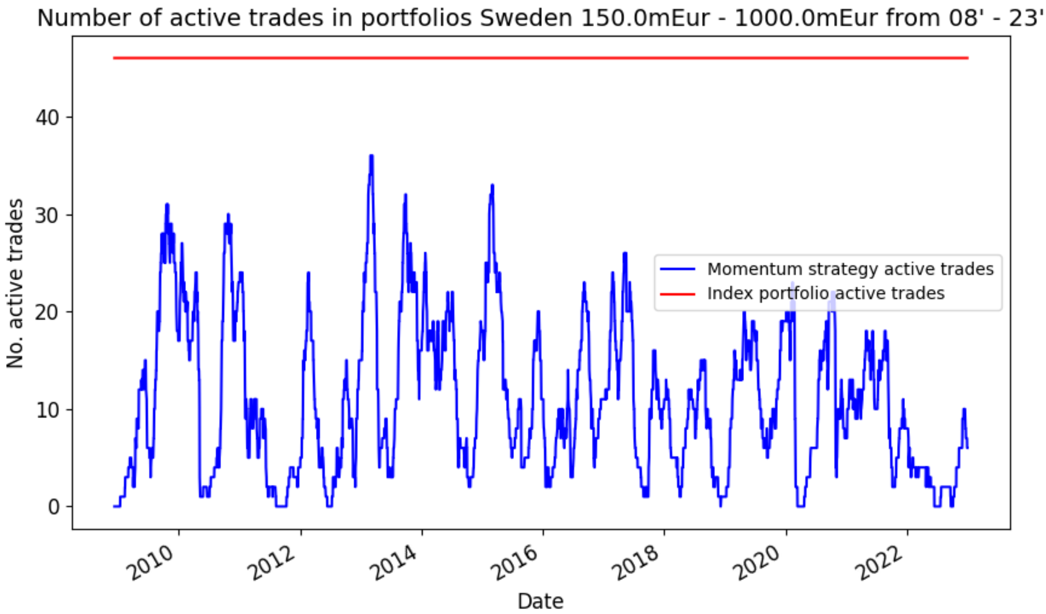
Figure 16: Return and active trades for the Denmark small-cap portfolio between 2018-2023.

G.2 Mid-cap portfolios

G.2.1 Sweden mid-cap 2008-2023



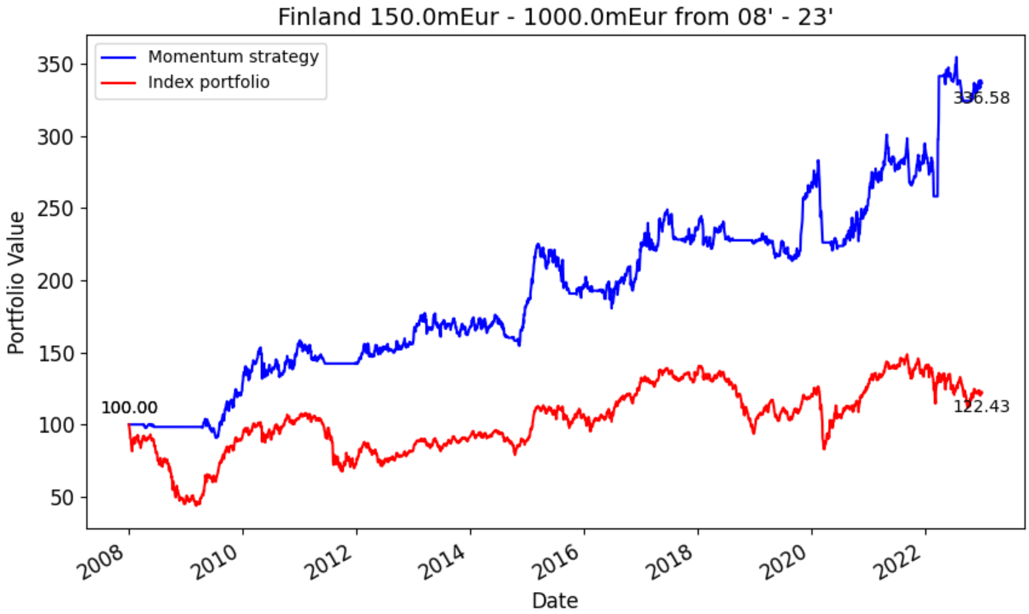
(a) Portfolio value



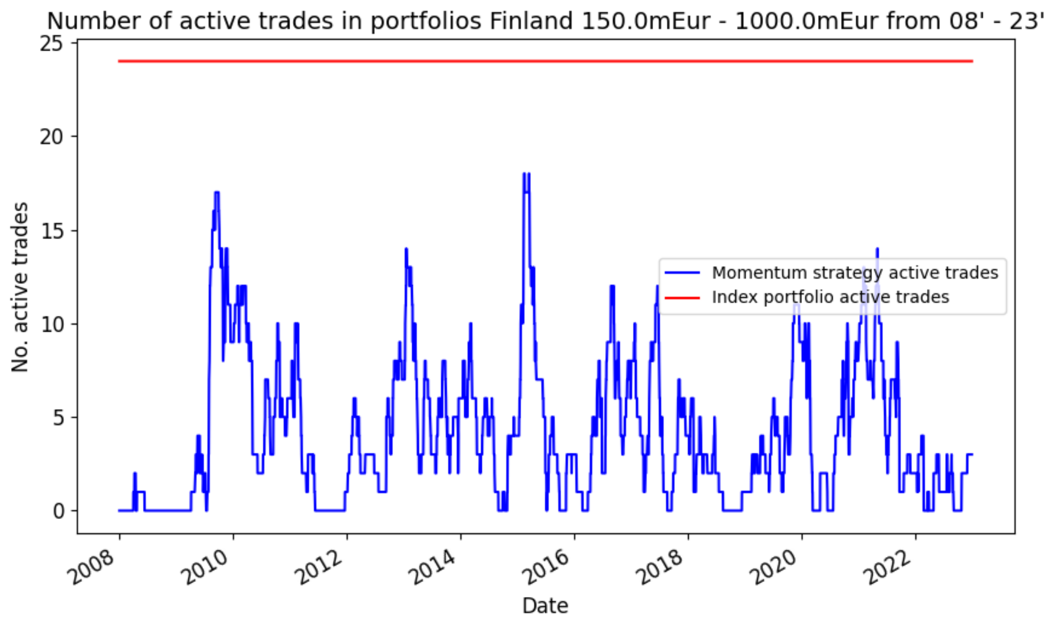
(b) Active trades during the research period.

Figure 17: Return and active trades for the Sweden mid-cap portfolio between 2008-2023.

G.2.2 Finland mid-cap 2008-2023



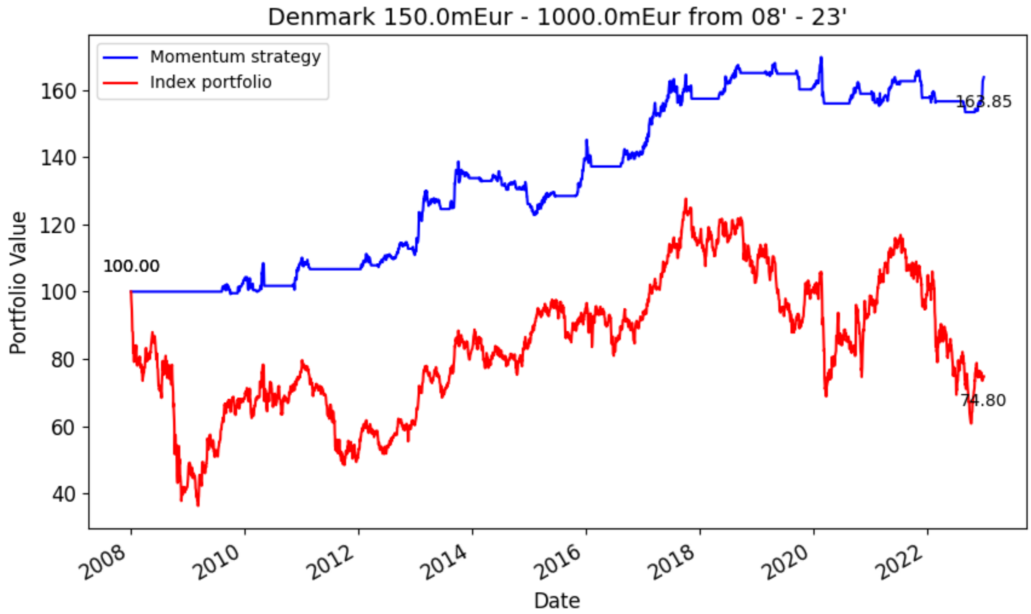
(a) Portfolio value



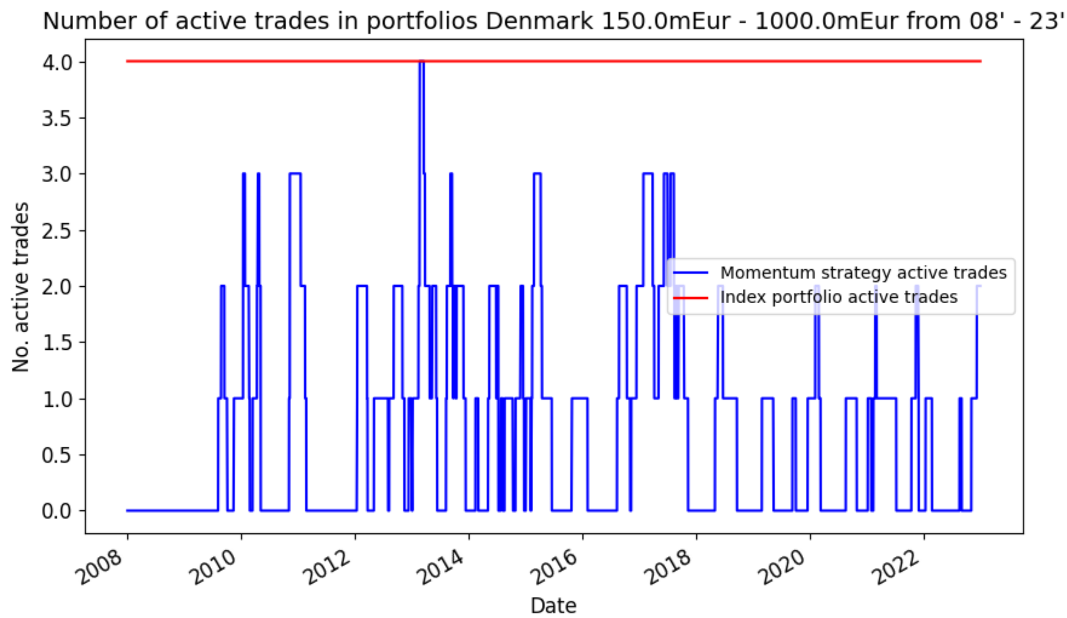
(b) Active trades during the research period.

Figure 18: Return and active trades for the Finland mid-cap portfolio between 2008-2023.

G.2.3 Denmark mid-cap 2008-2023



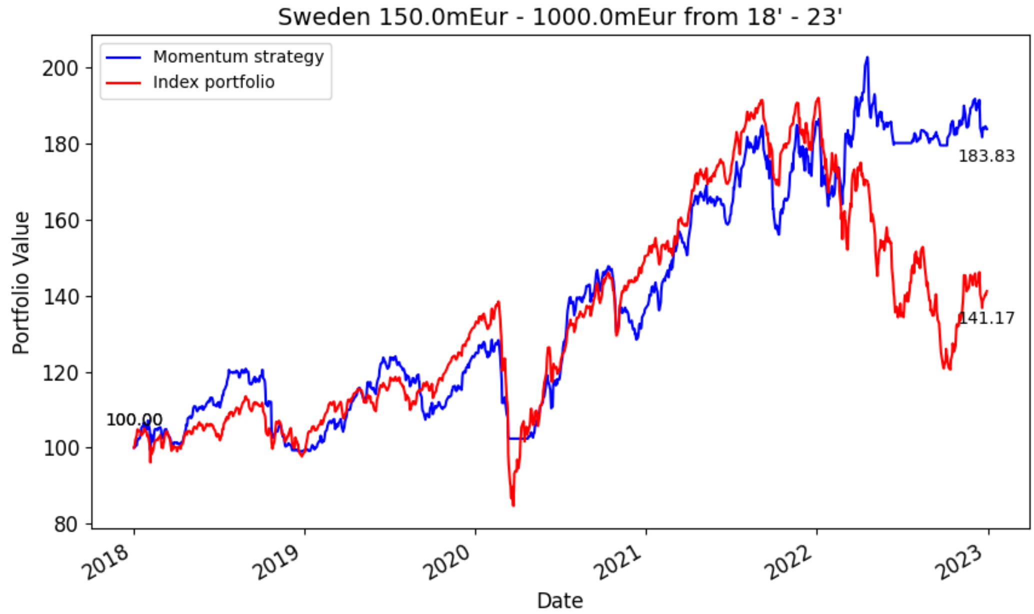
(a) Portfolio value



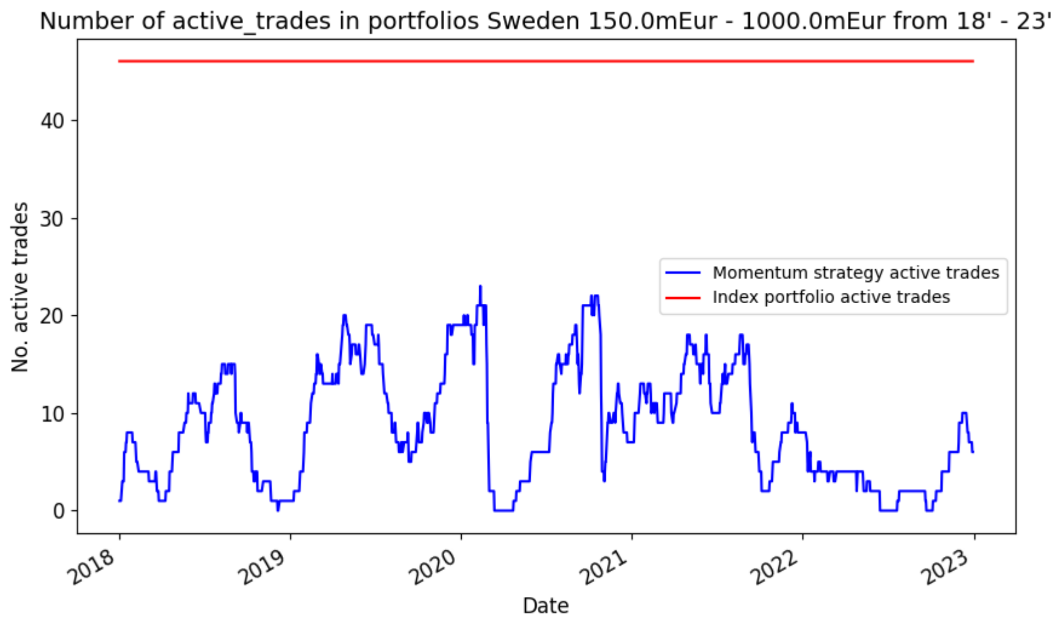
(b) Active trades during the research period.

Figure 19: Return and active trades for the Denmark mid-cap portfolio between 2008-2023.

G.2.4 Sweden mid-cap 2018-2023



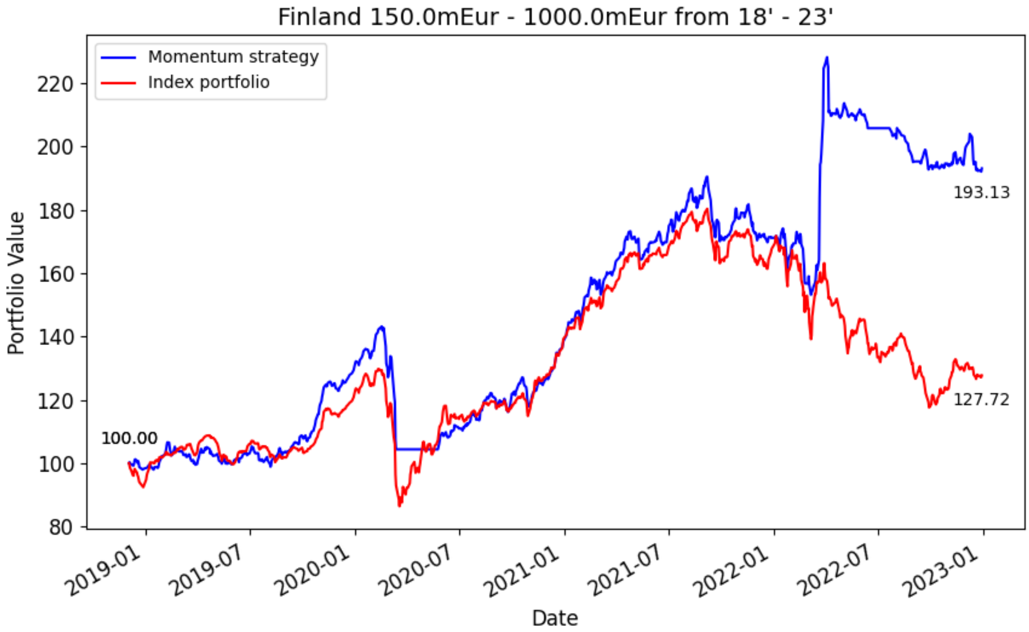
(a) Portfolio value



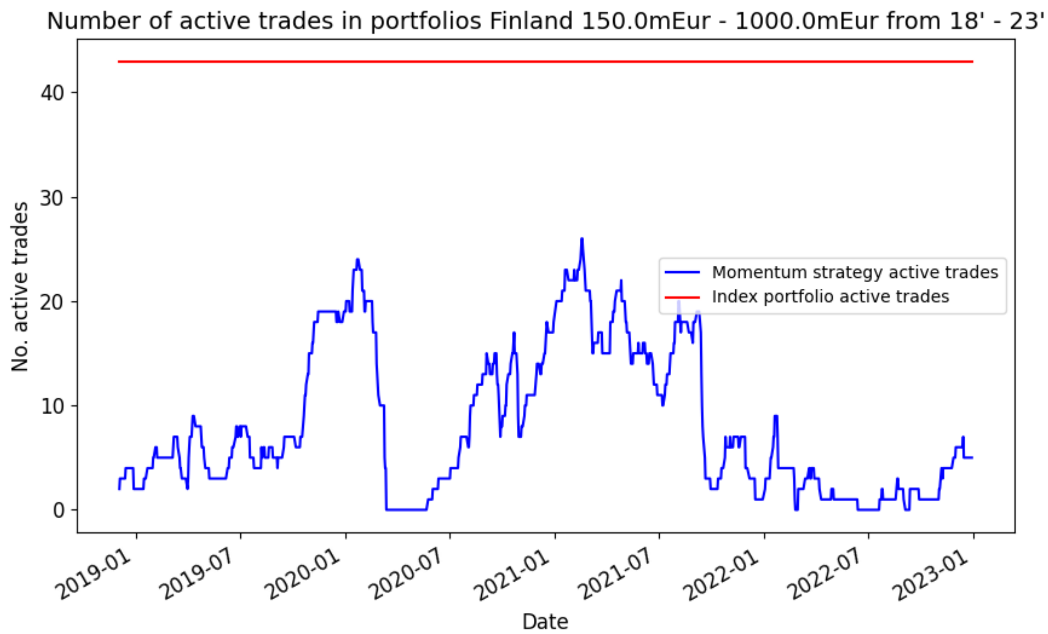
(b) Active trades during the research period.

Figure 20: Return and active trades for the Sweden mid-cap portfolio between 2018-2023.

G.2.5 Finland mid-cap 2018-2023



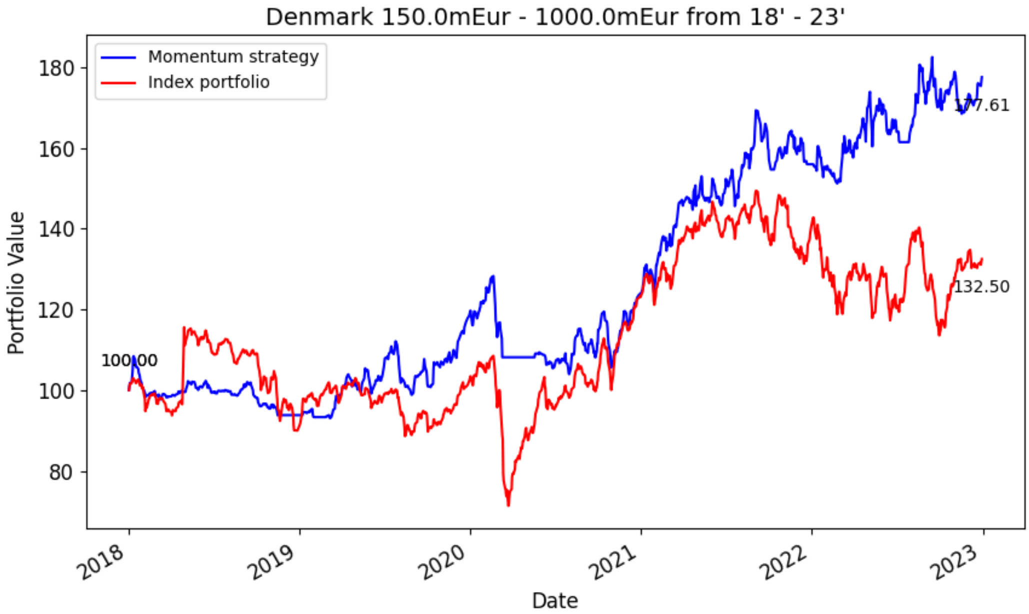
(a) Portfolio value



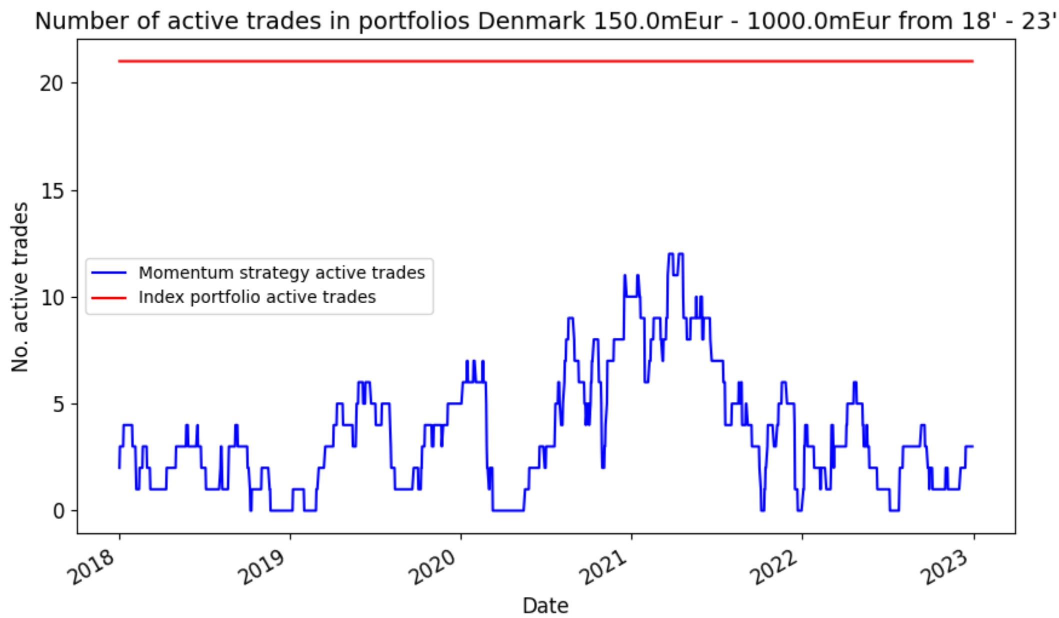
(b) Active trades during the research period.

Figure 21: Return and active trades for the Finland mid-cap portfolio between 2018-2023.

G.2.6 Denmark mid-cap 2018-2023



(a) Portfolio value

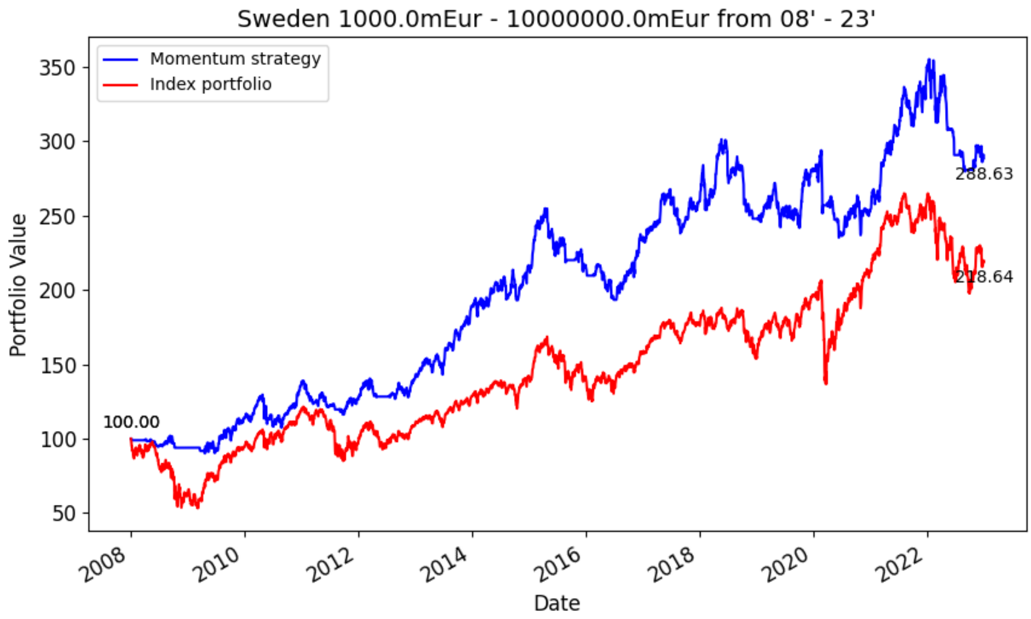


(b) Active trades during the research period.

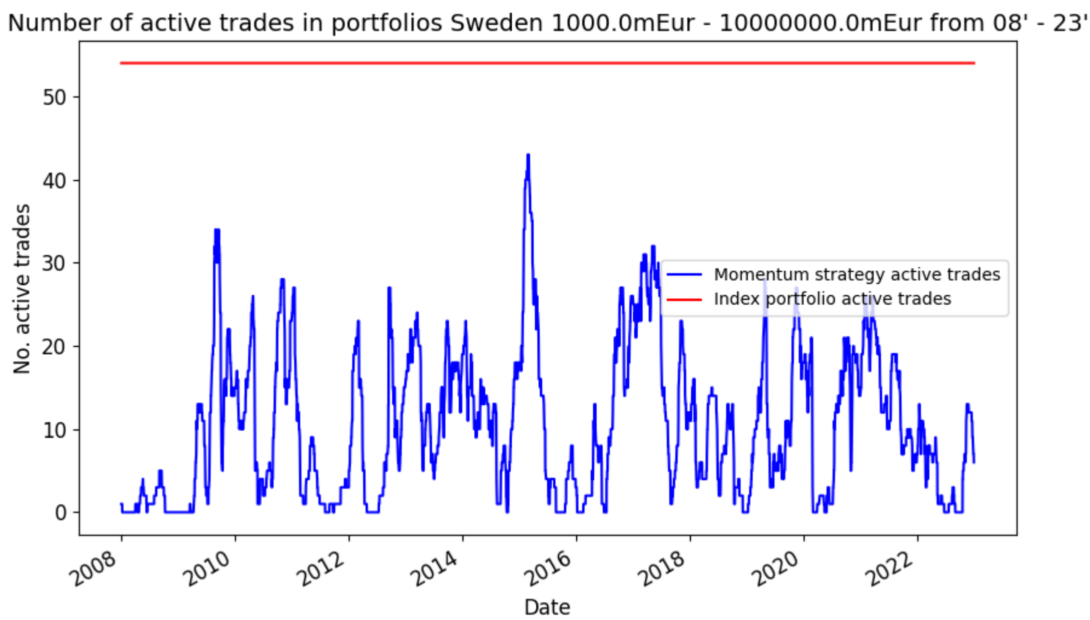
Figure 22: Return and active trades for the Denmark mid-cap portfolio between 2018-2023.

G.3 Large-cap portfolios

G.3.1 Sweden large-cap 2008-2023



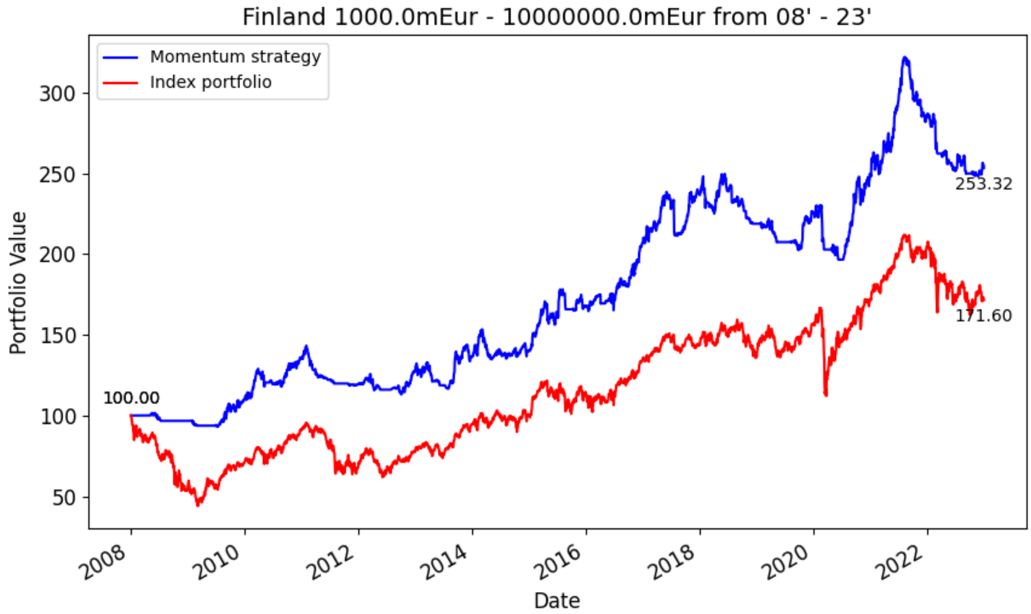
(a) Portfolio value



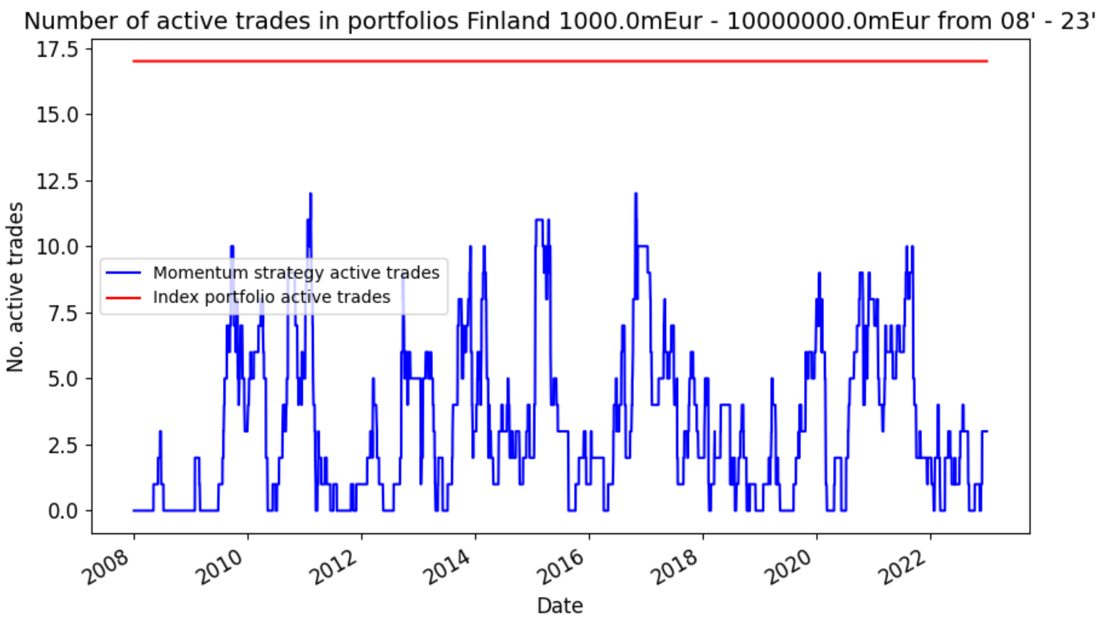
(b) Active trades during the research period.

Figure 23: Return and active trades for the Sweden large-cap portfolio between 2008-2023.

G.3.2 Finland large-cap 2008-2023



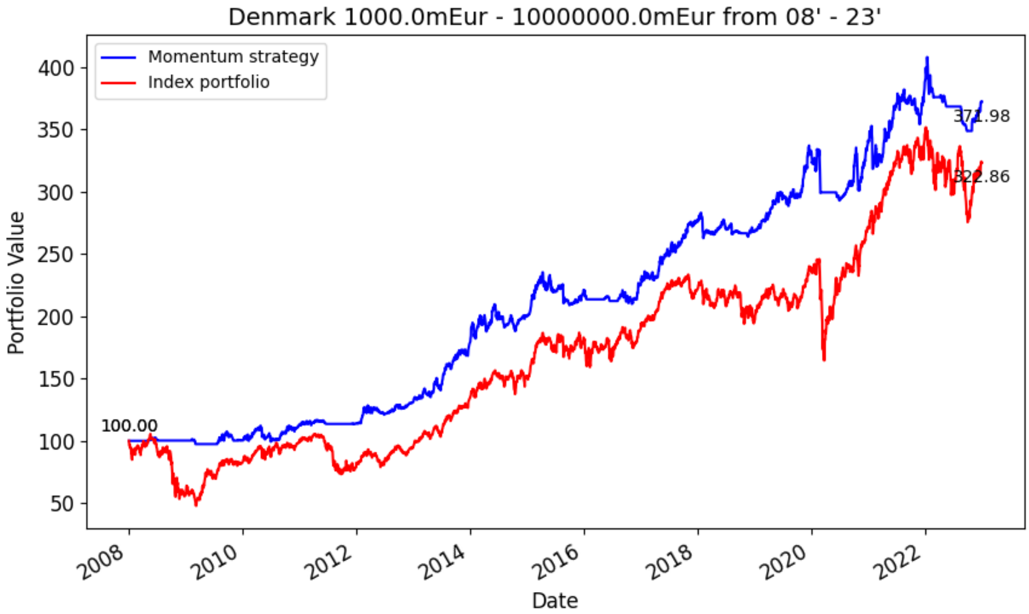
(a) Portfolio value



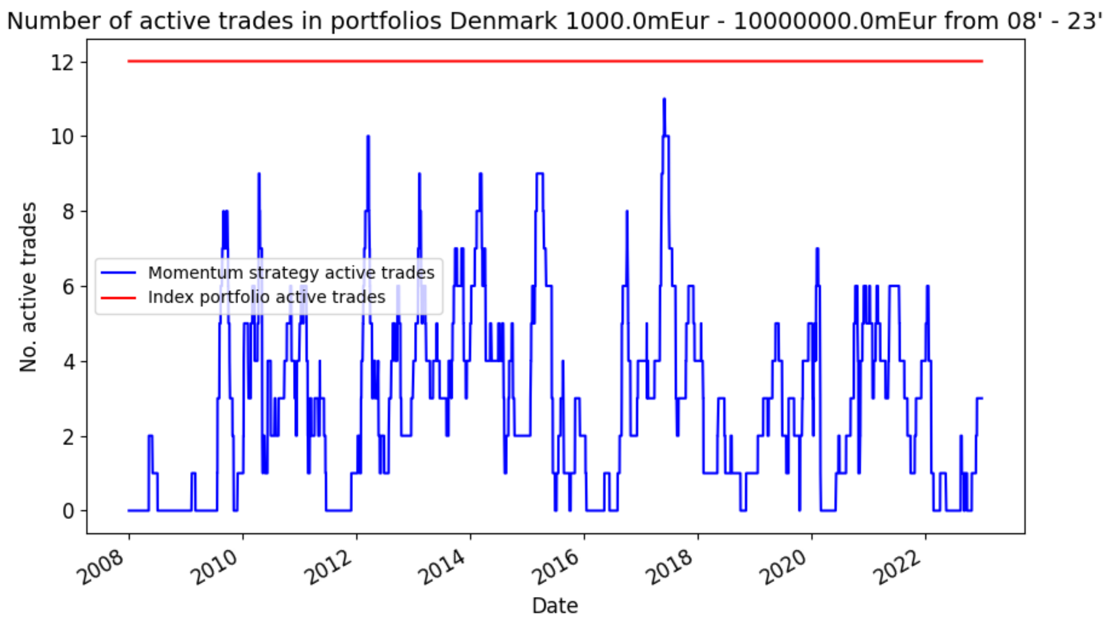
(b) Active trades during the research period.

Figure 24: Return and active trades for the Finland large-cap portfolio between 2008-2023.

G.3.3 Denmark large-cap 2008-2023



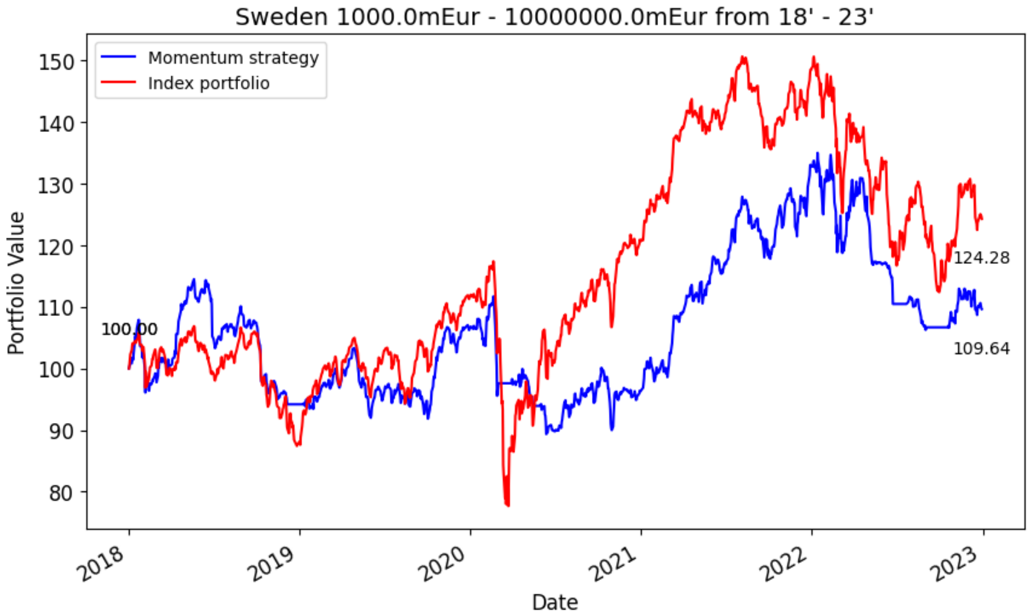
(a) Portfolio value



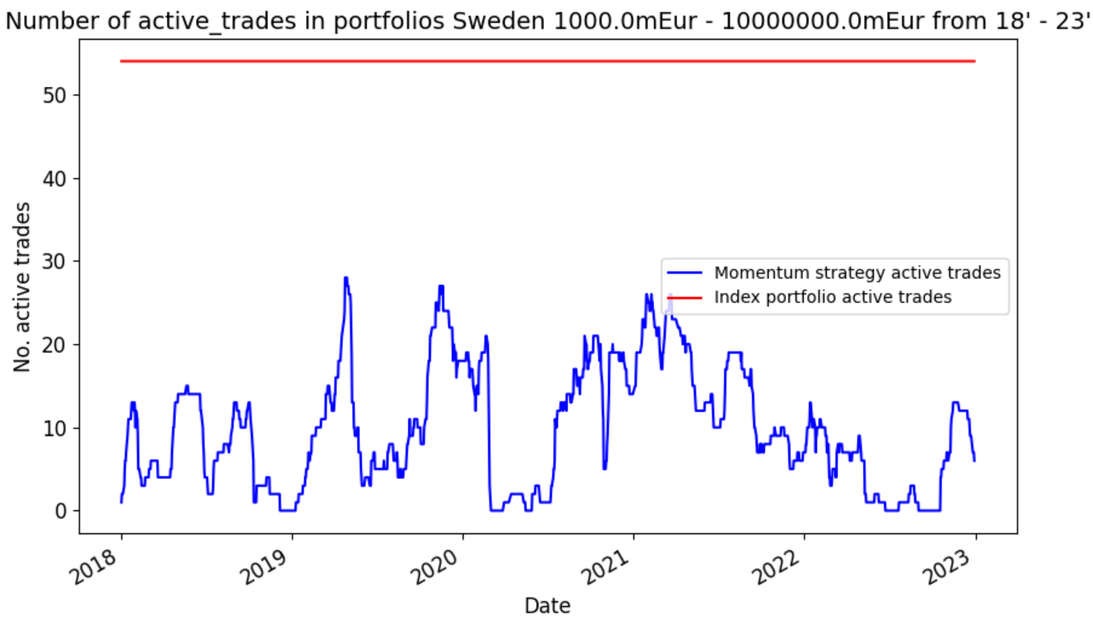
(b) Active trades during the research period.

Figure 25: Return and active trades for the Denmark large-cap portfolio between 2008-2023.

G.3.4 Sweden large-cap 2018-2023



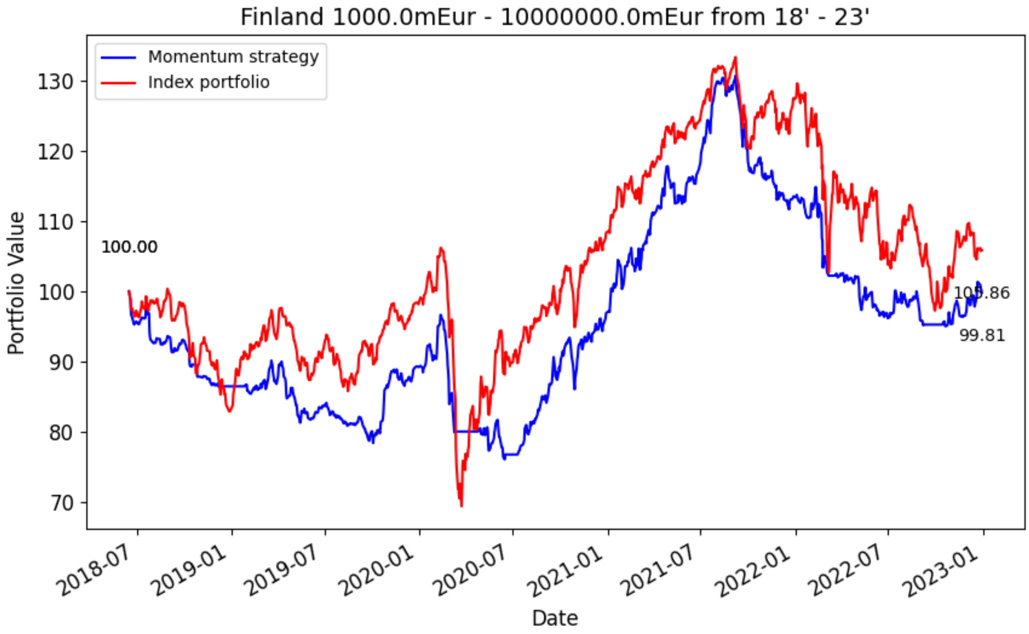
(a) Portfolio value



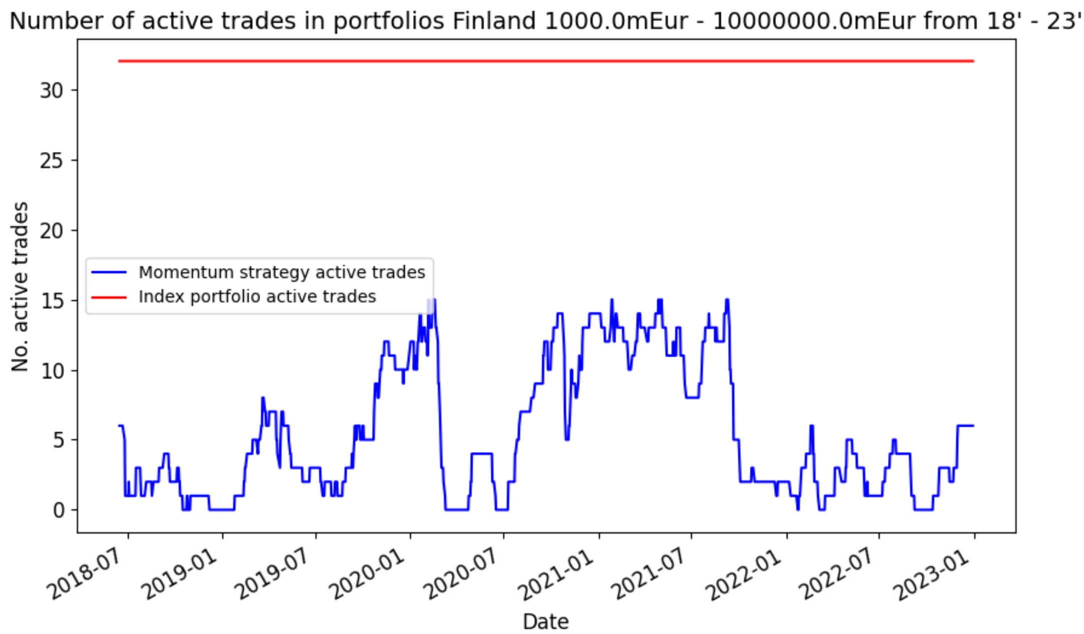
(b) Active trades during the research period.

Figure 26: Return and active trades for the Sweden large-cap portfolio between 2018-2023.

G.3.5 Finland large-cap 2018-2023



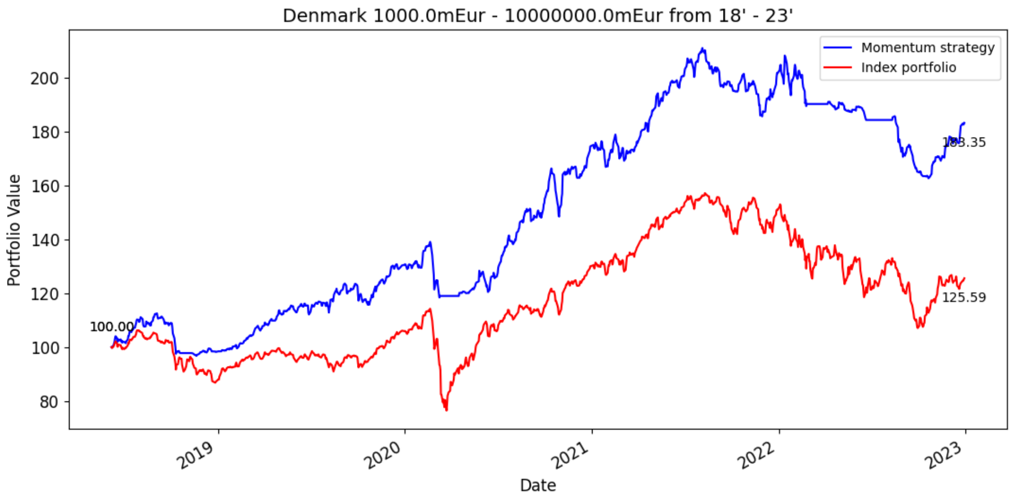
(a) Portfolio value



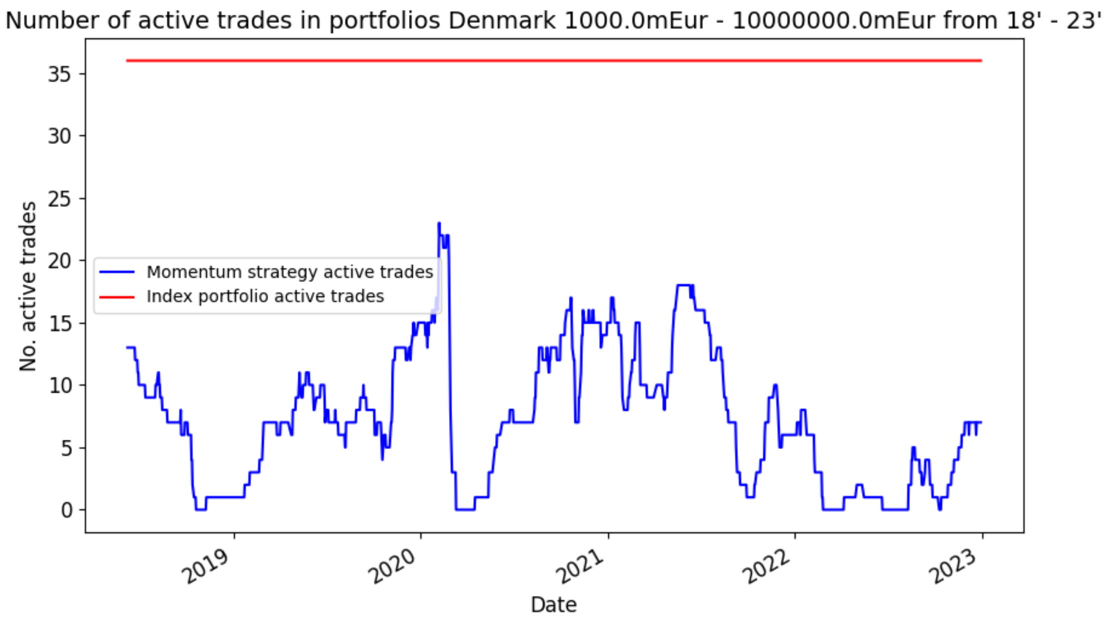
(b) Active trades during the research period.

Figure 27: Return and active trades for the Finland large-cap portfolio between 2018-2023.

G.3.6 Denmark large-cap 2018-2023



(a) Portfolio value



(b) Active trades during the research period.

Figure 28: Return and active trades for the Denmark large-cap portfolio between 2018-2023.