Master's Thesis

Momentum Investment Strategies

A Study of Momentum Returns and the January Effect in the Nordic Stock Markets

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Abstract

This study contributes to the discussion of the profitability of momentum investment strategies and the degree to which the January Effect is still present in today's developed stock markets by examining long-, intermediate- and short-term momentum strategies. The formation of the portfolio in the long-term strategy is based on past performance from the period t-12 to t-2, where t is the month of formation. The portfolios in the intermediate- and short-term strategies are formed based on past performance in t-12 to t-7 and t-6 to t-2 respectively. This thesis is based on a sample of 1,254 unique public companies listed on stock exchanges in Denmark, Sweden, Finland and Iceland in the time period 01.01.2007 to 31.01.2021.

We find that the three zero-cost momentum strategies analysed have been profitable in the Nordic stock markets across this time period with significant average monthly excess returns. While we observe that long-term and short-term strategies perform better than the intermediate-term strategy, we are not able to conclude that one strategy performs significantly better than the other based on statistical evidence. A division of the data sample into a small and large sub-sample provides evidence that significant momentum returns can be found among both small and large companies. However, we conclude that the small sample significantly outperforms the large sample in all cases, thereby indicating that the momentum effect is notably more profound in smaller firms. Finally, we find that even after adjusting for CAPM and the Fama-French three-factor model the momentum strategies continue to realise positive abnormal returns, why these are unable to fully explain the momentum returns achieved.

In terms of the January Effect, we detect a presence of this in the Nordic stock markets. We can document with a 10% significance level that investing in January results in significantly higher returns compared to investments conducted outside of January. Moreover, we observe that the January Effect has a negative impact on excess returns for each of the momentum strategies examined. In relation to this, we find that small firms on average tend to realise higher returns in January, and that the January Effect appears to be more profound in past losers regardless of size, which consequently results in lower momentum returns for the zero-cost strategies analysed.

Thus, by examining the performance of momentum investment strategies and the impact of the January Effect on said strategies from a contemporary perspective we contribute to current literature.

Table of Contents

List of figures

List of tables

1. Introduction

1.1. Background

Since the inception of stock markets, investors have tried to find strategies that can consistently beat the market; only few people have been able to do so consistently. Many studies on the other hand indicate that buying and holding a market portfolio or an ETF is, for the typical risk-adverse investor, the best strategy to follow based on the risk-return trade-off.

Scholars investigating the returns of mutual funds, e.g. Jensen (1968), have found that not even highly successful mutual funds are able to consistently outperform passively managed market benchmarks. Jensen (1968) finds that on average mutual funds are not able to beat the market even when research and other expenses are assumed to be zero. These results are in line with the efficient market hypothesis by Fama (1970). The efficient market hypothesis implies that stock prices are always at their fundamental value, why mutual funds should not be able to consistently beat the market.

Due to findings like these, there has been (and still is) much discussion about the viability of actively managed mutual funds when research indicates that the high commissions charged cannot be justified by the returns generated. However, market anomalies have been detected where prices deviate from those predicted by the efficient market hypothesis. One such example is the prevalence of momentum returns observed by various scholars. Momentum is *"the tendency of an object in motion to stay in motion"*[1]. In terms of stock markets this suggest that past performance is a strong predictor of future returns. In the momentum investment strategy, the investor buys past winners and sells past losers, i.e. stocks which over- and underperform relative to their peers.

The notion of momentum on financial markets is a widely researched topic which has received significant attention from the 1990's since the study by Jegadeesh and Titman (1993) was published. In their study they examine 16 different momentum investment strategies based on look-back and holding periods of 3, 6, 9 and 12 months respectively, and documented monthly positive abnormal returns of 1% in the short-term. Since then many scholars have applied the same methodology as Jegadeesh and Titman, where some have found robust performance (e.g. Rouwenhorst, 1998), while others have found price reversals (e.g. Liu and Lee, 2001).

[1] Novy-Marx (2012), pp. 1

Another widely researched anomaly is the consistent occurrence of the January Effect. Several scholars, e.g. Grundy and Martin (2001), have found that the momentum strategy obtains negative returns in January. Several arguments have been put forward to explain why the January anomaly exists. Grundy and Martin (2001) argue that the negative January loss can be explained by a bet against the size effect, whereas others argue that the January loss is due to "tax-loss selling" and "window dressing". On the other hand, more recent studies claim that the January anomaly has diminished over time, see e.g. Schwert (2003) or Perez (2018).

In other words, we have identified a fragmented view on the profitability of momentum strategies and the degree to which seasonal anomalies such as the January Effect still persists in current developed stock markets. As of such we wish to test the possibility of realising significant positive returns following a relatively simple trading strategy based on past performance, as well as examine the implications of the January Effect on said strategy.

1.2 Problem Statement

The purpose of this thesis is to conduct an empirical study of the profitability of various momentum investment strategies and determine the extent to which the January Effect exist in the Nordic stock markets. Thus, to contribute to previous findings, the main research question in this thesis is:

Main research question

Do long-term, intermediate-term and short-term momentum investment strategies obtain positive returns and to what degree is the January Effect present in the Nordic stock markets in the time period 2007 – 2021?

Underlying research questions:

To answer the main research question, we investigate different characteristics of the momentum and January Effect. Thus, in this study we examine these characteristics both from a theoretical and empirical view. The following sub-questions will provide us with a broader understanding and contribute to answering the main research question:

- What are the implications of traditional and behavioural finance theories for our study?
- What results have other scholars obtained when studying the presence of momentum and the January Effect in equity markets?
- What implications does a proposed January Effect have on the return of momentum strategies analysed in this study?
- How can traditional and behavioural finance theories explain the findings obtained in this study?

Thus, with this problem statement we add to existing literature as follows. First, by focusing on a more recent time period with a length deemed adequate we update the findings within this research field. Second, to the best of our knowledge and based on a review of previous literature, this is the first study to conduct an empirical analysis of the impact of the January Effect on momentum returns in the Nordic stock markets in the time period 2007 – 2021.

1.4 Delimitation

As already stated, the primary focus of this thesis is to examine the profitability of various momentum investment strategies and the degree to which the January Effect is present in the Nordic stock markets. For this purpose, the data sample used in this thesis will be based on secondary data. Due to our empirical analysis being primarily based on quantitative data this will allow us to include data from a larger number of companies. The data sample included is limited to companies listed on the Nordic stock markets. For the purpose of this study the Nordic stock markets include Denmark, Sweden, Finland and Iceland. Thus, throughout this study when we refer to the Nordic stock markets it does not include Norway. However, this does not mean that dual-listed companies, i.e. companies with stocks listed on two different stock exchanges, with shares traded in both Norway and e.g. Sweden are excluded from the sample, since it will be a part of our sample of companies listed in Sweden. Norway is excluded from the data sample due to limited data availability in terms of identifying delisted companies in Norway throughout the time period analysed in this study.

Additionally, this study will exclude data prior to 2006 due to limited information about delisted companies on the Nordic stock markets prior to this date. By excluding data prior to this date, we limit the impact of survivorship bias on our results.

Despite the empirical analysis being limited to the Nordic stock markets we still conduct a review of previous papers examining different markets and sample periods in order to gain a broader understanding of momentum and the January Effect. Moreover, this is done for comparison purposes.

While this study is primarily relevant to professional investors due to the character of the investigated trading strategies and the resources required to perform these, the findings obtained may also be relevant to private investors. A thorough discussion of the specific implications of our findings for professional versus private investors remains beyond the scope of this study.

1.5 Thesis Structure

With the preceding sections in this chapter having described the motivation for and purpose of this thesis. The purpose of this section is to give the reader an overview of the overall structure of the remainder of this thesis. The thesis is structured as follows:

2. Theory: In this chapter, we present theories which the thesis is based upon. The purpose of this chapter is to give the reader an understanding of the implications of traditional and behavioural finance theories on the momentum and January Effect.

3. Literature review: In chapter 3 we review relevant previous literature to provide the reader with an overview of previous methodologies applied and results obtained.

4. Empirical methodology: In continuation of the former chapter we describe the methodologies applied in terms of both data collection, formation of portfolios, performance measures, statistical tests applied, etc.

5. Results: In the 5th chapter of the thesis we present the results obtained in our empirical analyses and compare these with findings of previous studies outlined in chapter 3.

6. Implementation issues: The 6th chapter will go through practical implementation issues of the strategies proposed in this thesis.

7. Discussion: In this chapter we discuss different explanations for the results achieved in chapter 5.

8. Conclusion: Finally, we summarize the findings answering the main research question as well as the implications of our results for future research.

2. Theory

In this chapter we will focus on both traditional and behavioural finance theories to gain a deeper understanding of how stock markets behave. The theories outlined in this chapter will be used throughout this thesis as a point of reference for further analysis and discussion of our findings.

This chapter is divided into two main sections focusing on traditional and behavioural finance theories respectively. In the traditional finance section, we first focus on Modern Portfolio Theory (MPT) introduced by Harry Markowitz in 1952. Subsequently, we will describe the Capital Asset Pricing Model, Arbitrage Pricing Theory, the three-factor model and the Efficient Market Hypothesis. In the second main section, we will focus on prospect theory, anchoring and adjustment, the disposition effect, herding and representativeness as we believe these will contribute with relevant insights.

2.1 Modern Portfolio Theory

2.1.1 Portfolio return and risk

According to Markowitz (1952), selecting a portfolio of stocks can be divided into two phases. Firstly, investors may focus on observation and experience to form expectations about the forthcoming performance of the stocks observed. Secondly, investors will form a portfolio of stocks based on their expectations. Markowitz (1952) primarily focuses on the second stage in his modern portfolio theories. Markowitz first drew attention to the practice of portfolio diversification and how investors can reduce the standard deviation of possible portfolio returns with a well-diversified portfolio (Brealey, Myers, & Allen, 2020). The principles introduced by Markowitz in 1952 laid the foundation for many financial theories developed since then (Ibid).

The two main constituents of MPT are return and risk and the relationship between these. The return of each stock in the portfolio can be calculated using the following formula:

$$R_t = \frac{P_t - P_{t-1} + D_t}{P_{t-1}} \quad \textbf{(2.1)}$$

$R_t = return\ at\ time\ t$

$P_t = price\ of\ stock\ at\ time\ t$

$D_t = dividend\ at\ time\ t$

As evident from the formula above, the total stock return is the result of both an appreciation in the price plus dividends paid out to the stockholder. The risk of an investment depends on the dispersion of potential outcomes and is typically more complicated to calculate than calculating return as risk can be measured in different ways. The most common statistical measures of risk are *variance* and *standard deviation* (Brealey, Myers, & Allen, 2020). The equations for calculating variance and standard deviation are presented below:

$$Var(R) = E(R_t - \bar{R}_t)^2 \quad \textbf{(2.2)}$$

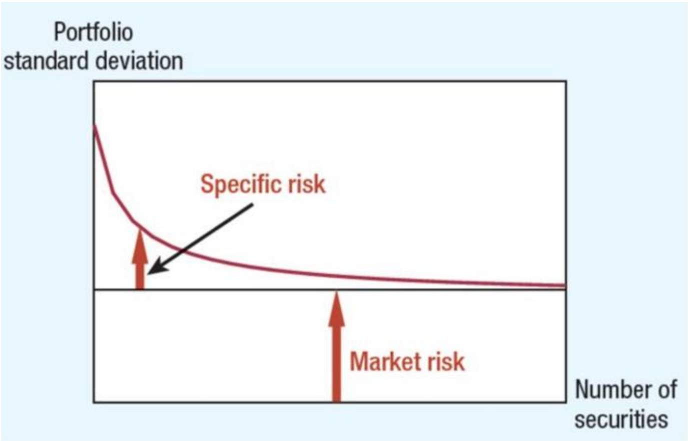
$R_t = actual\ return$

$\bar{R}_t = expected\ return$

$$SD(R) = \sqrt{VAR(R)} \quad \textbf{(2.3)}$$

Variance is a measure of how "spread out" returns are, i.e. the greater the variance, the greater the volatility in returns and consequently the greater the risk of the investment. The standard deviation on the other hand tells you the average deviation from the mean return and is easier to interpret as it is measured in the same unit as the returns themselves. Equation 2.1 to 2.3 shown above are the return and risk calculations for an individual stock, however in MPT it is assumed that investors do not hold securities in isolation but instead hold *portfolios* of assets (Ibid). Hence, the risk of an individual stock depends on its contribution to the risk of the entire portfolio. If the returns of stocks do not move in exact lockstep, investors can construct a portfolio of risky assets that are less volatile than the individual securities included in the portfolio. Thus, a stock held in isolation may appear as risky, but when it is included as part of a portfolio it may be risk reducing due to its correlation with the other assets held. Figure 2.1 below illustrates the relationship between diversification and risk.

Figure 2.1: Diversification benefits



Source: Brealey, Myers, & Allen (2020)

As evident from the figure above, adding more stocks to the portfolio decreases the standard deviation, i.e. risk, of the portfolio thus indicating positive benefits of diversification. The figure also illustrates that the marginal benefit of diversification decreases as the number of stocks included in the portfolio increases. Nevertheless, no matter how many stocks are included in the portfolio, you can never completely eliminate all risk. The risk that investors can eliminate by diversifying their portfolio is called unsystematic or idiosyncratic risk (Brealey, Myers, & Allen, 2020). Unsystematic risk can be eliminated due to the fact that many of the threats a company is exposed to are specific to that company. The risk that investors cannot avoid, irrespective of how much they diversify, is called systematic risk (Ibid). Systematic risk affects all companies as there are economywide perils that threaten the overall market.

To determine the effect of diversification on portfolio risk, the investor must know the covariance between the stocks included in the portfolio. Covariance measures how two stocks move relative to each other. The covariance between two stocks can be calculated using the following formula:

$$\sigma_{12} = \rho_{12} * \sigma_1 * \sigma_2 \quad \textbf{(2.4)}$$

$\sigma_{12} = covariance\ between\ stock\ 1\ and\ 2$

$\rho = correlation\ coefficient\ between\ stock\ 1\ and\ 2$

$\sigma = standard\ deviation$

The correlation coefficient is always a pure value and is between -1 and 1. If there is a perfect negative correlation between two stocks, the correlation coefficient is -1, whereas if they are perfectly correlated the correlation coefficient is 1. Lastly, if expected stock returns are completely unrelated, the correlation coefficient is zero. When the correlation is not exactly 1 there is a benefit of diversification. Assuming the portfolio only includes two stocks, the portfolio risk can be calculated using the following formula (Ibid):

$$Portfolio\ variance = x_1^2\sigma_1^2 + x_2^2\sigma_2^2 + 2(x_1 x_2 \rho_{12} \sigma_1 \sigma_2) \quad \textbf{(2.5)}$$

$x_1 = proportion\ invested\ in\ stock\ 1$

$x_2 = proportion\ invested\ in\ stock\ 2$

The portfolio standard deviation is calculated as the square root of the portfolio variance. As mentioned previously, adding more stocks to the portfolio decreases risk. The general formula for calculating variance when the portfolio includes more than two stocks is as follows (Brealey, Myers, & Allen, 2020):

$$Portfolio\ variance = \sum_i \sum_j x_1 * x_j * Cov(R_i, R_j) \quad \textbf{(2.6)}$$

As evident from the variance formula above, the total portfolio risk is driven by the covariances between the stocks included. As the number of stocks included increases in an equally weighted portfolio, the portfolio variance will approach the average covariance. If the average covariance is zero the investor can eliminate all risk by diversifying their portfolio. However, most of the stocks available to investors are often interrelated in a web of covariances, thus limiting the opportunity to eliminate risk completely. To determine how a stock will contribute to the risk of a portfolio, divide by the portfolio standard deviation in formula 2.6 to obtain (Ibid):

$$SD(R_P) = \sum_i x_i * SD(R_i) * Corr(R_i, R_P) \quad \textbf{(2.7)}$$

$SD(R_i) = total\ risk\ of\ i$

$Corr(R_i, R_P) = Fraction\ of\ i's\ risk\ that\ is\ common\ to\ P$

The formula above also illustrates that when the correlation is not exactly 1 there is a benefit of diversification as mentioned previously. It is now clear that the relevant risk of a diversified portfolio is the systematic risk of the stocks included. The systematic risk of a stock is measured by its sensitivity to market movements. This is also referred to as *beta*. Stocks with a beta above 1 moves in the same direction as the market and tend to move more than the market, whereas stocks with a beta between 0 and 1 will move less. On the other hand, stocks with a beta less than 0 will move in the opposite direction of the market. The beta of a stock can be defined as (Ibid):

$$\beta_i^P \equiv \frac{SD(R_i) * Corr(R_i, R_P)}{SD(R_P)} = \frac{covariance\ with\ the\ market}{variance\ of\ the\ market} \quad \textbf{(2.8)}$$

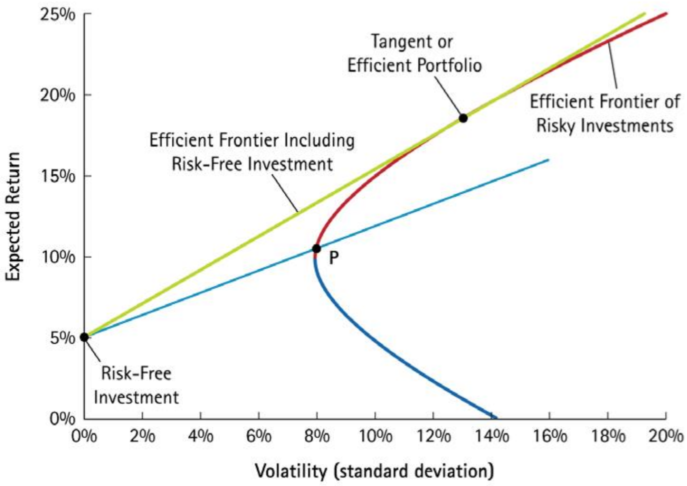
2.1.2 Portfolio formation

Now that we have a good understanding of how diversification can reduce the risk of a portfolio we can focus on how investors can apply this knowledge when building their portfolio of stocks. Based on beliefs about stocks' expected returns and covariances, the investor has a choice of various combinations of expected portfolio returns and risk (standard deviation) depending on the proportion invested in the individual stocks (Markowitz, 1952). According to Markowitz (1952), the investor would (or should) want to select a portfolio that lies along the efficient frontier. These efficient portfolios offer the highest expected return at any given level of risk. When forming the portfolio, the investor also has the opportunity to introduce short selling. The investor can short sell a stock by borrowing and selling the stock now and then return it at a future date. Investors do so if they expect the price of the stock to decrease. Stocks that have been shorted will have a negative weight in the portfolio. Thus, by introducing short selling, the investor can extend the efficient frontier.

Until now we have only included common stocks in the portfolio. If we introduce borrowing or lending money at a risk-free rate of interest, the investor can extend the range of portfolio opportunities (Brealey, Myers, & Allen, 2020). To determine the optimal portfolio including a risk-free asset (r_f) and a risky portfolio of stocks, the investor should find the best efficient portfolio of risky assets. If the investor has graphed the efficient frontier of risky assets, as seen in Figure 2.2 below, the best efficient portfolio is found at the tangency point on the efficient frontier starting from the vertical axis at r_f. The efficient portfolio is the portfolio with the highest Sharpe ratio. The Sharpe ratio measures the risk-adjusted return of a portfolio. To calculate the Sharpe ratio, the following formula can be used:

$$Sharpe\ ratio = \frac{portfolio\ excess\ return}{portfolio\ volatility} = \frac{E[R_P]-r_f}{SD(R_P)} \quad \textbf{(2.9)}$$

Figure 2.2: Efficient portfolio



Source: Brealey, Myers, & Allen (2020)

As mentioned above, any optimal portfolio is a combination of the risk-free asset and the efficient portfolio. An investor's risk preferences will determine how much to invest in the risk-free asset versus the efficient portfolio. A highly risk averse investor will invest a larger proportion in the risk-free asset compared to a less risk averse investor, but both types of investors will hold the same portfolio of risky assets. If the investor is considering adding a stock *i* to the portfolio of risky assets, the investor should only invest in the stock if the excess return compensates for the additional risk added to the portfolio. To determine the minimum return required on the stock in order to include it in the portfolio, the investor can use the capital asset pricing model (CAPM) as defined by William Sharpe, John Lintner and Jack Treynor (Brealey, Myers, & Allen, 2020):

$$R_i = r_f + \beta_i^P * (E[R_P] - r_f) \quad \textbf{(2.10)}$$

$\beta_i^P = beta\ of\ stock\ i\ to\ the\ portfolio$

$E[R_P] = expected\ return\ portfolio$

In a competitive market, the investor's required return varies in direct proportion to the covariance between the stock and the portfolio, i.e. beta, since unsystematic risks are eliminated in a well-diversified portfolio. If the expected return does not meet the return requirements as depicted by the formula above, adding the stock will not improve the portfolio's Sharpe ratio.

As already stated, the investor will optimally hold the efficient portfolio of risky assets, why the appropriate rate of return on stock *i* should be determined based on the beta relative to the efficient portfolio (Ibid):

$$E[R_i] = R_i \equiv r_f + \beta_i^{eff} * (E[R_{eff}] - r_f) \quad \textbf{(2.11)}$$

The assumptions behind CAPM and the implications of these will be elaborated in the following section.

2.1.3 The Capital Asset Pricing Model

CAPM has since become one of the most important models describing the relationship between risk and return. The CAPM is based on the following assumptions:

1. Investors are risk averse and only care about expected return and risk.
2. Investors can buy and sell stocks at competitive prices and have no costs of transaction.
3. Investors can lend or borrow indefinite amounts of money at r_f.

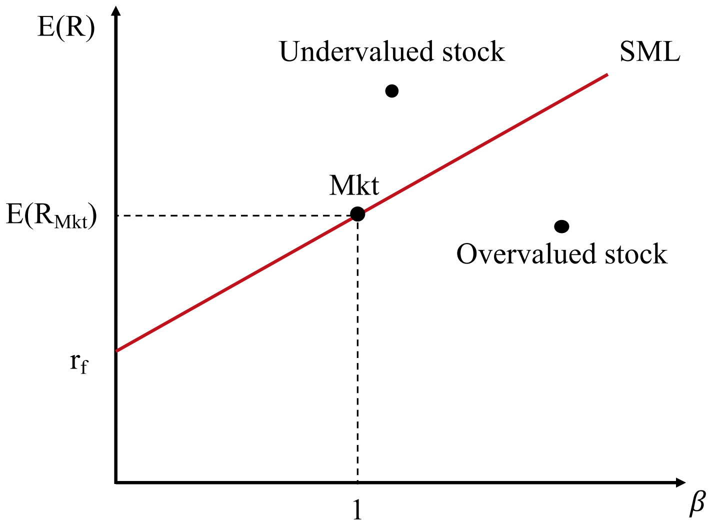
4. Investors have identical anticipations about the correlations, volatilities and expected returns of stocks.

The assumptions above imply that investors like high expected return and a low standard deviation, why they should only be interested in holding efficient portfolios. However, since investors can lend or borrow money at r_f, one portfolio will have a higher Sharpe ratio than the others, why this will be the most efficient portfolio. As stated previously, the formation of the most efficient portfolio depends on the investor's anticipations about returns and risk of stocks. Due to the assumption that investors have identical anticipations, all investors should hold the same portfolio of risky assets, i.e. the market portfolio, and a risk-free asset. Based on these assumptions the required rate of return on stock *i* can be calculated using the following formula:

$$E[R_i] = R_i = r_f + \beta_i^{Mkt} * (E[R_{Mkt}] - r_f) \quad \textbf{(2.12)}$$

The linear relationship between a stock's required rate of return and its beta is illustrated by the security market line (SML), As shown in the figure below, SML is graphed as a straight line through the risk-free asset and the market portfolio.

Figure 2.3: Security Market Line



Source: Own creation

According to CAPM, in equilibrium all stocks should lie along the SML. This also implies that all stocks with the same beta (systematic risk) should provide the same rate of return. If this was not the case investors would invest in undervalued stocks that provide a higher expected return at the given level of risk (beta). This would lead to an increase in the price of the undervalued stock and as a result lead to a decrease in expected return until equilibrium is restored. Thus, according to CAPM the financial markets are very competitive and efficient.

2.1.4 Arbitrage Pricing Theory & the Three-Factor Model

Since its inception CAPM has been recognized as one of the most important models explaining the relationship between risk and required return. However, the plausibility of the CAPM theory has been questioned in part due to its simplicity. CAPM is a one-factor model, where expected return depends only on the stock's sensitivity to fluctuations in the market portfolio, i.e. beta is the only reason why expected returns vary. This assumption was questioned in 1976 by Stephen Ross when he introduced arbitrage pricing theory (APT). In contrast to the CAPM, Ross (1976) argues that the efficient market portfolio plays no significant role in determining expected return. According to APT, expected return is a function of various macroeconomic factors and the stock's sensitivity to these factors. Thus, the expected return, similar to CAPM, depends on economywide factors and not unsystematic risks that are company specific. Expected return according to APT can be calculated using the following formula:

$$E[R_i] = r_f + \beta_{i1}\left(r_{factor1} - r_f\right) + \beta_{i2}\left(r_{factor2} - r_f\right) + \cdots + \beta_{in}(r_{factorn} - r_f) \quad \textbf{(2.13)}$$

$\beta_{in} = sensitivity\ of\ stock\ i's\ return\ to\ factor\ n$

$r_{factorn} - r_f = expted\ risk\ premium\ associated\ with\ factor\ n$

The value of the macroeconomic factors in the APT return formula are the same for all stocks. The factor sensitivity on the other hand differs with some securities being more sensitive to a specific factor than others (Ibid), i.e. an oil company is more sensitive to an oil price factor than a beverage company. For the arbitrage pricing relationship to hold this also implies that stocks with the same sensitivity to macroeconomic factors should offer the same return. However, in practice, APT is difficult to apply to determine expected returns as the theory does not say which factors to include in the formula, nor does it tell us what the value of the macroeconomic factors should be (Ibid).

Since then many scholars have tried to define which market factors to include to capture market risks with the purpose of estimating expected return. A well-known model is the three-factor model introduced by Fama and French in 1993. Fama and French points out the imprecision of using the CAPM or APT model to determine expected returns, why they introduced the three-factor model. In a study of stocks listed on NYSE, AMEX and NASDAQ Fama and French (1993 and 1995) identify three factors that affect expected stock returns and profitability. According to Fama and French (1993 and 1995) the estimation of stock returns is best captured by a market factor, size factor and book-to-market (B/M) factor. Fama and French (1993 and 1995) found that companies with a small market capitalization and a high B/M ratio performed better than the average stock. The formula for the three-factor model is as follows:

$$E[R_i] = r_f + \beta_{market}\left(E[R_{Mkt}] - r_f\right) + \beta_{size}\left(r_{size\ factor}\right) + \beta_{BTM}\left(r_{B/M\ factor}\right) \quad \textbf{(2.14)}$$

$r_{size}factor = difference\ in\ return\ between\ small\ and\ large\ company\ stocks$
$r_{B/M} = difference\ in\ return\ between\ high\ B/M\ stocks\ and\ low\ B/M\ stocks$

In this model, the expected return depends on the stock's sensitivity to aforementioned factors. As in the CAPM and APT model, the three-factor model is also mainly concerned with the risk that investors cannot avoid, irrespective of how much they diversify, i.e. systematic risk.

2.1.5 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) was first introduced in 1970 by E. Fama. According to Fama (1970), financial markets are efficient when stock prices fully incorporate all available information. This implies that in efficient markets stock prices are always at the fair level, i.e. fundamental value, given the information available (Fama E. F., 1970). Stock prices change only when new information affecting the fair value level is released. Since the competition to find mispriced stocks and price trends is very intense, stock prices will adjust immediately as soon as a new trend or new information is released. This results in an elimination of any additional profit opportunities, since the stock price immediately changes to its new fair value. Moreover, it is impossible to predict stock price changes as no one can guess tomorrow's news, why stock prices are said to follow random walks. Consequently, in an efficient market, investors should not be able to beat the market consistently.

Fama (1970) argues that the following three conditions are consistent with market efficiency and helps explain why stock prices *"obviously"* fully incorporate all available information in efficient markets. Firstly, there are no transaction costs of trading stocks. Secondly, all market participants can without incurring any costs gain access to all available information. Lastly, all market participants agree on the effect of available information on both the current and future stock price (Fama E. F., 1970). However, Fama (1970) realises that these conditions are not descriptive of markets in practice, why three levels of market efficiency are suggested, contingent on the information included in the stock price. The first level of market efficiency is the weak form of efficiency (Ibid). In the weak form of efficiency, the stock price incorporates all information about the past, e.g. past price changes, economic data, etc. Thus, if weak form efficiency holds, investors cannot achieve excess returns consistently by analysing historical price changes. In the semi-strong form of efficiency, stock prices adjust immediately to new relevant public information such as earnings announcements, merger proposals, etc. This implies, that investors cannot beat the market consistently neither with historical nor fundamental analysis. Lastly, in the strong form of efficiency stock prices immediately reflect all new relevant information, both public and private information. Consequently, not even company insiders will be able to use inside information to achieve abnormal results in strong form efficient markets.

2.1.6 Implications

The traditional finance theories described in the preceding sections imply that investors should not be able to obtain profitable returns by employing momentum investment strategies, nor should we find any other market anomalies such as the January Effect. Following traditional finance theories stock prices reflect the true fundamental value, why it will be extremely difficult to identify under- or overvalued stocks. According to the EMH, the stock price reflects all available information and instantaneously adjust to new information, why stocks are argued to follow a random walk.

Aforementioned factors imply that investment strategies based on previous price movements and market anomalies should not be able to beat the market. Thus, according to traditional finance theories the optimal risky portfolio to hold is a market index. To conclude, if we are able to obtain positive momentum returns and find evidence of the January Effect traditional finance theories cannot fully explain the workings of financial markets. This leads us to the next section which will focus on behavioural finance theories.

2.2 Behavioural Finance

The traditional finance theories outlined in the previous sections rest on the assumptions that markets are efficient and that both investors and markets are perfectly rational at all times. However, empirical evidence such as bubbles, where prices deviate largely from the intrinsic value, post-earnings announcement drift, the momentum effect, etc. all contradict the implications of traditional finance theory. Advocates of traditional finance argue that these findings are irregularities and does not reflect how financial markets truly function. However, the consistent occurrence of these "irregularities" gave rise to what we know as behavioural finance.

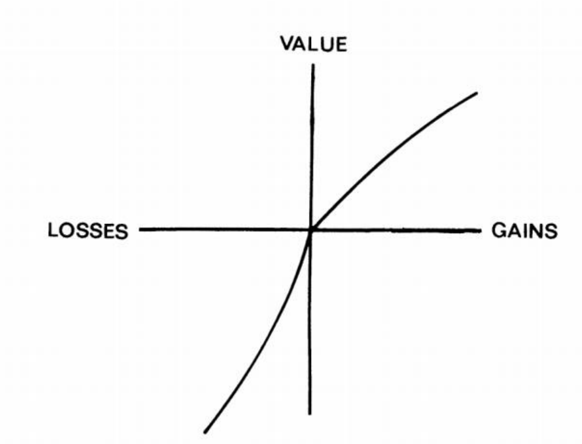
The origin of behavioural finance can be traced back to Kahneman and Tversky (1974 and 1979), who introduced essential theories laying the foundation for behavioural finance. In behavioural finance, the assumptions of market efficiency and rationality are abandoned. Instead, behavioural finance uses psychological and social principles to understand and explain investor behaviour and consequently market movements. In the following sections we will present a number of theories deemed relevant for the explanation of market anomalies such as the momentum and January Effect.

2.2.1 Prospect Theory

One of the theories explaining why stock prices may deviate from its intrinsic value is prospect theory introduced by Kahneman and Tversky (1979). In prospect theory it is assumed that people value losses and gains differently as losses are suggested to have a larger emotional impact than an equivalent gain. This is also rereferred to as the *loss-aversion theory* and explains why people tend to make decisions based on expected gains instead of losses (Ibid). Moreover, Kahneman and Tversky (1979) find that when individuals are faced with decisions providing the same expected outcome, people will prefer the outcome obtained with certainty over the outcome with less probability. This phenomenon is referred to as the *certainty effect* and differs from what has been proposed by traditional utility theory. This tendency combined with the theory of loss-aversion contributes to individuals seeking risk when options involve sure losses and risk avoidance when there is a choice of assured gains (Ibid). This pattern is referred to as the *reflection effect* (Ibid). Additionally, Kahneman and Tversky (1979) find that individuals tend to simplify decisions when evaluating different alternatives by ignoring information that is shared by the different options. This results in inconsistent preferences when people are presented with different options providing the same outcome, but introduced in different forms. This tendency is also called the *isolation effect* (Ibid).

Abovementioned decision patterns combined with the notion that people make decisions based on their relative change in wealth and not absolute change result in the s-shaped value function seen below.

Figure 2.4: Value Function



Source: Kahneman and Tversky (1979)

As evident from the figure above, the value function is concave for gains while it is both convex and steeper for losses indicating a loss-aversion. In summary, prospect theory suggests that prices may deviate from the fundamental value potentially resulting in market anomalies.

2.2.2 Anchoring and adjustment

According to Kahneman and Tversky (1974), many decisions about uncertain future events, e.g. investments, are often based on a number of heuristic principles to reduce the complexity of estimating probabilities and values. Heuristics are mental shortcuts and rule-of-thumb strategies used for decision making and problem solving. Kahneman and Tversky (1974) describes three heuristic principles used to make decisions about uncertain events, of which *anchoring and adjustment* is one of the heuristics introduced. They find that people often make decisions based on an initial value which is then adjusted to reach the final result. Thus, different initial values will result in biased decisions. This phenomenon is also referred to as *anchoring* (Kahneman & Tversky, 1974). Moreover, they found that the adjustments often were insufficient. These findings imply that investors will anchor their estimates to past information while at the same time insufficiently adjust their views when new information is published. Consequently, investors will make systematic and predictable errors. This is in contrast to the EMH which assumes that all market participants agree on the effect of available information on the stock price.

2.2.3 The disposition effect

Based on the theories of loss aversion described previously, Shefrin and Statman (1985) introduced the disposition effect. Shefrin and Statman (1985) found a general disposition among investors to realize gains too soon and hold on to losers too long. The disposition effect is partly explained by the regret aversion bias, which describes how investors may resist to realize a loss because realizing a loss would imply that you have to admit you were wrong and made a mistake (Shefrin & Statman, 1985). Additionally, the longing for pride and the avoidance of potential regret results in investors realising gains too soon (Ibid).

Selling winners too soon may create a downward pressure on stock prices slowing down the upward adjustment of the stock price when new information is made available (Hurst, Ooi, & Pedersen, 2013). On the other hand, holding on to losers too long may keep stock prices inflated and prevent them from decreasing as fast as depicted by efficient market theory (Ibid).

2.2.4 Herding

Herding behaviour is a phenomenon where investors tend to imitate the actions of other individuals instead of acting based on their own opinions and analysis (Bikhchandani, Hirshleifer, & Welch, 1992). In financial markets investors may decide to invest in stocks due to herding. Hence, herding behaviour can mislead investors and result in radical shifts in equilibrium (Ibid). Various drivers of herding behaviour have been put forward in the literature, of which information-based herding introduced by Bikhchandani et al. (1992) is widely recognized. They argue that herding behaviour can be explained by information cascades, where investors imitate others as they lack confidence in their own information and consequently discard their own signals. Information-based herding is more likely to occur when there is a high degree of uncertainty about the information available and when it is highly complex (Ibid). Another driver of herding behaviour is reputation-based herding (Scharfstein & Stein (1990) and Graham (1999)). Scharfstein & Stein (1990) argue that investors may imitate trades made by others to signal that their decisions do not deviate too significantly from peers. The rationale is that incurring losses with a group of other individuals will not damage the investor's reputation to the same degree as if trades were based on own estimates that deviate from that of peers.

2.2.5 Representativeness

Another heuristic principle presented by Kahneman and Tversky (1974) is *representativeness.* Representativeness refers to the tendency of estimating and judging decisions based on stereotypes and the degree to which it resembles past events. They find that people tend to put more weight on representativeness than on relevant information about prior probabilities, or base rates, of the outcome (Kahneman & Tversky, 1974). In other words, people neglect statistical estimates of how common the event is in general and thereby also ignore the phenomenon of regression towards the mean. They also argue that people are insensitive to the size of the sample when making decisions. Hence, people tend to base their beliefs on too small a sample and thereby disregard the notion of potential distribution errors when using small samples.

The representativeness heuristic may lead to serious errors since relevant elements necessary to estimate probabilities may be excluded when decisions are based on representativeness. In terms of financial markets this may occur when investors go long in companies which recently experienced a share price appreciation and conversely short stocks that have dropped in price.

2.2.6 Implications

To summarize, behavioural finance theories describe how cognitive errors can impact the actions taken by investors. In contrast to traditional finance theories, investors are considered human beings and not always 100% rational as they are influenced by e.g. heuristics and limits to self-control. In terms of this thesis, these findings imply that market anomalies such as the momentum and January Effect can to some degree be explained by behavioural finance theories. According to behavioural finance, irrational decisions as a consequence of e.g. anchoring and herding, can result in persistent mispricing where stock prices deviate from the fundamental value depicted by traditional finance. Consequently, these persistent market anomalies suggest that investors may be able to generate positive returns by leveraging technical trading strategies that examine historical data and by taking into consideration the implications of behavioural finance theories. Examples of such strategies are the momentum investment strategies examined in this thesis.

3. Literature review

The following chapter aims to create an overview of the previous research and studies of momentum and seasonal anomalies present in equity markets. The chapter is divided into three sections focusing on the momentum and the January Effect. The first section describes the concept of momentum strategies and goes through historical empirical findings to give the reader an understanding of the concept of momentum as well as proposed explanations for the profits to be found applying this strategy. Furthermore, we present literature focusing on optimization of momentum strategies and momentum studies including the Nordics. In the second section we review literature focusing on the concept of seasonal anomalies and the January Effect. The third section will explore and combine previous studies and findings of both concepts to explain the connection between the two market anomalies.

3.1 The Momentum Effect

3.1.1 Profitability and explanation of momentum strategies

"If stock prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist."

This is the rationale used by Jegadeesh and Titman (1993) in the first study to present the concept of momentum, in which they examine a variety of strategies that buy stocks with high historical returns while simultaneously selling stocks that have realised poor returns over the same time period. More specifically, the strategies take a long position in past "winners" and a short position in past "losers". Jegadeesh and Titman (1993) define "winners" as the historically top performing decile of stocks whereas losers are defined as the bottom decile. The different strategies investigated differentiate in their lookback- and holding-period; each strategy holds a different combination of 3-, 6-, 9- and 12-months lookback- and holding-periods, resulting in a total of 16 unique strategies. Jegadeesh and Titman (1993) apply monthly returns of NYSE and AMEX stocks based on a sample period from 1965 – 1989 as the base for analysis. Findings document that these strategies on average yield significant and abnormal returns of about one percent per month for the following year (annual returns of 12.01%). However, they find that some of the abnormal returns which occurred in the first year after portfolio formation disappeared in the following two years. Through the authors' own interpretation of their findings, they provide a plausible reason for the observed short-term abnormal returns as well as the long-term reversal of returns. Jegadeesh and Titman (1993) argue that the market underreacts to information about the short-term prospects of the firm, while overreacting to long-term prospects of the firm. This interpretation is consistent with more recent theory of trend life cycles as proposed by Hurst, Ooi and Pedersen (2013).

Following the initial studies of momentum strategies, the results and their profitability were generally accepted by academics, portfolio managers and stock analysists alike, however the source of the profits and the interpretation of the evidence was still widely debated (Jegadeesh and Titman, 2001). Some scholars argued that the results proved as a strong indication of "market inefficiency" (e.g. Barberis, Schleifer & Vishny, 1998; Hong and Stein, 1999) while others pinned the returns of the strategies as compensation for risk or a product of data mining (e.g. Conrad and Kaul, 1998; Fama and French, 1996).

Chan, Jegadeesh & Lakonishok (1996) applied the 6-month/6-month strategy, which was widely regarded as the best momentum strategy, to test the hypothesis of being able to predict future returns based on firms' past-earnings announcements. They find compelling results that for the first 6 months the returns surrounding the earnings announcement days are able to account for a large part of the spread between "winners" and "losers" in the momentum portfolio. This would imply that momentum profits seem to be, at least partially, driven by underreactions to firm-specific information, consistent with the conclusion made by Jegadeesh and Titman (1993). This view would later gain further support by the findings of Grundy and Martin (2001). Similarly, Barberis et al. (1998) report that it is the tendency for investors to stick with their original beliefs and past information, that results in the slow reaction to new information and stocks trading below their intrinsic value and as of such the momentum effect.

In their paper from 1996 on multifactor explanations of asset pricing anomalies, Fama and French would try to explain the profits of momentum strategies and other anomalies by applying the Fama-French three-factor model (Fama and French, 1993). If the profits were to be explained by the model it would pin the profitability of momentum strategies as a compensation for risk and would imply that the "winner" portfolio contains more risk than the "loser" portfolio. The risk factors of the model as explained in the previous chapter are beta (market risk), market capitalization (size) and book-to-market values (value). Fama and French hypothesized that the "winner" portfolio would consist of stocks with high beta values, small market capitalizations and high book-to-market values. However, Fama and French fail to account for the profitability of momentum strategies using the three-factor Model calling it "the main embarrassment of the model", and instead argue that data mining appears to be the most likely explanation of the momentum effect.

In order to rule out the possibility of data mining bias Rouwenhorst (1998) was the first to conduct an analysis of momentum strategies in a market other than the American market. Investigating the momentum effect using sample data for 2,190 different companies across 12 European countries during the period of 1980 to 1995. Through applying the same methodology as Jegadeesh and Titman, all countries except Sweden were shown to produce significant abnormal positive returns. The strongest momentum effect was found in Spain, followed by the Netherlands, Belgium and Denmark. Furthermore, Jegadeesh and Titman (2001) and Chan, Tong & Hameed (2000) would re-examine their previous studies to investigate and de-myth some of the criticism surrounding momentum strategies. Jegadeesh and Titman (2001) extended their initial 6-month/6-month strategy from their original study, with 8 more years in the sample period, and found remarkably similar results to their first study in 1993, with the strategy still proving to be profitable. Chan et al. (2000) applied the momentum strategies to global equity market indices. They too found momentum strategies to remain profitable.

Other authors have tried to rationalize momentum using different approaches. Lee and Swaminathan (2000) find a correlation between higher trading volumes and momentum return, where stocks with high (low) past trading volumes generate lower (higher) future returns. While Chordia and Shivakumar (2002) test for macroeconomic variables that can capture momentum payoffs and find that the original momentum strategies only generate positive payoffs during expansionary time-periods, while generating negative returns during economic downturns. The findings of the latter study support the risk-based hypotheses for momentum profits. Sagi and Seasholes (2007) point out that firm specific attributes such as dividends, credit ratings, turnover, firm expansion, idiosyncratic volatility and capital investments are deciding factors in determining momentum profits.

In 2008 Fama and French would revisit their studies of momentum and other market anomalies, this time examining separate sorts of microcaps, small stocks and big stocks on each anomaly variable, using data for NYSE Amex and Nasdaq stocks in the period of 1963-2005. In terms of the methodology for examining the momentum variable, the paper forms portfolios based on 12-month historical returns, skipping the most recent month. While Fama and French does not succeed in explaining the momentum profits with the CAPM or the three-factor model, the findings document a size effect, suggesting that the momentum effect is only evident in small and micro-sized portfolios. Interestingly, the documentation of a size effect would appear again in the papers of O'Brien, Brailsford & Gaunt (2010) and Alhenawi (2015), however, contrary to the findings of Fama and French (2008), these papers showed that the momentum effect was larger in bigger firms. Alhenawi (2015) would examine the interaction of momentum and the size effect, reporting that in markets experiencing bull-like trends, firms would grow rapidly and as a result it is possible that both the effect of momentum and size is a result of general upwards growth in the market. Booth et al. (2016) document findings consistent with those of Fama and French (2008), and demonstrate that firm size, as a proxy for risk, captures the momentum effect, finding significant momentum returns only in the case of small-cap stocks. More recently Han and Li (2017) have found that significant momentum profits only arrive when investors feel optimistic, supporting behavioural explanations of momentum, while Filippou, Gozluklu & Taylor (2018) provide evidence in support of rational explanations by linking performance of momentum portfolios to political risk.

To summarize, a large part of the academic literature agrees on the profitability of momentum strategies, however, there is still a fragmented view on the sources of the profits, split into two large schools of thoughts. The first being rational- or risk-based explanations and the second being behavioural explanations or explanations suggesting market inefficiency. Within these schools of thoughts previous studies have found contradicting evidence for both hypotheses, thus demanding further research on the topic.

3.1.2 Optimization of momentum strategies

While the original momentum strategy suggested by Jegadeesh and Titman (1993) saw much use throughout the early 2000s, the strategy showed poor performance during the economic downturn of 2007-2010 (e.g. Daniel and Moskowitz, 2016; Fan, Li and Liu, 2018). As of such, literature regarding momentum would shift its focus to optimization of the strategy to perform better, especially during times of increased volatility (Singh & Walia, 2020). Some of these optimizations include those of Blitz, Huij, and Martens (2011) who found that "Residual Momentum" performs better than the traditional momentum strategy during times of economic crisis. The difference between residual momentum and regular momentum lies in the stock selection process. In the residual momentum strategy, stocks are selected based on their stock return after adjusting for the Fama-French factors, as opposed to the traditional strategy where stocks are selected based on their total return. The profitability of residual momentum and its superiority to the original strategy in times of financial crisis is also supported by more recent research such as Chang, Ko, Nakano and Rhee (2018) and Lin (2019).

Novy-Marx (2012) was the first to publish a paper on intermediate-term momentum which postulates that the momentum effect is driven by firms' performance 12 to 7 months prior to portfolio formation, and not due to a tendency of recent "winners" and "losers" to keep rising and falling. Novy-Marx finds that while strategies based on recent historical performance generate positive returns, the profitability of those based on an intermediate-term horizon generate even larger returns. While initially examining a cross section of US equities the study is also extended to international equity markets and finds similar results in these markets. Furthermore, Novy-Marx suggests that the predictive power of recent historical returns have diminished over time, while those of intermediate-term horizon have performed consistently and have become even more profitable over time.

More recently, scholars have gained an increased interest in time-series momentum, also referred to as absolute momentum, first suggested and tested by Asness, Moskowitz and Pedersen (2013), who examined the momentum effect using time-series data instead of cross-sectional. Specifically, the time-series momentum strategy chooses a position in every financial asset based on the past returns of the individual financial asset. This means that instead of splitting the universe into top decile winners and bottom decile losers, the time-series momentum strategy takes a long position in a given asset if it has had positive historical returns and a short position if it has had negative returns. This means that in theory the time-series momentum strategy can be a full long or short position, as opposed to the original momentum strategy which by nature is a long-short strategy with zero capital requirement. The profitability of absolute momentum has since been explored and confirmed by numerous research studies such as He and Li (2015), Bird, Gao and Yeung (2017), Goyal and Jegadeesh (2018) and He, Li and Li (2018). To account for the problem of poor performance during times of economic downturns, some research studies have implemented different types of volatility scaling in absolute momentum strategies, with Fan et al. (2018) determining that the strategy based on dynamic volatility scaling generates the best returns.

In summary, due to the poor performance of the original momentum strategy in the subprime crisis, there was a shift in literature to focusing more on optimizing the strategies. Recently, the literature has focused more on the idea and profitability of time-series momentum.

3.1.3 Momentum in the Nordics

In their paper on momentum around the world Chui, Titman and Wei (2010) try to examine how cultural differences influence the return of momentum strategies. Chui et al. (2010) argue that momentum profits are more likely to be persistent in countries with a higher individualism score based on the cultural dimensions developed by Hofstede (2001). In line with their hypothesis, they find that countries such as Denmark, Sweden and Finland, which all have a relatively high individualism score of 74, 71 and 63 respectively, achieve significant momentum profits. Similarly Gong, Liu and Liu (2015) examine 26 major international markets, including Sweden, Denmark and Finland for intermediate and short-term momentum, using the methodology of Novy-Marx (2012) and Fama and French (2008) respectively. They find that 12 countries have significant momentum profits from both strategies tested, including Denmark, Sweden and Finland, using a sample from 1982-2012. However, contrasting studies do exist, as Rouwenhorst (1998) found significant momentum profits for Denmark, but insignificant profits for Sweden, using a sample from 1978-1995. Consistent with these findings Goyal and Wahal (2015) find no compelling evidence for intermediate- or short-term momentum in either Denmark, Sweden or Finland, looking at a sample from 1980-2010. To conclude, there is a fragmented view on momentum profits in Nordic countries which demands further research.

Overall, momentum strategies have proved to be an efficient and one of the most consistent ways to "beat the market" across all asset classes (Asness et al., 2013), with a wide range of strategies proven successful through backtests in the American and European market, as well as the Asian-Pacific and emerging financial markets. The source of the profits has divided the academic literature, ranging from behavioural theories to compensation for risk and macroeconomic variables. Furthermore, there still exists contradicting evidence regarding momentum profits in the Nordic countries which thus demands further research.

3.2 The January Effect

3.2.1 Initial observation and explanations for the January Effect

The efficient market hypothesis suggests that it is not possible to outperform the market once you adjust appropriately for risks (Fama, 1970).

The turn-of-the-year effect otherwise referred to as the 'January Effect' is one of the most well researched topics on capital market phenomena. The January Effect refers to the observation that stock returns in January seems to be higher than returns in other months of the year. The first observation and description of the effect was around 1942 by investment banker Sidney B. Wachtel (Wachtel, 1942). However, a more fleshed out analysis did not exist until the study by Rozeff and Kinney (1976) was published. Rozeff and Kinney (1976) provided the first empirical evidence of the January Effect in the United States, documenting seasonal patterns on the New York Stock exchange over the sample period 1904-1974. Specifically, the paper found the average returns in January to be 3.5% compared to 0.5% in the other months. Following this paper, the seasonal anomaly gained increased attention from academics and practitioners.

Gultekin and Gultekin (1983) was the first study to examine and investigate seasonal anomalies outside of the United States. They used data samples for 16 industrialized countries in Europe and Asia-Pacific in the period 1959-1979 and documented a seasonal anomaly in most of their examined countries, including Denmark and Sweden. For the countries with significant evidence, except for Australia, the seasonal anomaly coincided with the end of the tax year. For all countries this was in January, except for the UK which ends their tax year in April. Gultekin and Gultekin (1983) thus conclude that they find evidence of a seasonal pattern in the stock returns of most major industrial countries, manifesting in a significantly large mean return at the end of the tax year, i.e. the January Effect.

Several other studies continued to confirm the January Effect in different sample periods and countries. Ho (1990) examined 8 emerging markets in the Asia-Pacific region and found the January Effect in six of them. While Lakonishok and Smidt (1988) confirmed the January Effect in the US for a different sample period. And as the existence of the January Effect was generally accepted, the initial wave of papers studying the rationale and explanations of the January Effect would soon follow.

Initially, studies such as Roll (1983) and Keim (1983) would attribute the existence of the January Effect to the size effect, also referred to as the small-firm effect. This hypothesis would later be tested and confirmed by Lakonishok and Smidt (1988). Furthermore, Reinganum (1983) pointed out that the January returns were higher for small firms whose prices had declined in the previous year, and the excess returns in the first five days were not observed for small "winners". These findings implied that stocks with negative returns over the previous year would have higher returns in January. Branch and Chang (1990) found that this effect was further enhanced for stocks with low share prices.

The beforementioned research was motivated by a possible explanation of the January Effect based on tax-loss selling. Tax-loss selling implies that stocks which have incurred losses for investors at the latter months of the tax year will continue to decrease in price as investors sell them off to realize capital losses. These stocks will then, following the new year, bounce back due to the absence of selling pressure and possible repurchase from investors. The findings of Gultekin and Gultekin (1983) are consistent with this hypothesis. Agrawal and Tandon (1994) further supports the tax-loss selling hypothesis, finding results consistent with Gultekin and Gultekin (1983), confirming the tax-loss selling hypothesis and January Effect for 18 different countries, except for the UK where they find a similar effect in April.

While the tax-loss selling hypothesis is widely regarded as the most likely explanation for the January Effect (Chen & Singal, 2004), the argument is not universally accepted. Thaler (1987) argues that while tax-loss selling seem relevant in explaining the January Effect, it cannot be the entire explanation. This is supported by the findings of Kato and Schallheim (1985) who find an observed January Effect in Japan, where no capital gains tax or loss offset existed at the time. Another example is Berges, McConnell and Schlarbaum (1984) who examine stocks in Canada, which had no capital gains tax before 1972, yet documents a January Effect prior to 1972. Furthermore, Haug and Hirschey (2006) find that there is no significant impact on the January Effect from large tax reforms such as the Reform act in the US in 1986. A multitude of other studies find abnormally large returns in January despite the tax year for individuals not ending in December (e.g. Brown, Keim, Kleidon and Marsh, 1983; Fountas and Segredakis, 2002).

The second most popular explanation behind the January Effect is that of window dressing. Initially proposed by Haugen and Lakonishok (1988), the window dressing argument is built upon the idea

that fund managers will try to make their portfolio look as attractive as possible at the end of December, which is the time where the detailed portfolio composition is reported to investors (Lakonishok, Schleifer, Thaler and Vishny, 1991). Managers therefore try to accommodate this ambition by selling their losing stocks at the end of the year and only keep the winning stocks, thereby creating an illusion to investors of a strong performing portfolio with an abundance of stocks having realized positive returns. The funds gained from selling the losing stock in December is then reinvested into the same stock in January, thereby driving up the price. Lakonishok et al. (1991) find that in every quarter, funds sell poorly performing stocks and that this pattern is accelerated in the fourth quarter.
Chen and Singal (2004) test the hypothesis put forward by Lakonishok et al. (1991) and argue that if window dressing is the main driver of the January Effect there should be seasonal anomalies present in the other quarters. They therefore study the period of June through July and obtain findings which suggest that window dressing is not the reason for the January Effect.

Other less popular explanations for the January Effect include the liquidity hypothesis (Ogden, 1990), which argues that a substantial increase in business activity in December yields an increase in liquidity in January and pushes up the price of stocks. However, the liquidity hypothesis has received criticism for not explaining why the January Effect is primarily present in small stocks as an increase in liquidity and profits at year end should affect the entire market. Anderson (2007) suggests that phycological factors such as a change in mindset following Christmas and New Year's cause investors to act irrationally. This is consistent with the findings of Ciccone (2011) who argues that investor optimism is at its peak during January.

3.2.2 Recent literature on the January Effect

More recent literature has had more contradicting results regarding the persistence of the January Effect. Schwert (2003) examines the US market in the period from 1980 to 2001 and concludes that the January Effect has weakened but is still existent. Klock and Bacon (2014) test the efficient market hypothesis by backtesting a strategy of buying tax "losers" in December and selling the same stocks in January, for the years 2010, 2011 and 2012. If the efficient market hypothesis holds, this strategy should not yield above normal returns. Given their findings they conclude that the market is not efficient with respect to year-end selling and the January Effect, and that the January Effect is still present in today's markets.

Other studies (e.g. Marquering, Nisser and Valla, 2006; Perez 2018) find that the January Effect has now disappeared from developed markets. Perez (2018) investigates whether the January Effect still exists in modern day emerging and developed markets. He does this in a systematic and global way by studying the performance of 106 indexes in 86 different countries and jurisdictions over a sample period of 2002-2017. He finds that while the January Effect is still present in some emerging markets, it seems to be decreasing over time or being non-existent especially in developed and advanced markets, thereby implying that the market has adjusted to the January Effect. Patel (2016) examine US and international stock returns from 1997-2014 and find evidence which suggests that the January Effect does not exist anymore in US stock returns. Plastun, Gupta, Wohar and Sibande (2019) conduct one of the most recent studies and sample periods testing the January Effect. Testing a century of data from the US stock market in the period spanning from 1900-2018 and focusing on the evolution of the January Effect, they find that the effect was most prominent during the 1950-1960s and that it has disappeared from stock returns in more recent times.

Some studies still find evidence for the existence of the January Effect to varying degrees. Haug and Hirschey (2006) find the January Effect to still be prevalent in US equities, which is consistent with the findings of Jacobsen, Mamun and Visaltanachoti (2005). Li and Gong (2015) find the January Effect to still persist in Japan and Gharaibeh (2017) found evidence for the January Effect in Morroco and Jordan during the period 1988-2014.

To summarize, it is evident that the issue of the January Effect has attracted a lot of attention from academics and practitioners alike, with the first observation of significantly higher returns in January being presented several decades ago. The two most widely accepted explanations for the January Effect include the tax-loss selling hypothesis and window dressing. Finally, in more recent literature and sample periods there seem to be a trend in developed markets for the January Effect to dissipate, implying that markets are becoming more efficient. However, there is some contradicting evidence surrounding the persistence of the January Effect in different markets, which implies a need for further research on the topic.

3.3 Momentum in January

This section will create a connection between the theories, empirical studies and evidence surrounding momentum strategies and the January Effect. The characteristics of the phenomena have been described in the previous sections in detail but will briefly be summarized in this section.

The momentum strategy involves buying securities that have been rising while shorting those that have been falling. Betting on the fact that the stocks that have historically performed well (poorly) will continue their upwards (downwards) trend in the short-term. Due to its consistent performance and profitability across all major asset classes, the momentum strategy (and its many branches of alterations and modifications) has historically been and is still one of the most widely used investment strategies by academics and practitioners around the world.

The January Effect is a seasonal anomaly that has been observed in the month of January, where equities on average see a seasonal increase in stock prices compared to the other months. The effect has predominantly been found in small-cap stocks. The two main explanations for the January Effect is those of tax-loss selling and window dressing. Tax-loss selling suggests that investors will sell their losing stocks at the end of the tax year to incur a capital loss, then reinvest those funds in January, causing the prices of the stocks to rise. Window dressing implies that hedge fund managers will sell off losing stocks in their portfolio to present a more attractive picture to investors, when the portfolio is presented at the beginning of January. The stocks sold off will then be added back to the portfolio later in January.

What does the existence of a January Effect imply for momentum strategies? Since investors are buying winners and shorting losers the performance of the momentum strategy is based on the winning stocks having positive returns and the losing stock having negative returns in the short-term. If it is assumed that the January Effect is caused by tax-loss selling, then stocks that have performed poorly in the months leading up to December will perform worse in December due to the downward selling pressure caused by investors. This means that if the January Effect exists the momentum strategy should perform better in December compared to other months. However, in January we should see a reversal of momentum when these poor performing stocks are bought back causing their stock price to increase. As of such, with the existence of a January Effect, the momentum strategy should perform worse in January compared to the other months of the year due to losers outperforming winners in that month.

The following section will discuss the findings of previous studies on the connection between momentum and the January Effect, coupled with implications for profitability.

Already in the initial study of momentum by Jegadeesh and Titman (1993) the aspect of seasonality is mentioned and examined. In accordance with the previously mentioned hypothesis, Jegadeesh and Titman (1993) find that the momentum strategies lead to consistent monetary losses in January. These findings are backed up by Sias (2007) as well as Grundy and Martin (2001) who show that the substantial loss of momentum profits in January is due to short selling of losers that tend to be extremely small firms.
These findings are consistent with the existence of a January Effect, that stocks with negative returns over the previous year have higher returns in January, that the tax-loss selling hypothesis is a valid explanation for the January Effect, and that the January Effect is concentrated primarily in small firms.

More recently Yao (2012) examined an even stronger connection between momentum and the January Effect. His study shows that the abnormal returns of losers in January can completely explain the successful returns of the long-term contrarian strategy, a strategy that buys losers and sell winners in a 2 to 5-year period. Furthermore, he finds that the outperformance of the intermediate-term momentum strategy, as suggested by Novy-Marx (2011), compared to the short-term momentum strategy can be explained by the strategy betting less against the small firm size effect and as of such suffer less substantial losses in January. Specifically, he finds that the short-term momentum strategy go long in small firms but shorts extremely small firms, while the intermediate-term strategy buys and sells slightly larger firms. More importantly he also finds that once the January influences are controlled for, the short-term and intermediate-term strategies achieve approximately equal momentum profits outside of January.

Zaremba (2015) examines the January Effect in the country level value and momentum strategies. Eight distinct strategies in 78 different markets are examined in the period from 1995 to 2015 and performance is tested for seasonal patterns. Zaremba (2015) finds that during the past 20 years value strategies have performed well in January and poorly in December, while momentum strategies have performed well in December and poorly in January. These observations are consistent with the explanations of the January seasonality and January Effect being related to the tax-loss selling and window dressing effects. However, due to a lack of statistical significance the null hypothesis of the same returns in January and December was not rejected.

In summary, previous authors have found that traditional momentum strategies experience significantly worse returns in January and better returns in December compared to other months. Most studies have attributed this to the existence of the January Effect, tax-loss selling and the small-firm effect. However, more empirical and statistically significant evidence is required on the topic and thus demands further research.

4. Empirical Methodology

With the two preceding chapters having presented various theories and literature deemed relevant for the empirical study, the following chapter will present the research approach used to answer our research questions. First, we describe the data used in the empirical analysis, including choice of markets, variables, sample period, final data construction etc. Second, we describe the methodology used for formation of relative-strength portfolios and construction of the three momentum strategies analysed in this study. Third, we provide the approach for calculating stock returns, determining statistical significance as well as application of the CAPM and the Three- and Four- factor models. Finally, we discuss the methodology applied for determining the presence of the January Effect.

4.1 Data

In order to answer our research questions a rich set of data has been collected. Furthermore, due to the scale of the study, secondary data has been applied in the empirical analysis. Using secondary data give us the opportunity to conduct a longitudinal analysis, i.e. using concentrated samples over a longer time period, thereby allowing us to test for the profitability of momentum investment strategies and for the persistence of the January Effect. Moreover, secondary data has been used extensively by previous existing literature for their empirical analysis.

4.1.1 Data Sources and collection

The data collection process can be divided into two steps. In the first step, S&P Capital IQ, a comprehensive market intelligence platform containing financial information about both private and public companies, was used to collect monthly information on market capitalization and dividend- and stock split- adjusted closing prices. Data was collected for companies that as of 31st of January 2021 were listed on the relevant stock exchanges. Please see section 4.2 for a more in-depth explanation of the stock exchanges included in the analysis.

In the second step, information about companies that had been delisted from the stock exchanges examined during our sample period was collected as follows. Firstly, to identify the companies which had been delisted we reviewed Nasdaq's Nordic Surveillance Reports from 2006 to 2020. Once all the delisted companies were identified, S&P Capital IQ was used again to collect their historical data, thus enabling us to conduct a more thorough empirical analysis and reduce survivorship bias. If we were to not include delisted companies in our sample this could potentially distort the results of our findings, as the sample would not provide a complete representation of the historical market situation and equity universe. We refer to appendix 1 for a complete list of companies and their tickers included in the data sample.

4.1.2 Data Variables

The following section presents the variables employed in the analysis. The data sample consists of monthly dividend and stock split adjusted closing stock prices for each company included. In order to gain a better understanding of the overall value of the stocks and make informed investment decisions adjusted stock prices have been applied. Adjusted stock prices includes the impact of dividends, stock splits, seasoned equity offerings, etc. Thus, using adjusted stock prices have allowed us to conduct a more accurate analysis of historical performance as the impact of beforementioned factors are excluded.

Moreover, for the purpose of portfolio formation and conducting sub-analyses we have collected the market capitalization of each company. All market capitalizations have been converted to DKK through the S&P Capital IQ database applying the appropriate historical spot rate. This has been done to easily compare the size of companies across multiple stock exchanges. The codes applied in the S&P Capital IQ excel plugin to collect historical data are as follows:

- Adjusted closing prices = IQ_CLOSEPRICE_ADJ
- Market capitalization = IQ_MARKETCAP

4.1.3 Data Intervals

Our analysis has been conducted based on-end-of month adjusted stock prices. Using monthly data points is in line with a large part of previous literature and allows us to compare our results with previous findings. Alternatively, we could have used daily or weekly data points in our analysis, as this would have given us a more comprehensive collection of data and consequently provide us with a basis for a more nuanced and exhaustive analysis. However, it can be argued that in practice investors will most likely not develop an investment strategy based on daily or weekly rebalancing of the portfolio due to transaction costs, time availability, etc., why an empirical analysis based on monthly data points is deemed adequate by the authors of this study.

4.1.4 Data Adjustments

A number of selection criteria has been applied in our data collection strategy. In line with previous studies, we have excluded listed mutual and investment funds from our data sample. These have been excluded from our study due to their strong correlation with other stocks applied in our analysis. Another important factor to consider when employing a momentum investment strategy is share liquidity, i.e. how easily stocks can be bought or sold. Thus, the next criteria in our data collection strategy was in relation to the share class included in the analysis. For each company we have included only one share class, since they are often highly correlated. Previous studies have excluded Class A shares in their analysis as these are argued to be less liquid than Class B shares. However, we found that for some companies Class A shares had a higher trading volume than Class B shares. Hence, in order to ensure that our data sample only includes shares with the highest liquidity, we have examined the trading volume of each company's stocks currently listed in the last full calendar year, i.e. 2020, to identify the most liquid stocks. In terms of delisted companies, we examined each company's last year of trading to identify the share type with the highest liquidity. In summary, for companies with multiple share classes and companies listed on more than one stock exchange, e.g. Nordea which is listed in both Denmark, Sweden and Finland, the share with the highest trading volume was included in the final data sample.

In addition to A- and B-shares, some companies have preference shares. Preference shares may be defined as a hybrid of common stocks and bonds, since they have different rights than common shares, e.g. preference shareholders receive dividends before common shareholders. Furthermore, in most cases preference shares only comprise a small percentage of total shares outstanding, why they are typically less liquid than common shares. As a result of these factors, preference shares have been excluded from the data sample.

4.2 Stock Exchanges

As was evident from the literature review several scholars have studied the profitability of momentum investment strategies. However, we also identified a need for more studies focusing on both the profitability of momentum strategies and the January Effect in the Nordic stock markets. Thus, our data sample includes companies listed on Nasdaq Main Market and Nasdaq First North Growth Market (NFNGM) in either Denmark, Sweden, Finland or Iceland. To our knowledge other scholars have not included both the Main Market and NFNGM in their studies. Hence, we contribute to existing literature by focusing on both markets in our analysis. The data sample does not include companies listed on Spotlight Stock Market, as these companies are typically smaller growth companies, why they are considered significantly more risky than mature companies. Moreover, due to a lack of data availability in terms of delisted companies, the Spotlight Stock Market was also excluded to reduce potential survivorship bias. Companies listed on the Oslo Stock Exchange were also excluded from the data sample.

Focusing on several stock exchanges results in a considerably larger data sample, thereby enhancing the probability of achieving statistically significant results in our analysis. Moreover, our analysis will become more representative of the implications and profitability of momentum investment strategies in practice, where investors in most cases will focus on multiple stock exchanges. In total 1,254 stocks have been included in the data sample. [2]

4.3 Sample Period

As mentioned previously, our analysis is based on monthly stock prices in the time period 01.01.2006 – 31.01.2021. We deliberately chose this time period for a number of reasons. First, in order to assure a large number of data points were collected we chose an adequately long time period to improve the credibility of our results. Second, we have identified a need for a study focusing on a more recent time period to analyse the efficiency of stock markets, and consequently if the profitability of momentum strategies and the January Effect has diminished compared to previous studies. Third, during this time period companies experienced a significant downturn in stock prices in the financial crisis of 2007-08, and by including this period we stress-test the profitability of our investment strategies and analyse its implications for the January Effect.

[2] For descriptive statistics on the data sample and portfolios, refer to section 4.6

4.4 Formation of portfolios

In this section we will describe the portfolio formation strategy applied in the analysis. The formation strategy can be divided into three distinct steps.

4.4.1 Exclusion based on market capitalization

In line with previous studies (see e.g. Jegadeesh and Titman, 2001) we sort out small companies in the first step of our formation strategy. More specifically we exclude companies with a market capitalization below a pre-determined level at the time of portfolio formation (referred to as point *t* hereafter). The minimum pre-determined market capitalization is initially set at 100 DKK million, and increases with a fixed growth rate each year to account for the general increase in total market size during the period of analysis. The annual growth rate applied to the market capitalization requirement is 5.11% (monthly growth rate of 0.416%) and is calculated as the compounded annual growth rate (CAGR) of the total market capitalization of our total data sample from January 2007 (first month of portfolio formation) to January 2021 (last month of portfolio formation). Thus, in January 2007 we apply a minimum required market capitalization of 100 DKK million and in January 2021 the minimum requirement has increased to ~200 DKK million.

The proposed growth rate for our minimum market capitalization requirement is calculated as follows:

$$Monthly\ Growth\ Rate = \left(\frac{Total\ Market\ Cap_{Jan2021}}{Total\ Market\ Cap_{Jan2007}}\right)^{\frac{1}{168}} - 1 \quad \textbf{(4.1)}$$

Where 168 is the number of months between January 2007 and January 2021.

A minimum market capitalization is implemented for several reasons. First, by excluding small companies our investment strategy is more in line with technical trading strategies implemented in practice, where small companies typically are excluded. Second, small companies tend to have a higher illiquidity risk, why a reasonably sized investment in these could cause a significant increase in share price due to their size and illiquidity. Moreover, in terms of our shorting positions, including illiquid stocks could prove difficult in practice as we might not be able to find anyone willing to lend us the stocks needed to take the position.

4.4.2 Identifying winners and losers

In the second step of our formation strategy, for every formation month *t* we rank the individual stock returns over a pre-determined look-back period.[3] In line with previous studies we apply the decile ranking method, where stocks are ranked in ascending order based on historical cumulative returns and arranged into 10 equally large subgroups (P1 to P10). Stocks with the highest return in the specific look-back period are included in the top decile (P10). These stocks are defined as the winners of the specific look-back period. Similarly, stocks with the lowest return are grouped in the bottom decile (P1) and defined as the losers. We only include companies where data is available for the entire look-back period, i.e. from the beginning of the look-back period to the end. For each of the different momentum strategies presented below, a long position is put in the winner portfolio and a short position in the loser portfolio for a single month *t* in which the zero-cost portfolio is formed and held. On average for every formation month *t*, across the sample period examined, ~52 stocks are included in both the winner and loser portfolio respectively.[4] We deemed this number of firms as adequate, why we found the decile ranking method sufficient for the purpose of this study. Furthermore, by including a large number of firms in each portfolio we should be diversifying away all possible idiosyncratic risk.

4.4.3 Portfolio weight

In the third and final step of our portfolio formation strategy the weight allocated to each stock included in the portfolio is determined. Overall, two different approaches can be used to allocate weights in the portfolio, either the equal weighted or the value weighted method. In an equal weighted portfolio, we invest the same amount of money in each stock included, irrespective of the company's market capitalization. Hence, individual stock performance carries equal importance when calculating the overall portfolio return. The equally weighted method favours small companies by giving them the same weight as larger companies. This means that our portfolio may have a large portion of the total money invested in smaller companies, which may prove difficult in practice. In contrast, a value weighted portfolio distributes weights based on each company's market capitalization relative to the other companies included in the portfolio. Consequently, a value weighted portfolio will invest more in larger companies. Thus, constructing a portfolio based on

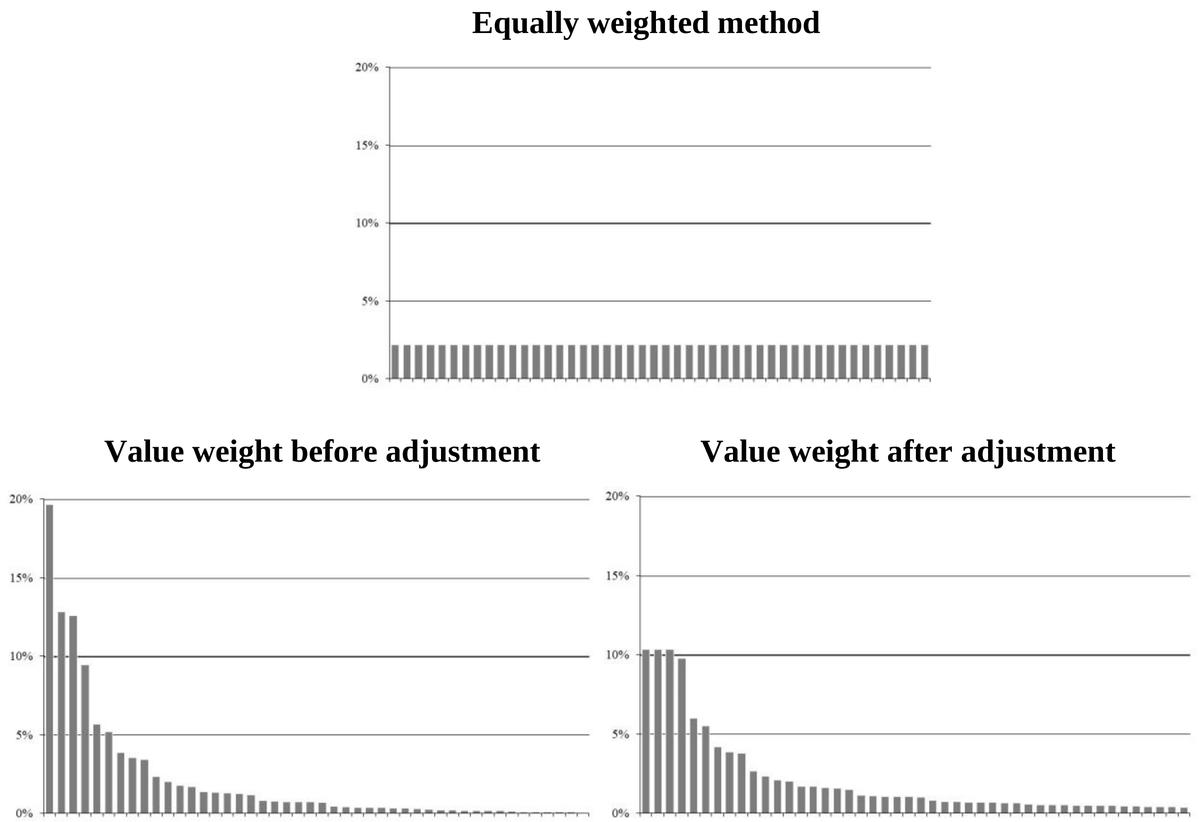
[3] See section 4.5 for more information regarding momentum strategies and look-back periods examined.
[4] For more information regarding the descriptive statistics, please refer to section 4.6.

market capitalization may result in a highly skewed weight distribution due to the significant size differences.

There are both advantages and disadvantages associated with both approaches. Thus, for the purpose of this study we have adopted both an equal- and an adjusted value weighted methodology. By implementing a minimum market capitalization (step 1 in the formation strategy) we hope to mitigate some of the practical issues of the equally weighted methodology. Furthermore, to reduce the potential skewness associated with the value weighted methodology we have implemented a maximum weight cap for equities in our portfolios. Specifically, if an equity makes out more than 10% of the total value weighted portfolio, the exceeding weight will be distributed evenly to all companies throughout the portfolio. Figure 4.1 below graphically depicts the equally weighted and adjusted value weighted methods applied in this study.

Figure 4.1: Equal and adjusted value weighting

The following figures are an illustrative example of the portfolio weighting methods applied in the analysis. The equally weighted method evenly distributes invested capital to all companies in a portfolio, regardless of market capitalization. The adjusted value weighting method initially sets a maximum weight cap at 10% for individual stocks in the portfolio. The exceeding weight is then distributed evenly to all companies in the portfolio. As of such in the third figure we see stocks with a weight slightly larger than 10% after the redistribution.



Source: Own creation

4.5 Momentum strategies

For the purpose of this study we test the profitability of various zero-cost momentum strategies. A zero-cost strategy does as the name suggests, not entail any out-of-pocket requirements or upfront expenses for the investor, however, this is under the assumption that we disregard costs of shorting and transaction costs.[5] More specifically in a zero-cost momentum strategy the investor takes a long position in past winners, i.e. P10 in this study, and a short position in past losers, i.e. P1. The capital investment position taken in each portfolio is the same, which essentially means that the cash inflow from shorting the loser portfolio is reinvested in the winner portfolio.

As of such, for this strategy to be profitable the P10 portfolio must perform better than the P1 portfolio. In other words, short-selling means speculating in the price of the stock decreasing. Since the investor takes a short position in the P1 portfolio, the investor will achieve a higher (lower) return if the value of these stocks decreases (increases) and vice versa for the P10 portfolio.

With the establishment of how the portfolios will be constructed in the analysis, this section will outline the different investment strategies analysed to test the profitability of momentum investing and the January Effect. We examine three distinct momentum strategies to increase both the scope and reliability of our analysis. The first strategy examines long-term momentum as proposed by Fama and French (2008). In this strategy stocks are selected based on the performance from the period t-12 to t-2. In other words, when the first portfolio is constructed in start of January 2007, the look-back period where past stock performance is examined, will be from start of January 2006 to the end of November 2006. In accordance with previous studies, we implement a one-month lag period between the end of the look-back and start of the holding period. Implementing a one-month lag period may reduce the potential impact of short-term reversals, the bid-ask bounce and lagged reaction effects.

In the literature review we outlined how previous studies are predominantly focused on the optimal length of the look-back period over which historical returns are examined to construct the portfolio. An example is the study by Jegadeesh & Titman (1993) who evaluate momentum profitability based on look-back periods of 3, 6, 9 and 12 months. On the other hand, very few scholars have focused on the optimal length of the lag period between the look-back and holding period. Novy-Marx (2012) argues that implementing a lag period of six months between the look-back and holding period will result in higher returns. In other words, stocks are selected based on the performance from the period

[5] For more information regarding transaction costs and costs related to shorting, we refer to chapter 6.

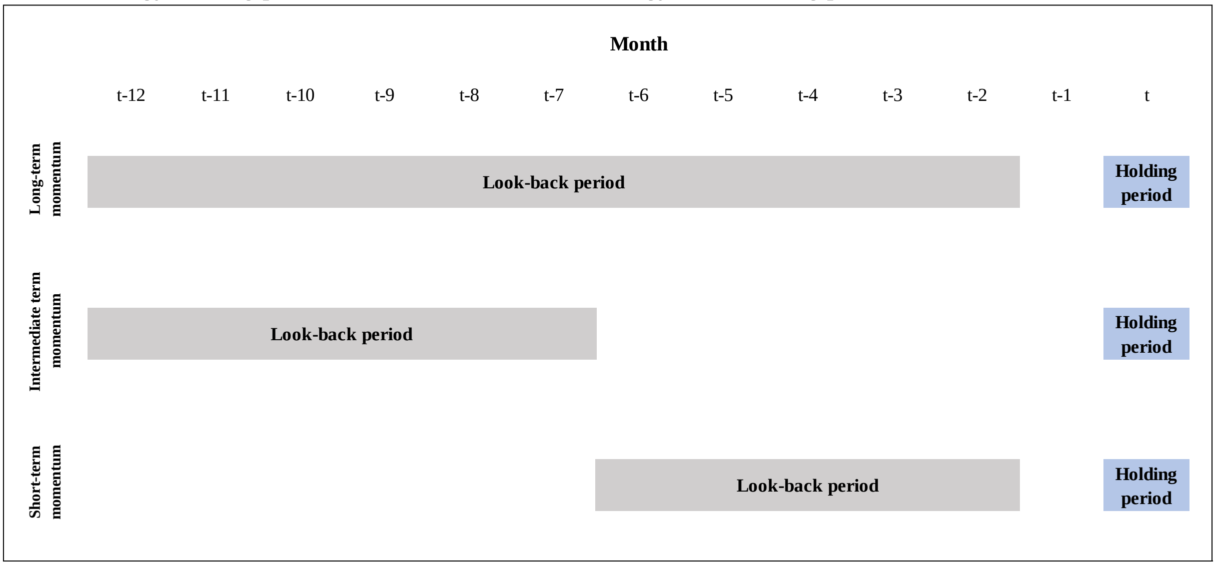
t-12 to t-7. Hence, in the second strategy we examine intermediate-term momentum as proposed by Novy-Marx (2012). The first portfolios are constructed in January 2007, while the first look-back and ranking period for this strategy will be from start of January 2006 to the end of June 2006.

Finally, we examine a short-term momentum strategy adapted from Jegadeesh and Titman (1993). In this strategy stocks are selected based on the performance from the period t-6 to t-2. To keep the strategies more comparable the first formation month for this strategy is still January 2007 and the corresponding look-back period is from start of July 2006 to the end of November 2006.

The formation of the portfolios in abovementioned strategies all follow the methodology described in section 4.4, why it is only the look-back period that differs between the strategies. In line with previous studies (see e.g. Yao, 2012; Novy-Marx, 2012), the holding period in the strategies described above will be fixed at one month to keep the strategies manageable and to avoid overlapping portfolios. Moreover, this will allow us to easily conduct a split of January investing and non-January investing in our analysis. At the end of each holding period the portfolio formation process described above is repeated. As of such in the beginning of every formation month *t*, the long-short positions from the previous month are closed, and the new portfolio for the coming month is constructed. Figure 4.2 below graphically illustrates the momentum strategies examined in this study.

Figure 4.2: Momentum strategies

The following figure is an illustrative example of the momentum investment strategies examined in the analysis. Each strategy longs past winners and shorts past losers. The long-term strategy ranks the past performance of stock returns based on a look-back period from t-12 to t-2, the intermediate-term strategy ranking period is from t-12 to t-7 and the short-term strategy ranking period is from t-6 to t-2. Each strategy has a holding period of one month.



Source: Own creation

4.6 Descriptive statistics

Table 4.1 below presents descriptive statistics for the total sample and for the average portfolio at the time of formation (*t*) across the sample period. Over the entire sample period we have included 1,254 unique companies in our analysis. This includes 1,002 currently listed companies and 252 which were delisted during our sample period. Across our period of analysis, an additional 162 companies were delisted, however due to a lack of data availability these are not included in the final data sample. The numbers presented in Panel B illustrates averages at the time of formation *t* after excluding companies with a market capitalization below the pre-determined level as explained in section 4.4.1. On average we consider 518 firms at the time of each formation month resulting in ~52 companies per decile. This also implies that on average our zero-cost momentum strategy includes 104 companies in each holding period. As evident from the avg. market cap and the median, our sample is highly dispersed in terms of size with some very big companies driving up the average market cap. The average total market capitalization at the time of formation was 8,895 DKK billion. To put this in perspective to the current market situation, the total market capitalization of our sample as of January 2021 is approximately 15,000 DKK billion.

Table 4.1: Descriptive statistics

Descriptive statistics for the sample period January 2007 – January 2021. Panel A shows descriptive statistics for the total sample, whereas Panel B represents statistics for the average formation month *t* in the sample period after excluding companies with a market capitalization below the pre-determined level.

Panel A	Descriptive statistics
	Total sample
Total number of firms across sample	1,254
Number of currently listed firms	1,002
Delisted firms	252
Panel B	
	Averages for time *t*
Number of firms considered at time *t*	518
Number of firms in a decile portfolio	52
Total capitalization (DKK billion)	8,895
Avg. market cap (DKK million)	16,891
Median (DKK million)	1,412

Source: Own creation

4.7 Stock returns

4.7.1 Look-back period returns

As mentioned earlier, to identify winners and losers, companies are ranked using the decile method based on stock returns during the look-back period. The following formula is used to calculate cumulative stock returns over the look-back period:

$$R_i = \frac{P_{i,1} - P_{i,0}}{P_{i,0}} \quad \textbf{(4.2)}$$

$R_i = Return\ on\ stock\ i$

$P_{i,1} = Adjusted\ stock\ price\ of\ i\ in\ end\ of\ look - back\ period$

$P_{i,0} = Adjusted\ stock\ price\ of\ i\ in\ beginning\ of\ look - back\ period$

This formula is similar to formula 2.1 with the only difference being that stock prices in formula 4.2 are adjusted for dividends and stock splits.

4.7.2 Portfolio return

Equally and adjusted value weighted portfolios

For the portfolios in the analysis that are constructed based on an equal weighted scheme, the monthly portfolio return is calculated as the arithmetic mean of each company's monthly return. Thus, the formula for calculating monthly portfolio return is as follows:

$$R_P = \frac{1}{n} \sum_{i=1}^{n} R_i \quad \textbf{(4.3)}$$

$n = number\ of\ companies\ in\ portfolio$

The calculation of return for the portfolios constructed based on the adjusted value weight scheme is conducted as follows. First, individual weights for each stock are computed using the methodology outlined in section 4.4.3. Next, these weights are multiplied with the respective monthly return of each stock, and finally the sum of the products is calculated to get the monthly returns. As a formula this is written as:

$$R_P = \sum_{i=1}^{n} R_i * w_i \quad \textbf{(4.4)}$$

$n = number\ of\ companies\ in\ portfolio$

Excess return

Throughout the analysis excess returns are used as a primary performance measure for our momentum strategies. Whenever we refer to excess returns, we refer to the return of a portfolio in excess of the risk-free interest rate. As of such the formula for excess return of a portfolio is as follows:

$$R_P^e = R_P - r_f \quad \textbf{(4.5)}$$

$r_f = risk - free\ rate$

For the monthly risk-free rate, historical data for the Swedish 1-month T-bill rate has been collected from riksbank.se. The Swedish risk-free rate has been applied due to easily available data and has been found adequate under the assumption that the risk-free rates for Nordic countries have been relatively similar over the course of our sample period.

Zero-cost portfolios

To calculate the zero-cost portfolio return, i.e. a portfolio with a long position in P10 and a short position in P1, the following formula is used:

$$R_{P10-P1}^e = R_{P10} - R_{P1} \quad \textbf{(4.6)}$$

There is no differentiation between returns and excess returns for the zero-cost portfolios due to the following equation's display of equality. As of such we use the terms interchangeably for momentum strategies throughout this study.

$$R_{P10-P1}^e = R_{P10-P1} = (R_{P10} - r_f) - (R_{P1} - r_f) = R_{P10} - R_{P1} \quad \textbf{(4.7)}$$

Performance measures

Having established how monthly portfolio returns are calculated, we consolidate these to calculate the average monthly excess return of the individual investment strategies (long-term, intermediate-term and short-term) and relative strength portfolios (P1 to P10), throughout the sample period analysed. The most widely used measure of average is the arithmetic mean. Thus, to calculate average portfolio return the sum of all the monthly returns is divided by the total number of months in the sample period, i.e. 169 observations.

Furthermore, the monthly standard deviation of excess returns is calculated using the following formula:

$$SD(R_P^e) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \quad \textbf{(4.8)}$$

$N = number\ of\ observations$

$x_i = Excess\ return\ for\ month\ i$

$\bar{x} = Average\ monthly\ excess\ return$

While the annualized Sharpe ratio is calculated as follows:

$$SR_{annualized} = \frac{\overline{R_P^e}}{SD(R_P^e)} * \sqrt{12} \quad \textbf{(4.9)}$$

The first term calculates the monthly Sharpe ratio by dividing the average monthly excess return with its standard deviation. The second term annualizes the ratio.

4.7.3 Returns for delisted companies

In terms of measuring returns for companies which are delisted during the holding period the following is assumed. For companies delisted due to bankruptcy we assume a return of -100% and for companies delisted due to other reasons return is assumed to be 0%. In other words, when companies are delisted for other reasons than bankruptcy, we receive cash equivalent to the amount invested in the beginning of the holding period. Thus, the cause of each delisting has been examined using the Nasdaq Nordic Surveillance reports in order to determine their effect on the estimated return. Of the 252 delisted companies included in the analysis 41 of these were delisted due to bankruptcy.

4.8 Statistical tests

In this section, the various statistical methods used to test the credibility and significance of our results will be covered.

Throughout the analysis several two-sided t-tests have been conducted to test if our results are statistically significant. Two-sided tests have been chosen as opposed to one-sided tests for the following reasons. First, to increase the credibility of statistical significance. Second, as the excess returns for loser portfolios generally hover around zero, achieving both negative and positive values, a two-tailed test was deemed more appropriate.

One-sample t-tests are used throughout the study to test whether a given mean is statistically different from a specified value. Unless otherwise specified, the one-sample t-tests tests against the null hypothesis that the mean is equal to 0.

The following formula calculates the t-statistic for a one-sample t-test:

$$t = \frac{\bar{x} - \mu_0}{\frac{SD}{\sqrt{N}}} \quad \textbf{(4.10)}$$

$SD = Sample\ standard\ deviation$

$\bar{x} = Sample\ mean$

$\mu_0 = Specified\ value\ for\ null\ hypothesis\ (equal\ to\ 0\ in\ most\ cases)$

Two-sample t-tests assuming unequal variances, otherwise known as Welch's t-tests, are applied to test whether the mean returns of our proposed strategies are significantly different from each other. For the two-sample t-tests the t-statistic is defined by the following formula:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{SD_1^2}{N_1} + \frac{SD_2^2}{N_2}}} \quad \textbf{(4.11)}$$

$N_i = number\ of\ observations\ for\ a\ given\ sample$

$SD_i = Sample\ standard\ deviation$

$\bar{x}_i = Sample\ mean$

4.8.1 Regression methodology

Coupled with our one- and two-sample t-tests we also perform a range of regression analyses throughout the study. These regressions are used in accordance with the CAPM and three- and four-factor models. All regressions are computed in excel using the ordinary least squares (OLS) method.

The ordinary least squares regression model is defined as follows:

$$y = \alpha + \beta_1 * x_1 + \beta_2 * x_2 + \cdots + \beta_i * x_i + \varepsilon \quad \textbf{(4.12)}$$

$y = Dependent\ variable$

$\beta_i = Regression\ coefficients$

$\alpha = Intercept$

$\varepsilon = Error\ term$

For each estimated regression coefficient and for the intercept an associated test-statistic is computed that follows a t-distribution, like the previous one-sample and two-sample t-tests. This t-statistic is used when evaluating the statistical significance of each regression coefficient. The test statistic for the OLS method is defined as the coefficient divided by its standard error. Unless otherwise stated, the null hypothesis for the OLS regressions is that the regression coefficients are equal to zero.

4.8.2 Assumptions

In accordance with the application of statistical t-tests and regression methodology we assume the following assumptions hold about our data sample:

1. Linearity
2. Random sampling of observations
3. Conditional mean equal to zero
4. No linear relationship between independent variables
5. Homoscedasticity
6. Normality

The OLS methodology has been extensively used by other studies, why we deem the test of these assumptions as outside the scope of this paper. However, we realise that due to the nature of stock data some assumptions such as homoscedasticity and normality may not hold.

4.9 Market Index and factor models

To gain a better understanding of the profitability of the momentum strategies outlined in section 4.5, we regress the returns obtained from these with a chosen market index. The purpose of comparing the momentum returns we obtain with a market index is to examine whether our returns can be explained by the systematic risk of the market. In other words, we test the hypothesis of whether the momentum strategies produce significant profits by systematically picking high-risk stocks. If we observe momentum returns being positive and statistically significant after accounting for the market risk, it implies that the efficient market hypothesis and CAPM first introduced by Fama (1970) does not explain the momentum effect.

For the purpose of this study the MSCI (Morgan Stanley Capital International) Nordic Countries Index will be used as a benchmark for market performance. The index includes companies listed in Denmark, Sweden, Norway and Finland and captures approximately 85% of the free-float adjusted market capitalization in each country. The index is value-weighted and includes 79 constituents of which approximately 8% of these are from Norway[6] (MSCI, 2021). Moreover, the index is adjusted for dividend payments allowing us to make a more accurate comparison of the obtained momentum returns versus market returns. Based on these factors we find the MSCI Nordic Countries Index suitable for this study.

Much like the market index, we employ the use of other risk factors for the three- and four-factor models, as proposed by Fama & French (1996) and Carhart (1997) respectively. For a more in-depth explanation of these models we refer to section 2.3. The other risk factors applied in the three-factor model, aside from market risk, are those of SMB (small-minus-big) and HML (high-minus-low). These factors represent the risk associated with stocks of different size and book-to-market values. The factors predict that more risk is associated with stocks that are small and stocks that have high-book-to-market values. The final factor that is applied in the four-factor model controls for momentum (winners-minus-losers).

The monthly values for these factors across our sample period, have been collected from the Kevin R. French website. It should be noted that these factors have been computed using stocks from multiple countries in Europe, and not just the countries analysed in this study. A list of countries used to compute these factors can be found in appendix 2.

[6] As of March 31, 2021

4.10 Market dependent beta

To examine whether the market betas of our strategies vary with market conditions, we apply the following regression.

$$R_t^e = \alpha + \beta^{up} D_t [R_m^e] + \beta^{down} (1 - D_t)[R_m^e] + \varepsilon_t \quad \textbf{(4.13)}$$

$R^e = Excess\ return\ of\ strategy$

$\alpha = Intercept$

$\beta^{up} = Beta\ in\ up\ markets$

$\beta^{down} = Beta\ in\ down\ markets$

$R_m^e = Excess\ return\ of\ market$

$D = Dummy\ variable$

$\varepsilon = Error\ term$

Down markets are defined as all the months where the market experience negative excess returns, and up markets are defined as months with positive excess returns. As of such, D is a dummy variable equal to one if the excess returns of the MSCI index in month *t* is positive, and otherwise equal to zero.

4.11 January Effect

4.11.1 Marginal strategies

For the purpose of determining the degree to which the January Effect is present in the Nordic stock markets and determine its impact on the profitability of the momentum strategies we employ the marginal strategy method as depicted by Yao (2012). In the marginal strategy, you still take a long position in past winners and a short position in past losers and stocks are also still ranked using the decile approach. The marginal strategy differs from the traditional momentum strategy where performance is evaluated based on performance in month t-x, where x is between 1 to 12. Thus, stocks are ranked based on the performance in a <u>single month</u>. To understand the January Effect better we will conduct an analysis using marginal strategies that only includes January investing, and an analysis that excludes January investing. In the analysis we will also apply both the equal- and adjusted value-weighted methodology.

In summation, the portfolio formation of marginal strategies is equivalent to the process described in section 4.4 with the only difference being in terms of the look-back period, where in the previous formation strategies we would rank stocks based on performance in more than one month.

4.12 Software

For the purpose of this study all portfolio formation, portfolio return calculations, regressions and statistical tests have been conducted in excel. For gathering of data, the S&P Capital IQ excel plugin has been applied, which pulls adjusted closing prices and market capitalization from the Capital IQ database, given an equity's ticker and a given date.

5. Empirical Results

The following chapter will present the results of our analysis in accordance with the following structure. First, we focus on the overall momentum returns for the three strategies outlined in section 4.5. Second, we analyse the momentum returns of size sub-samples to examine the implications of size and the small-firm effect on momentum. Finally, we investigate the degree to which the January Effect is present in the Nordic stock market, as well as its implications for our momentum strategies.

Throughout this chapter we will present inferential statistics to assess whether our results can be used to draw conclusions based on our data sample. With 169 observations, i.e. total formation periods in our analysis, and the application of two-sided t-tests a t-statistic of 2.576 implies a 1% significance level, whereas t-statistics of 1.960 and 1.645 implies significance levels at 5% and 10% respectively.

5.1 Overall momentum returns

This section examines whether momentum strategies have been profitable in the Nordic stock markets (excluding Norway) for the sample period covering January 2007 to January 2021. Table 5.1 below presents the average monthly excess returns, the standard deviation of excess returns and the annualized Sharpe ratios of relative-strength portfolios formed from the past performance of stocks 12-to-2 months, 12-to-7 months, and 6-to-2 months prior to portfolio formation. The three different historical performance horizons correspond respectively to the long-term, intermediate-term and short-term momentum strategies analysed in this study. For each strategy and for every formation month *t*, stocks are ranked based on their historical cumulative returns and are distributed into decile portfolios. The first decile portfolio (P1) contains the worst performing stocks, while the tenth decile portfolio (P10) contains the best performing stocks of the same period. The return of each momentum (winner-minus-loser) strategy is presented in the second to last row of every panel (P10-P1). In Panel A results for the equal weighted portfolios are presented, whereas Panel B presents results based on an adjusted value weighting method[7]. Each presented t-statistic is a two-sided test against the null hypothesis that past winners do not outperform past losers, i.e., that the excess returns of each momentum strategy is not significantly different from zero.

In total, three different sets of strategies with two different weighting methods have been formed and examined to test for significant momentum returns. As is evident from table 5.1 below, there is a clear pattern throughout all strategies that higher decile portfolios consistently outperform lower decile portfolios both in terms of mean returns but also in terms of the annualized Sharpe ratio. As of such for every different ranking strategy, winners (P10) outperform losers (P1) by a large margin resulting in positive excess returns for all momentum strategies. As implied by the t-tests, these returns are all statistically significant at the 1% level, thereby indicating that the profitability of the momentum strategies is not caused by simple luck or due to chance.

The largest mean return and Sharpe ratio is realised by the equally weighted short-term momentum strategy (6-2 strategy), with average monthly excess return of 2.0 percent and an annualized Sharpe ratio of 1.4. If we examine this strategy in the context of the other equally weighted strategies we observe a sizeable (0.57%), but not statistically significant, difference in excess returns compared to the intermediate-term strategy (12-7 strategy) (t-stat = 1.61). When comparing the short- and long-term strategy (12-2 strategy) the difference in returns is close to zero, and also not statistically significant (t-stat = 0.26). Finally, comparing the equally weighted 12-2 and 12-7 strategies we find a large difference in average monthly excess returns (0.51%), which is statistically significant at the 10% level (t-stat = 1.91).

[7] For more information on the applied methodology for adjusted value weighting, we refer to section 4.4.3

Table 5.1: Overall momentum returns

Average monthly excess returns (in percent), standard deviation of excess returns (in percent) and annualized Sharpe ratios of relative-strength portfolios created based on the historical performance of stocks in the Nordic markets. The t-stats are two-sided and tests whether excess returns of buying past winners and selling past losers is significantly different from zero. P1 is defined as losers while P10 is defined as winners. P10-P1 represents the respective momentum strategy. The sample period spans from January 2007 to January 2021. The portfolios in Panel A are formed based on the equal weighted scheme, whereas portfolios in Panel B are based on an adjusted value weight scheme.

	Long-term momentum (12-2)			Intermediate-term momentum (12-7)			Short-term momentum (6-2)		
	Mean	SD (%)	SR	Mean	SD (%)	SR	Mean	SD (%)	SR
Panel A: *equal weight*									
P1	-0.39	7.96	-0.17	-0.17	6.98	-0.09	-0.51	7.71	-0.23
P2	0.07	6.09	0.04	0.09	5.94	0.05	0.32	6.10	0.18
P3	0.35	5.64	0.21	0.63	5.50	0.40	0.58	5.53	0.36
P4	0.62	5.22	0.41	0.73	5.49	0.46	0.60	5.27	0.39
P5	0.71	5.32	0.46	0.80	5.14	0.54	0.75	5.14	0.50
P6	0.99	4.92	0.69	0.73	4.96	0.51	0.80	5.05	0.55
P7	0.99	4.98	0.69	1.01	5.24	0.66	1.06	5.05	0.73
P8	1.18	5.10	0.80	0.98	5.12	0.67	1.11	4.98	0.77
P9	1.15	5.30	0.75	1.17	5.34	0.76	1.06	5.20	0.71
P10	1.55	5.47	0.98	1.26	5.83	0.75	1.50	5.64	0.92
P10 - P1	1.94	5.47	1.23	1.43	4.20	1.18	2.00	4.96	1.40
t-Stat.	[4.62]			[4.43]			[5.25]		
Panel B: *Adj. value weight*									
P1	-0.25	8.07	-0.11	0.03	6.87	0.01	-0.23	7.57	-0.10
P2	0.37	6.23	0.21	0.06	6.05	0.04	0.48	6.30	0.26
P3	0.51	6.06	0.29	0.65	5.79	0.39	0.74	5.84	0.44
P4	0.55	5.67	0.34	0.73	5.82	0.44	0.82	5.35	0.53
P5	0.70	5.40	0.45	0.81	5.13	0.55	0.73	5.25	0.48
P6	1.10	4.97	0.76	0.72	4.72	0.53	0.79	5.27	0.52
P7	0.79	4.95	0.55	0.91	5.29	0.60	0.89	5.02	0.61
P8	0.99	5.01	0.69	0.92	5.04	0.63	0.91	4.88	0.65
P9	1.12	5.21	0.74	1.14	5.38	0.74	1.03	4.99	0.72
P10	1.40	5.53	0.88	1.38	5.83	0.82	1.22	5.61	0.75
P10 - P1	1.65	6.48	0.88	1.35	5.05	0.93	1.45	5.56	0.90
t-Stat.	[3.31]			[3.48]			[3.38]		

Source: Own creation

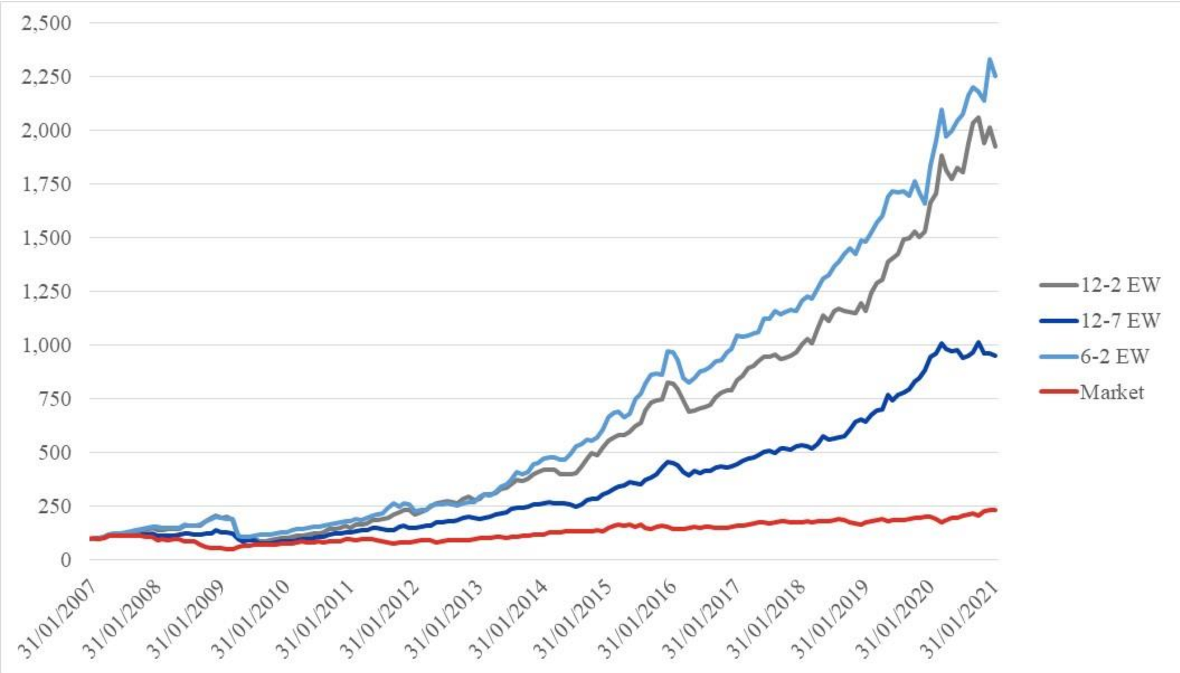
The returns for the adjusted value weighted strategies tell a similar story. Here the average return of 1.65 percent generated by the 12-2 strategy is higher than the other strategies, however the differences in returns are less prominent than in the equal weighted method and as of such no statistical significance was found between these. Since we in both cases cannot reject the null hypothesis that the short-, intermediate- and long-term momentum strategies produce identical returns, our observations are in contrast to the findings of e.g. Novy-Marx (2012) who found that the intermediate-term strategy produce significantly higher returns than the short-term strategy.

While we do not find statistical significance to draw any conclusions that one strategy significantly outperforms the others, figure 5.1 below presents the indexed cumulative returns for the three equally weighted momentum strategies and the MSCI Nordic index. From this figure it is evident that in the beginning of the sample period the three strategies obtain somewhat similar returns, whereas from the middle of our sample period the long- and short-term strategies perform considerably better than the intermediate-term strategy. The figure also illustrates that the short-term strategy performs slightly better than the long-term strategy as depicted previously. All strategies heavily outperform the market across our sample period. When comparing the strategies with the market index it is important to bear in mind that the momentum strategies shown are equal weighted whereas the market index is value weighted.

It should be noted that while all the strategies performed poorly during the financial crisis, the graph does not depict this well. As of such, for more information regarding the performance of momentum strategies during the financial crisis we refer to the next section.

Figure 5.1: Cumulative returns of equal-weighted momentum strategies

Indexed cumulative returns of the three equally weighted momentum strategies and the value weighted MSCI Nordic index from 01.01.2007 to 31.01.2021.



Source: Own creation

If we return to table 5.1 and examine the source of profits in the zero-cost portfolios, we can deduce that the winner and loser portfolios (P10 and P1) of the 12-2 and 6-2 strategies are relatively similar in both returns and standard deviation for both equal weighting and value weighting. However, in particular for the equal weighted 12-7 strategy we see less negative returns for the loser portfolio and smaller positive returns for the winner portfolio which ultimately results in less excess return for the strategy overall. In general, it holds true across all strategies that the past winners generate high returns, whereas the past losers generate mostly negative returns. These observations should be encouraging for an investor pursuing momentum strategies, since the investor should be able to generate higher returns by shorting losers and buying winners compared to a strategy merely focusing on buying past winners. Furthermore, since all the strategies are zero-cost based the investor will not have to take money out-of-pocket disregarding margin requirements and transaction costs.

When comparing the different weighting methods, we find that the returns and Sharpe ratios are lower for the value weighted zero-cost portfolios compared to the equally weighted. The largest disparity is found between the short-term momentum returns, where the monthly mean return for the equally weighted portfolio is 2.0 percent and the value weighted method generates a 1.45 percent average monthly return. The higher return of the equally weighted methods suggests that momentum profits are, at least partially, driven by smaller companies, since the value weighted portfolios are more heavily invested in the large companies included in the portfolio. This observation is most prominent in the 12-2 and 6-2 strategies, while the difference between the 12-7 weighting methods is relatively small and insignificant. Similarly, when comparing Sharpe ratios across the weighting methods, all value weighted strategies realise very similar results, with Sharpe ratios ranging from 0.88 to 0.93. However, for equal weighting the Sharpe ratios of each strategy is markedly higher ranging from 1.18 to 1.43, with the short-term strategy observed to have the largest Sharpe ratio compared to the other strategies. These two observations imply that small firms as a driver for momentum profits may be present in all strategies, but is more prominent in the long- and especially the short-term strategies, while the intermediate-term strategy profits may not be driven as heavily by small companies.

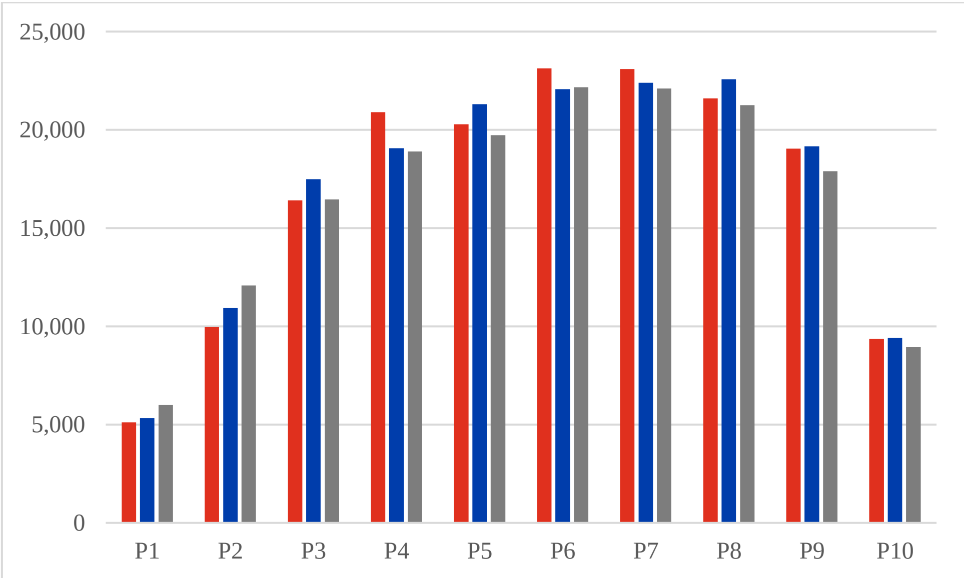
To gain a further understanding of average company size and its implications for our proposed strategies, table 5.2 presents the average market capitalizations and medians for companies in every constructed decile portfolio.

Table 5.2 and figure 5.2: Average market capitalizations and medians

Average market capitalizations and medians for constructed relative-strength portfolios across the entire sample period. P1 is the decile of stocks with the lowest past returns, and P10 is the decile of stocks with the highest returns in the same period. Values are presented in DKK million. The red bar chart represents the 12-2 strategy, the blue represents the 12-7 and the grey represents the 6-2.

	Long-term momentum (12-2)		Intermediate-term momentum (12-7)		Short-term momentum (6-2)	
	Avg. market cap	Median	Avg. market cap	Median	Avg. market cap	Median
P1	5,110	541	5,333	595	5,989	638
P2	9,968	1,033	10,950	1,097	12,085	1,131
P3	16,401	1,532	17,478	1,455	16,454	1,426
P4	20,894	1,857	19,058	1,746	18,902	1,668
P5	20,277	2,105	21,303	2,202	19,731	1,985
P6	23,127	2,629	22,065	2,554	22,167	2,449
P7	23,095	2,925	22,393	2,646	22,106	2,636
P8	21,602	2,808	22,575	2,763	21,255	2,577
P9	19,048	2,411	19,158	2,524	17,891	2,351
P10	9,358	1,160	9,409	1,155	8,940	1,099

Average market capitalizations



Source: Own creation

The average values for market capitalization and medians of companies in their respective portfolio provide us with further confirmation that the average company for winner and loser portfolios are predominantly small. If we look at figure 5.2, we see that all three strategies follow a similar distribution of market capitalization, with the larger companies being more concentrated in the middle portfolios. In table 5.2 we also observe a large discrepancy between median and average market cap for every portfolio, this indicates that each portfolio holds few very large companies which cause the average market cap to inflate, however, the distribution of medians across portfolios is relatively similar to that of average market capitalization. Furthermore, the fact that we see the smallest companies having the lowest average returns, implies a negative relation between size and expected return and thus suggests that size as a risk factor will not be able to explain the momentum effect.

An interesting observation is that while companies in P10 and P1 are both on average smaller than companies in portfolio P2 to P9, the losers portfolio appears to contain firms that on average are nearly half the size of the companies in P10. This indicates that momentum profits are not only driven by smaller firms but by small firms outperforming even smaller firms. This finding is consistent with the findings of e.g. Jegadeesh and Titman (1993), Rouwenhorst (1998), Fama and French (2008) and Booth et. al. (2016) among others, who all found the momentum effect to be concentrated in small firms. However, an interesting and important note to consider when examining these results is that the momentum strategies themselves are self-fulfilling in having the average winner be larger than the average loser. To understand this, we can consider two firms having the same size at time t-12, one firm performs well over the next year (Firm A) while the other firm performs poorly (Firm B). Following the strategy, we will long Firm A and short Firm B at time *t* when we construct our portfolio, however as performance persists Firm A will now be larger than Firm B at the time of investment. The size differential may thus be due to how the strategy itself is constructed. Section 5.2 will go more in depth with the aspect of size and its implications for momentum strategies and test the hypothesis of a small firm effect as a driver for momentum.

To summarize this section, by examining a sample period covering January 2007 to January 2021 we determined that zero-cost momentum strategies have been profitable in the Nordic market across this time period, and as of such that past winners consistently outperform past losers regardless of the momentum strategy chosen. We tested for significant differences between the strategies but were unable to make a conclusion based on statistical evidence, though the best performing strategy in terms of returns and Sharpe ratio was the equally weighted short-term strategy. Moreover, we found that the equally weighted strategies outperformed the value weighted strategies in all cases, thereby indicating that momentum profits are predominantly present in small firms. We further tested this hypothesis by examining the average market cap of each portfolio and found that the firms of the bottom decile portfolio on average are smaller than the firms in the winner decile. Furthermore, we found that both winner and loser portfolios on average are smaller than the rest of the sample portfolios. This raises the questions of whether momentum profits are limited to smaller stocks and is driven by small stocks outperforming even smaller stocks. The answer to these questions will be covered in section 5.2.

5.1.1 Risk adjusted returns

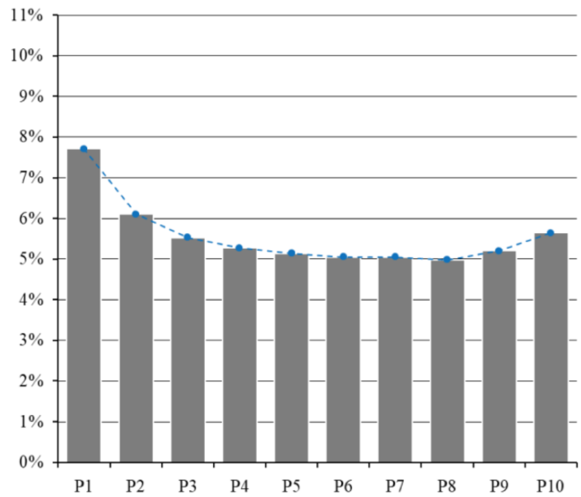
In the previous section we confirmed the profitability of our momentum strategies across our sample period. The following sections will introduce the aspect of risk by applying the CAPM and Fama-French 3 Factor model to determine whether these profits can be explained and attributed to these types of risk, or if the strategies generate a positive abnormal return (α) despite introducing these factors.

Standard deviation

First, we examine table 5.1 in terms of the standard deviation of the decile portfolios. Looking at the standard deviations it is evident that they follow almost a U-shape. This finding is also presented in figure 5.3, which illustrates the standard deviation of the deciles in the equally weighted long-term strategy. The U-shape infers that on average companies in the most extreme portfolios, i.e., P1 and P10, have a higher standard deviation of return than companies in the mid deciles. This finding is in line with the study by Rouwenhorst (1998) reviewed in chapter 3, who also found that the standard deviation of the decile portfolios follows this shape. The U-shape of the standard deviation of returns is easily explained by the fact that stocks with a higher standard deviation are more likely of realising extreme returns. As of such, our strategies pick and sort these stocks into our extreme portfolios more often. While this explains the shape of figure 5.3, it fails to account for why we observe high standard deviations being associated with both high and low returns, as per the excess returns of P10 and P1 observed in table 5.1. We will attempt to provide an explanation for this by examining our returns in a CAPM context.

Figure 5.3: Standard deviations for P1 to P10

Standard deviations for relative-strength portfolios of the equal-weighted long-term momentum strategy (12-2). Due to similarity of results the corresponding figures for the remaining strategies have not been posted, but can be deduced from the values of table 5.1



Source: Own creation

If we take a closer look at the standard deviation of the excess return of our winner-minus-loser strategies we see that they range between 4.20 to 5.47 for equally weighted strategies and 5.05 to 6.48 for value weighted strategies per month. This level of volatility is in most cases worse or similar to the volatility of a long position in a middle decile portfolio (i.e., P4 to P7), which indicates that the momentum strategy portfolios may not be extremely well-diversified. It should be noted however, that if we compare excess return per level of volatility (Sharpe ratio) the momentum strategies strongly outperform the middle deciles in every case.

CAPM

This section will apply the CAPM to determine whether our observed momentum profits can be explained and attributed to market exposure. As of such the systematic risk of the market will be the first risk-factor introduced to help explain our excess return. Table 5.3 presents the estimated market betas and alpha values for each relative-strength portfolio. These values have been computed using monthly returns of the portfolios in the sample period, covering January 2007 to January 2021, relative to the MSCI Nordic index during the same period.

Much like how the standard deviation is a measure of risk, the market beta measures the level of systematic risk each portfolio is subject to, or in other words, their correlation with the market. It should be noted that the market betas do not capture idiosyncratic risk, however, due to the number of firms in each portfolio, much of the idiosyncratic risk should have been diversified away. As of such by introducing the market as a risk factor, we test the hypothesis of whether the momentum strategies produce significant profits by systematically picking high-risk stocks.

Table 5.3: Portfolio market β and abnormal returns α

Market betas and CAPM alphas (in percent) for the relative-strength portfolios. The reported values for each portfolio have been computed relative to The Morgan Stanley Capital International (MSCI) Nordic index, using the CAPM and monthly excess returns from January 2007 to January 2021. The MSCI Nordic index includes large cap stocks from the countries of Denmark, Sweden, Finland, and Norway and captures 85% of the total market value of these countries. The index is value-weighted and adjusted for dividends and stock splits. t-statistics are two-sided and presented in square brackets. t-Stat (β) tests whether beta is significantly different from 1 for all relative-strength portfolios except for the zero-cost portfolio (P10-P1) where the null hypothesis is 0. Similarly, t-Stat α tests whether alpha is significantly different from 0.

	Long-term momentum (12-2)				Intermediate-term momentum (12-7)				Short-term momentum (6-2)			
	Market β	t-Stat. (β)	α_{CAPM}	t-Stat. (α)	Market β	t-Stat. (β)	α_{CAPM}	t-Stat. (α)	Market β	t-Stat. (β)	α_{CAPM}	t-Stat. (α)
Panel A: *equal weight*												
P1	1.33	[4.07]	-1.21	[-3.15]	1.14	[1.81]	-0.87	[-2.48]	1.33	[4.31]	-1.32	[-3.72]
P2	1.03	[0.47]	-0.57	[-1.95]	1.05	[0.85]	-0.55	[-2.12]	1.08	[1.41]	-0.35	[-1.31]
P3	1.05	[1.06]	-0.30	[-1.39]	1.01	[0.29]	0.00	[0.01]	1.00	[-0.05]	-0.04	[-0.18]
P4	0.97	[-0.63]	0.01	[0.07]	1.02	[0.54]	0.10	[0.48]	0.96	[-0.92]	0.00	[0.02]
P5	0.97	[-0.57]	0.11	[0.52]	0.93	[-1.54]	0.23	[1.08]	0.96	[-0.97]	0.15	[0.80]
P6	0.91	[-2.25]	0.43	[2.20]	0.91	[-2.08]	0.17	[0.86]	0.93	[-1.63]	0.23	[1.13]
P7	0.92	[-1.93]	0.43	[2.18]	0.98	[-0.44]	0.40	[2.03]	0.92	[-1.86]	0.49	[2.40]
P8	0.92	[-1.77]	0.61	[2.87]	0.93	[-1.53]	0.41	[1.96]	0.90	[-2.26]	0.56	[2.70]
P9	0.96	[-0.92]	0.56	[2.52]	0.98	[-0.44]	0.56	[2.64]	0.96	[-0.86]	0.47	[2.31]
P10	0.89	[-1.82]	1.00	[3.64]	1.00	[0.03]	0.64	[2.38]	0.91	[-1.42]	0.93	[3.25]
P10 - P1	-0.44	[-5.25]	2.21	[5.61]	-0.13	[-1.94]	1.52	[4.69]	-0.41	[-5.46]	2.26	[6.34]
Panel B: *Adj. value weight*												
P1	1.32	[3.77]	-1.07	[-2.66]	1.17	[2.44]	-0.69	[-2.13]	1.34	[4.78]	-1.05	[-3.17]
P2	1.15	[2.86]	-0.34	[-1.38]	1.10	[1.86]	-0.62	[-2.48]	1.18	[3.64]	-0.25	[-1.06]
P3	1.18	[4.50]	-0.22	[-1.13]	1.11	[2.51]	-0.04	[-0.18]	1.13	[3.08]	0.04	[0.21]
P4	1.10	[2.45]	-0.13	[-0.68]	1.12	[3.05]	0.04	[0.19]	1.05	[1.53]	0.17	[1.02]
P5	1.05	[1.33]	0.05	[0.30]	1.00	[0.02]	0.19	[1.16]	1.02	[0.59]	0.10	[0.60]
P6	0.97	[-0.94]	0.50	[3.11]	0.92	[-2.43]	0.15	[1.01]	1.03	[0.73]	0.15	[0.90]
P7	0.96	[-1.26]	0.20	[1.20]	1.03	[0.83]	0.28	[1.64]	0.95	[-1.38]	0.31	[1.64]
P8	0.98	[-0.70]	0.39	[2.44]	0.97	[-0.81]	0.32	[1.87]	0.93	[-1.98]	0.34	[1.96]
P9	0.95	[-1.05]	0.53	[2.53]	1.04	[1.01]	0.50	[2.77]	0.94	[-1.45]	0.45	[2.51]
P10	0.91	[-1.58]	0.84	[3.04]	1.02	[0.42]	0.75	[2.89]	0.93	[-1.22]	0.65	[2.34]
P10 - P1	-0.42	[-4.06]	1.91	[3.96]	-0.14	[-1.75]	1.44	[3.70]	-0.41	[-4.74]	1.70	[4.18]

Source: Own creation

Examining the market betas for the relative-strength portfolios we see that they range from 0.89 to 1.34 across all strategies. While most of these portfolio betas are close to 1.0, we see a tendency for all of the lower deciles i.e. P1, P2, P3, to have slightly higher market betas than their higher decile counterparts. This indicates that the lower decile portfolios contain more risky stocks than the upper decile. This is especially true for the loser portfolios which exhibit the highest beta values, ranging from 1.14 to 1.34. This is consistent with findings of e.g. Jegadeesh and Titman (1993) who also found beta values of loser portfolios to be significantly higher than the other deciles. This seems consistent with our previous discussion of a U-shaped volatility curve, coupled with our finding of the loser portfolio containing smaller than average firms. Furthermore, the beta value of the loser portfolio for the intermediate term momentum strategy is considerably lower than the other two strategies, which is consistent with the less negative returns and smaller standard deviation of the strategy, which can be observed in Table 5.1.

If we bring our attention to the zero-cost portfolios we see negative beta values across the board, this is of course caused by the larger betas of the loser portfolios compared to the winner portfolios. The beta values for the 12-2 and 6-2 strategies are very similar at around -0.4 for each strategy, significant at the 1% level, which indicates that these strategies are not completely market neutral, and thus does not hedge systematic risk. The 12-7 strategy, however, does not have a market beta significantly different from 0 and should work as hedge against the market.

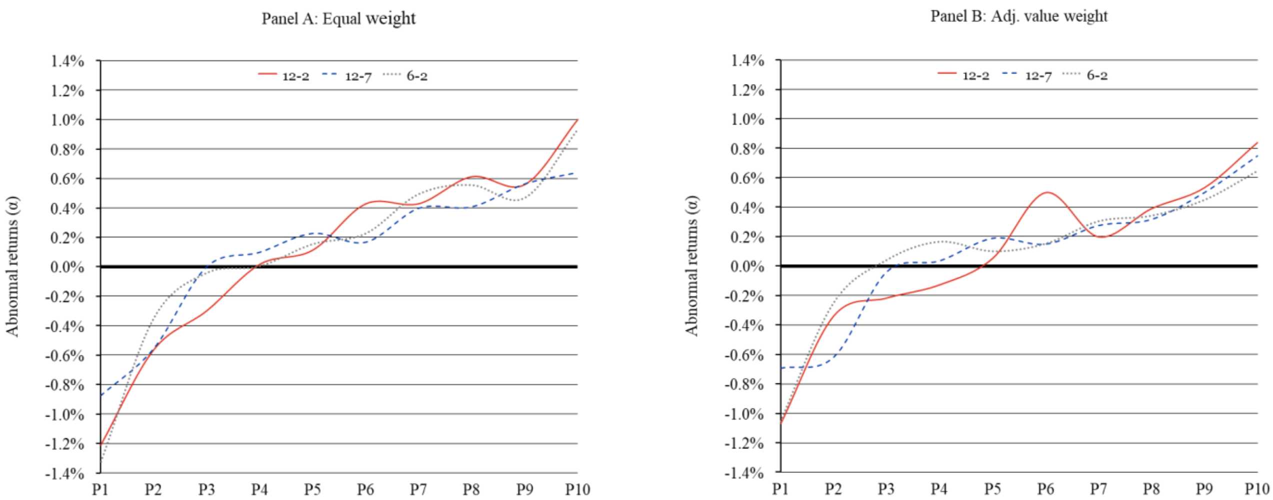
If we were to have our excess returns be fully explained by a negative beta, the market would need negative excess returns on average over the past 15 years, which is empirically untrue. The average monthly excess market return of the MSCI Nordic index for our sample period is 0.62 percent. For the beta to fully explain the momentum returns of around 1.5 to 2 percent per month, the market beta of the winner portfolio would have to exceed the beta of the loser portfolio by 2.5 to 3. As of such we can conclude that the market beta does not explain all of our excess returns. This amount of return that cannot be explained by beta is referred to as abnormal returns, otherwise known as alpha (α).

The alpha values represent the amount of excess return that cannot be explained by the market risk factor, as of such a positive and significant alpha for our zero-cost portfolios is an indicator of the momentum effect. As we can see from table 5.3, all alpha values for our zero-cost portfolios are positive and statistically significant at the 1% significance level. The highest level of alpha is realized by the equally weighted long-term and short-term strategies at 2.21 and 2.26 percent, respectively. While the corresponding equally weighted intermediate-term momentum strategy realises an alpha of 1.52 percent. The dispersions and relative differences between these alpha values, across all strategies and weighting methods, closely resemble the previously posted excess returns of table 5.1. As of such we see no significant difference between the short-term and long-term strategy in the equally weighted method, but a larger difference in the value weighted method. Furthermore, we still see that the intermediate-term strategy realises smaller returns than its counterparts across both weighting methods, and the largest disparity between alphas to be between the weighting methods of the short-term strategy.

It is interesting to note that the alpha values of the zero-cost portfolios are slightly higher than the excess returns observed in our initial analysis. This is caused by the negative market beta and stands as a further sentiment of the inability for the CAPM and the market risk factor to fully explain the momentum effect.

Figure 5.4: Abnormal returns (α) to relative-strength portfolios

Illustrative overview of the average monthly abnormal returns to equally weighted and adjusted value weighted relative-strength portfolios. Computed using the CAPM and average monthly excess returns relative to the MSCI Nordic Index. The X-axis holds the different portfolios P1 to P10, where P1 is past losers and P10 is past winners. The Y-axis holds the values for alpha. The figure differs between the long-term (solid red), intermediate-term (dashed blue) and short-term (dotted grey) momentum strategies. The sample period covers January 2007 to January 2021. Panel A depicts equal-weighted strategies, while Panel B depicts adjusted value weighted strategies.



Source: Own creation

If we bring our attention to the decile portfolios, we see that all winner and loser portfolios realise statistically significant alpha values. An important observation to make is the almost linear relationship between the relative-strength portfolios and abnormal returns present across all strategies and both weighting methods. By plotting P1 to P10 against abnormal returns, figure 5.4 illustrates this notion graphically. The figure depicts a steeper curve for the 12-2 and 6-2 strategies compared to the 12-7 strategy. Though much of this steepness stems from the larger concentrations in the tail end of the distributions.

For most strategies, a larger source of abnormal returns seems to stem from the short side, this is especially true for the short-term strategy, where we see for the value-weighted method 1.05 percent of abnormal returns coming from the short side while only 0.65 percent comes from the long-side. The reason for this is that the loser portfolios have a larger absolute value of expected abnormal returns compared to the winner portfolios. This implies that the momentum effect is driven more by the underperformance of losers, compared to the outperformance of winners. This is consistent with the findings of e.g. Hong et. al. (2000) who found similar results. The only exception to this seems to be the value weighted 12-7 strategy where both the winner and loser portfolio contribute roughly evenly to the abnormal returns. This is consistent with the findings of e.g. Novy-Marx (2012).

To summarize this section, we first conclude that even after adjusting for systematic risk the momentum strategies continue to realise positive abnormal returns not explained by the CAPM. Second, we show that there is a close to linear relationship between our decile portfolios and expected abnormal returns. Finally, we conclude that in most cases a larger part of momentum profits stem from the underperformance of losers instead of the outperformance of winners.

Market dependent betas

In the previous section we found that both the short-term and long-term strategies have a negative correlation with the market that is statistically significant. This would suggest that these strategies generate stronger profits in market downturns, which is contradictory to our own findings as well as previous literature that found the momentum strategy to perform poorly during the subprime crisis of 2007-2010 (see appendix 3 for graph on trailing Sharpe ratio). To address this finding, we examine whether the market betas of our strategies vary with market conditions. For varying market betas to explain our positive returns it would require that losers have a higher beta than winners in down markets and a lower beta in up markets. Down markets are defined as the months where the market experiences negative returns, while up markets are defined as months with positive returns.

Table 5.4: Market dependent betas and abnormal returns

Alpha and beta values for the relative-strength portfolios. The reported alpha and beta values for each portfolio have been computed relative to The Morgan Stanley Capital International (MSCI) Nordic index, using monthly excess returns from January 2007 to January 2021 and the following regression:

$$R_t^e = \alpha + \beta^{up} D_t [R_m^e] + \beta^{down} (1 - D_t)[R_m^e] + e_t$$

Where D is a dummy variable equal to one if the excess returns of the MSCI index in month t is positive and equal to zero otherwise. R_m^e is the excess return of the MSCI index. t-statistics are two-sided and presented in square brackets. t-Stats for up and down-market beta tests whether the beta value is significantly different from 1 for P1 and P10, whereas for P10-P1 we test if they are significantly different from 0. Lastly, t-Stat α tests whether alpha is significantly different from 0.

Portfolio	α	t-Stat. (α)	β^{up}	t-Stat. (β^{up})	β^{down}	t-Stat. (β^{down})	Adj. R^2
			Panel A: *equal weight*				
Long-term (12-2)							
P1	-2.36	[-4.38]	1.68	[4.79]	1.01	[0.08]	0.63
P10	1.16	[2.96]	0.84	[-1.51]	0.94	[-0.60]	0.58
P10 - P1	3.52	[6.43]	-0.84	[-5.79]	-0.07	[-0.51]	0.20
Intermediate-term (12-7)							
P1	-1.47	[-2.94]	1.32	[2.40]	0.97	[-0.27]	0.59
P10	0.86	[2.23]	0.93	[-0.64]	1.06	[0.66]	0.65
P10 - P1	2.34	[5.12]	-0.39	[-3.19]	0.10	[0.86]	0.06
Short-term (6-2)							
P1	-2.38	[-4.79]	1.65	[4.93]	1.03	[0.22]	0.67
P10	0.99	[2.39]	0.90	[-0.94]	0.93	[-0.69]	0.57
P10 - P1	3.37	[6.79]	-0.75	[-5.73]	-0.10	[-0.79]	0.20
			Panel B: *adj. value weight*				
Long-term (12-2)							
P1	-2.50	[-4.49]	1.76	[5.16]	0.92	[-0.58]	0.62
P10	1.07	[2.71]	0.84	[-1.56]	0.97	[-0.27]	0.59
P10 - P1	3.57	[5.35]	-0.93	[-5.23]	0.05	[0.33]	0.15
Intermediate-term (12-7)							
P1	-1.24	[-2.68]	1.34	[2.74]	1.01	[0.13]	0.64
P10	1.13	[3.05]	0.91	[-0.95]	1.13	[1.41]	0.68
P10 - P1	2.37	[4.30]	-0.43	[-2.94]	0.12	[0.84]	0.05
Short-term (6-2)							
P1	-1.91	[-4.09]	1.60	[4.85]	1.10	[0.81]	0.69
P10	0.57	[1.43]	0.95	[-0.45]	0.91	[-0.95]	0.60
P10 - P1	2.48	[4.30]	-0.65	[-4.24]	-0.19	[-1.31]	0.14

Source: Own creation

The findings from table 5.4 show that market dependent betas do not explain our abnormal returns. Although we do see that the betas vary on market conditions, the alpha values have actually increased, compared to our previous regression. Losers still exhibit a higher and more statistically significant beta than winners in the up markets, with up market betas ranging from 1.32 to 1.76 for loser portfolios and 0.84 to 0.95 for winner portfolios. We see almost identical betas for losers and winners in the down market all with values close to 1.0. Interestingly this implies that our strategies are market neutral in down markets. However, due to the significant alphas for every strategy we can conclude that we cannot explain the momentum profits with market dependent betas.

Through a further examination of the monthly data returns for our strategies we observe that the worst performing month for all strategies is in April 2009, with strategies experiencing up to -47% returns for that month. This is the month where the financial market transitioned from the financial crisis, and achieved positive returns throughout the whole market, as the MSCI index achieved market returns of +20% for that month. The negative beta for our strategy in up markets, implies that for times where the market is growing heavily our strategies will experience negative returns. This is consistent with what we see in April 2009. The reasoning for these strong negative returns can be found in losers gaining a reversal of returns at a faster rate than winners, which causes the losers to considerably outperform winners in the months following a crisis. This explains the high beta for the loser portfolios in up markets, and as of such the negative beta for our strategies. This finding is illustrated in figure 5.5 below, which clearly illustrates the substantially negative momentum return in April 2009, where the loser portfolio obtained returns of ~52% whereas the winning portfolio only achieved a return of ~8%.

Figure 5.5: Cumulative return for equal weighted 12-2 strategy

Indexed cumulative return for the long-term momentum strategy from 01.01.2007 to 31.12.2012. 12-2 EW P1 is defined as losers while 12-2 EW P10 is defined as winners. 12-2 EW represents the cumulative return for the long-term zero-cost momentum strategy.

Source: Own creation

Three factor and four factor regressions

In the previous sections we observed positive and significant alpha values for all strategies across both weighting methods after adjusting for systematic risk and market dependent betas. This section will add on several risk factors other than the market risk captured in the CAPM model to try and explain the abnormal momentum profits. Following the methodology of Fama and French, the other risk factors of the three-factor model include those of size (Small-minus-big) and value (High-minus-low). Coupled with this we will conduct a separate regression where we include a fourth momentum factor (Winners-minus-losers).

Table 5.5: Momentum strategy factor loadings

Results of regressions on long-, intermediate-, and short-term momentum strategies and the risk factors MKT (market excess returns), SMB (size), HML (book-to-market value) and MOM (winners-minus-losers). Alpha values are posted in percent, while t-statistics are in square brackets. The MKT factor is the excess return of the MSCI Nordic index, while the remaining factors have been obtained from the Kenneth R. French website, computed based on stocks from multiple European countries[8]. The sample period covers January 2007 to January 2021. Panel A depicts equal-weighted strategies, while Panel B depicts adjusted value weighed strategies. Refer to appendix 4 for regressions on winner and loser portfolios.

Panel A: *Equal weight*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(7A)	(8A)	(9A)	(10A)	(11A)	(12A)
Alpha	1.94	2.21	2.00	1.36	1.43	1.52	1.40	0.94	2.00	2.26	2.18	1.64
	[4.62]	[5.61]	[5.26]	[4.32]	[4.43]	[4.69]	[4.38]	[3.32]	[5.25]	[6.34]	[6.08]	[5.25]
MKT		-0.44	-0.31	-0.09		-0.13	-0.06	0.11		-0.41	-0.36	-0.17
		[-5.25]	[-3.71]	[-1.20]		[-1.94]	[-0.78]	[1.62]		[-5.46]	[-4.49]	[-2.35]
SMB			-0.40	-0.35			-0.33	-0.29			-0.26	-0.22
			[-2.05]	[-2.22]			[-1.98]	[-2.03]			[-1.39]	[-1.37]
HML			-0.62	0.11			-0.38	0.14			-0.26	0.34
			[-4.11]	[0.73]			[-2.95]	[1.07]			[-1.83]	[2.38]
MOM				0.93				0.66				0.77
				[9.53]				[7.44]				[7.91]
Adj. R2		0.137	0.219	0.494		0.016	0.070	0.300		0.146	0.161	0.389

Panel B: *Adj. value weight*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)	(7B)	(8B)	(9B)	(10B)	(11B)	(12B)
Alpha	1.65	1.91	1.57	0.71	1.35	1.44	1.23	0.65	1.45	1.70	1.55	0.94
	[3.31]	[3.96]	[3.40]	[1.99]	[3.48]	[3.70]	[3.23]	[1.97]	[3.38]	[4.18]	[3.80]	[2.63]
MKT		-0.42	-0.25	0.05		-0.14	-0.04	0.17		-0.41	-0.34	-0.12
		[-4.06]	[-2.45]	[0.62]		[-1.75]	[-0.41]	[2.22]		[-4.74]	[-3.76]	[-1.52]
SMB			-0.21	-0.15			-0.23	-0.18			-0.06	-0.01
			[-0.89]	[-0.81]			[-1.15]	[-1.09]			[-0.27]	[-0.04]
HML			-0.87	0.10			-0.57	0.09			-0.36	0.34
			[-4.71]	[0.62]			[-3.72]	[0.58]			[-2.21]	[2.06]
MOM				1.24				0.84				0.89
				[11.07]				[8.10]				[8.02]
Adj. R2		0.084	0.184	0.530		0.012	0.081	0.340		0.113	0.128	0.370

Source: Own creation

[8] See appendix 2 for a complete list of countries

Table 5.5 shows all regressions for the zero-cost portfolios. The first column in each strategy presents the previously reported mean average returns in table 5.1. The second column presents the alpha and market betas for our previously conducted CAPM regressions. The third and fourth columns present the three- and four-factor regression results.

From the first two specifications in each strategy, we derived the following two conclusions: momentum strategies have been profitable in the Nordic market during the years 2007-2021 and continues to produce abnormal returns after adjusting for systematic risk. If we observe column three, we see alpha values ranging from 1.23 to 2.18 percent with high associated t-statistics. This shows that alpha is still significant and positive for all strategies after adjusting for the SMB (size) and HML (Value) factors. As of such we can conclude that the three-factor model does not explain the momentum effect, which is in line with previous studies of Jegadeesh and Titman (1993) and Fama and French (1996), who refer to it as the "main embarrassment of the three-factor model". However, we do see that the alpha values decrease as more factors are added to the model as well as an increase in the adjusted R^2, which indicates that the three-factor and four-factor models are able to explain a larger part of the abnormal momentum profits than the CAPM could.

Taking a closer look at the risk factors in column three we see that for the short-term (specification 11A and 11B) and long-term strategies (specification 3A and 3B) the beta coefficient of the market is still significant and negative, ranging from -0.25 to -0.36. While the intermediate-term strategy (7A and 7B) retains a completely insignificant exposure to the market, with a beta of -0.06 and -0.04. We also observe a negative factor loading on the SMB factor for all strategies, this indicates much like our previous findings that the loser portfolios on average contains smaller companies than the winner portfolios, as the loser portfolios have a higher SMB factor-loading than their winner counterpart. This is also consistent with why we see larger negative coefficients to size in the equally weighted methods compared to the value weighted method. It should be noted that the size factor only is significant at the 5% significance level in the 12-2 and 12-7 equally weighted strategies (3A and 7A), while none of the value weighted strategies show any significant correlation with size. Our finding of a non-significant loading on SMB for the short-term strategy (11A) is somewhat surprising, considering that we saw the largest disparity of excess returns between the equally weighted and value weighted short-term strategy.

For the HML factors we also see large negative coefficients which are statistically significant at the 5% level across all strategies, except the equally weighted short-term strategy (11A) which holds an HML-coefficient of -0.26 (t-stat = 1.83). This heavy negative factor loading on HML is in line with findings of previous studies (e.g. Fama and French, 2008; Novy-Marx, 2012), and indicates that our loser portfolios are more tilted towards containing stocks with a higher book-to-market value than our winner portfolios. Intuitively, this makes sense as losers have seen a decrease in market value, which all things equal will increase their book-to-market value, compared to winners who have experienced an increase in market value and as of such a lower B/M value.

Once we include the fourth factor, i.e. momentum, we see that the alphas relative to the model are much smaller. Including the MOM factor as an explanatory variable reduces the alphas remarkably, as the strategies, not surprisingly, load heavily and significantly on the factor. Furthermore, by introducing the MOM factor we reduce the negative loadings on the other three factors: MKT, SMB and HML and see a remarkable increase in adjusted R^2 for all strategies. This shows that the four-factor model explains more of our abnormal returns compared to the three-factor model and CAPM. Nevertheless, it is interesting to note that even after introducing the MOM factor we still see significant positive alphas for all equally weighted strategies (4A, 8A and 12A) and for the short-term value-weighted strategy (12B), ranging from 0.94 to 1.64 percent. The alphas for the long-term and intermediate-term value weighted strategy (4B and 8B) are slightly smaller at 0.71 and 0.65 percent respectively and significant at the 10% significance level.

The positive and significant alpha values observed in the four-factor model, may be a result of the factors being computed based on other European countries not included in our sample. Furthermore, if we examine the methodology of the construction of the Fama and French momentum factor, we see that winner and loser portfolios are constructed using different breakpoints than in our portfolio formation. The Kevin French website defines the winner and loser portfolios used to construct the momentum factor as the top and bottom 30% of stocks based on t-12 to t-2 months past performance. As of such, we see that our investment strategy is notably more extreme in its stock selection and portfolio construction, which could explain the inability of the four-factor model to explain our returns.

To test this hypothesis, the winner and loser portfolios have been constructed based on the 30th and 70th percentile of the 12-2 month lagged returns of stocks in our sample. To keep the test more in line with Fama and French we furthermore apply the adjusted value weighted strategy.

Table 5.6: Fama-French Momentum

Results of regressions on the adjusted value weighted 12-2 strategy and the risk factors MKT, SMB, HML and MOM. Alpha values are posted in percent, while t-statistics are in square brackets. The winner and loser portfolios have been constructed based on the 30th and 70th percentile of the 12-2 month lagged returns of stocks in our sample.

Independent	y = Long-term momentum (12-2)			
variable	(1)	(2)	(3)	(4)
Alpha	0.70	0.84	0.70	0.18
	[2.53]	[3.20]	[2.71]	[0.96]
MKT		-0.24	-0.16	0.02
		[-4.27]	[-2.83]	[0.50]
SMB			-0.18	-0.14
			[-1.35]	[-1.48]
HML			-0.40	0.19
			[-3.89]	[2.21]
MOM				0.75
				[12.96]
Adj. R2		0.099	0.179	0.594

Source: Own creation

Table 5.6 presents the results of a less extreme momentum strategy, more in line with the methodology applied by Fama and French. Looking at specification 1, we can see that this strategy still realises significant and positive monthly average excess returns of 0.70 percent. This is considerably lower compared to the return obtained previously using our "original" 12-2 strategy. We see that even after introducing the risk factors of specification 2 and 3, we still observe a significant and positive alpha, indicating that momentum profits are still obtainable when using a less aggressive strategy and that the three-factor model is still unable to explain the profits. Finally, we see that once we control for momentum in specification 4 our alpha is small and insignificant, coupled with a high adjusted R^2 and a strongly significant factor loading on the MOM factor. As of such, we can conclude that the four-factor model fully explains the abnormal returns of the less extreme Fama French Momentum strategy.

To summarize this section, we find that the CAPM and three-factor model were unable to fully explain the profits realised by the momentum strategies analysed in this study. Furthermore, we find that after controlling for momentum in a four-factor model we still achieved significant abnormal returns. It should be noted however, that the results might be explained by an alternate asset pricing model with different specifications and incorporations of risk factors and risk premia. In line with this, using a less extreme momentum strategy, we find that the four-factor model fully explains the abnormal momentum profits.

5.2 Size sub-sample

Following up on the previous observation in section 5.1, this section will examine the influence of firm size on momentum returns to determine whether momentum profits are limited to small firms.

Table 5.7: Size sub-samples

Descriptive statistics for sub-samples based on size, across the sample period January 2007 – January 2021. Companies with a market capitalization below the predetermined minimum market capitalization, as explained in section 4.4, are excluded from the sample. The numbers in the table presented are averages from across the whole sample period. This means that the numbers represent what an average formation month *t* looks like, and not the current market situation. To put in perspective, the total market capitalization of our total sample as of January 2021 is approximately 15,000 DKK billion.

	Size sub-samples		
	Small	Large	Total sample
Number of firms	259	259	518
% of firms	50%	50%	100%
Total capitalization (DKK billion)	146	8,749	8,895
% of total capitalization	2%	98%	100%
Avg. market cap (DKK million)	547	33,267	16,891
Median (DKK million)	442	7,135	1,412

Source: Own creation

To determine the effect of firm size we have divided our total sample into sub-samples based on the median of total average market capitalization across the whole sample period. The sample is split into two groups: a small group consisting of the lower half of the total sample and a large group consisting of the upper half. Table 5.7 above clearly illustrates the substantial skewness and dispersion of firm size in our data sample. The small sub-sample includes 50% of the companies in the total sample, yet it only accounts for 2% of the total market capitalization. Additionally, we can see that the average company in the large sample is 60 times larger than the average company in the small group based on market capitalization. As of such we find our method of dividing our total sample as an adequate solution for testing the influence of firm size.

Table 5.8 below presents the average monthly excess returns, the standard deviation of excess returns, the annualized Sharpe ratios as well as the market beta and CAPM alpha values, for the small and large size sub-samples. Only results for the equal weighted portfolios are presented below, due to the equal- and value weighted portfolios obtaining similar results. For the value-weighted results we refer to appendix 5.

Table 5.8: Size sub-sample momentum returns

Average monthly excess returns (in percent), standard deviation of excess returns (in percent), annualized Sharpe ratios, market betas and CAPM alphas (in percent) of equal weighted winner and loser portfolios created based on the historical performance of stocks in the Nordic markets. The small sub-sample presents the lower half of our full sample based on market capitalization, the large sub-sample presents the upper half. P1 is defined as losers while P10 is defined as winners. P10-P1 represents the respective momentum strategy. The t-stats are two-sided and tests whether excess returns, beta and alpha of P10-P1 are significantly different from zero. The sample period spans from January 2007 to January 2021.

	Small					Large				
	Mean	SD (%)	SR	β_{Market}	α_{CAPM}	Mean	SD (%)	SR	β_{Market}	α_{CAPM}
Long-term (12-2)										
P1	-0.56	8.86	-0.22	1.34	-1.39	0.23	7.92	0.10	1.39	-0.63
P10	1.65	6.39	0.89	0.93	1.07	1.50	5.58	0.93	0.91	0.94
P10 - P1	2.20	6.46	1.18	-0.40	2.45	1.27	6.02	0.73	-0.48	1.57
t-Stat.	[4.44]			[-3.96]	[5.11]	[2.74]			[-5.25]	[3.61]
Intermediate-term (12-7)										
P1	-0.31	7.98	-0.13	1.17	-1.03	0.53	6.69	0.28	1.14	-0.17
P10	1.02	6.32	0.56	0.95	0.43	1.44	6.04	0.83	1.06	0.78
P10 - P1	1.33	5.14	0.90	-0.21	1.46	0.90	4.92	0.64	-0.08	0.96
t-Stat.	[3.37]			[-2.57]	[3.73]	[2.39]			[-1.01]	[2.50]
Short-term (6-2)										
P1	-0.88	8.56	-0.36	1.29	-1.68	0.47	7.92	0.21	1.45	-0.42
P10	1.31	6.42	0.71	0.95	0.73	1.44	5.58	0.90	0.94	0.87
P10 - P1	2.19	6.19	1.23	-0.34	2.41	0.97	5.40	0.62	-0.51	1.29
t-Stat.	[4.61]			[-3.45]	[5.17]	[2.33]			[-6.43]	[3.42]

Source: Own creation

If we examine the mean excess return of each strategy, we see that all strategies obtain positive and statistically significant returns in both sub-samples, ranging from 0.90 to 2.20 percent. However, if we compare the returns of the zero-cost strategies across sub-samples, we find a notable difference in performance, with the small sample outperforming the large sample for all strategies. The largest difference in return is observed in the short-term strategy where the small sample realises an average excess return of 2.19 percent and the large sample an average return of 0.97 percent. This difference is statistically significant at the 1% level (t-stat = 2.70). For the remaining two strategies, the difference in excess return between the small and large sample in the long-term (0.93%) is significant at the 5% level (t-stat = 2.02), while the intermediate-term strategy shows no substantial difference between its small and large sample (t-stat = 0.96).

The difference in returns between small and large is consistent with our findings in the previous section, where we found that equally weighted methods outperform value weighted methods across all strategies. Furthermore, we also previously found the largest disparity of returns in the short-term strategy, giving us a stronger indication that the small firm effect is more concentrated in the short-term. Similar results are found when considering each strategy's Sharpe ratio, with notably larger Sharpe ratios for the small sample.

If we examine the large sample on its own, we observe that the zero-cost portfolios (P10-P1) realise returns and Sharpe ratios smaller than the corresponding winner portfolio (P10) of each respective strategy. The momentum strategies realise returns in the range of 0.90 to 1.27 percent, whereas the winner portfolios realise returns in the range of 1.44 to 1.50 percent. The lower returns of the zero-cost portfolios can be explained by the observation that no loser portfolio (P1) in the large sample realises negative returns. However, once we account for market exposure, each zero-cost portfolio generates a positive and statistically significant alpha that is higher than the alpha generated for the winner portfolios. This indicates that albeit comparatively smaller, the momentum effect still exists in large companies.

If we consider the source of profits for each strategy, we can compare the difference in performance of the P1 and P10 deciles in the small and large sample respectively. Comparing the P10 deciles we observe a relatively similar performance across the board, except for the intermediate-term strategy with a notable difference in mean returns (0.42%). Examining the mean returns of the P1 deciles we observe a sizeable discrepancy in performance between the small and large samples. The loser portfolios in the small sample realise returns between -0.88 and -0.31 percent compared to returns between 0.23 to 0.53 percent in the large sample.

Moreover, we observe that beta values for every portfolio are close to what we observed in Table 5.3, with significantly negative betas between -0.34 to -0.51 for the long- and short-term strategies, while the beta for the intermediate-term strategy is now significantly negative in the small sample (-0.21) but still market neutral in the large sample (-0.08). We find higher alpha values across the board for the small sample compared to the large sample. If we observe the source of the alpha, we see that for the small sample the majority stems from the short side, in contrast to the large sample, where a larger part of the alpha derives from the long side. These findings suggest that the difference in alpha and momentum returns observed between small and large firms, are driven by the underperformance of the loser portfolios in the small sample compared to the large sample.

Table 5.9: Average market capitalizations and medians – Sub-sample

Average market capitalizations and medians for constructed relative-strength portfolios across the entire sample period. P1 is the decile of stocks with the lowest past returns, and P10 is the decile of stocks with the highest returns in the same period. Panel A presents the small sub-sample, panel B presents the large sub-sample. Values are presented in DKK million.

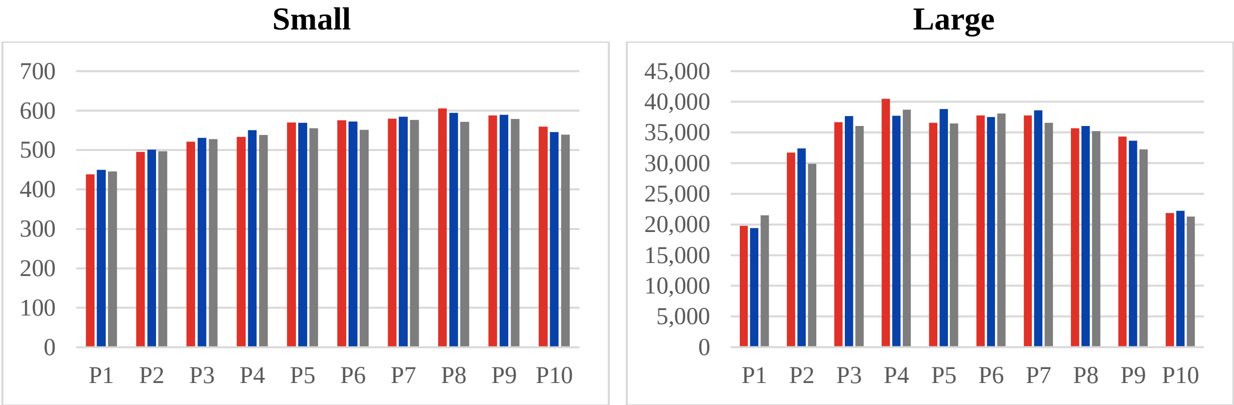
	Long-term momentum (12-2)		Intermediate-term momentum (12-7)		Short-term momentum (6-2)	
	Avg. market cap	Median	Avg. market cap	Median	Avg. market cap	Median
Panel A: *small*						
P1	438	330	450	343	446	342
P2	495	391	501	394	497	400
P3	521	422	531	420	528	434
P4	534	433	551	456	538	438
P5	570	478	569	470	555	470
P6	575	488	572	479	551	464
P7	579	486	585	508	577	495
P8	606	526	595	514	572	482
P9	588	507	590	509	578	494
P10	560	473	546	460	539	452
Panel B: *large*						
P1	19,769	4,973	19,393	4,715	21,487	4,926
P2	31,748	7,231	32,385	7,643	29,898	7,175
P3	36,672	8,597	37,653	9,222	36,034	8,751
P4	40,478	9,735	37,710	9,275	38,697	9,010
P5	36,599	10,100	38,848	9,855	36,459	9,333
P6	37,763	10,007	37,527	10,084	38,096	9,659
P7	37,773	10,225	38,629	10,371	36,584	10,030
P8	35,691	9,713	36,081	9,139	35,232	8,908
P9	34,339	8,789	33,667	8,421	32,232	8,234
P10	21,863	5,711	22,237	6,320	21,307	5,488

Source: Own creation

Table 5.9 presents the average market cap and median for our relative strength portfolios for each of the two sub-samples. Compared to our total sample, we can see that the small sub-sample is more size-neutral across the different portfolios. While for the large sub-sample we find a relatively similar distribution of average market capitalization as we did in our previous analysis (refer to table 5.2). It is interesting to note that for the small sample, the smallest companies are no longer concentrated in both extremes (P1 and P10), but rather in the lower decile portfolios (P1, P2 and P3). Furthermore, we still observe winners on average being larger than losers in both cases.

Figure 5.6 Average market capitalizations – Sub-sample

Illustrative overview of average market capitalizations for constructed relative-strength portfolios across the entire sample period. Values are presented in DKK million. The red bar chart represents the 12-2 strategy, the blue represents the 12-7 and the grey represents the 6-2.



Source: Own creation

In summation, considering our findings in this section in conjunction with the ones in the previous section, we can conclude that we find significant and positive momentum profits for small as well as large companies. However, we find significantly higher momentum returns in our small sample compared to large sample and can thus conclude that momentum profits are more concentrated in smaller firms. Furthermore, we find that the disparity in momentum profits between the two samples is caused by the underperformance of losers in the short side of the small sample.

Factor regressions

The following section will apply the same methodology as section 5.5.1 and examine the small and large sub-samples in the context of the three- and four-factor models. It should be noted that the posted findings are for the equally weighted method only, and we refer to appendix 6 for the corresponding value weighted results.

Table 5.10: Momentum strategy factor loadings – Sub-sample

Results of regressions on long-, intermediate-, and short-term momentum strategies and the risk factors MKT (market excess returns), SMB (size), HML (book-to-market value) and MOM (winners-minus-losers). Alpha values are posted in percent, while t-statistics are in square brackets. The MKT factor is the excess return of the MSCI Nordic index, while the remaining factors have been obtained from the Kenneth R. French website, computed based on stocks from multiple European countries[9]. The sample period covers January 2007 to January 2021. Panel A depicts results from the small sub-sample, while Panel B depicts the large sub-sample. Refer to appendix 6 for regressions on value weighted results.

Panel A: *Small*

Independent variable	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(7A)	(8A)	(9A)	(10A)	(11A)	(12A)
Alpha	2.20	2.45	2.32	1.71	1.33	1.46	1.37	0.97	2.19	2.41	2.38	1.86
	[4.44]	[5.11]	[4.82]	[3.86]	[3.37]	[3.73]	[3.49]	[2.57]	[4.61]	[5.17]	[5.08]	[4.20]
MKT		-0.40	-0.32	-0.10		-0.21	-0.15	-0.01		-0.34	-0.29	-0.11
		[-3.96]	[-2.95]	[-0.98]		[-2.57]	[-1.70]	[-0.09]		[-3.45]	[-2.79]	[-1.06]
SMB			-0.37	-0.32			-0.32	-0.28			-0.47	-0.43
			[-1.49]	[-1.44]			[-1.55]	[-1.50]			[-1.96]	[-1.94]
HML			-0.42	0.27			-0.31	0.15			-0.20	0.39
			[-2.20]	[1.35]			[-1.95]	[0.85]			[-1.07]	[1.89]
MOM				0.89				0.58				0.75
				[6.45]				[4.93]				[5.42]
Adj. R2		0.086	0.120	0.298		0.038	0.070	0.190		0.067	0.092	0.230

Panel B: *Large*

Independent variable	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)	(7B)	(8B)	(9B)	(10B)	(11B)	(12B)
Alpha	1.27	1.57	1.22	0.47	0.90	0.96	0.68	0.10	0.97	1.29	1.09	0.50
	[2.74]	[3.61]	[2.97]	[1.44]	[2.39]	[2.50]	[1.85]	[0.32]	[2.33]	[3.42]	[2.93]	[1.58]
MKT		-0.48	-0.33	-0.06		-0.08	0.05	0.25		-0.51	-0.42	-0.21
		[-5.25]	[-3.60]	[-0.84]		[-1.01]	[0.61]	[3.51]		[-6.43]	[-5.08]	[-2.91]
SMB			-0.06	0.00			-0.13	-0.09			-0.11	-0.06
			[-0.27]	[0.01]			[-0.70]	[-0.56]			[-0.58]	[-0.40]
HML			-0.84	0.02			-0.70	-0.05			-0.50	0.17
			[-5.10]	[0.12]			[-4.81]	[-0.34]			[-3.36]	[1.19]
MOM				1.10				0.83				0.86
				[10.87]				[8.56]				[8.70]
Adj. R2		0.141	0.259	0.569		0.006	0.129	0.398		0.199	0.250	0.487

Source: Own creation

Consistent with previously posted regressions, Table 5.10 presents all regressions for sub-sample zero-costs portfolios. The first column in each strategy presents the mean average returns, the second column presents the alpha and market betas for CAPM regressions, and the third and fourth columns present the three- and four-factor regression results.

[9] See appendix 2 for a complete list of countries

If we observe column three we see that all strategies, except the 12-7 strategy for the large sample (specification 7B), produce positive alphas all significant at the 1% significance level, in the range of 1.09 to 2.38 percent. As of such we conclude that even after risk-adjusting for size and value we get a significant alpha and a momentum effect in both the small and large sample. In line with our regression on the full sample, we still observe decreasing alpha values and increasing adjusted R^2 as we add more factors to the model, indicating that the three-factor and four-factor models are able to explain a larger part of the abnormal momentum profits than the CAPM.

Focusing on the specific risk factors we do not see a significant loading on the SMB factor, for any of the strategies except the short-term strategy (specification 11A) in the small sample (t-stat = 1.96). This is to be somewhat expected, due to the fact that our samples should be more size-neutral after splitting our full sample by the median. This brings us back to the question of whether or not momentum is driven by small firms outcompeting even smaller firms. Since we do not observe a significant negative SMB factor loading, i.e that loser portfolios are more tilted towards containing smaller firms compared to the winner portfolios, we are more inclined to reject the previously stated hypothesis.

For the short-term (specification 11A and 11B) and long-term strategies (specification 3A and 3B) the beta coefficient of the market is significant and negative, ranging from -0.29 to -0.42. While the intermediate-term strategy (7A and 7B) retains a completely insignificant exposure to the market, with a beta of -0.15 and -0.05. For the HML factors we see large negative coefficients which are statistically significant at the 5% level across all strategies, except the small sample short-term strategy (11A) which holds an HML-coefficient of -0.20 (t-stat = -1.07). These results are almost identical to our previous regressions in table 5.5. Once we control for momentum in column four, we find significant alphas in our small sample, but small and insignificant alphas in the large sample. Much like in our previous regressions we deduce that the cause of significant alpha values in the four-factor model are caused by our more extreme momentum strategy, compared to the Fama and French type strategy used to compute the MOM factor.

To summarize, we conclude that despite our initial hypothesis, we found significant momentum profits in both our small and large sample, even after accounting for common risk factors. Furthermore, we found that the small sample significantly outperformed the large sample in all cases.

We thus conclude that the momentum effect exists in both small and large firms but are significantly more concentrated in smaller firms. Finally, we conclude that the difference between the source of profits for strategies in the large vs. the small sample could be found in the short side for the small sample. Further indicating that the stronger momentum effect found in the small firms are driven by the underperformance of losers compared to the overperformance of winners.

5.3 January Effect

While the characteristics of the January Effect have been described in detail in section 3.4, we provide a short description to facilitate the discussion of this upcoming section. The January Effect is a seasonal anomaly observed in the month of January, where equities on average see a larger increase in stock prices compared to other months. The effect has predominantly been found in small-cap stocks. The main theory behind the cause of the January Effect is tax-loss selling, stating that investors will sell losing stocks in December to realise a capital loss, and then proceed to buy them back in January. As of such, in theory we should see a reversal of momentum in January, caused by the upwards buying pressure on losers, which consequently lead to a negative return for our momentum strategies.

5.3.1 January returns

To determine the impact of the January Effect on monthly returns we distinguish between non-January and January returns. Non-January reflects the returns from investing in all months other than January. And naturally, January returns reflect returns realised only from January investing. The decomposition of profits will allow us to analyse the performance of each individual strategy in- and out-side of January, while simultaneously comparing each strategy's performance in January to each other.

Table 5.11: Stock returns in January

Panel A depicts average monthly excess returns (in percent), standard deviation of excess returns (in percent) and annualized Sharpe ratios of an equal weighted portfolio of all stocks in our data sample across our sample period from January 2007 to January 2021. Panel B presents the same measures for the value weighted MSCI Nordic index across our sample period. Overall cover returns for the entire calendar year. January cover returns only in January. Non-January cover returns in any month other than January.

Panel A: Own sample

Equal weight	Overall	January	Non-January
Mean	0.72	3.03	0.50
SD	5.29	5.08	5.27
SR	0.47	2.06	0.33

Panel B: MSCI

MSCI: *Value weight*	Overall	January	Non-January
Mean	0.62	0.59	0.62
SD	4.68	5.24	4.64
SR	0.46	0.39	0.46

Source: Own creation

The first row and column in Panel A of table 5.11 represents, for our intents and purposes, the average monthly excess returns if one were to invest an equal amount in every stock available on the Nordic market for the past 14 years, using monthly rebalancing.[10] When we observe the mean return values for January, we see a much higher value compared to that of non-January investing, with January investing realising average monthly excess returns of 3.03 percent (t-stat = 2.31) while investing outside of January only realises 0.50 percent monthly return. To examine whether this result is a cause of significant outliers in our January observations, we apply a two-sample t-test to test against the null hypothesis that the mean excess returns of January investing and non-January investing in Panel A of table 5.11 are identical (t-Stat. = 1.78). Due to the low number of observations in January (n = 15), we get a relatively low t-stat compared to the magnitude of difference between non-January and January returns. However, we can still conclude with a significance level of 10%, that investing in January using equal weights yields significantly higher returns than investing outside of January. This implies the presence of a January Effect in the Nordic Markets.

Panel B of table 5.11 applies the same methodology as Panel A but for the value weighted MSCI Nordic index. In Panel B we see no statistically significant difference in mean returns between January and non-January investing. While the MSCI Nordic index covers 85% of the total market value of the Stock exchanges in the Nordics, a large part of the total market capitalization is made up

[10] This is disregarding transaction costs, stocks below our minimum market cap requirement and missing data from our data sample.

of a few large companies. This indicates that the January Effect may only be present in small-cap stocks. This is supported by a number of academics, who argue that the January Effect exists primarily in small companies (e.g. Roll 1983).

5.3.2 Marginal strategies

To further examine the degree to which the January Effect is present in the Nordic stock markets we employ the marginal strategy method, adopted from Novy-Marx (2012) and Yao (2012). This method lets us examine the autocorrelation of returns for our zero-cost portfolios, as well as help us gain a better understanding of the apparent success of our strategies. The marginal strategies, much like our previously applied momentum strategies, long past winners and short past losers. However, they differ from momentum strategies in the way stocks are ranked based on previous performance. In every formation month *t,* each marginal strategy longs winners and shorts losers based on past performance in a single month, this month being 1 to 12 months "lagged" behind month *t.* These stocks are then held throughout formation month *t,* like in our previous strategies. For example, for 6-month lagged returns, portfolios are formed in the beginning of month *t*, based on winners and losers in month t-6. In total, we end up with 12 distinct marginal strategies. In line with how we defined our previous momentum strategies as 12-2, 12-7 and 6-2 based on their lookback periods, we can define our marginal strategies in a similar fashion as 12-12, 11-11, 10-10 etc.

The upper panel of figure 5.7 presents the average monthly returns of our 12 winner-minus-loser marginal strategies. These strategies essentially represent the autocorrelation of returns, for month *t*. To understand this, we take an example: If we look at the t-1 marginal strategy in January 2007, we long the winners and short the losers of December 2006, likewise the t-2 marginal strategy will create a portfolio based on November 2006 winners and losers. A month passes, we are now in February 2007, the t-1 strategy will now buy the winners and sell the losers of January 2007, while the t-2 strategy will buy the same winners and the same losers of December 2006 as the t-1 strategy did the month prior. As of such we can see that throughout the investment periods, the t-2 strategy will long and short the same companies as the t-1 strategy, just lagging one month behind. The same holds true for the remaining strategies and their respective lag periods, i.e. t-3 to t-12. To summarize, we invest in the same companies for all strategies, but at different points in time, as of such the marginal strategies serve as an indicator of the autocorrelation of returns for month *t*.

Figure 5.7: Marginal strategies

Average monthly excess returns of P10-P1 portfolios for marginal strategies. The upper panel presents overall returns where the investment period covers any calendar month, the middle panel only includes investments in January while the bottom panel includes investments from any month other than January. Blue bars present the returns for equally weighted portfolios and grey bars present results for adjusted value weighted portfolios.

Source: Own creation

Looking at the upper panel of figure 5.7 we find that the P10-P1 marginal strategies predominantly generate positive returns. This indicates a positive autocorrelation associated with past winners continuing to outperform past losers. This observation is also consistent with findings obtained previously in this chapter, where we found significantly positive returns for all our momentum strategies, regardless of their different lookback periods. Moreover, when looking at the upper panel, we see that the prior 6-to-2 months demonstrate a slightly higher return autocorrelation compared to month 12-to-7. The highest autocorrelation is observed in the second and third lagged month returns. These findings suggest that short-term past performance contributes slightly more to momentum return than intermediate-term past performance. This is consistent with the findings of section 5.1, where we observe higher excess and abnormal returns for our short-term strategy compared to the intermediate-term strategy. These observations contradict those of Yao (2012) and Novy-Marx (2012), who found that intermediate-term past performance contributes more to momentum returns than short-term.

Furthermore, we see that the only month showing negative autocorrelation for the overall result is t-1 for the value-weighted strategy. This is in line with the one-month reversal observed by e.g. Jegadeesh (1990), who states that strong winners from the prior month are more likely to have close prices at the ask-price rather than the bid-price, and as of such tend to underperform losers from the previous month, who are more likely to have close prices at the bid. This is also the reason why we skip the latest month in each of our momentum strategies. It should be noted however, that by examining the t-statistics in Table 5.12 for the 1-month lag returns of the overall returns, we can see that neither the returns of the equally weighted nor the value weighted strategy are significantly different from zero. As of such we cannot conclude with a relevant significance level that we observe the 1-month reversal in our overall results.

Table 5.12: Marginal strategies

Average monthly excess returns (in percent) of P10-P1 portfolios for marginal strategies. The t-stat tests whether excess returns of buying past winners and selling past losers, are significantly different from zero. The portfolios in Panel A are formed based on the equal-weighted scheme, whereas portfolios in Panel B are based on an adjusted value-weighted scheme. The values of this table corresponds with the values presented in figure 5.7.

Panel A: E*qual weight*												
Lag	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**	**-10**	**-11**	**-12**
Overall	0.47	1.41	1.34	0.47	1.04	0.60	0.47	0.57	0.79	0.23	0.56	0.97
	[1.76]	[4.62]	[5.29]	[1.68]	[4.29]	[2.29]	[1.70]	[2.11]	[3.35]	[0.86]	[2.56]	[4.36]
January	-3.29	-0.79	-0.39	-1.32	1.74	0.62	-1.12	-0.18	-0.55	-0.12	-1.26	1.42
	[-3.01]	[-0.59]	[-0.32]	[-1.39]	[1.27]	[0.67]	[-0.95]	[-0.16]	[-1.11]	[-0.15]	[-1.50]	[1.48]
Non January	0.81	1.62	1.52	0.63	0.97	0.59	0.62	0.64	0.94	0.26	0.71	0.90
	[3.13]	[5.28]	[6.02]	[2.14]	[4.11]	[2.15]	[2.19]	[2.31]	[3.71]	[0.93]	[3.19]	[3.95]

Panel B: *Adj. value weight*												
Lag	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**	**-10**	**-11**	**-12**
Overall	-0.02	0.83	1.36	0.25	1.11	0.19	0.50	0.21	0.73	0.33	0.82	0.46
	[-0.06]	[2.39]	[4.59]	[0.75]	[3.85]	[0.60]	[1.76]	[0.65]	[2.32]	[1.15]	[3.37]	[1.62]
January	-3.36	-2.62	-1.39	-1.47	0.70	-1.05	-1.10	-0.20	-1.44	-0.37	-0.31	-0.50
	[-2.45]	[-1.87]	[-1.26]	[-1.00]	[0.52]	[-0.97]	[-1.43]	[-0.14]	[-1.29]	[-0.38]	[-0.33]	[-0.58]
Non January	0.29	1.16	1.63	0.39	1.12	0.30	0.67	0.25	0.96	0.40	0.90	0.53
	[0.91]	[3.33]	[5.38]	[1.17]	[3.84]	[0.90]	[2.22]	[0.77]	[2.96]	[1.34]	[3.58]	[1.76]

Source: Own creation

The mid and bottom panels of figure 5.7 present the returns of marginal strategies for January and non-January respectively. Non-January is identical to the Overall results after excluding returns from January. Naturally, January results consist of returns obtained only from investing in January. When looking at the January results we observe a clear pattern of negative autocorrelation returns. This pattern is not observed in any of the other 11 months.[11] Specifically, we observe negative autocorrelations between all returns obtained in January and their own lagged performance except for portfolios formed based on returns in month t-5, t-6 and t-12 respectively. Comparatively, Yao (2012) observed negative autocorrelations for all lag periods except for t-12. Thus, our results are to some degree in line with the findings of Yao (2012). The positive returns in month t-12 may be explained by seasonality, as the strategy buys the past winners and shorts past losers of the preceding January, and as of such it would seem reasonable to believe that some stocks consistently achieve positive returns in January due to a seasonal aspect, which may cause the positive returns for the t-12 strategy. Regarding the returns from the January t-5 (EW &VW) and t-6 (EW) marginal strategy, we observe that longing winners and shorting losers of the preceding July and August respectively, results in positive returns in January. Since the return autocorrelations for January are based on observations

[11] Refer to appendix 7 for marginal strategy returns in months other than January.

from January 2007 to January 2021, the sample includes relatively few observations, why our results are highly sensitive to outliers. Consequently, we see that the majority of the marginal strategy returns of January are not statistically significant. However, we still observe a clear pattern in the January observations compared to other months, which gives further support and justification of our hypothesis that the January Effect is present in the Nordic stock markets and implies that momentum strategies experience negative returns in January. Furthermore, we see in the bottom panel of figure 5.7 that marginal strategies for non-January generally realises higher returns as the impact of negative January returns have been eliminated. These hypotheses will be further examined in the following section.

5.3.3 January Effect and momentum strategies

The results obtained in the preceding sections implied that the January Effect is present in the Nordic stock markets and that momentum strategies on average experience negative returns in January. This section will further examine these hypotheses and the impact of the January Effect on the three momentum investment strategies examined in this thesis.

Table 5.13: January returns

Average monthly excess returns (in percent) of relative-strength portfolios created based on the historical performance of stocks in the Nordic markets. Overall cover returns for the entire calendar year. January cover returns only in January. Non-January cover returns in any month other than January. The t-stats are two-sided and tests whether excess returns of buying past winners and selling past losers is significantly different from zero. The sample period spans from January 2007 to January 2021. The portfolios in Panel A are formed based on the equal weighted scheme, whereas portfolios in Panel B are based on an adjusted value weight scheme.

	Long-term momentum (12-2)			Intermediate-term momentum (12-7)			Short-term momentum (6-2)		
	Overall	January	Non-january	Overall	January	Non-january	Overall	January	Non-january
Panel A: *equal weight*									
P1	-0.39	4.50	-0.87	-0.17	4.57	-0.64	-0.51	3.58	-0.91
P2	0.07	4.24	-0.34	0.09	3.03	-0.21	0.32	3.43	0.03
P3	0.35	2.28	0.16	0.63	2.90	0.41	0.58	3.39	0.31
P4	0.62	2.50	0.43	0.73	2.54	0.56	0.60	2.82	0.37
P5	0.71	2.79	0.51	0.80	2.77	0.62	0.75	2.34	0.58
P6	0.99	2.58	0.83	0.73	2.15	0.58	0.80	2.64	0.62
P7	0.99	2.78	0.82	1.01	2.61	0.85	1.06	2.86	0.88
P8	1.18	2.10	1.09	0.98	2.27	0.86	1.11	2.00	1.02
P9	1.15	2.31	1.03	1.17	2.64	1.02	1.06	2.01	0.97
P10	1.55	4.19	1.29	1.26	4.37	0.95	1.50	4.84	1.17
P10 - P1	1.94	-0.30	2.16	1.43	-0.19	1.59	2.00	1.26	2.08
t-Stat.	[4.62]	[-0.21]	[4.91]	[4.43]	[-0.19]	[4.66]	[5.25]	[0.72]	[5.33]
Panel B: *Adj. value weight*									
P1	-0.25	3.83	-0.62	0.03	2.80	-0.24	-0.23	3.33	-0.55
P2	0.37	2.36	0.16	0.06	1.60	-0.09	0.48	2.26	0.31
P3	0.51	1.92	0.38	0.65	1.95	0.52	0.74	2.23	0.59
P4	0.55	1.64	0.43	0.73	1.19	0.69	0.82	1.80	0.72
P5	0.70	1.79	0.58	0.81	1.40	0.75	0.73	1.91	0.61
P6	1.10	1.62	1.03	0.72	1.92	0.60	0.79	2.13	0.65
P7	0.79	1.33	0.72	0.91	1.32	0.87	0.89	1.75	0.79
P8	0.99	0.30	1.04	0.92	1.62	0.85	0.91	0.30	0.95
P9	1.12	1.22	1.10	1.14	1.57	1.10	1.03	0.56	1.07
P10	1.40	1.94	1.33	1.38	2.83	1.24	1.22	1.62	1.16
P10 - P1	1.65	-1.89	1.95	1.35	0.04	1.48	1.45	-1.71	1.71
t-Stat.	[3.31]	[-1.08]	[3.78]	[3.48]	[0.04]	[3.55]	[3.38]	[-0.86]	[4.01]

Table 5.13 presents the average monthly excess returns of our momentum strategies and constructed relative strength portfolios. The first column of each strategy is a repost of previous results from table 5.1, while the second column presents the average excess returns of January investing, and the final column presents the excess returns associated with non-January investing.

For all zero-cost strategies we observe a large discrepancy in returns when comparing January and non-January investing, with non-January outperforming January in every case. Every January momentum strategy, except for the equally weighted short-term strategy, realises returns that are negative or close to zero. The value weighted 12-2 strategy performs the worst in January, with average monthly excess returns of -1.89 percent, while the 6-2 strategy performs the best with returns of 1.26 percent. Comparatively non-January strategies realise average monthly returns ranging from 1.48 to 2.16 percent. These results are in line with our hypothesis of a proposed January Effect in the Nordic market and consequently poor performance of momentum strategies in January. These results are also consistent with the results of multiple previous studies (e.g. Jegadeesh and Titman, 1993; Grundy and Martin, 2001) who all found momentum strategies to realise significant losses in January. It should be noted however, that while we do observe that momentum strategies underperform in January compared to other months, we do not obtain statistically significant results for underperformance in all strategies. t-statistics for every zero-cost strategy, testing against the null that January returns and Non-January returns for momentum strategies are identical, are posted below in table 5.14.

Table 5.14: Two-sample t-tests

Results from two-sample t-tests testing against the null that January returns and Non-January returns of long-, intermediate- and short-term momentum strategies are identical. t-statistics are presented in square brackets.

t-Stat. (Jan vs. Non-Jan)	Long-term (12-2)	Intermediate-term (12-7)	Short-term (6-2)
Equal weight	[1.68]	[1.52]	[0.59]
Adj. value weight	[2.14]	[1.06]	[2.23]

Source: Own creation

We can reject the null hypothesis that momentum returns in January are identical to momentum returns outside of January at a 5% significance level for the long- and short-term value weighted strategies. We can also reject the null at a 10% significance level for the equally weighted long-term strategy. However, we do not find statistical significance for the remaining three strategies.

If we bring our attention to the equally weighted relative-strength portfolios in table 5.13 (Panel A: P1 to P10) we see that January portfolios outperform non-January portfolios across all strategies, with January portfolios realising average monthly returns ranging from 2.00 to 4.84 percent while non-January obtain returns ranging from -0.91 to 2.16 percent. Comparatively the value weighted portfolios in January also generally outperform their non-January counterpart across all strategies, with returns ranging from 0.30 to 3.83 percent in January compared to a range of -0.62 to 1.33 percent in Non-January. We also see that the equally weighted portfolios in most cases generate higher returns than value weighted in January. This is consistent with our finding of section 5.3.1 that small stocks on average experience a larger increase in stock prices in January compared to large stocks.

If we compare the equally weighted to the value weighted method in table 5.13, it is interesting to note that we observe the largest negative return to our zero-cost portfolios in the value weighted scheme. This is despite the fact, that we previously observed the January Effect to primarily exist in small-cap stocks. If we look at the distribution of returns for relative strength portfolios across strategy in the equally weighted method, we see that for January, returns are more concentrated in both extremes (i.e. P1 and P10), as opposed to non-January where we see a more linear relation between decile portfolios and monthly returns. This is in contrast to the theory of tax-loss selling, which states that due to a reinvestment of funds from investors, past losers will experience upwards buying pressure and consequently an increase in price. As of such, we would expect to see a larger part of January returns being concentrated in P1 for the equally weighted strategy.

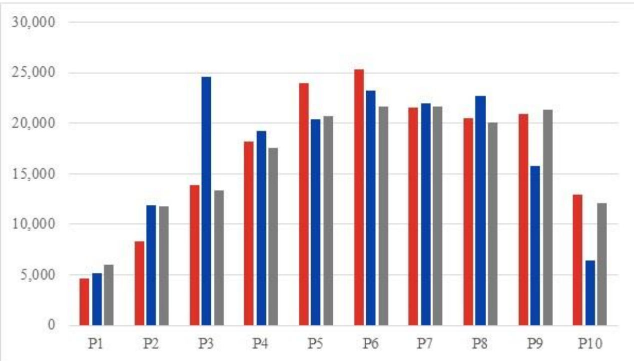
A plausible explanation for why we observe the largest negative return to our zero-cost portfolios in the value weighted scheme may be that the driving forces of the January Effect are two-fold. First, we see that in January small companies experience a larger increase in share price compared to larger companies, we observe this in table 5.11, and in table 5.13, this implies that the first major driver of the January effect is the small-firm effect, as suggested by e.g. Roll (1983). Second, we see that increasing the weights of larger companies in our portfolio, as per Panel B of table 5.13, realises more negative momentum returns, caused by a larger decrease in P10 as compared to P1 going from equal weight to value weight. This implies that the second driving force of the January Effect is one that favours past losers. In summation, we see that small companies benefit from the January Effect in January, however once we reduce the influence of small companies, we find the January Effect being profound in losers.

Table 5.15 and figure 5.8: Market cap January and Non-January

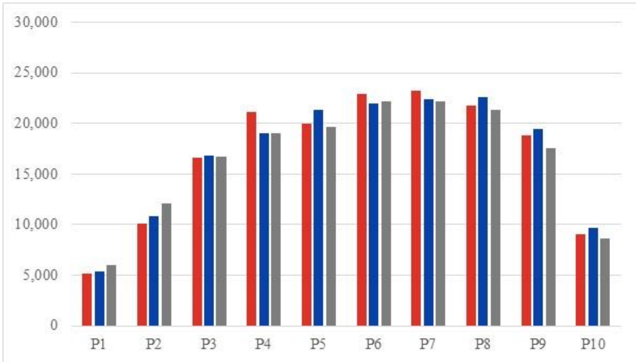
Average market capitalizations and medians for constructed relative-strength portfolios across the entire sample period, split by January and non-January. Values are presented in DKK million. The red bar chart represents the 12-2 strategy, the blue represents the 12-7 and the grey represents the 6-2.

	Long-term momentum (12-2)				Intermediate-term momentum (12-7)				Short-term momentum (6-2)			
	January		Non-January		January		Non-January		January		Non-January	
	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median
P1	4,646	478	5,155	547	5,174	664	5,348	588	5,954	615	5,992	640
P2	8,313	980	10,130	1,038	11,911	1,178	10,856	1,089	11,778	1,096	12,115	1,135
P3	13,905	1,323	16,644	1,552	24,553	1,368	16,789	1,464	13,334	1,409	16,757	1,428
P4	18,137	2,058	21,162	1,838	19,216	1,749	19,043	1,746	17,518	1,518	19,037	1,682
P5	23,918	2,148	19,923	2,101	20,391	2,258	21,391	2,197	20,680	1,958	19,638	1,987
P6	25,377	2,508	22,908	2,641	23,246	2,283	21,950	2,581	21,670	2,528	22,215	2,441
P7	21,517	2,817	23,249	2,936	22,000	2,953	22,431	2,616	21,700	2,473	22,146	2,652
P8	20,521	3,377	21,708	2,752	22,700	2,325	22,563	2,806	20,100	3,168	21,368	2,520
P9	20,931	3,202	18,865	2,334	15,745	1,781	19,490	2,596	21,317	3,079	17,558	2,280
P10	12,892	1,144	9,014	1,162	6,371	1,081	9,705	1,162	12,126	1,144	8,630	1,095

January



Non-January



Source: Own creation

To gain a further understanding of our results, table 5.15 presents the average market cap for companies in each strategy split into January and Non-January investing. We see that the distribution of market cap slightly differs across January and non-January investing, however, once we consider the median, we see a relatively similar size distribution across all strategies and months. This indicates like our previous results, that the smallest companies are still located in P1, and that the companies in the extreme deciles are smaller than the average company in the sample. It is important to note, after considering this finding, that the two prementioned forces of the January effect are self-enforcing as the loser portfolio on average is considered to contain the smallest firms of the sample.

To summarize, we conclude that the January Effect has an observed negative impact on excess returns for each of the proposed momentum strategies of this study. Moreover, we propose in accordance with previous studies that the January effect is more profound in smaller companies and in past losers. The next section will apply our size sub-samples to further examine this hypothesis.

5.3.4 January Effect and size sub-samples

In the following section we look further into the hypothesis that smaller companies obtain higher returns in the month of January compared to non-January months, as well as our proposed driving forces of the January Effect.

Table 5.16: Sub-sample returns in January

Panel A depicts average monthly excess returns (in percent), standard deviation of excess returns (in percent) and annualized Sharpe ratios of an equal weighted portfolio of all stocks in our small sub-sample from January 2007 to January 2021. Panel B presents the same measures for the large sub-sample. Overall cover returns for the entire calendar year. January cover returns only in January. Non-January cover returns in any month other than January.

Panel A: Small sub-sample

Small: equal weight	Overall	January	Non-January
Mean	0.54	4.41	0.17
SD	5.28	5.10	5.16
SR	0.36	3.00	0.11

Panel B: Large sub-sample

Large: equal weight	Overall	January	Non-January
Mean	0.90	1.63	0.83
SD	5.53	5.36	5.56
SR	0.56	1.06	0.52

Source: Own creation

Table 5.16 presents the average monthly excess returns, the standard deviation of excess returns and annualized Sharpe ratios of two equal-weighted portfolios containing all stocks of our small and large sub-sample respectively. As is evident from the table, we observe a notable difference in January excess returns when comparing the small and large sub-sample, with the small sample obtaining returns of 4.41 percent whereas the large sample realises returns of 1.63 percent. Testing against the null that the difference in January returns (2.78%) is equal to zero we obtain a significant result at the 1% significance level (t-stat = 4.37). Looking at Panel A we see that returns for our small sample are driven heavily by the returns obtained in January. Testing the difference in January and non-January returns in the small sample we get a very significant result at the 1% level (t-stat = 3.04). When looking at the large sub-sample in Panel B we also observe a sizeable difference between January and non-January returns. However, we do not find the difference in returns (0.80%) to be statistically significant from zero. These results coupled with the fact that we do not find a significant difference in January and non-January returns for the large sample, provides further evidence of the small-firm effect as a main driver of the January Effect.

Table 5.17: January momentum returns size sub-sample

Average monthly excess returns (in percent) of relative-strength portfolios created based on the historical performance of stocks in the Nordic markets. Overall cover returns for the entire calendar year. January cover returns only in January. Non-January cover returns in any month other than January. The t-stats are two-sided and tests whether excess returns of buying past winners and selling past losers is significantly different from zero. The sample period spans from January 2007 to January 2021. Panel A presents the small sub-sample, panel B presents the large sub-sample. Refer to appendix 8 for average market capitalizations and medians for the small and large sub-sample, split by January and non-January.

	Long-term momentum (12-2)			Intermediate-term momentum (12-7)			Short-term momentum (6-2)		
	Overall	January	Non-january	Overall	January	Non-january	Overall	January	Non-january
Panel A: *small*									
P1	-0.56	5.48	-1.15	-0.31	5.95	-0.92	-0.88	4.46	-1.40
P2	-0.48	5.44	-1.06	-0.30	4.72	-0.79	-0.24	4.81	-0.73
P3	-0.06	4.29	-0.48	-0.03	4.17	-0.44	0.22	3.63	-0.10
P4	0.23	3.20	-0.06	0.78	3.61	0.50	0.21	3.48	-0.13
P5	0.77	3.40	0.51	0.56	4.47	0.18	0.64	4.50	0.26
P6	0.46	3.79	0.14	0.72	3.12	0.48	0.77	3.73	0.48
P7	1.06	3.50	0.82	0.74	3.03	0.52	1.00	3.36	0.78
P8	1.21	3.73	0.96	1.00	4.43	0.66	1.31	4.60	1.00
P9	1.17	4.78	0.82	1.26	4.34	0.96	1.26	4.42	0.95
P10	1.65	6.48	1.17	1.02	6.22	0.52	1.31	7.07	0.76
P10 - P1	2.20	1.00	2.32	1.33	0.27	1.43	2.19	2.61	2.16
t-Stat.	[4.44]	[0.51]	[4.50]	[3.37]	[0.21]	[3.43]	[4.61]	[1.02]	[4.59]
Panel B: *large*									
P1	0.23	1.63	0.10	0.53	3.08	0.29	0.47	2.17	0.33
P2	0.58	2.57	0.38	0.55	0.79	0.53	0.74	2.21	0.60
P3	0.74	1.78	0.64	0.71	1.40	0.63	0.74	2.30	0.59
P4	0.84	2.06	0.71	0.71	1.12	0.67	0.75	1.63	0.65
P5	1.00	2.23	0.88	0.91	1.56	0.85	0.93	1.03	0.90
P6	1.11	1.25	1.07	0.99	1.93	0.88	0.92	2.14	0.79
P7	0.78	1.35	0.71	1.02	1.55	0.96	0.96	1.40	0.90
P8	1.10	0.78	1.11	1.10	0.85	1.11	1.03	0.44	1.08
P9	1.13	0.83	1.16	1.01	1.53	0.96	0.94	0.90	0.92
P10	1.50	1.19	1.51	1.44	1.53	1.42	1.44	1.47	1.43
P10 - P1	1.27	-0.44	1.41	0.90	-1.55	1.13	0.97	-0.70	1.10
t-Stat.	[2.74]	[-0.26]	[2.92]	[2.39]	[-1.09]	[2.89]	[2.33]	[-0.45]	[2.54]

Source: Own creation

Table 5.17 presents monthly average excess returns of our sub-sample momentum strategies, split on January and non-January returns. In line with the small-firm effect, and the findings of table 5.16, we find that the small sample relative-strength portfolios perform better than the large sample portfolios, evident across all strategies. Small sized portfolios realise monthly returns ranging from 3.03 to 7.07 percent while large portfolios realise monthly returns ranging from 0.44 to 3.08 percent. If we turn our attention to the momentum strategies and their January returns, we see that non-January continues to outperform January in all strategies except for the small sample short-term strategy, which surprisingly yields average returns of 2.61 percent, however when we examine the standard deviation of returns for this strategy (9.55%) we can deduce that this is caused by significant outliers. It should be noted again that the January momentum results are not statistically significant from zero, as they all realise t-statistics below the critical values.

We find similar results to table 5.13 once we examine the momentum effect across the small and large samples. We observe the large sample strategies realise negative returns in January, which indicates that the January Effect is not limited to just small firms. This is a sentiment to our second proposed driver for the January Effect, i.e. that past losers realise higher returns in January regardless of size.

To summarize, we find that small firms on average tend to realise higher returns in January, and that this effect is especially profound in small losers and small winners. Furthermore, we find an observed January Effect in losers which consequently results in lower momentum returns for the zero-cost strategies analysed in this study. However, due to non-relevant levels of significance we cannot reject the null hypothesis and cannot conclude that the January Effect causes significant negative returns for our momentum strategies. Finally, based on these results we draw the conclusion that the driving forces of the observed January Effect are two-fold. The first force is predominant in small companies, while the second force is found in past losers regardless of size. Chapter 7 will further discuss the findings of this chapter and relate these to applicable explanations and theories.

6. Implementation issues

In the preceding chapter we presented and analysed the results obtained. Here we found that both the short-, intermediate- and long-term momentum investment strategies obtained positive and statistically significant monthly returns. Thus, on paper these momentum strategies appear to be profitable. However, in practice we may find that these strategies are not as profitable as depicted above. Two important factors were neglected in the analysis, namely the impact of transaction costs on profitability and potential constraints on short-selling in practice. Hence, the following chapter will discuss the impact of beforementioned factors on the profitability of our momentum strategies.

6.1 Transaction costs

In the literature review, we found that not all previous studies consider the impact of transaction costs. However, we believe that in order to reflect returns obtainable in practice we should estimate the impact of transaction costs on our strategies. We may find that the individual momentum strategies are significantly profitable on paper, i.e. without transaction costs, however when transactions costs are included these strategies may not "survive" (remain profitable). Thus, we increase the credibility of our backtests by providing a more realistic view, and will consequently cater this study more towards both practitioners and academics.

To adjust a backtest, we must first have an estimate of expected transaction costs. To create an estimate for these it is important to first understand the various components. First, part of the costs can be attributed to commissions and other types of direct costs to the broker for executing the transaction. Second, the costs of short-selling are typically higher than simply buying a share due to the costs of borrowing the securities to be sold. Third, the bid-ask spread, i.e. the difference between the bid and ask price. The bid-ask spread represents a transaction cost, since if you buy a stock and immediately sell it again you lose money equivalent to the spread. For illiquid stocks the bid-ask spread will be higher and represent a larger cost to the investor. Fourth, an indirect cost of trading is market impact costs. If an investor invests a substantial amount of money in a company it will push share prices up, whereas selling shares will push prices down. This is referred to as market impact costs and are often neglected by private investors in particular.

Adjusting a backtest for transaction costs is especially important when the investment strategy is based on frequent transactions. Hence, to get a better understanding of the impact of transaction costs we conduct a sensitivity analysis in which we apply different rates for transaction costs. For the purpose of this study, we have applied the following rates; 0.10%, 0.50%, 1.00% and 2.00%. Given these rates we adjust our returns as follows. Whenever a trade occurs, we calculate expected transaction costs and subtract these from returns. Thus, at the end of each holding period as we rebalance our portfolio we first calculate the return on the portfolio. Next, depending on the stocks to be included in the new portfolio and the change in value of each stock during the holding period we compute the required rebalancing such that the new portfolio is equally weighted. Based on the changes of positions in each individual stock we calculate transaction costs and subtract these from the portfolio return. Table 6.1 below presents the impact of adjusting our analysis for beforementioned rates.

Table 6.1: Sensitivity analysis of transaction costs

This table presents average monthly excess returns of the equal-weighted short-, intermediate- and long-term momentum investment strategies after transaction costs. t-statistics are two-sided and presented in square brackets. The t-stat is two-sided and tests whether excess returns of buying past winners and selling past losers after transaction costs, is significantly different from zero.

	Transaction costs				
	0.00%	0.10%	0.50%	1.00%	2.00%
Long-term strategy (12-2)	1.94	1.83	1.37	0.80	-0.33
	[4.62]	[4.34]	[3.26]	[1.91]	[-0.79]
Intermediate-term strategy (12-7)	1.43	1.29	0.71	-0.02	-1.48
	[4.43]	[3.99]	[2.19]	[-0.07]	[-4.60]
Short-term strategy (6-2)	2.00	1.84	1.21	0.41	-1.17
	[5.25]	[4.83]	[3.17]	[1.09]	[-3.09]

Source: Own creation

If we examine the table above, we find that all strategies remain profitable and statistically significant at the 1% significance level after accounting for transaction costs of 0.10%. When transaction costs are raised to 0.50% the intermediate-term strategy is significant at the 5% level whereas the other strategies are significant at the 1% level. When transaction costs are raised to 1.00% only the long-term and short-term strategy remains profitable, however only the long-term strategy is significant at the 10% level. With this being said, we find that transaction costs of 1.00% or more is rather conservative considering that Jegadeesh and Titman (1993) assumed transaction costs of 0.50% in their study, which at the time was considered conservative, and since then transaction costs have declined. The purpose of testing our results with transaction costs of 1.00% and 2.00% is to test the robustness of the strategies.

The average monthly excess market return was 0.62 percent during the time period analysed in this study. Thus, each of the three momentum strategies examined obtained higher returns than the market index when applying transaction costs of 0.50%. This finding further illustrates the robustness and profitability of our momentum investment strategies. Moreover, the observation that the momentum strategies are profitable even after adjusting for transaction costs further contradicts the efficient market hypothesis.

Another interesting finding in table 6.1 is that the short-term and intermediate-term strategy appears to be more sensitive to transaction costs than the long-term strategy. This is evident from the relative drop in returns, where the returns of the 6-2 and 12-7 strategies decrease more in comparison to the long-term strategy. Thus, when adjusting for transaction costs the long-term strategy provides a higher return than the short-term strategy, whereas previously the short-term strategy provided a slightly higher return than the other strategies. This observation suggests that there is less rebalancing in the long-term strategy. We can rationalise this from the following example. First, consider a stock that in a single month experiences extreme returns, say +500%, but relatively normal returns in every other month. This stock is likely to be included in every strategy for every month where the look-back period covers the extreme returns. As of such, for strategies with longer look-back periods (i.e. the 12-2 strategy) this particular stock will be a part of the winner portfolio for more months in a row than for strategies with shorter look-back periods (i.e. the 6-2 and 12-7 strategy). This means that less rebalancing will be required in the 12-2 strategy compared to the other strategies.

To summarize, we find that even after adjusting for reasonable transaction costs of 0.5%, our momentum investment strategies still remain profitable.

6.2 Short-selling implications

In practice the investor may experience implementation issues and other difficulties affecting the profitability of the strategies examined in this thesis. As mentioned previously, in a short sale the investor borrows stocks, typically from a broker who has borrowed the shares from a stock lender, and then subsequently sells the shares at the current market price. Later the investor must buy back the shares and return them to the broker to close the short position. Thus, to open a short position, the investor must initially find a broker who is willing to lend the investor the stocks. On the Nordic stock markets this may prove to be difficult as there is only a limited number of stocks which can be reliably shorted. If we use Nordnet, one of the largest brokers in the Nordics as an example, we can see that only the larger and more liquid companies can be shorted. Thus, if we were to implement our strategies in practice this would have a great impact on the feasibility of our proposed zero-cost strategies. In other words, in practice we may not be able to take a short position in the past losers. Consequently, this will have a substantial impact on the profitability of our investment strategies, as we found in section 5.1 that the market cap of the past losers on average were significantly lower than the rest of the sample. Moreover, we found that a large part of the momentum profits was generated from our short positions in these smaller companies.

Another implication neglected in the analysis is that to open a short position the investor must have a margin account. Brokers typically have a minimum margin value requirement, i.e. maintenance margin or security margin, which the investor must fulfil at all times when the position is open. Thus, if the stock price increases the investor must deposit more cash into the margin account to avoid the position being closed by the broker. At Nordnet the maintenance margin varies from 15-100% of the equity value (Nordnet, 2021). When the investor opens a short position he/she must also pay a lending fee and interest on the margin loan.

Other important risk factors an investor should keep in mind when opening a short position are the risks of a short squeeze, risk that the security is recalled and the potential unlimited downside. A short squeeze arises when investors are forced to close their short position by buying back the shares as a result of a jump in the stock price. Thus, if many investors do this simultaneously it will push up the stock price. This may create an upward going spiral as the buying back of shares results in higher prices forcing more investors to close their short position to avoid margin calls (Pedersen, 2015). Second, investors may risk that the shares are recalled by the stock lender. If that is the case the investor must buy the shares at the current share price and potentially incur high loses. Finally, investors must be aware of the skewed potential payoff associated with short positions. In theory there are no limits as to how much the stock price can increase, whereas the stock price can only drop by 100%. In other words, there is an unlimited downside of potential losses whereas potential profit is limited to 100%.

To summarize, we outline multiple difficulties associated with shorting that in practice may lead to the unprofitability of our momentum strategies. However, a thorough analysis of the practical implications for the investment strategies examined remains beyond the scope of this thesis.

7. Discussion

In chapter 5 and 6 we present the findings from our empirical analysis of long-, intermediate- and short-term momentum strategies and the extent to which the January Effect is present in the Nordic stock Markets. In this chapter we discuss the findings of the previous chapters and relate these to applicable explanations and theories.

7.1 Data snooping

As stated previously, in efficient markets assets reflect all information available, why investors should not be able to earn abnormal risk-adjusted returns using momentum investment strategies. Thus, some scholars have argued that observed abnormal momentum returns are a cause of data snooping bias. Generally, data snooping is an important element to consider when conducting financial studies such as an analysis of investment strategies which are based on large samples of data (Parmler & Gonzalez, 2007). Data snooping is a form of statistical bias occurring when the researcher adjusts his/her data sample after looking at the data for the purpose of achieving a specific result or fit the results to a particular theory. Data snooping can also refer to neglecting or leaving out data on purpose to obtain a desired result. For the purpose of this study we included delisted companies in the analysis namely to avoid data snooping and the survivorship bias. During our sample period 414 companies were delisted for various reasons. Due to a lack of data availability 162 of these companies were not included in our final data sample. Hence, some may argue that the results obtained in our analysis are biased. While we do acknowledge that our data sample is incomplete, due to its scale and the total number of companies included in the sample (1254), we argue than an inclusion of 162 delisted companies would not change the conclusions drawn in this paper. Moreover, since our results are in line with many of the previous studies, we consider our results to be robust.

7.2 Momentum explained based on behavioural finance

Our empirical analysis in chapter 5 showed that the common risk factors of market exposure, size and value were not able to fully explain the significant momentum returns obtained in the three strategies examined. In an attempt to rationalise our findings, this section will draw upon the explanations and theories of behavioural finance.

Previous literature has argued that momentum returns can be explained by the notion of under- and overreaction caused by irrational behaviour of investors. The under- and overreaction trend cycle can be explained as follows. A positive company announcement such as improved earnings, a successful acquisition, etc. may cause the fundamental value of the company to increase, however the market initially underreacts to this positive change in fundamental value. As a result of the initial underreaction the stock price continues to rise for a period of time until the stock price reflects the company's true fundamental value (Hurst, Ooi, & Pedersen, 2013). A trend-following investor, i.e. an investor using momentum strategies, will invest due to the initial price increase and thereafter profit from the continued increase until prices reach equilibrium. Other factors may result in a price drift and result in the stock price moving past the fundamental value, leading to an overreaction. In the following sections we will discuss various drivers of under- and overreaction.

7.2.1 Underreaction

Underreaction to company announcements

An argument for underreaction is the behavioural propensity of anchoring and insufficiently adjusting one's views. As outlined in section 2.2.2 people anchor their views to past information and additionally make insufficient adjustments to new information. This behavioural tendency may cause investors to underreact to positive company announcements such as improved earnings.
In the analysis of momentum returns adjusted for firm size (section 5.2), we found that momentum returns were considerably higher among smaller firms compared to larger firms. As of such one could argue that underreaction is more profound in smaller firms. An argument for why we may see this, is that news supposedly travels slower for smaller firms, as they typically receive less analyst coverage than bigger firms. This argument is also in line with the findings of Hong and Stein (1999) who found a considerably longer price drift for companies with small amounts of analyst coverage. Thus, it can be argued that companies may underreact due to low paced distribution of information.

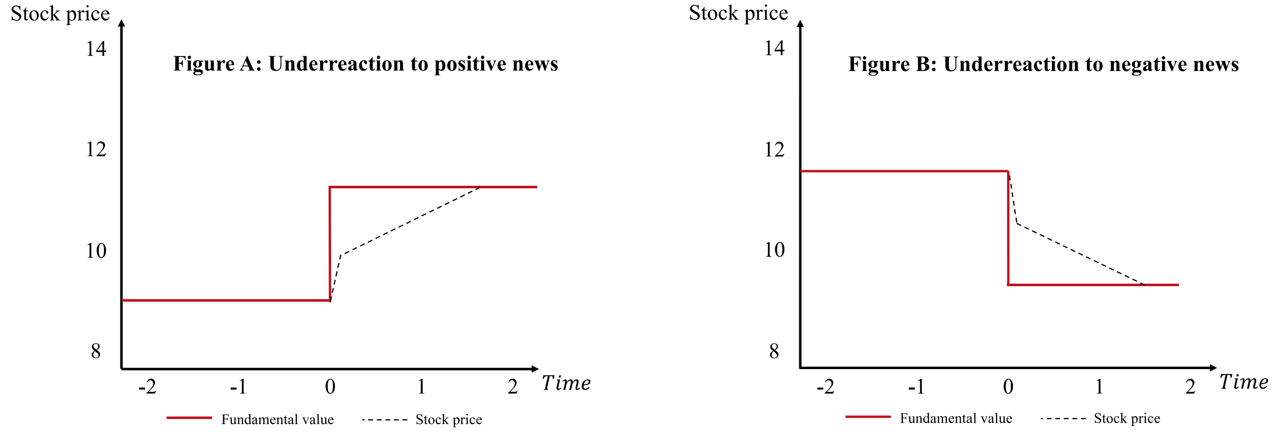
The observation of underreaction to company news and earnings announcements leading to momentum returns is also researched by Jegadeesh and Titman (1993) who examined the pattern between earnings announcements and momentum returns. They found that for the first 6 months surrounding the earnings announcement days, returns for past winners outperform past losers by more than 0.7% on average. This implies that momentum profits seem to be, at least partially, driven by underreactions to firm-specific company announcements. This finding may explain why we observe momentum returns in our analysis.

The impact of the disposition effect

Another factor which may lead to an initial underreaction to news and consequently positive momentum returns is the disposition effect. As explained in section 2.2.3, Shefrin and Statman (1985) found a general disposition among investors to realize gains too soon and hold on to losers too long. Thus, according to the disposition effect when positive company announcements are released investors tend to sell winners too soon, whereas when news affect the stock price negatively investors tend to hold on too long. These behavioural patterns may create downward pressure on stock prices in case of good news and inflated stock prices when bad news are published. Thus, the stock price underreacts to news and as a result does not reflect the fundamental value of the company. As suggested by Frazzini (2006) this underreaction caused by the disposition effect results in price predictability and post-announcement drift. This initial underreaction and subsequent post-announcement drift is illustrated in figure 7.1 below. As evident from the figure below, investors using the zero-cost momentum investment strategy can take advantage of the unrealized capital gains and losses due to the slow and insufficient adjustments to company announcements.

Figure 7.1: Underreaction to news

Figure A illustrates how a stock may underreact to positive news and the subsequent positive price drift. Figure B demonstrates how a stock may underreact to negative news and the following negative price drift. News are announced at time 0.



Source: Own creation

In chapter 5 we found that a larger part of the abnormal profits to our momentum strategies stem from the short-side and the underperformance of small losers. This indicates that for small firms the underreaction to negative news is greater than the corresponding underreaction to positive news. This is also in accordance with loss-aversion theory as suggested by Kahneman and Tversky (1974), which states that investors value losses and gains differently. As of such, investors are more likely to hold onto losers for too long than they are realising gains too soon, which causes a larger underreaction to negative news than positive news.

7.2.2 Overreaction

As we saw in the previous section a number of behavioural factors may result in an initial underreaction to announcements causing stock prices to drift for a period of time after the announcement. In addition to this, there are a number of other factors which may cause stock prices to increase beyond its intrinsic value, i.e. an overreaction of stock prices.

Overreaction caused by herding behaviour

It can be argued that herding behaviour may lead to trend continuation and consequently result in stock prices overreacting. As outlined previously, herding behaviour is a phenomenon where investors tend to imitate the actions of other individuals instead of acting based on their own opinions and analysis. As momentum investors start to invest during the post-announcement drift to profit from trend continuation it will push the stock price towards its fundamental value. However, other investors may choose to ignore their own private signals and follow the trend with no regards to the intrinsic value. This behaviour push prices above its fundamental value and thereby lead to higher momentum returns.

The herding behaviour is not only seen among investors, but it has also been documented among equity research analysts, who provide research coverage of public companies (Welch, 2000). These analysts may also engage in herding behaviour and follow the crowd, i.e. come up with the same recommendations about whether to buy, sell or hold. This irrational behaviour by equity analysts may lead to incorrect research coverage potentially resulting in overreaction.

Representativeness

Another argument why stock prices may overreact can be explained by the heuristic principle of representativeness. Representativeness is the tendency of estimating and judging decisions based on stereotypes and the degree to which it resembles past events. In terms of stock price overreaction to company announcements, the representativeness heuristic implies that investors will look at recent trends and consider these as representative for the fundamental value. Thus, investors will take a long position in stocks which have increased in value and vice versa for stocks which have dropped in value. Consequently, this behaviour causes the post-announcement drift to continue and exceed beyond the fundamental value resulting in overreaction.

7.2.3 Critique of behavioural finance explanations

From the perspective of traditional finance, using behavioural finance theories to explain momentum returns would contradict traditional finance theories such as the efficient market hypothesis, which argues that all market participants are able to efficiently incorporate new information when it is published and agree on its impact on the stock price. However, we still find our results more in line with behavioural finance due to the inability of the CAPM and our applied three-factor model to explain the abnormal positive returns of our strategies.

With this being said, several researchers have documented a long-term price reversal in the stock markets (see e.g. De Bondt and Thaler, 1985; Jegadeesh and Titman, 2001). This indicates that behavioural theories can be used to rationalise short-term stock market behaviour and the momentum returns obtained, however fall short in explaining long-term behaviour. This also implies that markets are inefficient in the short-term, whereas in the long-term markets are efficient and market behaviour in the long term is better explained by the traditional finance theories outlined in chapter 2. Thus, a natural extension to this study on momentum returns would be to investigate the profitability of long-term momentum strategies based on our data sample.

7.3 Explanations for the January Effect

Reflecting upon the findings obtained in the analysis, we found that the January Effect is present in the Nordic stock markets and that it is more profound among smaller firms. These finding are consistent with those documented by Roll (1983), Kleim (1983) and Lakonishok and Smidt (1988). On the other hand, Patel (2016) and Perez (2018) document that the January Effect has disappeared suggesting that the markets have become efficient in accordance with the efficient market hypothesis.

The sources of the January Effect have been widely debated, however the two most accepted explanations are tax-loss selling and window dressing. The tax-loss selling hypothesis argues that investors sell stocks before year-end, which have realised losses during the previous year to incur capital losses resulting in lower taxes on capital gains. Subsequently, prices revert in January due to the reduced selling pressure and potential repurchase from investors. This phenomenon may explain why we observe notably higher returns for both small and large losers in January compared to non-January months in our sample.

On the other hand, if markets are said to be efficient as argued by Fama (1970), the tax-loss selling hypothesis cannot explain the argument. Thus, other scholars argue that tax-loss selling cannot provide the whole explanation. It is beyond the scope of this thesis to test the tax-loss selling hypothesis. However, considering the results documented by previous scholars and our findings it could be interesting to test if we also observe tax-loss selling behaviour and if this could also provide an explanation for our results.

Another potential explanation why we observe a January Effect in the Nordic stock markets may be explained by the phenomenon of window dressing. The window dressing hypothesis suggests that portfolio managers will try to make their portfolio look as profitable as possible before year end where these are reported to investors. Portfolio managers may therefore sell poorly performing stocks and companies deemed too risky for some investors to make the portfolio appear attractive. In other words, portfolio managers want to avoid disclosing that they have invested in losing stocks, thereby creating the impression that the portfolio managers performed well. One may also argue that the window dressing behaviour can be explained by the herding behaviour, described in section 2.2.5, where investors tend to imitate other people. Portfolio managers may sell off poorly performing as well as small and risky stocks to signal that their investment decisions do not deviate too significantly from peers. This behaviour creates a downward price pressure in December due to the divestment of aforementioned stocks, whereas in January these stocks are reacquired pushing up prices. To summarize, this phenomenon may explain why we observe a small firm effect in January, since small firms in general are considered more risky than larger firms and explain why we find that losers perform notably better in January compared to non-January. However, since the tax-loss selling and window dressing phenomenon depicts similar results it may be difficult to conclude which phenomenon is a better explanation of our results, as it can prove challenging to control for either factor when examining the January Effect. To test if window dressing can explain our results we could test for seasonal anomalies in the other quarters where portfolio managers are evaluated, however this is beyond the scope of this thesis.

An alternative, and less popular, argument for why we observe a small firm effect in January may be explained by psychological factors. It can be argued that people tend to become more optimistic in the month of January due to the new year, new mindset phenomenon (Ciccone, 2011). Investor optimism is argued to be at its peak during January, thereby potentially explaining why we observe a small firm effect in January. In other words, investors are less risk averse why they are more prone to invest in smaller and more risky firms compared to non-January months.

8. Conclusion

The purpose of this study was to test the profitability of long-, intermediate- and short-term momentum investment strategies as well as determine the degree to which the January Effect exists in the Nordic stock markets.

By examining a sample period covering January 2007 to January 2021, this study concludes that the three distinct zero-cost strategies which longs and shorts stocks based on historical performance of 12-to-2 months, 12-to-7 months, and 6-to-2 months prior to portfolio formation respectively, generated significant excess returns in the Nordic stock market across this period. The study documents that each strategy realised average monthly excess returns of approximately 1.5 to 2.0 percent. As of such, in line with previous literature, this study provides further evidence of the profitability of strategies betting on past winners consistently outperforming past losers. Furthermore, through the application of statistical tests, this study finds no significant difference in performance between each of the three proposed momentum strategies. However, a notable difference in performance is observed comparing the long- and short-term strategies to the intermediate-term strategy.

Furthermore, this study conducts a thorough examination of the size implications associated with momentum strategies through the application of small and large sub-samples constructed based on the median of total market capitalization, as well as equally- and adjusted value weighting methods. The study concludes that the momentum effect is found in both large and small firms, although a stronger effect is found in smaller firms. This is documented through significantly positive momentum profits in both the small and large sub-sample, and a significant difference in returns comparing strategies of the small sample with strategies of the large sample. Furthermore, the study finds that the disparity in momentum profits between the two samples is caused by the underperformance of losers in the short side of the small sample. It is also documented that the loser portfolios of each strategy contain smaller companies than the winner portfolios, and that the winner and loser portfolios contain smaller than average companies.

Through application of the CAPM and the Fama-French three-factor model, using common risk factors of: market exposure, size and value, the study concludes that neither of these asset pricing models succeed in explaining the abnormal profits realised in each of the three momentum strategies.

These findings are consistent across both size sub-samples as well as the overall sample. As of such, the documented findings show inconsistency with the market efficiency hypothesis. Additionally, the study finds, using a four-factor model after controlling for momentum that some strategies still realise significant abnormal returns. These returns become small and insignificant through the application of a less extreme momentum strategy more in line with the methodology applied by Fama and French.

To determine the presence of the January Effect in the Nordic stock markets, as well as its impact and implications for the proposed momentum strategies, a decomposition of overall profits was conducted to distinguish between January and non-January returns. Based on this analysis, this study concludes that a perceived and statistically significant January effect has been observed in the Nordic stock markets for the sample period covering January 2007 to January 2021. Furthermore, it is concluded that the January Effect has had a negative impact on excess returns for each of the proposed momentum strategies of this study. However, due to non-relevant levels of significance the study cannot reject the null hypothesis that the January Effect causes insignificant negative returns for our momentum strategies. Moreover, it is documented that small firms on average tend to realise higher returns in January, and that this effect is especially profound in small losers and small winners. Finally, the study proposes two driving forces for the January Effect, the first force being predominant in small companies, while the second force is found in past losers regardless of size.

To determine the practical implications and possible issues associated with implementing the proposed zero-costs strategies in real life, a sensitivity analysis on transaction costs and strategy returns is conducted. The study concludes that all strategies retain significant positive excess returns after accounting for transaction costs of 0.5%. Furthermore, it is found that the long-term strategy is least susceptible to large transaction costs due to a lower number of required trades. Thus, the study concludes that the best performing strategy in a real-life setting would be the 12-2 strategy. The study further touches upon real-life implementation in its discussion on short-selling implications and finds that a true copy of the strategies analysed in this study would be exceedingly difficult to implement due to shorting issues associated with small and illiquid stocks.

Finally, possible explanation and rationales for the proposed findings are discussed. Considering the inability of traditional financial theories and models to explain previously mentioned conclusions, the study turns to behavioural finance theories in search of an answer. The study finds the disposition effect and herding effect, and subsequent under- and overreaction to news in stock prices as the most likely explanation for the perceived momentum effect.

Based on the conclusion that the three momentum investment strategies are profitable in the short term and that other scholars have documented long-term price reversal, a natural extension of this study would be to investigate the hypothesis of long-term price reversal based on our sample. Moreover, this study found evidence of the January Effect, however the analysis conducted was based on monthly observations. Hence, it would be interesting to investigate how the January returns are distributed throughout the month, as of such this thesis encourages further study using daily stock price observations.

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Appendix 1: List of companies and tickers

24Storage AB (publ) (OM:24STOR)
2cureX AB (publ) (OM:2CUREX)
3L System AB (publ.) (OM:3L)
A.P. Møller - Mærsk A/S (CPSE:MAERSK B)
A/S Nørresundby Bank (CPSE:NRSU)
A/S Vinderup Bank (CPSE:VIND)
AAC Clyde Space AB (publ) (OM:AAC)
AAK AB (publ.) (OM:AAK)
Aalborg Boldspilklub A/S (CPSE:AAB)
Aallon Group Oyj (HLSE:AALLON)
Aarhus Lokalbank Aktieselskab (CPSE:AARHUS)
AB Electrolux (publ) (OM:ELUX B)
AB Fagerhult (OM:FAG)
AB Geveko (publ) (OM:GVKO B)
AB Industrivärden (publ) (OM:INDU C)
AB Lindex (OM:LDEX)
AB Sagax (publ) (OM:SAGA B)
AB Sardus (OM:SARD)
AB SKF (publ) (OM:SKF B)
AB Traction (OM:TRAC B)
AB Volvo (publ) (OM:VOLV B)
ABB Ltd (OM:ABB)
Abliva AB (publ) (OM:ABLI)
Absolent Group AB (publ) (OM:ABSO)
AcadeMedia AB (publ) (OM:ACAD)
AcadeMedia AB (publ) (OM:ACAD)
Acando AB (publ.) (OM:ACAN B)
Acarix AB (publ) (OM:ACARIX)
Acconeer AB (publ) (OM:ACCON)
AcouSort AB (publ) (OM:ACOU)
Acroud AB (publ) (OM:ACROUD)
Actavis Group ehf. (ICSE:ACT)
Actic Group AB (publ) (OM:ATIC)
Active Biotech AB (publ) (OM:ACTI)
Adapteo Oyj (OM:ADAPT)
AdCityMedia AB (publ) (OM:ACM)
AdderaCare AB (OM:ADDERA)
AddLife AB (publ) (OM:ALIF B)
Addnode Group AB (publ) (OM:ANOD B)
Addtech AB (publ.) (OM:ADDT B)
ADDvise Group AB (publ) (OM:ADDV B)
Admicom Oyj (HLSE:ADMCM)
Advenica AB (publ) (OM:ADVE)
Adventure Box Technology AB (publ) (OM:ADVB(
AegirBio AB (publ) (OM:AEGIR)
Aerocrine AB (OM:AERO B)
ÅF Pöyry AB (publ) (OM:AF B)
Afarak Group Oyj (HLSE:AFAGR)
Affecto Oyj (HLSE:AFE1V)
Affitech AS (CPSE:AFFI)
Africa Energy Corp. (OM:AEC)
Africa Oil Corp. (OM:AOI)
Agat Ejendomme A/S (CPSE:AGAT)
Agellis AB (OM:AGIS)
AGES Industri AB (publ) (OM:AGES B)
AGF A/S (CPSE:AGF B)
Agillic A/S (CPSE:AGILC)
Agrokultura AB (OM:AGRA)
Ahlsell AB (publ) (OM:AHSL)
Ahlstrom-Munksjö Oyj (HLSE:AM1)
Ahtium Oyj (HLSE:TLV1V)
Aino Health AB (publ) (OM:AINO)
Akelius Residential Property AB (publ) (OM:AKEL
Aktia Pankki Oyj (HLSE:AKTIA)
Aktiebolaget Fastator (publ) (OM:FASTAT)
Aktieselskabet Schouw & Co. (CPSE:SCHO)
Ålandsbanken Abp (HLSE:ALBBV)
Alcadon Group AB (publ) (OM:ALCA)
Aldata Solution Oyj (HLSE:ALD1V)
Alefarm Brewing A/S (CPSE:ALEFRM)
Alelion Energy Systems AB (publ) (OM:ALELIO)
Alfa Laval AB (publ) (OM:ALFA)
Alimak Group AB (publ) (OM:ALIG)
ALK-Abelló A/S (CPSE:ALK B)
All Cards Service Center AB (OM:ACSC)
Allarity Therapeutics A/S (OM:ALLR)
Allenex AB (publ) (OM:ALNX)
Allgon AB (OM:ALLG B)
Alligator Bioscience AB (publ) (OM:ATORX)
ALM Equity AB (publ) (OM:ALM)
Alm. Brand A/S (CPSE:ALMB)
Alma Media Oyj (HLSE:ALMA)
Altia Oyj (HLSE:ALTIA)
AlzeCure Pharma AB (publ) (OM:ALZCUR)
Alzinova AB (OM:ALZ)
Amasten Fastighets AB (publ) (OM:AMAST)
Ambea AB (publ) (OM:AMBEA)
Ambu A/S (CPSE:AMBU B)
Amer Sports Corporation (HLSE:AMEAS)
Annehem Fastigheter AB (OM:ANNE B)
Annexin Pharmaceuticals AB (publ) (OM:ANNX)
Anoto Group AB (publ) (OM:ANOT)
Apetit Oyj (HLSE:APETIT)
AQ Group AB (publ) (OM:AQ)
Aqeri Holding AB (publ)
Aqualife A/S (CPSE:AQUA)
Arcam AB (publ) (OM:ARCM)
ArcAroma AB (publ) (OM:AAA)
Arcoma AB (OM:ARCOMA)
Arctic Minerals AB (publ) (OM:ARCT)
Arctic Paper S.A. (OM:ARP)
Arion banki hf. (OM:ARION SDB)
Arise AB (publ) (OM:ARISE)
Arjo AB (publ) (OM:ARJO B)
Arkil Holding A/S (CPSE:ARKIL B)
AroCell AB (publ) (OM:AROC)
Artificial Solutions International AB (publ) (OM:AS
Artimplant AB (OM:ARTI B)
AS Tallink Grupp (HLSE:TALLINK)
Asarina Pharma AB (publ) (OM:ASAP)
Ascelia Pharma AB (publ) (OM:ACE)
Asgaard Group A/S (CPSE:ASGGRO)
Aspire Global plc (OM:ASPIRE)
Aspiro AB (OM:ASP)
Aspiro AB (OM:ASP)
Aspo Oyj (HLSE:ASPO)
Aspocomp Group Oyj (HLSE:ACG1V)
ASSA ABLOY AB (publ) (OM:ASSA B)
Astralis Group A/S (CPSE:ASTGRP)
AstraZeneca PLC (OM:AZN)
Atari SA (OM:ATA SDB)
Athena investments (CPSE:ATHENA)
Athena IT-Group A/S (CPSE:ATHENA)
Atlas Copco AB (OM:ATCO A)
Atria Oyj (HLSE:ATRAV)
Atrium Ljungberg AB (publ) (OM:ATRLJ B)
Attendo AB (publ) (OM:ATT)
Atvexa AB (publ) (OM:ATVEXA B)
Audientes A/S (CPSE:AUDNTS)
Audiodev AB (OM:AUDV B)
Auriant Mining AB (publ) (OM:AUR)
Autoliv, Inc. (OM:ALIV SDB)
Availo AB (publ) (OM:AVAILO)
Avanza Bank Holding AB (publ) (OM:AZA)
Avega Group AB (publ) (OM:AVEG B)
Avensia AB (publ) (OM:AVEN)
Avidly Oyj (HLSE:AVIDLY)
AVTECH Sweden AB (publ) (OM:AVT B)
Awardit AB (publ) (OM:AWRD)
Axfood AB (publ) (OM:AXFO)
aXichem AB (OM:AXIC A)
Axis AB (publ) (OM:AXIS)
Axlon Group AB (publ) (OM:AXLN)
Axolot Solutions Holding AB (publ) (OM:AXOLOT
Ayima Group AB (publ) (OM:AYIMA B)
Azelio AB (publ) (OM:AZELIO)
B3 Consulting Group AB (publ) (OM:B3)
Bactiguard Holding AB (publ) (OM:BACTI B)
Balco Group AB (OM:BALCO)
Ballingslöv International AB (OM:BALL)
Bambuser AB (publ) (OM:BUSER)
Bang & Olufsen a/s (CPSE:BO)
Basware Oyj (HLSE:BAS1V)
Bavarian Nordic A/S (CPSE:BAVA)
Bayn Group AB (publ) (OM:BAYN)
BBS-Bioactive Bone Substitutes Oyj (HLSE:BONEI
BE Group AB (publ) (OM:BEGR)
Beijer Alma AB (publ) (OM:BEIA B)
Beijer Electronics Group AB (publ) (OM:BELE)
Beijer Ref AB (publ) (OM:BEIJ B)
Bergman & Beving AB (publ) (OM:BERG B)
Bergs Timber AB (publ) (OM:BRG B)
Berlin IV A/S (CPSE:BERLIV B)
Besqab AB (publ) (OM:BESQ)
Betsson AB (OM:BETS B)
Better Collective A/S (OM:BETCO)
Betting Promotion Sweden AB (publ) (OM:BETT)
BHG Group AB (publ) (OM:BHG)
Bilia AB (publ) (OM:BILI A)
BillerudKorsnäs AB (publ) (OM:BILL)
Bilot Oyj (HLSE:BILOT)
BIMobject AB (OM:BIM)
Binero Group AB (publ) (OM:BINERO)
BioArctic AB (publ) (OM:BIOA B)
BioGaia AB (publ) (OM:BIOG B)
Biohit Oyj (HLSE:BIOBV)
BioInvent International AB (publ) (OM:BINV)
Biolin Scientific Holding AB (OM:BLIN)
BioMar Holding A/S (CPSE:BIOMAR)
Biophausia AB (OM:BIOP)
BioPorto A/S (CPSE:BIOPOR)
Bioservo Technologies AB (publ) (OM:BIOS)
Biotage AB (OM:BIOT)
BioTie Therapies Oy (HLSE:BTT1V)
Biovica International AB (publ) (OM:BIOVIC B)
Bio-Works Technologies AB (publ) (OM:BIOWKS)
Birka Line ABP (HLSE:BKLAV)
Bittium Oyj (HLSE:BITTI)
Björn Borg AB (publ) (OM:BORG)
Blue Vision A/S (CPSE:BLVIS A)
BoConcept Holding A/S (CPSE:BOCON B)
Boliden AB (publ) (OM:BOL)
Boliga Gruppen A/S (CPSE:BOLIGA)
BoMill AB (publ) (OM:BOMILL)
Bonäsudden Holding AB (publ) (OM:BONAS)
Bonava AB (publ) (OM:BONAV B)
Bonesupport Holding AB (publ) (OM:BONEX)
Bong AB (publ) (OM:BONG)
Boozt AB (publ) (OM:BOOZT)
Boreo (HLSE:YEINT)
Botnia Exploration Holding AB (publ) (OM:BOTX)
Boule Diagnostics AB (publ) (OM:BOUL)
Bravida Holding AB (publ) (OM:BRAV)
Brd. Klee A/S (CPSE:KLEE B)
Bredband2 i Skandinavien AB (publ) (OM:BRE2)
Brighter AB (publ) (OM:BRIG)
Brim hf. (ICSE:BRIM)
Bringwell AB (publ) (OM:BWL)
Brinova Fastigheter AB (publ) (OM:BRIN B)
Brødrene A & O Johansen A/S (CPSE:AOJ P)
Brødrene Hartmann A/S (CPSE:HART)
Brøndbyernes IF Fodbold A/S (CPSE:BIF)
Broström AB (OM:BRO B)
BTS Group AB (publ) (OM:BTS B)
Bublar Group AB (publ) (OM:BUBL)
Bufab AB (publ) (OM:BUFAB)
Bulten AB (publ) (OM:BULTEN)
Bure Equity AB (publ) (OM:BURE)
Byggmästare Anders J Ahlström Holding AB (publ)
Byggmax Group AB (publ) (OM:BMAX)
ByggPartner i Dalarna Holding AB (publ) (OM:BYC
CAG Group AB (publ) (OM:CAG)
Calliditas Therapeutics AB (publ) (OM:CALTX)
Camurus AB (publ) (OM:CAMX)
Cantargia AB (publ) (OM:CANTA)
Capacent Holding AB (publ) (OM:CAPAC)
Caperio Holding AB (OM:CAPE)
Capilon AB (OM:CAPN)
Capio AB (publ) (OM:CAPIO)
CapMan Oyj (HLSE:CAPMAN)
Cardo AB (OM:CARD)
Cargotec Corporation (HLSE:CGCBV)
Carl Lamm Holding AB (OM:CLHO)
Carlsberg A/S (CPSE:CARL B)
CashGuard AB (OM:CASH B)
Castellum AB (publ) (OM:CAST)
Catella AB (publ) (OM:CAT B)
Catena AB (publ) (OM:CATE)
Catena Media plc (OM:CTM)
Caverion Oyj (HLSE:CAV1V)
Cavotec SA (OM:CCC)
cBrain A/S (CPSE:CBRAIN)
CDON AB (OM:CDON)
Cell Impact AB (publ) (OM:CI B)
Cell Network AB (OM:MAND)
CellaVision AB (publ) (OM:CEVI)
Cellink AB (publ) (OM:CLNK B)
Cemat A/S (CPSE:CEMAT)
ChemoMetec A/S (CPSE:CHEMM)
Chr. Hansen Holding A/S (CPSE:CHR)
Christian Berner Tech Trade AB (publ) (OM:CBTT
ChromoGenics AB (OM:CHRO)

Cibus Nordic Real Estate AB (publ) (OM:CIBUS)	Demant A/S (CPSE:DEMANT)	Enento Group Oyj (HLSE:ENENTO)	Fondia Oyj (HLSE:FONDIA)
Cimber Sterling Group A/S (CPSE:CIMBER)	Den Jyske Sparekasse (CPSE:DJS)	Enersense International Oyj (HLSE:ESENSE)	Footway Group AB (publ) (OM:FOOT B)
Cinnober Financial Technology AB (publ) (OM:CIN	Detection Technology Oyj (HLSE:DETEC)	Enersize Oyj (OM:ENERS)	Formpipe Software AB (publ) (OM:FPIP)
CirChem AB (publ) (OM:CIRCHE)	DevPort AB (publ) (OM:DEVP B)	Eniro AB (publ) (OM:ENRO)	Forstædernes Bank A/S (CPSE:FORST)
Cision AB (OM:CSN)	DFDS A/S (CPSE:DFDS)	Enlabs AB (publ) (OM:NLAB)	Fortinova Fastigheter AB (Publ) (OM:FNOVA B)
Citycon Oyj (HLSE:CTY1S)	DGC One AB (OM:DGC)	Enorama Pharma AB (publ) (OM:ERMA)	Fortum Oyj (HLSE:FORTUM)
Clas Ohlson AB (publ) (OM:CLAS B)	Diadrom Holding AB (publ) (OM:DIAH)	EnQuest PLC (OM:ENQ)	Fram Skandinavien AB (OM:FRAM B)
Clavister Holding AB (publ.) (OM:CLAV)	Diamyd Medical AB (publ) (OM:DMYD B)	Enzymatica AB (OM:ENZY)	Freja eID Group AB (publ) (OM:FREJA)
Clean Motion AB (publ) (OM:CLEMO)	DiBa A / S (CPSE:DIBA)	Eolus Vind AB (publ) (OM:EOLU B)	Frill Holding AB (publ) (OM:FRILL B)
Cleantech Building Materials Plc (CPSE:CBM)	DIBS Payment Services AB (publ.) (OM:DIBS)	EOS Russia (OM:EOS)	FRISQ Holding AB (publ) (OM:FRISQ)
Clemondo Group AB (publ) (OM:CLEM)	Dicentia DK A/S (CPSE:DICENT)	Epiroc AB (publ) (OM:EPI A)	FS Finans III A/S (CPSE:AMAG)
Climeon AB (publ) (OM:CLIME B)	Digia Oyj (HLSE:DIGIA)	Episurf Medical AB (publ) (OM:EPIS B)	F-Secure Oyj (HLSE:FSC1V)
Clinical Laserthermia Systems AB (publ) (OM:CLS I	Digitalist Group Plc (HLSE:DIGIGR)	eQ Oyj (HLSE:EQV1V)	Fynske Bank A/S (CPSE:FYNBK)
Cloetta AB (publ) (OM:CLA B)	Dignitana AB (publ.) (OM:DIGN)	EQT AB (publ) (OM:EQT)	G4S plc (CPSE:G4S)
Codan A/S (CPSE:CODAN)	Diös Fastigheter AB (publ) (OM:DIOS)	Erria A/S (CPSE:ERRIA)	G5 Entertainment AB (publ) (OM:G5EN)
Collector AB (publ) (OM:COLL)	DistIT AB (publ) (OM:DIST)	Essity AB (publ) (OM:ESSITY B)	Gabather AB (publ) (OM:GABA)
Coloplast A/S (CPSE:COLO B)	Divio Technologies AB (publ) (OM:DIVIO B)	Etrion Corporation (OM:ETX)	Gabriel Holding A/S (CPSE:GABR)
Columbus A/S (CPSE:COLUM)	Djurslands Bank A/S (CPSE:DJUR)	Etteplan Oyj (HLSE:ETTE)	Gaming Corps AB (publ) (OM:GCOR)
Com Hem Holding AB (publ) (OM:COMH)	DK Company A/S (CPSE:DKC)	European Wind Investment A/S (CPSE:EWII)	Gaming Innovation Group Inc. (OM:GIGSEK)
CombiGene AB (publ) (OM:COMBI)	Dome Energy AB (publ) (OM:DOME)	Evli Pankki Oyj (HLSE:EVLI)	Gant Company AB (OM:GANT)
Componenta Corporation (HLSE:CTH1V)	Dometic Group AB (publ) (OM:DOM)	Evolution Gaming Group AB (publ) (OM:EVO)	Gapwaves AB (publ) (OM:GAPW B)
Comptel Oyj (HLSE:CTL1V)	Doro AB (publ) (OM:DORO)	Evox Rifa Group Oyj (HLSE:ERG1V)	Garo Aktiebolag (publ) (OM:GARO)
Concejo AB (publ) (OM:CNCJO B)	Dovre Group Plc (HLSE:DOV1V)	Ework Group AB (publ) (OM:EWRK)	Gasporox AB (publ) (OM:GPX)
Concentric AB (publ) (OM:COIC)	Doxa AB (publ) (OM:DOXA)	EWPG Holding AB (publ) (OM:ECOWVE)	Generic Sweden AB (OM:GENI)
Concordia Maritime AB (publ) (OM:CCOR B)	Drillcon AB (publ) (OM:DRIL)	Exel Composites Oyj (HLSE:EXL1V)	Genmab A/S (CPSE:GMAB)
Conferize A/S (CPSE:CONFRZ)	DSV Panalpina A/S (CPSE:DSV)	EXINI Diagnostics AB (publ) (OM:EXINI)	Genova Property Group AB (publ) (OM:GPG)
Confidence International AB (publ.) (OM:CONF)	Duni AB (publ) (OM:DUNI)	Exiqon A/S (CPSE:EXQ)	Genovis AB (publ.) (OM:GENO)
Connecta AB (OM:CNTA)	DuPont Nutrition Bioscience Aps (CPSE:DCO)	ExpreS2ion Biotech Holding AB (publ) (OM:EXPR	GeoSentric Oyj (HLSE:GEO1V)
Consti Oyj (HLSE:CONSTI)	Duroc AB (publ) (OM:DURC B)	Exsitec Holding AB (publ) (OM:EXS)	German High Street Properties A/S (CPSE:GERHSP
Coor Service Management Holding AB (OM:COOR	Dustin Group AB (publ) (OM:DUST)	F.E. Boarding (CPSE:BORD B)	Getinge AB (OM:GETI B)
Copenhagen Capital A/S (CPSE:CPHCAP ST)	EAB Group Oyj (HLSE:EAB)	Fabege AB (publ) (OM:FABG)	GHP Specialty Care AB (publ) (OM:GHP)
Copperstone Resources AB (OM:COPP B)	EAC Invest A/S (CPSE:EAC)	Faron Pharmaceuticals Oy (HLSE:FARON)	Glaston Oyj Abp (HLSE:GLA1V)
Corem Property Group AB (publ) (OM:CORE B)	Eastnine AB (publ) (OM:EAST)	Fasadgruppen Group AB (publ) (OM:FG)	Glitnir HoldCo ehf. (ICSE:GLB)
Corline Biomedical AB (OM:CLBIO)	Ecoclime Group AB (publ) (OM:ECC B)	Fast Ejendom Danmark A/S (CPSE:FED)	Glunz & Jensen Holding A/S (CPSE:GJ)
Cortus Energy AB (publ) (OM:CE)	Edgeware AB (OM:EDGE)	Fastighets AB Balder (publ) (OM:BALD B)	GN Store Nord A/S (CPSE:GN)
CPSE:SPENN (CPSE:NPINV)	Eezy Oyj (HLSE:EEZY)	Fastighets AB Trianon (publ) (OM:TRIAN B)	Gofore Oyj (HLSE:GOFORE)
C-Rad AB (publ) (OM:CRAD B)	Efecte Oy (HLSE:EFECTE)	Fastilium Property Group AB (OM:CTEC)	GomSpace Group AB (publ) (OM:GOMX)
Cramo Oyj	Effnetplattformen AB (publ) (OM:EFFP)	FastPartner AB (publ) (OM:FPAR A)	Götenehus Group AB (publ) (OM:GHUS B)
Creades AB (OM:CRED A)	EG A/S (CPSE:EDB)	FastPassCorp A/S (CPSE:FASTPC)	GPX Medical AB (publ) (OM:GPXMED)
Crunchfish AB (publ) (OM:CFISH)	Ege Carpets A/S (CPSE:EGE B)	Fazer Services AB (OM:FKS B)	Gränges AB (publ) (OM:GRNG)
Cryptzone Group AB (publ) (OM:CZON B)	Egetis Therapeutics AB (publ) (OM:EGTX)	Feelgood Svenska AB (publ) (OM:FEEL)	Greater Than AB (OM:GREAT)
CTT Systems AB (OM:CTT)	EgnsINVEST Ejendomme Tyskland A/S (CPSE:EGN	Fellow Finance Oyj (HLSE:FELLOW)	Green Landscaping Group AB (publ) (OM:GREEN)
Curalogic A/S (CPSE:CUR)	Eik fasteignafélag hf. (ICSE:EIK)	Fenix Outdoor International AG (OM:FOI B)	Green Mobility A/S (CPSE:GREENM)
Curando Nordic AB (publ) (OM:CUR)	Eimskipafélag Íslands hf. (ICSE:EIM)	Ferroamp Elektronik AB (publ) (OM:FERRO)	Green Wind Energy (CPSE:GW)
CybAero AB	Elanders AB (publ) (OM:ELAN B)	Ferronordic AB (publ) (OM:FNM)	GrønlandsBANKEN A/S (CPSE:GRLA)
Cyber Security 1 AB (publ) (OM:CYB1)	Elcoteq SE (HLSE:ELQAV)	Festi hf. (ICSE:FESTI)	GTECH Sweden Interactive AB (OM:BOSS)
Cybercom Group AB (OM:CYBE)	Elecster Oyj (HLSE:ELEAV)	Filo Mining Corp. (OM:FIL)	Guard Therapeutics International AB (publ) (OM:GU
Cyxone AB (publ) (OM:CYXO)	Electra Gruppen AB (publ) (OM:ELEC)	Fingerprint Cards AB (publ) (OM:FING B)	Guideline Geo AB (publ) (OM:GGEO)
Dagon AB (publ) (OM:DAG)	Electrolux Professional AB (publ) (OM:EPRO B)	Finnair Oyj (HLSE:FIA1S)	Gunnebo Industries AB (OM:GIAB)
Dampskibsselskabet Norden A/S (CPSE:DNORD)	Elekta AB (publ) (OM:EKTA B)	Fionia Holding A/S (CPSE:FIONIA)	Gyldendal A/S (CPSE:GYLD A)
Dan-Ejendomme Holding A/S (CPSE:DEH)	ElektronikGruppen BK AB (OM:ELGR B)	Firefly AB (publ) (OM:FIRE)	H & M Hennes & Mauritz AB (publ) (OM:HM B)
Danish Aerospace Company A/S (CPSE:DAC)	Elisa Oyj (HLSE:ELISA)	FirstFarms A/S (CPSE:FFARMS)	H. Lundbeck A/S (CPSE:LUN)
Dannemora Mineral AB (OM:DMAB B)	Ellen AB (publ) (OM:ELN)	Fiskars Oyj Abp (HLSE:FSKRS)	H+H International A/S (CPSE:HH)
Dansk Industri Invest A/S (CPSE:DII)	Ellwee AB (publ) (OM:ELLWEE)	FIT Biotech Oy (HLSE:FITBIO)	Hagar hf (ICSE:HAGA)
Danske Andelskassers Bank A/S (CPSE:DAB)	Elos Medtech AB (publ) (OM:ELOS B)	Flexion Mobile Plc (OM:FLEXM)	Haldex AB (publ) (OM:HLDX)
Danske Bank A/S (CPSE:DANSKE)	Eltel AB (publ) (OM:ELTEL)	FlexQube AB (publ) (OM:FLEXQ)	Hampidjan Hf. (ICSE:HAMP)
Dantax A/S (CPSE:DANT)	Embracer Group AB (publ) (OM:EMBRAC B)	FLSmidth & Co. A/S (CPSE:FLS)	Handicare Group AB (publ) (OM:HANDI)
Dataproces Group A/S (CPSE:DATA)	Empir Group AB (OM:EMPIR B)	Flügger group A/S (CPSE:FLUG B)	Hansa Biopharma AB (publ) (OM:HNSA)
DDM Holding AG (OM:DDM)	Enad Global 7 AB (publ) (OM:EG7)	Fluicell AB (publ) (OM:FLUI)	Hanza Holding AB (publ) (OM:HANZA)
DecideAct A/S (CPSE:ACT)	Enalyzer A/S (CPSE:ENALYZ)	FM Mattsson Mora Group AB (publ) (OM:FMM E	Happy Helper A/S (CPSE:HAPPY)
Dedicare AB (publ) (OM:DEDI)	Endomines AB (publ) (OM:ENDO)	FME Europe AB (OM:FME B)	Harboes Bryggeri A/S (CPSE:HARB B)
Deltaq A/S (CPSE:DELTAQ)	Enea AB (publ) (OM:ENEA)	Fodelia Oyj (HLSE:FODELIA)	Harvia Oyj (HLSE:HARVIA)
Deltek Danmark A/S (CPSE:MACO)	Enedo Oyj (HLSE:ENEDO)	FOM Technologies A/S (CPSE:FOM)	Havsfrun Investment AB (publ) (OM:HAV B)

HEBA Fastighets AB (publ) (OM:HEBA B)
Hedegaard A/S (CPSE:HEDE)
Hedera Group AB (publ) (OM:HEGR)
Heeros Oyj (HLSE:HEEROS)
Heliospectra AB (publ) (OM:HELIO)
Hembla AB (publ) (OM:HEM B)
Hemcheck Sweden AB (publ) (OM:HEMC)
Hemfosa Fastigheter AB (publ) (OM:HEMF)
Hemtex AB (publ) (OM:HEMX)
Herantis Pharma Oyj (HLSE:HRTIS)
Hexagon AB (publ) (OM:HEXA B)
Hexatronic Group AB (publ) (OM:HTRO)
HEXPOL AB (publ) (OM:HPOL B)
Hifab Group AB (publ.) (OM:HIFA B)
HiQ International AB (publ) (OM:HIQ)
Hitech & Development Wireless Sweden Holding AE
HKScan Oyj (HLSE:HKSAV)
HL Display Holding AB (OM:HL B)
HMS Networks AB (publ) (OM:HMS)
Höganäs AB (publ) (OM:HOGA B)
Hoist Finance AB (publ) (OM:HOFI)
Hoivatilat Oyj (HLSE:HOIVA)
Holdingselskabet af 8. maj 2013 A/S (CPSE:LAST I
Holmen AB (publ) (OM:HOLM B)
Home Properties AB (OM:HOPR)
Honkarakenne Oyj (HLSE:HONBS)
House of Friends AB (publ) (OM:HOFF)
Hövding Sverige AB (publ) (OM:HOVD)
Hoylu AB (publ) (OM:HOYLU)
HRC World Plc (CPSE:HRC)
hubbr AB (publ) (OM:HUBR B)
Hufvudstaden AB (publ) (OM:HUFV A)
Huhtamäki Oyj (HLSE:HUH1V)
Humana AB (publ) (OM:HUM)
HusCompagniet A/S (CPSE:HUSCO)
Husqvarna AB (publ) (OM:HUSQ B)
Hvidbjerg Bank A/S (CPSE:HVID)
Hypefactors A/S (CPSE:HYPE)
IAR Systems Group AB (publ) (OM:IAR B)
IC Group A/S (CPSE:IC)
ICA Gruppen AB (publ) (OM:ICA)
Iceland Seafood International hf. (ICSE:ICESEA)
Icelandair Group hf. (ICSE:ICEAIR)
Icelandic Group hf. (ICSE:IG)
Iconovo AB (publ) (OM:ICO)
Idogen AB (publ) (OM:IDOGEN)
Ilkka-Yhtymä Oyj (HLSE:ILK2S)
Image Systems AB (OM:IS)
Immunicum AB (publ) (OM:IMMU)
Immunovia AB (publ) (OM:IMMNOV)
Impact Coatings AB (publ) (OM:IMPC)
Implantica AG (OM:IMP A SDB)
Incap Oyj (HLSE:ICP1V)
InCoax Networks AB (publ) (OM:INCOAX)
InDex Pharmaceuticals Holding AB (publ) (OM:IND
Industrial and Financial Systems, IFS AB (publ) (ON
Indutrade AB (publ) (OM:INDT)
Infant Bacterial Therapeutics AB (publ) (OM:IBT B
Infrea AB (OM:INFREA)
Inission AB (publ) (OM:INISS B)
Innofactor Oyj (HLSE:IFA1V)
Insplorion AB (publ) (OM:INSP)
Instalco AB (publ) (OM:INSTAL)

Integrum AB (publ) (OM:INTEG B)
Interavanti Oyj (HLSE:INA1S)
InterMail A/S (CPSE:IMAIL)
International Petroleum Corporation (OM:IPCO)
Intervacc AB (publ) (OM:IVACC)
Intrum AB (publ) (OM:INTRUM)
Invajo Technologies AB (publ) (OM:INVAJO)
Investeringsselskabet Luxor A/S (CPSE:LUXOR B)
Investment AB Latour (publ) (OM:LATO B)
Investment AB Öresund (publ) (OM:ORES)
Investor AB (publ) (OM:INVE B)
Investors House Oyj (HLSE:INVEST)
Invisio AB (publ) (OM:IVSO)
Invuo Technologies AB (OM:INVUO)
Inwido AB (OM:INWI)
Inzile AB (publ) (OM:INZILE)
Irisity AB (publ) (OM:IRIS)
IRLAB Therapeutics AB (publ) (OM:IRLAB A)
IRRAS AB (publ) (OM:IRRAS)
Isofol Medical AB (publ) (OM:ISOFOL)
ISR Immune System Regulation Holding AB (publ) (
ISS A/S (CPSE:ISS)
ITAB Shop Concept AB (publ) (OM:ITAB B)
I-Tech AB (OM:ITECH)
Itiviti Group AB (OM:ORC)
Ivisys AB (publ) (OM:IVISYS)
iZafe Group AB (publ) (OM:IZAFE B)
Jeeves Information Systems AB (OM:JEEV)
Jensen & Møller Invest A/S (CPSE:JMI)
Jetpak Top Holding AB (publ) (OM:JETPAK)
Jeudan A/S (CPSE:JDAN)
JLT Mobile Computers AB (publ) (OM:JLT)
JM AB (publ) (OM:JM)
Jobindex A/S (CPSE:JOBNDX)
John Mattson Fastighetsföretagen AB (publ) (OM
JonDeTech Sensors AB (publ) (OM:JDT)
Josemaria Resources Inc. (OM:JOSE)
Julius Tallberg-Kiinteistöt Oyj (HLSE:JTK1V)
Jutlander Bank A/S (CPSE:JUTBK)
Jyske Bank A/S (CPSE:JYSK)
K2A Knaust & Andersson Fastigheter AB (publ) (O
KABE Group AB (publ.) (OM:KABE B)
Kakel Max AB (publ) (OM:KAKEL)
Kaldalón hf. (ICSE:KALD)
Kallebäck Property Invest AB (publ) (OM:KAPIAB)
Kambi Group plc (OM:KAMBI)
Kamux Oyj (HLSE:KAMUX)
Kancera AB (publ) (OM:KAN)
KappAhl AB (publ) (OM:KAHL)
Karnov Group AB (publ) (OM:KAR)
Karo Pharma AB (publ) (OM:KARO)
Karolinska Development AB (publ) (OM:KDEV)
Kaupthing ehf (ICSE:KAUP)
KebNi AB (publ) (OM:KEBNI B)
Kemira Oyj (HLSE:KEMIRA)
Kentima Holding AB (publ) (OM:KENH)
Keskisuomalainen Oyj (HLSE:KSLAV)
Kesko Oyj (HLSE:KESKOB)
Kesla Oyj (HLSE:KELAS)
K-Fast Holding AB (publ) (OM:KFAST B)
Kindred Group plc (OM:KIND SDB)
Kinnevik AB (OM:KINV B)
Klakki ehf. (ICSE:EXISTA)

Klappir Grænar Lausnir hf. (ICSE:KLAPP B)
Klaria Pharma Holding AB (publ.) (OM:KLAR)
Klövern AB (publ) (OM:KLOV B)
KMT Group AB (OM:KMT)
Knowit AB (publ) (OM:KNOW)
Københavns Lufthavne A/S (CPSE:KBHL)
Kojamo Oyj (HLSE:KOJAMO)
Kollect on Demand Holding AB (publ) (OM:KOLL)
KONE Oyj (HLSE:KNEBV)
Konecranes Plc (HLSE:KCR)
Konsolidator A/S (CPSE:KONSOL)
Kontigo Care AB (publ) (OM:KONT)
Kopy Goldfields AB (publ) (OM:KOPY)
Kotipizza Group Oyj (HLSE:PIZZA)
Kreditbanken A/S (CPSE:KRE)
Kungsleden AB (publ) (OM:KLED)
Kvika banki hf. (ICSE:KVIKA)
L E Lundbergföretagen AB (publ) (OM:LUND B)
Labeyrie Fine Foods PLC (ICSE:A)
Lagercrantz Group AB (publ) (OM:LAGR B)
Lammhults Design Group AB (publ) (OM:LAMM B
Lån & Spar Bank A/S (CPSE:LASP)
Land & Leisure A/S (CPSE:LL B)
Lappland Goldminers AB (OM:GOLD)
Lassila & Tikanoja Oyj (HLSE:LAT1V)
Lauritz.com Group A/S (OM:LAUR)
LBI hf. (ICSE:LAIS)
LeadDesk Oy (HLSE:LEADD)
Leading Edge Materials Corp. (OM:LEMSE)
LED iBond International A/S (CPSE:LEDIBOND)
Ledstiernan AB (OM:LEDS B)
Lehto Group Oyj (HLSE:LEHTO)
LeoVegas AB (publ) (OM:LEO)
LIDDS AB (publ) (OM:LIDDS)
Lifco AB (publ) (OM:LIFCO B)
LifeClean International AB (publ) (OM:LCLEAN)
LightLab Sweden AB (OM:LLSW B)
Lime Technologies AB (publ) (OM:LIME)
Lindab International AB (publ) (OM:LIAB)
Link Prop Investment AB (publ) (OM:LINKAB)
Lipidor AB (publ) (OM:LIPI)
Litium AB (publ) (OM:LITI)
Liv ihop AB (publ) (OM:LIVI)
Logistea AB (publ) (OM:LOG)
Lohilo Foods Ab (Publ) (OM:LOHILO)
Lokalbanken i Nordsjaelland A/S (CPSE:LOKA)
Lollands Bank A/S (CPSE:LOLB)
Loomis AB (publ) (OM:LOOMIS)
Loudspring Oyj (HLSE:LOUD)
Lucara Diamond Corp. (OM:LUC)
Lundin Energy AB (publ) (OM:LUNE)
Lundin Gold Inc. (OM:LUG)
Lundin Mining Corporation (OM:LUMI)
Luxbright AB (publ) (OM:LXB)
Lyko Group AB (publ) (OM:LYKO A)
M.O.B.A. Network AB (publ) (OM:MOBA)
Mackmyra Svensk Whisky AB (publ) (OM:MACK B
MAG Interactive AB (publ) (OM:MAGI)
Magle Chemoswed Holding AB (publ) (OM:MAGL
Magnolia Bostad AB (publ) (OM:MAG)
Maha Energy AB (publ) (OM:MAHA A)
Mälarvärme Holding AB (OM:VKG)
Malmbergs Elektriska AB (publ) (OM:MEAB B)

Mangold Fondkommission AB (OM:MANG)
Mantex AB (publ) (OM:MANTEX)
Marel hf. (ICSE:MAREL)
Marimekko Oyj (HLSE:MEKKO)
Martela Oyj (HLSE:MARAS)
Matas A/S (CPSE:MATAS)
Matse Holding AB (publ) (OM:MAT)
Mavshack AB (publ) (OM:MAV)
Max Bank (CPSE:MAX)
MaxFastigheter i Sverige AB (publ) (OM:MAXF)
Mdundo.com A/S (CPSE:MDUNDO)
MedCap AB (publ) (OM:MCAP)
MedCore AB (OM:MCOR)
Media and Games Invest plc (OM:M8G)
Medicover AB (publ) (OM:MCOV B)
Medivir AB (publ) (OM:MVIR B)
Mekonomen AB (publ) (OM:MEKO)
Melker Schörling AB (OM:MELK)
Mentice AB (publ) (OM:MNTC)
Mermaid A/S (CPSE:MERM)
Metsä Board Oyj (HLSE:METSB)
Metso Fabrics Corp. (HLSE:TAF1V)
Metso Outotec Oyj (HLSE:MOCORP)
Micro Systemation AB (publ) (OM:MSAB B)
Midsona AB (publ) (OM:MSON B)
Midsummer AB (publ) (OM:MIDS)
Midway Holding AB (publ) (OM:MIDW B)
Millicom International Cellular S.A. (OM:TIGO SDB)
Minesto AB (publ) (OM:MINEST)
MIPS AB (publ) (OM:MIPS)
Misen Energy AB (publ) (OM:MISE)
Mitsubishi Logisnext Europe Oy (HLSE:ROC1V)
Moberg Pharma AB (publ) (OM:MOB)
Modern Ekonomi Sverige Holding AB (publ) (OM:N
Modern Times Group Mtg AB (OM:MTG B)
Modul 1 Data AB (Publ) (OM:MOD1)
Molslinjen A/S (CPSE:MOLS)
Moment Group AB (OM:MOMENT)
Momentum Group AB (publ) (OM:MMGR B)
Monberg & Thorsen A/S (CPSE:MT B)
Møns Bank A/S (CPSE:MNBA)
Monsenso A/S (CPSE:MONSO)
MoxieTech Group AB (publ) (OM:MOXI)
MQ Holding AB (OM:MQ)
Mr Green & Co AB (publ) (OM:MRG)
MT Højgaard Holding A/S (CPSE:MTHH)
MultiQ International AB (publ) (OM:MULQ)
Munters Group AB (publ) (OM:MTRS)
Musti Group Oyj (HLSE:MUSTI)
Mycronic AB (publ) (OM:MYCR)
myFC Holding AB (publ) (OM:MYFC)
Nanexa AB (publ) (OM:NANEXA)
NanoCover A/S (CPSE:NANO)
Nanoform Finland Oyj (HLSE:NANOFH)
NAXS AB (publ) (OM:NAXS)
NCAB Group AB (publ) (OM:NCAB)
NCC AB (publ) (OM:NCC B)
Nederman Holding AB (publ) (OM:NMAN)
Nefab AB (OM:NEF B)
Neles Oyj (HLSE:NELES)
Nelly Group AB (publ) (OM:NELLY)
Neonet AB (OM:NEO)
Nepa AB (publ) (OM:NEPA)

Neste Oyj (HLSE:NESTE)	NTR Holding A/S (CPSE:NTR B)	Photocat A/S (OM:PCAT)	Resurs CNC AB (OM:RES B)
Net Insight AB (publ) (OM:NETI B)	Nuevolution AB (publ) (OM:NUE)	PiezoMotor Uppsala AB (publ) (OM:PIEZO)	Resurs Holding AB (publ) (OM:RESURS)
NetBooster Holding A/S (CPSE:NBOOST)	NunaMinerals A/S (CPSE:NUNA)	Pihlajalinna Oyj (HLSE:PIHLIS)	Revenio Group Oyj (HLSE:REG1V)
Netcompany Group A/S (CPSE:NETC)	Nurminen Logistics Oyj (HLSE:NLG1V)	Piippo Oyj (HLSE:PIIPPO)	RIAS A/S (CPSE:RIAS B)
NetJobs Group AB (publ) (OM:NJOB)	Nyfosa AB (publ) (OM:NYF)	Platzer Fastigheter Holding AB (publ) (OM:PLAZ E	Ringkjøbing Landbobank A/S (CPSE:RILBA)
Netmore Group AB (publ) (OM:NETM B)	Oasmia Pharmaceutical AB (publ) (OM:OASM)	Plc Uutechnic Group Oyj (HLSE:UUTEC)	Rizzo Group AB (publ) (OM:RIZZO B)
NetOnNet AB	Oberthur Technologies AB (OM:XPON)	Polygiene AB (publ.) (OM:POLYG)	RLS Global AB (publ) (OM:RLS)
Netop Solutions A/S (CPSE:NETOP)	Oboya Horticulture Industries AB (publ) (OM:OBO	Polyplank AB (publ) (OM:POLY)	RNB Retail and Brands AB (publ) (OM:RNBS)
Nets A/S (CPSE:NETS)	Odd Molly International AB (publ) (OM:ODD)	Ponsse Oyj (HLSE:PON1V)	Robert Friman International AB (publ) (OM:FRIM)
New Nordic Healthbrands AB (publ) (OM:NNH)	Odico A/S (CPSE:ODICO)	Poolia AB (publ) (OM:POOL B)	Robit Oyj (HLSE:ROBIT)
New Wave Group AB (publ) (OM:NEWA B)	OEM International AB (publ) (OM:OEM B)	PowerCell Sweden AB (publ) (OM:PCELL)	Roblon A/S (CPSE:RBLN B)
Newcap Holding A/S (CPSE:NEWCAP)	Offentliga Hus i Norden AB (publ) (OM:OFFHUS)	Pöyry Oyj (HLSE:POY1V)	ROCKWOOL International A/S (CPSE:ROCK B)
Newton Nordic AB (OM:NEWTON)	Okmetic Oyj (HLSE:OKM1V)	Precio Fishbone AB (publ) (OM:PRCO B)	Rolling Optics Holding AB (publ) (OM:RO)
Nexam Chemical Holding AB (publ) (OM:NEXAM)	Olicom A/S (CPSE:OLI)	Precise Biometrics AB (publ) (OM:PREC)	Rörvik Timber AB (publ) (OM:RTIM B)
NexCom A/S (CPSE:NEXCOM)	Olvi Oyj (HLSE:OLVAS)	Precomp Solutions AB (publ) (OM:PCOM B)	Rottneros AB (publ) (OM:RROS)
Nexstim Plc (HLSE:NXTMH)	OM: ACRI A (OM:ACRI)	Prevas AB (OM:PREV B)	Rovio Entertainment Oyj (HLSE:ROVIO)
Next Games Oyj (HLSE:NXTGMS)	Oma Säästöpankki Oyj (HLSE:OMASP)	Pricer AB (publ) (OM:PRIC B)	Rovsing A/S (CPSE:ROV)
NextCell Pharma AB (OM:NXTCL)	Oncopeptides AB (publ) (OM:ONCO)	Prime Office A/S (CPSE:PRIMOF)	Royal Unibrew A/S (CPSE:RBREW)
NGS Group AB (publ) (OM:NGS)	Online Brands Nordic AB (publ) (OM:OBAB)	Privanet Group Oyj (HLSE:PRIVA)	RTX A/S (CPSE:RTX)
NIBE Industrier AB (publ) (OM:NIBE B)	Onxeo SA (CPSE:ONXEO)	Proact IT Group AB (publ) (OM:PACT)	RusForest AB (publ) (OM:RUSF)
Nicoccino Holding AB (publ) (OM:NICO)	OP Yrityspankki Oyj (HLSE:POH1S)	Probi AB (publ) (OM:PROB)	Rush Factory Oyj (HLSE:RUSH)
NIG Sverige AB (OM:ACAP B)	OptiFreeze AB (publ) (OM:OPTI)	ProfilGruppen AB (publ) (OM:PROF B)	S2Medical AB (publ) (OM:S2M)
Nilfisk Holding A/S (CPSE:NLFSK)	Optomed Oyj (HLSE:OPTOMED)	Projektengagemang Sweden AB (publ) (OM:PENG	Saab AB (publ) (OM:SAAB B)
Nilörngruppen AB (OM:NIL B)	Oral Hammaslääkärit Plc (HLSE:ORA1V)	Promore Pharma AB (publ) (OM:PROMO)	Safeture AB (publ) (OM:SFTR)
Nilsson Special Vehicles AB (publ) (OM:NILS)	Orexo AB (publ) (OM:ORX)	ProstaLund AB (publ) (OM:PLUN)	Saga Furs Oyj (HLSE:SAGCV)
Niscayah Group AB (OM:NISC B)	OrganoClick AB (publ) (OM:ORGC)	Prostatype Genomics AB (publ) (OM:PROGEN)	Salcomp Plc (HLSE:SAL1V)
Nitro Games Oyj (OM:NITRO)	Oriflame Swiss Holding AG (OM:ORI)	Protect Data AB (OM:PROT)	SaltX Technology Holding AB (OM:SALT B)
Nixu Oyj (HLSE:NIXU)	Origo hf. (ICSE:ORIGO)	PunaMusta Media Oyj (HLSE:PUMU)	SalusAnsvar AB (OM:SALA B)
NKT A/S (CPSE:NKT)	Oriola Oyj (HLSE:OKDBV)	PV Enterprise Sweden AB	Samhällsbyggnadsbolaget i Norden AB (publ) (OM
NNIT A/S (CPSE:NNIT)	Orion Oyj (HLSE:ORNBV)	QleanAir Holding AB (publ) (OM:QAIR)	Sampo Oyj (HLSE:SAMPO)
Nobia AB (publ) (OM:NOBI)	Orphazyme A/S (CPSE:ORPHA)	Qlife Holding AB (publ) (OM:QLIFE)	Sandvik AB (publ) (OM:SAND)
Nobina AB (publ) (OM:NOBINA)	Ørsted A/S (CPSE:ORSTED)	Q-linea AB (publ) (OM:QLINEA)	Saniona AB (publ) (OM:SANION)
NoHo Partners Oyj (HLSE:NOHO)	Ortivus AB (publ) (OM:ORTI B)	Qliro AB (publ) (OM:QLIRO)	Sanistål A/S (CPSE:SANI)
Nokia Corporation (HLSE:NOKIA)	Oscar Properties Holding AB (publ) (OM:OP)	Q-Med AB (OM:QMED)	Sanoma Oyj (HLSE:SAA1V)
Nokian Renkaat Oyj (HLSE:TYRES)	OssDsign AB (publ) (OM:OSSD)	QPR Software Oyj (HLSE:QPR1V)	SAS AB (publ) (OM:SAS)
Nolato AB (publ) (OM:NOLA B)	Össur hf. (CPSE:OSSR)	Qt Group Oyj (HLSE:QTCOM)	Satair A/S (CPSE:SAT)
Nord Insuretech Group AB (OM:NORDIG)	Østjydsk Bank A/S (CPSE:OJBA)	Quartiers Properties AB (publ) (OM:QUART)	Savosolar Oyj (OM:SAVOS)
Nordax Group AB (publ) (OM:NDX)	Outokumpu Oyj (HLSE:OUT1V)	QuiaPEG Pharmaceuticals Holding AB (publ) (OM:(	SAV-Rahoitus Oyj (HLSE:SAV1V)
Nordea Bank Abp (OM:NDA SE)	Ovaro Kiinteistösijoitus Oyj (HLSE:OVARO)	Radisson Hospitality AB (publ) (OM:RADH)	Saxlund Group AB (publ) (OM:SAXG)
Nordfyns Bank A/S (CPSE:NRDF)	Ovzon AB (publ) (OM:OVZON)	Railcare Group AB (publ) (OM:RAIL)	ScandBook Holding AB (publ) (OM:SBOK)
Nordic Aluminium Oyj (HLSE:NOA1V)	OW Bunker A/S (CPSE:OW)	Raisio plc (HLSE:RAIVV)	Scandi Standard AB (publ) (OM:SCST)
Nordic Blue Invest A/S (CPSE:NOBIN)	OXE Marine AB (publ) (OM:OXE)	Raketech Group Holding PLC (OM:RAKE)	Scandic Hotels Group AB (publ) (OM:SHOT)
Nordic Entertainment Group AB (publ) (OM:NENT	Oyj Ahola Transport Abp (HLSE:AHOLA)	Ramirent Oyj (HLSE:RAMI)	ScandiDos AB (publ) (OM:SDOS)
Nordic Flanges Group AB (publ) (OM:NFGAB)	P/F Atlantic Petroleum (CPSE:ATLA DKK)	Randstad (OM:PROE B)	Scandinavian Biogas Fuels International AB (publ) (
Nordic ID Oyj (HLSE:NORDID)	P/F BankNordik (CPSE:BNORDIK CSE)	Ranplan Group AB (OM:RPLAN)	Scandinavian Brake Systems A/S (CPSE:SBS)
Nordic Iron Ore AB (publ) (OM:NIO)	Pallas Group AB (publ) (OM:PALS B)	Rapala VMC Corporation (HLSE:RAP1V)	Scandinavian ChemoTech AB (publ) (OM:CMOTEC
Nordic Mines AB (publ) (OM:NOMI)	Pandora A/S (CPSE:PNDORA)	Rasta Group AB (OM:RAST)	Scandinavian Enviro Systems AB (publ) (OM:SES)
Nordic Paper Holding AB (publ) (OM:NPAPER)	Pandox AB (publ) (OM:PNDX B)	Ratos AB (publ) (OM:RATO B)	Scandinavian Investment Group A/S (CPSE:SIG)
Nordic Service Partners Holding AB (OM:NSP B)	Panostaja Oyj (HLSE:PNA1V)	Rautaruukki Corporation (HLSE:RTRKS)	Scandinavian Tobacco Group A/S (CPSE:STG)
Nordic Shipholding A/S (CPSE:NORDIC)	Papilly AB (publ) (OM:PAPI)	Raute Oyj (HLSE:RAUTE)	Scanfil Oyj (HLSE:SCANFL)
Nordic Waterproofing Holding AB (OM:NWG)	Paradox Interactive AB (publ) (OM:PDX)	RaySearch Laboratories AB (publ) (OM:RAY B)	Scanfil Sweden AB (OM:PART)
Nordjyske Bank A/S (CPSE:NORDJB)	Park Street Nordicom A/S (CPSE:PSNRDC A)	Re:NewCell AB (publ) (OM:RENEW)	ScanMining AB (OM:SCMI)
Nordnet AB (publ) (OM:SAVE)	PARKEN Sport & Entertainment A/S (CPSE:PARKI	Readly International AB (publ) (OM:READ)	Scanworld TravelPartner AB (OM:TP)
North Media A/S (CPSE:NORTHM)	Partnera Oy (HLSE:PARTNE1)	ReadSoft AB (OM:RSOF B)	Scape Technologies A/S (CPSE:SCAPE)
Northbaze Group AB (publ) (OM:NBZ)	Paxman AB (publ) (OM:PAX)	Realfiction Holding AB (publ) (OM:REALFI)	SciBase Holding AB (publ) (OM:SCIB)
Norvestia Oyj (HLSE:NORVE)	Peab AB (publ) (OM:PEAB B)	Recipharm AB (OM:RECI B)	Scout Gaming Group AB (publ) (OM:SCOUT)
NOTE AB (publ) (OM:NOTE)	Peab Industri AB (OM:PIND B)	Reginn hf. (ICSE:REGINN)	Sdiptech AB (publ) (OM:SDIP B)
NovaCast Technologies AB (publ) (OM:NCAS B)	Penneo ApS (CPSE:PENNEO)	Reitir fasteignafélag hf. (ICSE:REITIR)	Seafire AB (publ) (OM:SEAF)
Novo Nordisk A/S (CPSE:NOVO B)	Per Aarsleff Holding A/S (CPSE:PAAL B)	Rejlers AB (publ) (OM:REJL B)	Seamless Distribution Systems AB (publ) (OM:SDS
Novotek AB (OM:NTEK B)	Pergo (Europe) AB (OM:PERG)	Reka Industrial Oyj (HLSE:REKA)	Seanet Maritime Communications AB (publ) (OM:S
Novozymes A/S (CPSE:NZYM B)	Petrogrand AB (publ) (OM:PETRO)	Relais Group Oyj (HLSE:RELAIS)	SeaTwirl AB (publ) (OM:STW)
NP3 Fastigheter AB (publ) (OM:NP3)	Pfizer Inc. (OM:PFE)	Rella Holding A/S (CPSE:RELLA)	SECITS Holding AB (publ) (OM:SECI)
NTG Nordic Transport Group A/S (CPSE:NTG)	Pharmacolog i Uppsala AB (publ) (OM:PHLOG B)	Remedy Entertainment Oyj (HLSE:REMEDY)	Seco Tools AB (OM:SECO B)

Sector Alarm Oy (HLSE:TUT1V)
Sectra AB (publ) (OM:SECT B)
Securitas AB (OM:SECU B)
Sedana Medical AB (publ) (OM:SEDANA)
Selena Oil &Gas Holding AB (publ) (OM:SOGH)
Selskabet af 1. september 2008 A/S (CPSE:ROSK)
Seluxit A/S (CPSE:SLXIT)
Semcon AB (publ) (OM:SEMC)
Sensec Holding AB (publ) (OM:SECS)
Sensys Gatso Group AB (publ) (OM:SENS)
SenzaGen AB (OM:SENZA)
Senzime AB (publ) (OM:SEZI)
Serneke Group AB (publ) (OM:SRNKE B)
Serstech AB (OM:SERT)
ShaMaran Petroleum Corp. (OM:SNM)
Shape Robotics A/S (CPSE:SHAPE)
Sievi Capital Oyj (HLSE:SIEVI)
Signatur Fastigheter AB (publ) (OM:SIGN B)
Siili Solutions Oyj (HLSE:SIILI)
Silkeborg IF Invest A/S (CPSE:SIF)
Silmäasema Oyj (HLSE:SILMA)
SimCorp A/S (CPSE:SIM)
Síminn hf. (ICSE:SIMINN)
Simris Alg AB (publ) (OM:SIMRIS B)
Sinch AB (publ) (OM:SINCH)
SinterCast AB (publ) (OM:SINT)
Sivers Semiconductors AB (OM:SIVE)
Sjælsø Gruppen A/S (CPSE:SJGR)
Sjóvá-Almennar tryggingar hf. (ICSE:SJOVA)
SJR in Scandinavia AB (publ) (OM:SJR B)
Skælskør Bank Aktieselskab (CPSE:SKLS)
SKAKO A/S (CPSE:SKAKO)
Skandinaviska Enskilda Banken AB (publ) (OM:SEE
Skanditek Industriförvaltning AB (OM:STEK)
Skåne-möllan AB (publ) (OM:SKMO)
Skanska AB (publ) (OM:SKA B)
Skånska Energi AB (OM:SEAB B)
Skeljungur hf. (ICSE:SKEL)
SkiStar AB (publ) (OM:SKIS B)
Skjern Bank A/S (CPSE:SKJE)
Sláturfélags Suðurlands svf. (ICSE:SFS B)
Slitevind AB (OM:SLITE)
Small Cap Danmark A/S (CPSE:SCD)
Smart Eye AB (publ) (OM:SEYE)
Softronic AB (OM:SOF B)
Solar A/S (CPSE:SOLAR B)
Solnaberg Property AB (publ) (OM:SOLNA)
SolTech Energy Sweden AB (publ) (OM:SOLT)
Solteq Oyj (HLSE:SOLTEQ)
Sonetel AB (publ) (OM:SONE)
Soprano Oyj (HLSE:SOPRA)
Sotkamo Silver AB (HLSE:SOSI1)
SP Group A/S (CPSE:SPG)
Spar Nord Bank A/S (CPSE:SPNO)
Sparbank A/S (CPSE:SPB)
Sparekassen Fyn A/S (CPSE:SPFA)
Sparekassen Hvetbo A/S (CPSE:HVETBO)
Sparekassen Sjælland-Fyn A/S (CPSE:SPKSJF)
SpectraCure AB (publ) (OM:SPEC)
SpectrumOne AB (publ) (OM:SPEONE)
Speqta AB (publ) (OM:SPEQT)
Spiffbet AB (OM:SPIFF)
Sponda Plc (HLSE:SDA1VN0107)

Sportamore AB (publ) (OM:SPOR)
Sprint Bioscience AB (publ) (OM:SPRINT)
SRAB Shipping AB (OM:SRAB)
SRV Yhtiöt Oyj (HLSE:SRV1V)
SSAB AB (publ) (OM:SSAB B)
SSH Communications Security Oyj (HLSE:SSH1V)
SSM Holding (OM:SSM)
Starbreeze AB (publ) (OM:STAR B)
Stayble Therapeutics AB (publ) (OM:STABL)
Stendörren Fastigheter AB (publ) (OM:STEF B)
Stenhus Fastigheter i Norden AB (publ) (OM:SFAS
Stenocare A/S (CPSE:STENO)
Stille AB (OM:STIL)
Stillfront Group AB (publ) (OM:SF)
Stockmann Oyj Abp (HLSE:STCBV)
Stockwik Förvaltning AB (publ) (OM:STWK)
Stonesoft Oyj (HLSE:SFT1V)
Stora Enso Oyj (HLSE:STERV)
Storytel AB (publ) (OM:STORY B)
Strategic Investments A/S (CPSE:STRINV)
Strax AB (publ) (OM:STRAX)
Studentbostäder i Sverige AB (publ) (OM:STUDB(
Studsvik AB (publ) (OM:SVIK)
Suominen Oyj (HLSE:SUY1V)
Surgical Science Sweden AB (publ) (OM:SUS)
Svedbergs i Dalstorp AB (publ) (OM:SVED B)
Svejsemaskinefabrikken Migatronic A/S (CPSE:MI(
Svenska Aerogel Holding AB (publ) (OM:AERO)
Svenska Cellulosa Aktiebolaget SCA (publ) (OM:S
Svenska Handelsbanken AB (publ) (OM:SHB A)
Svenska Nyttobostäder AB (publ) (OM:NYTTO)
Svolder AB (publ) (OM:SVOL B)
Sweco AB (publ) (OM:SWEC B)
Swedbank AB (publ) (OM:SWED A)
Swedencare AB (publ) (OM:SECARE)
Swedish Match AB (publ) (OM:SWMA)
Swedish Orphan Biovitrum AB (publ) (OM:SOBI)
Swedish Stirling AB (publ) (OM:STRLNG)
Sydbank A/S (CPSE:SYDB)
Sýn hf. (ICSE:SYN)
Systemair AB (publ) (OM:SYSR)
Taaleri Oyj (HLSE:TAALA)
TagMaster AB (publ) (OM:TAGM B)
Takoma Oyj (HLSE:TAM1V)
Talenom Oyj (HLSE:TNOM)
Talentum Oyj (HLSE:TTM1V)
TalkPool AG (OM:TALK)
Tangiamo Touch Technology AB (publ) (OM:TANC
TC TECH Sweden AB (publ) (OM:TCT)
TCM Group A/S (CPSE:TCM)
TDC A/S (CPSE:TDC)
Technopolis Plc (HLSE:TPS1V)
Tecnotree Oyj (HLSE:TEM1V)
Tekla Oyj (HLSE:TLA1V)
Tele2 AB (publ) (OM:TEL2 B)
Teleca AB (OM:TELC B)
Telefonaktiebolaget LM Ericsson (publ) (OM:ERIC
Telelogic AB (OM:TLOG)
Teleste Corporation (HLSE:TLT1V)
Telia Company AB (publ) (OM:TELIA)
Tempest Security AB (publ) (OM:TSEC)
Teqnion AB (publ) (OM:TEQ)
TerraNet Holding AB (publ) (OM:TERRNT B)

Terveystalo Healthcare Oyj (HLSE:SUT1V)
Terveystalo Oyj (HLSE:TTALO)
Tethys Oil AB (publ) (OM:TETY)
TF Bank AB (publ) (OM:TFBANK)
The Drilling Company of 1972 A/S (CPSE:DRLCO)
The Lexington Company AB (publ) (OM:LEX)
Thrane &Thrane A/S (CPSE:THRAN)
Thule Group AB (publ) (OM:THULE)
Thunderful Group AB (OM:THUNDR)
Ticket Travel Group AB (publ) (OM:TICK)
TietoEVRY Oyj (HLSE:TIETO)
Tiimari Oyj Abp (HLSE:TII1V)
Tikkurila Oyj (HLSE:TIK1V)
Titanium Oyj (HLSE:TITAN)
Tivoli A/S (CPSE:TIV)
TM hf. (ICSE:TM)
Tobii AB (publ) (OM:TOBII)
Tokmanni Group Oyj (HLSE:TOKMAN)
Toleranzia AB (OM:TOL)
Topdanmark A/S (CPSE:TOP)
Topotarget A/S (CPSE:TOPO)
TORM plc (CPSE:TRMD A)
Torslanda Property Investment AB (publ) (OM:TOI
Totalbanken A/S (CPSE:TOTA)
Tourn International AB (publ) (OM:TOURN)
TradeDoubler AB (publ) (OM:TRAD)
Train Alliance Sweden AB (publ) (OM:TRAIN B)
Trainers’ House Oyj (HLSE:TRH1V)
Transcendent Group AB (publ) (OM:TRG)
Transmode AB (publ) (OM:TRMO)
Transtema Group AB (OM:TRANS)
Traton SE (OM:8TRA)
Travelmarket A/S (CPSE:TMCOM)
Tre Kronor Property Investment AB (publ) (OM:3K
Trelleborg AB (publ) (OM:TREL B)
Trention AB (OM:TRENT)
Tretti AB (OM:TRTI)
Tribona AB (publ) (OM:TRI)
Triboron International AB (publ) (OM:TRIBO B)
Tricorona AB (OM:TRIC)
Trifork A/S (CPSE:TRIFOR)
Troax Group AB (publ) (OM:TROAX)
TrustBuddy AB (publ) (OM:TBDY)
Tryg A/S (CPSE:TRYG)
Trygga Hem Skandinavien AB (OM:THEM)
Tulikivi Corporation (HLSE:TULAV)
Udviklingsselskabet af 01.08. 1975 A/S (CPSE:UDV
UIE PLC (CPSE:UIE)
Unibap AB (publ) (OM:UNIBAP)
Uniflex AB (publ) (OM:UFLX B)
United Bankers Oyj (HLSE:UNIAV)
Unlimited Travel Group UTG AB (publ) (OM:UTG)
UPM-Kymmene Oyj (HLSE:UPM)
Uponor Oyj (HLSE:UPONOR)
Upsales Technology AB (publ) (OM:UPSALE)
Urb-it AB (publ) (OM:URBIT)
VA Automotive i Hässleholm AB (publ) (OM:AUTC
Vacon Oyj (HLSE:VAC1V)
Vaisala Oyj (HLSE:VAIAS)
Valmet Oyj (HLSE:VALMT)
Valoe Oyj (HLSE:VALOE)
Vátryggingafélag Íslands hf. (ICSE:VIS)
VBG Group AB (publ) (OM:VBG B)

VEF Ltd. (OM:VEFL SDB)
Veg of Lund AB (publ) (OM:VOLAB)
Veloxis Pharmaceuticals A/S (CPSE:VELO)
Veoneer, Inc. (OM:VNE SDB)
Verisure Midholding AB (OM:SDIR B)
Verkkokauppa.com Oyj (HLSE:VERK)
Vertical ventures (OM:VEVEN)
Vertiseit AB (publ) (OM:VERT B)
Vestas Wind Systems A/S (CPSE:VWS)
Vestfyns Bank A/S (CPSE:VEFY)
Vestjysk Bank A/S (CPSE:VJBA)
Viafin Service Oyj (HLSE:VIAFIN)
Vicore Pharma Holding AB (publ) (OM:VICO)
Victor International AS (CPSE:VIINT)
Victoria Park AB (OM:VICP A)
Victoria Properties A/S (CPSE:VIPRO)
Vigmed Holding AB (publ) (OM:VIG)
Viking Line ABP (HLSE:VIK1V)
Viking Supply Ships AB (publ) (OM:VSSAB B)
Vincit Oyj (HLSE:VINCIT)
ViroGates A/S (CPSE:VIRO)
Vitec Software Group AB (publ) (OM:VIT B)
Vitrolife AB (publ) (OM:VITR)
VNV Global AB (publ) (OM:VNV)
Volati AB (OM:VOLO)
Vostok Gas Ltd. (OM:VGAS SDB)
Wallenstam AB (publ) (OM:WALL B)
Wannakey A/S (CPSE:WKEY)
Wärtsilä Oyj Abp (HLSE:WRT1V)
Wästbygg Gruppen AB (publ) (OM:WBGR B)
Waturu Holding A/S (CPSE:WATURU)
Waystream Holding AB (publ) (OM:WAYS)
WeSC AB (publ) (OM:WESC)
Westpay AB (OM:WPAY)
Wihlborgs Fastigheter AB (publ) (OM:WIHL)
Wilson Therapeutics AB (publ) (OM:WTX)
WindowMaster International A/S (CPSE:WMA)
WirTek A/S (CPSE:WIRTEK)
Wise Group AB (publ) (OM:WISE)
World Class Seagull International AB (OM:WCSI)
Wulff-Yhtiöt Oyj (HLSE:WUF1V)
XANO Industri AB (publ) (OM:XANO B)
Xbrane Biopharma AB (publ) (OM:XBRANE)
Xintela AB (publ) (OM:XINT)
XMReality AB (publ) (OM:XMR)
Xspray Pharma AB (publ) (OM:XSPRAY)
Xvivo Perfusion AB (publ) (OM:XVIVO)
YIT Oyj (HLSE:YIT)
Zaplox AB (OM:ZAPLOX)
Zealand Pharma A/S (CPSE:ZEAL)
ZetaDisplay AB (publ) (OM:ZETA)
Ziccum AB (publ) (OM:ZICC)
ZignSec AB (publ) (OM:ZIGN)
Zinzino AB (publ) (OM:ZZ B)
Zodiak Television AB (OM:ZODI B)
Zutec Holding AB (publ) (OM:ZUTEC)
Zwipe AS (OM:ZWIPE)

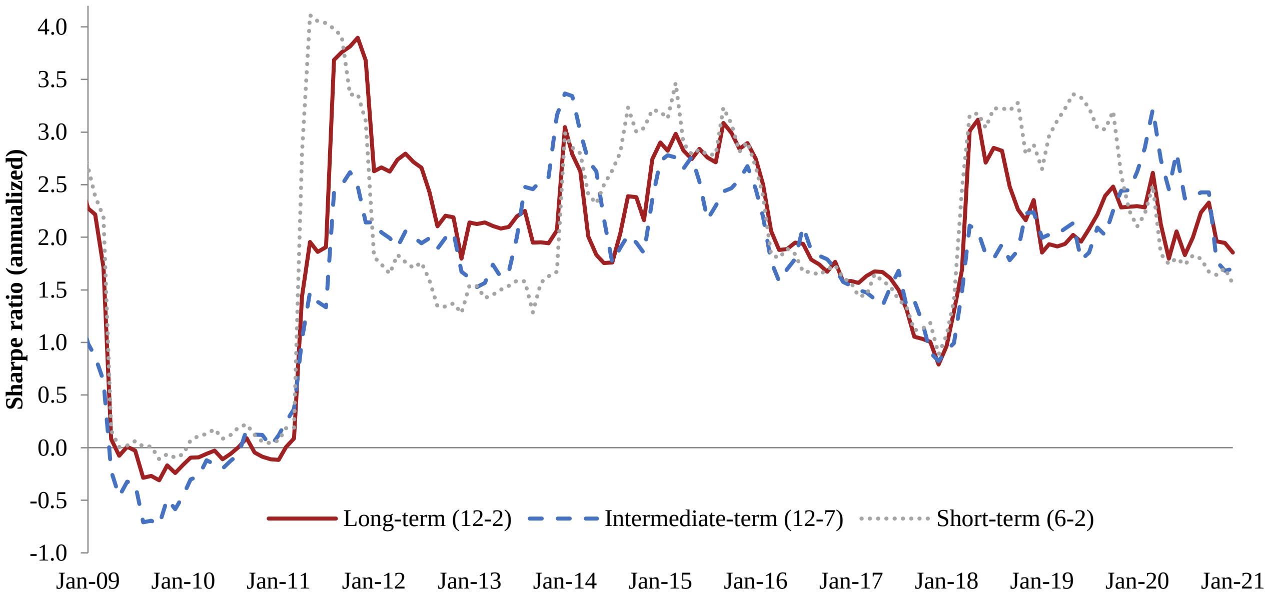
Appendix 2: Fama French Factor Geography

List of countries used to compute the common risk factors are applied in 3- and 4- factor models throughout this study. The risk factors have been collected from the Kenneth R. French website:

Country	Europe
Austria	✔
Belgium	✔
Switzerland	✔
Germany	✔
Denmark	✔
Spain	✔
Finland	✔
France	✔
Great Britain	✔
Greece	✔
Ireland	✔
Italy	✔
Netherlands	✔
Norway	✔
Portugal	✔
Sweden	✔

Source: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Appendix 3: 24-month trailing sharp ratio for momentum strategies



Appendix 4: 3-Factor Regressions: winner and loser portfolios

Results of regressions on winner and loser portfolios. Alpha values are posted in percent, while t-statistics are in square brackets. The MKT factor is the excess return of the MSCI Nordic index, while the remaining factors have been obtained from the Kenneth R. French website. The sample period covers January 2007 to January 2021. Panel A depicts equally weighted winners, Panel B depicts equally weighted losers, Panel C depicts value weighted winners and Panel D depicts value weighted losers.

Panel A: *EW Winners (P10)*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(7A)	(8A)	(9A)	(10A)	(11A)	(12A)
Alpha	1.55	1.00	0.87	0.60	1.26	0.64	0.55	0.36	1.50	0.93	0.85	0.64
	[3.68]	[3.64]	[3.48]	[2.53]	[2.81]	[2.38]	[2.28]	[1.51]	[3.45]	[3.25]	[3.22]	[2.47]
MKT		0.89	0.88	0.97		1.00	0.97	1.03		0.91	0.88	0.95
		[15.31]	[15.91]	[17.94]		[17.48]	[18.02]	[18.88]		[14.97]	[14.95]	[15.84]
SMB			0.85	0.87			0.88	0.89			0.85	0.87
			[6.60]	[7.29]			[7.06]	[7.45]			[6.24]	[6.59]
HML			-0.06	0.24			0.05	0.26			0.06	0.29
			[-0.63]	[2.23]			[0.47]	[2.39]			[0.56]	[2.43]
MOM				0.39				0.28				0.30
				[5.28]				[3.71]				[3.66]
Adj. R2		0.584	0.673	0.721		0.647	0.729	0.750		0.573	0.655	0.681

Panel B: *EW Losers (P1)*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)	(7B)	(8B)	(9B)	(10B)	(11B)	(12B)
Alpha	-0.39	-1.21	-1.14	-0.76	-0.17	-0.87	-0.85	-0.58	-0.51	-1.32	-1.33	-1.00
	[-0.64]	[-3.15]	[-3.41]	[-2.42]	[-0.32]	[-2.48]	[-2.79]	[-1.96]	[-0.85]	[-3.72]	[-4.16]	[-3.27]
MKT		1.33	1.19	1.06		1.14	1.02	0.93		1.33	1.24	1.12
		[16.29]	[16.12]	[14.69]		[15.16]	[15.13]	[13.59]		[17.52]	[17.36]	[15.87]
SMB			1.25	1.22			1.21	1.19			1.11	1.08
			[7.27]	[7.71]			[7.69]	[7.92]			[6.71]	[7.00]
HML			0.56	0.14			0.42	0.12			0.32	-0.05
			[4.23]	[0.95]			[3.48]	[0.89]			[2.51]	[-0.37]
MOM				-0.54				-0.38				-0.47
				[-5.55]				[-4.13]				[-4.97]
Adj. R2		0.614	0.723	0.767		0.579	0.700	0.729		0.648	0.728	0.763

Appendix 4: (cont.)

Panel C: *VW Winners (P10)*

Independent variable	y = Long-term momentum (12-2) (1C)	(2C)	(3C)	(4C)	y = Intermediate-term momentum (12-7) (5C)	(6C)	(7C)	(8C)	y = Short-term momentum (6-2) (9C)	(10C)	(11C)	(12C)
Alpha	1.40	0.84	0.67	0.38	1.38	0.75	0.62	0.39	1.22	0.65	0.52	0.30
	[3.29]	[3.04]	[2.60]	[1.57]	[3.08]	[2.89]	[2.55]	[1.65]	[2.83]	[2.34]	[1.98]	[1.15]
MKT		0.91	0.92	1.02		1.02	1.02	1.10		0.93	0.93	1.01
		[15.49]	[16.06]	[18.28]		[18.55]	[18.82]	[20.31]		[15.80]	[15.92]	[17.01]
SMB			0.68	0.70			0.66	0.67			0.67	0.69
			[5.08]	[5.70]			[5.21]	[5.66]			[4.98]	[5.33]
HML			-0.19	0.14			-0.10	0.16			-0.10	0.15
			[-1.86]	[1.22]			[-1.06]	[1.47]			[-1.00]	[1.24]
MOM				0.42				0.34				0.32
				[5.52]				[4.56]				[4.00]
Adj. R2		0.590	0.655	0.709		0.673	0.723	0.754		0.599	0.656	0.686

Panel D: *VW Losers (P1)*

Independent variable	y = Long-term momentum (12-2) (1D)	(2D)	(3D)	(4D)	y = Intermediate-term momentum (12-7) (5D)	(6D)	(7D)	(8D)	y = Short-term momentum (6-2) (9D)	(10D)	(11D)	(12D)
Alpha	-0.25	-1.07	-0.90	-0.33	0.03	-0.69	-0.61	-0.26	-0.23	-1.05	-1.04	-0.64
	[-0.41]	[-2.66]	[-2.42]	[-1.03]	[0.06]	[-2.13]	[-2.07]	[-0.96]	[-0.39]	[-3.17]	[-3.25]	[-2.18]
MKT		1.32	1.17	0.97		1.17	1.06	0.94		1.34	1.27	1.13
		[15.44]	[14.24]	[13.20]		[16.94]	[16.21]	[14.83]		[18.96]	[17.92]	[16.68]
SMB			0.89	0.85			0.88	0.86			0.73	0.70
			[4.66]	[5.24]			[5.84]	[6.20]			[4.43]	[4.70]
HML			0.67	0.03			0.46	0.07			0.26	-0.19
			[4.57]	[0.23]			[3.96]	[0.57]			[2.01]	[-1.41]
MOM				-0.82				-0.50				-0.57
				[-8.20]				[-5.86]				[-6.21]
Adj. R2		0.588	0.667	0.764		0.632	0.712	0.762		0.683	0.720	0.774

Appendix 5: Adjusted value weighted size sub-sample returns

Average monthly excess returns (in percent), standard deviation of excess returns (in percent), annualized Sharpe ratios, market betas and CAPM alphas (in percent) of adjusted value weighted winner and loser portfolios created based on the historical performance of stocks in the Nordic markets. The small sub-sample presents the lower half of our full sample based on market capitalization, the large sub-sample presents the upper half.

	Small					Large				
	Mean	SD (%)	SR	β_{Market}	α_{CAPM}	Mean	SD (%)	SR	β_{Market}	α_{CAPM}
Long-term (12-2)										
P1	-0.53	9.37	-0.20	1.45	-1.43	0.27	7.50	0.13	1.31	-0.53
P10	1.55	6.43	0.83	0.95	0.96	1.41	5.69	0.86	0.94	0.82
P10 - P1	2.08	6.86	1.05	-0.50	2.39	1.13	6.12	0.64	-0.36	1.36
t-Stat.	[3.94]			[-4.73]	[4.77]	[2.41]			[-3.75]	[2.97]
Intermediate-term (12-7)										
P1	-0.23	8.52	-0.09	1.28	-1.01	0.41	6.71	0.21	1.17	-0.31
P10	0.95	6.51	0.51	0.99	0.34	1.35	5.90	0.79	1.04	0.71
P10 - P1	1.18	5.49	0.74	-0.29	1.36	0.94	5.33	0.61	-0.13	1.02
t-Stat.	[2.79]			[-3.24]	[3.27]	[2.30]			[-1.45]	[2.48]
Short-term (6-2)										
P1	-1.05	9.04	-0.40	1.37	-1.90	0.41	7.45	0.19	1.37	-0.44
P10	1.26	6.59	0.66	0.98	0.66	1.17	5.67	0.71	0.97	0.57
P10 - P1	2.31	6.83	1.17	-0.39	2.55	0.76	5.49	0.48	-0.40	1.01
t-Stat.	[4.40]			[-3.62]	[4.99]	[1.80]			[-4.73]	[2.51]

Appendix 6: Adjusted value weighted size sub-sample regressions

Results of regressions on adjusted value weighted long-, intermediate-, and short-term momentum strategies. Alpha values are posted in percent, while t-statistics are in square brackets. The sample period covers January 2007 to January 2021. Panel A depicts results from the small sub-sample, while Panel B depicts the large sub-sample.

Panel A: *Small*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(7A)	(8A)	(9A)	(10A)	(11A)	(12A)
Alpha	2.08	2.39	2.22	1.58	1.18	1.36	1.22	0.83	2.31	2.55	2.50	1.91
	[3.94]	[4.77]	[4.43]	[3.44]	[2.79]	[3.27]	[2.99]	[2.09]	[4.40]	[4.99]	[4.83]	[3.92]
MKT		-0.50	-0.40	-0.18		-0.29	-0.19	-0.05		-0.39	-0.34	-0.13
		[-4.73]	[-3.61]	[-1.67]		[-3.24]	[-2.05]	[-0.52]		[-3.62]	[-2.93]	[-1.14]
SMB			-0.33	-0.28			-0.48	-0.45			-0.39	-0.35
			[-1.29]	[-1.22]			[-2.28]	[-2.26]			[-1.47]	[-1.41]
HML			-0.50	0.22			-0.46	-0.02			-0.24	0.43
			[-2.52]	[1.05]			[-2.84]	[-0.08]			[-1.19]	[1.92]
MOM				0.92				0.57				0.86
				[6.45]				[4.64]				[5.67]
Adj. R2		0.118	0.156	0.327		0.059	0.123	0.225		0.073	0.091	0.240

Panel B: *Large*

Independent	y = Long-term momentum (12-2)				y = Intermediate-term momentum (12-7)				y = Short-term momentum (6-2)			
variable	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)	(7B)	(8B)	(9B)	(10B)	(11B)	(12B)
Alpha	1.13	1.36	1.02	0.23	0.94	1.02	0.74	0.10	0.76	1.01	0.81	0.21
	[2.41]	[2.97]	[2.32]	[0.65]	[2.30]	[2.48]	[1.85]	[0.29]	[1.80]	[2.51]	[2.02]	[0.60]
MKT		-0.36	-0.23	0.06		-0.13	0.00	0.23		-0.40	-0.32	-0.11
		[-3.75]	[-2.30]	[0.70]		[-1.45]	[0.01]	[2.93]		[-4.73]	[-3.64]	[-1.40]
SMB			0.07	0.13			-0.08	-0.03			0.07	0.12
			[0.29]	[0.73]			[-0.37]	[-0.16]			[0.35]	[0.67]
HML			-0.78	0.13			-0.69	0.04			-0.45	0.23
			[-4.42]	[0.78]			[-4.35]	[0.23]			[-2.83]	[1.41]
MOM				1.15				0.93				0.87
				[10.59]				[8.83]				[7.94]
Adj. R2		0.078	0.178	0.511		0.012	0.114	0.399		0.118	0.161	0.394

Appendix 7: Monthly marginal strategies

Panel A: *Equal weight*

Lag	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**	**-10**	**-11**	**-12**	**Average**
Overall	0.47%	1.41%	1.34%	0.47%	1.04%	0.60%	0.47%	0.57%	0.79%	0.23%	0.56%	0.97%	0.74%
January	-3.29%	-0.79%	-0.39%	-1.32%	1.74%	0.62%	-1.12%	-0.18%	-0.55%	-0.12%	-1.26%	1.42%	-0.44%
February	-1.05%	1.17%	2.82%	1.05%	1.26%	0.87%	1.11%	0.55%	1.27%	1.05%	0.03%	1.04%	0.93%
March	1.94%	0.65%	0.60%	0.11%	0.87%	-0.58%	1.02%	0.06%	-0.25%	2.51%	1.47%	2.03%	0.87%
April	0.50%	0.01%	0.15%	-1.87%	-0.21%	-0.21%	-1.86%	0.14%	-0.91%	-1.27%	1.68%	1.68%	-0.18%
May	0.72%	1.76%	1.95%	-0.12%	1.48%	1.73%	2.30%	1.65%	2.02%	0.13%	-0.20%	0.92%	1.20%
June	1.09%	2.62%	1.27%	1.87%	1.77%	1.16%	1.26%	0.35%	-0.14%	-0.82%	-0.20%	0.77%	0.92%
July	-0.80%	1.85%	1.73%	-0.59%	0.79%	1.08%	0.26%	0.14%	0.82%	-0.08%	0.45%	-0.69%	0.41%
August	0.15%	0.98%	2.66%	2.45%	0.81%	0.00%	0.45%	0.48%	1.15%	-0.37%	-0.82%	-1.60%	0.53%
September	2.65%	1.93%	1.62%	0.08%	1.35%	0.47%	-0.62%	1.38%	1.48%	1.61%	-0.50%	0.65%	1.01%
October	0.37%	3.03%	0.61%	1.47%	-0.26%	0.66%	1.50%	1.31%	0.86%	0.83%	2.89%	1.47%	1.23%
November	1.91%	2.09%	0.91%	0.39%	1.40%	-0.07%	0.78%	0.30%	1.34%	-0.46%	1.90%	1.17%	0.97%
December	1.46%	1.75%	2.36%	2.07%	1.46%	1.40%	0.63%	0.63%	2.68%	-0.27%	1.10%	2.43%	1.47%

Panel B: *Adj. value weight*

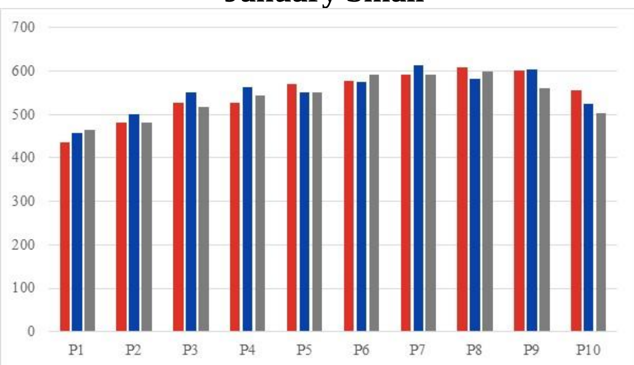
Lag	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**	**-10**	**-11**	**-12**	**Average**
Overall	-0.02%	0.83%	1.36%	0.25%	1.11%	0.19%	0.50%	0.21%	0.73%	0.33%	0.82%	0.46%	0.56%
January	-3.36%	-2.62%	-1.39%	-1.47%	0.70%	-1.05%	-1.10%	-0.20%	-1.44%	-0.37%	-0.31%	-0.50%	-1.09%
February	-1.71%	0.99%	2.60%	0.36%	0.38%	0.63%	1.64%	-0.05%	1.31%	1.19%	-0.81%	1.19%	0.64%
March	1.35%	-0.08%	2.07%	-0.73%	0.51%	-0.71%	-0.07%	-0.73%	-0.34%	2.45%	1.42%	2.05%	0.60%
April	-0.12%	0.05%	-0.70%	-1.97%	0.80%	0.98%	-0.90%	-0.88%	0.37%	-0.09%	1.75%	0.94%	0.02%
May	-0.23%	2.83%	2.96%	1.48%	2.46%	0.76%	1.31%	1.33%	2.12%	1.14%	0.47%	2.10%	1.56%
June	0.06%	2.78%	0.84%	2.01%	1.96%	0.20%	1.59%	1.21%	0.02%	-0.10%	0.42%	0.07%	0.92%
July	-0.95%	0.10%	1.43%	-0.14%	1.05%	0.29%	0.86%	0.04%	1.73%	-0.28%	0.87%	-0.56%	0.37%
August	-1.01%	-0.24%	2.80%	1.37%	1.65%	-0.82%	0.68%	-0.54%	0.08%	-0.25%	0.19%	-1.18%	0.23%
September	1.40%	1.91%	2.36%	-0.77%	1.38%	0.12%	-1.06%	0.15%	1.70%	0.57%	0.07%	-0.87%	0.58%
October	1.41%	2.33%	0.50%	1.65%	-0.57%	1.58%	1.05%	1.60%	0.55%	0.91%	2.64%	0.57%	1.19%
November	1.30%	0.90%	1.58%	0.20%	1.57%	-1.07%	1.40%	-0.34%	0.50%	-1.27%	1.64%	0.17%	0.55%
December	1.71%	1.16%	1.45%	0.84%	1.14%	1.39%	0.82%	1.00%	2.54%	0.15%	1.21%	1.37%	1.23%

Appendix 8: Market cap January sub-sample

Average market capitalizations and medians for small and large sub-sample relative-strength portfolios across the entire sample period, split by January and non-January. Values are presented in DKK million. The red bar chart represents the 12-2 strategy, the blue represents the 12-7 and the grey represents the 6-2.

	Long-term momentum (12-2)				Intermediate-term momentum (12-7)				Short-term momentum (6-2)			
	January		Non-January		January		Non-January		January		Non-January	
	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median	Avg. MC	Median
Panel A: *Small*												
P1	437	315	438	331	458	349	449	342	465	372	444	339
P2	481	380	496	392	502	393	501	394	483	368	499	403
P3	528	448	520	419	550	442	529	418	516	424	529	435
P4	528	407	534	435	563	474	549	454	544	454	538	437
P5	571	482	569	478	551	447	571	473	551	436	555	473
P6	576	492	575	488	574	482	572	479	593	512	547	459
P7	592	513	578	483	614	567	582	502	592	509	575	494
P8	608	550	606	523	582	482	596	517	599	523	569	478
P9	600	497	587	507	603	530	588	507	561	465	580	497
P10	556	471	560	473	525	408	548	465	502	412	543	456
Panel B: *Large*												
P1	18,833	4,970	19,860	4,973	18,787	5,120	19,452	4,675	24,931	6,015	21,152	4,820
P2	33,884	6,449	31,540	7,308	36,546	7,292	31,980	7,678	24,609	6,440	30,413	7,247
P3	25,674	7,420	37,743	8,712	47,243	10,532	36,719	9,094	30,020	7,396	36,620	8,883
P4	44,346	10,425	40,102	9,667	34,067	9,118	38,065	9,290	47,708	9,364	37,819	8,975
P5	39,976	12,519	36,270	9,865	42,161	10,370	38,526	9,805	32,340	8,736	36,860	9,391
P6	37,030	8,831	37,835	10,122	31,719	10,643	38,093	10,030	35,513	9,131	38,347	9,711
P7	38,134	9,277	37,738	10,317	44,548	11,385	38,053	10,272	33,173	8,859	36,917	10,144
P8	33,726	11,730	35,882	9,516	34,847	8,977	36,201	9,155	33,819	9,948	35,370	8,807
P9	34,587	8,983	34,315	8,770	30,959	6,033	33,931	8,654	37,312	10,001	31,737	8,062
P10	29,353	6,347	21,133	5,649	16,930	5,343	22,754	6,416	27,592	6,638	20,695	5,376

January Small



January Large