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SCHOOL OF BUSINESS, ECONOMICS AND LAW

Enhanced Risk-Adjusted Returns Through Momentum Adaptations

Analysis on Momentum Strategies in the Nordic Stock Market

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Date:	June 4th, 2021
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Abstract

Momentum strategies where one buys past winners and sells past losers are one of the most persistent stock market anomalies, showcasing abnormal returns across different markets, asset classes and time periods. Nevertheless, price momentum has been shown by the financial literature to possess considerable hazards, such as high volatility and crash risks. This has consequently led to the introduction of enhanced momentum strategies including both alpha and idiosyncratic momentum, that aim to provide abnormal returns with less risk. The purpose of the thesis is therefore to investigate and compare momentum strategies in the Nordic stock market to identify which strategy provides the best risk-adjusted returns. The results indicate that momentum profits also exist in the Nordics with support found for both behavioral- and risk-based explanations. Furthermore, the alpha momentum strategy consistently demonstrates superior risk-adjusted returns across multiple settings.

Keywords: Momentum Strategies, Momentum, Price Momentum, Idiosyncratic Momentum, Alpha Momentum, Momentum Adaptations, Constant-Volatility Scaling, Momentum Crash, Nordic Momentum, Volatility, Anomaly, Stock Returns.

Acknowledgements

Firstly, we would like to thank our supervisor Alexander Herbertsson for the guidance and feedback he has given us during our thesis journey. Secondly, we want to express our gratitude to the Graduate School of the University of Gothenburg for providing us with the tools and knowledge to conduct our study. Third and lastly, we want to thank our families and friends for their continuous support during the study period.

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1. Introduction

This thesis aims to compare the original price momentum strategy of Jegadeesh and Titman (1993) with adaptations introduced by other scholars, including both idiosyncratic and alpha momentum. Price momentum is one of the most discussed stock market anomalies in the financial literature, demonstrating that buying past winners and selling past losers can produce abnormal returns. Nevertheless, price momentum strategies are often volatile and possess substantial crash risks. As a consequence, a comparative investigation can be deemed beneficial to determine whether these adaptations provide enhanced risk-adjusted returns.

1.1 Background

Thanks to an increasing body of empirical research, larger amounts of stock market anomalies get discovered that potentially provide superior returns to investors. Stock market anomalies are empirical findings that demonstrate unusual behavior of securities that go against theories on asset-pricing, giving rise to profit opportunities due to inefficient markets (Schwert, 2003). Some well-known examples include the January effect, the days of the week anomaly and the outperformance of both small-caps and stocks with low book values (Cooper, McConnell & Ovtchinnikov 2006; Dicle & Levendis, 2014; Hou, Xue & Zhang, 2020). Nevertheless, many of these anomalies exploiting market inefficiencies vanish or reverse upon discovery (Black, 1993; McLean & Pontiff, 2016; Schwert, 2003).

"In particular, most of the so-called anomalies that have plagued the literature on investments seem likely to be the result of data mining. We have literally thousands of researchers looking for profit opportunities in securities. They are all looking at roughly the same data. Once in a while, just by chance, a strategy will seem to have worked consistently in the past. The researcher who finds it writes it up, and we have a new anomaly. But it generally vanishes as soon as it's discovered." (Black, 1993).

Furthermore, while some anomalies find robust evidence in the empirical literature, it does not necessarily lead to positive expected returns in practice (Roll, 1994). The difficulty of practical implementation highlights the efficiency of capital markets and follows the Efficient Market Hypothesis introduced by Fama (1970).

However, one stock market anomaly that has withstood the test of time is that of price momentum. The price momentum anomaly implies that buying past winners and selling past losers provides abnormal returns compared to the market. Abnormal returns, sometimes also referred to as excess returns or alpha, are returns exceeding those predicted by the utilized asset-pricing models. These momentum profits were firstly discovered by Jegadeesh and Titman (1993) and are nowadays well-established in the financial literature, documenting its existence for over 200 years. Moreover, evidence has been found across several countries and asset classes (Asness et al., 2014). The persistence of this anomaly forms a strong contrast to the assumption of efficient capital markets introduced earlier and therefore to this day still raises plenty of discussions among scholars.

1.2 Problem Discussion

As mentioned before, momentum has often demonstrated to provide abnormal returns, while its profits are one of the few anomalies that have not disappeared upon discovery (Hou et al., 2020). Literature often debates the imperfections of momentum strategies, for instance that momentum returns are mostly derived from small-cap stocks or that momentum profits disappear after the introduction of trading costs (Asness et al., 2014). Additionally, while profound evidence has been established for momentum in regions such as the North America and Europe, scholars have found contradicting results in Asia, most notably in Japan (Chui, Titman & Wei, 2000; Fama & French, 2012; Hameed & Kusnadi, 2002). Therefore, the momentum strategy is not a flawless approach with a guaranteed upside.

Notwithstanding several of the discussed issues, one of the most significant challenges to momentum strategies is their crash risk, meaning a sudden and prolonged period of negative returns. Both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) point out the potential downside of momentum strategies, wiping out years of returns in a relatively short period of time. This mostly occurs during times of market panic and high volatility with the Global Financial Crisis (2007-2009) being a notorious example. The dynamic exposure of momentum strategies towards systematic risk factors is commonly denoted as the reasoning behind these momentum crashes, while behavioral models have also been provided as a possible explanation. As a result, large potential drawdowns in returns frequently constitute the argumentation of critics on momentum strategies, which is why literature has searched for optimizations on the original price momentum strategy.

Most of these optimizations are concerned with minimizing the downside risks by reducing the market exposure of the momentum strategies. Blitz et al. (2011, 2020) therefore introduced their adaptation of the original price momentum called idiosyncratic momentum, which is a strategy that constructs the winner and loser portfolios based on the residuals from the Fama-French regression model. In addition to this, Hühn and Scholz (2018) were the first to introduce the alpha momentum strategy, which follows a similar approach to idiosyncratic momentum but bases its construction on past alpha values instead. Both authors have shown that their strategies produce lower levels of volatility and drawdowns without sacrificing momentum profits. Furthermore, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) demonstrated that volatility is forecastable, hence momentum strategies can be scaled to avoid severe drawdowns while maximizing returns.

Despite the above suggested optimizations, literature lacks to our knowledge a comprehensive overview comparing the aforementioned adaptations of the original price momentum strategy introduced by Jegadeesh and Titman (1993). These adaptations are solely compared with price momentum, yet not against each other, investigating the possible differences in returns and volatility. Besides that, scholars have often neglected the Nordic stock market and the profitability potential of momentum in this region. While some Nordic countries have been included in a European context, they have not been exclusively examined as one region or in isolation.

1.3 Research Purpose

Following the previously mentioned gaps in the literature, this thesis aims to compare the price momentum strategy of Jegadeesh and Titman (1993) with the idiosyncratic and alpha momentum strategies introduced by Blitz et al. (2011, 2020) and Hühn and Scholz (2018) respectively. In addition to this, the study will also include the so-called constant volatility scaling approach of Barroso and Santa-Clara (2015) to identify any significant differences. The strategies will be evaluated on performance measures such as monthly returns, volatility, maximum drawdowns and potential crash risks. All of this will furthermore be conducted on the Nordic stock market from 1995 to 2020.

The main contribution of the thesis is therefore three-folded. Firstly, the study will provide further evidence on the momentum anomaly and its perseverance in stock returns, adding to the existing body of literature discussing this phenomenon and its explanations. Secondly, this study will present original results suggesting the potential existence of momentum in the previously unexplored Nordic stock market. Third and most importantly, the study adds unprecedented insights regarding the performances of different momentum strategies, assessing which momentum approach produces the best risk-adjusted returns.

The following main findings were obtained from our studies in this thesis. The momentum anomaly appears to also exist in the Nordic stock market, providing statistically significant abnormal returns, including over different time periods and in individual countries. In line with the suggestions from the literature, support has been found for both risk- and behavioral-based explanations of momentum profits. Both alpha and idiosyncratic momentum exhibit lower levels of volatility and crash risks than the original price momentum strategy, which can be partly explained by their construction of having reduced exposure to systematic risk factors. Additionally, the constant-volatility scaling approach delivers abnormal returns as well, but does not eliminate the aforementioned risks to a similar degree while also possessing practical implications. Overall, the alpha momentum strategy is shown to consistently provide the best risk-adjusted returns across multiple settings.

2. Literature Review

In this section, the academic background, findings and theories regarding the topic of momentum strategies will be described, establishing the foundation for our own research approach in fulfilling the study's purpose. Firstly, the subject of the Efficient Market Hypothesis will be explained as this theory appears to be seriously challenged by the momentum anomaly. This is followed by a detailed discussion on the momentum strategy including its potential explanations and risks. Lastly, relevant adaptations of the original price momentum strategy will be outlined for future comparison purposes.

2.1 Efficient Market Hypothesis

Fama (1970) can be considered the pioneer regarding the theory of the Efficient Market Hypothesis (EMH). This theory envisions that security prices fully reflect all information available in the markets, implying that abnormal returns cannot be achieved assuming similar levels of risk acceptance and availability of information to market participants. Fama (1970) divides the empirical work into three different categories based on the nature of information. Firstly, strong-form efficiency involves security prices reflecting all known information, meaning that all participants have access to the relevant information both public and private. Secondly, semi-strong-form efficiency concerns that security prices reflect all information known solely to the public. The third and last category involves weak form efficiency, which means that current security prices include all historic data, hence past prices cannot be used to predict future prices. Fama (1970) highlights how tests on both the weak and semi-strong-form efficiency have provided support in favor of the EMH. However, the strong-form efficiency category is generally considered more unlikely, as this for example denies the fact that insiders can utilize their monopolistic access to information to extract excess returns.

The EMH theory has consequently also received plenty of critique, mainly based on the market history involving times of irrational price movements. Malkiel (2003) points out the argumentation of critics using the crash of 1987 and the internet bubble of 1999 as examples for irrational exuberance and mispricing of assets. In addition to this, Grossman and Stiglitz (1980) emphasize the need for inefficient markets to provide incentives for professionals to achieve excess returns by finding information that is not yet reflected in the current prices of securities.

All things considered, argumentations have been made both in favor and against the EMH theory. This debate has caused a large number of practitioners to indulge in producing investment strategies that can exploit inefficient markets by discovering so-called market anomalies (Hou et al., 2020). However, many of these anomalies are proven to be not statistically significant and those that do uphold statistical standards seem to disappear or weaken after their publications (Black, 1993; McLean & Pontiff, 2016; Schwert, 2003). Nevertheless, one noteworthy anomaly that appears to persist and remains pervasive in the financial literature is the momentum effect.

2.2 Momentum Strategy

The momentum effect originates from Jegadeesh and Titman (1993), who were the first authors to provide evidence through their study that abnormal returns can be achieved through buying past winners and selling past losers. Their momentum strategy demonstrated that buying stocks that outperformed the last three to twelve months continued to outperform in the subsequent periods and vice versa for those that underperformed. The result of their study therefore rejects the hypothesis of market efficiency and consequently presents a serious challenge to the EMH theory mentioned before. To test the momentum effect, the authors used 16 different strategies. Based on stock returns over the past 3, 6, 9 and 12 months, called the formation period, stocks are sorted into top (winners) and bottom (losers) deciles. Each month the strategy is to buy (long) the top and sell (short) the bottom decile and then hold this position for 1, 3, 6, 9 and 12 months, called the holding period. The “winner minus loser” portfolio (WML) is equally weighted and rebalanced monthly. By using a formation and holding period of 6 months during 1965 to 1989 the authors found that this strategy yields a compounded excess return of 12.01% per year on average.

Jegadeesh and Titman (1993) derived inspiration for their strategy from the studies conducted by De Bondt and Thaler (1985, 1987), who suggested that one can achieve excess returns by buying stocks that have performed poorly over the last three to five years and holding them for a similar period of time. Their argumentation is based on the overreaction hypothesis, which implies that markets overreact to unexpected news events, causing stock prices to defer from their fundamentals. This overreaction is however expected to correct itself, resulting in subsequent price reversals from which excess returns can be gained. While De Bondt and Thaler (1985, 1987) provide evidence for these excess returns, several authors have argued against the overreaction explanation of the results, including Jegadeesh and Titman (1993). According to those against the behavioral explanation, the returns of the so-called contrarian investment strategy can be explained by other factors, such as systematic risk and firm size (Ball & Kothari, 1989; Chan, 1988; Zarowin, 1990). Moreover, Fama and French (1996) found no empirical evidence for significant outperformance with the aid of their three-factor model. Interestingly however is that Fama and French (1996, 2016) are unable to explain the momentum effect found by Jegadeesh and Titman (1993) with their models.

Since its establishment, the momentum strategy has found strong support in the financial literature. Similar to Jegadeesh and Titman (1993), scholars predominantly investigated the momentum effect on stocks listed in the United States (Fama & French, 1996; Grundy & Martin, 2001; Jegadeesh & Titman, 2001). Evidence has nonetheless also been found in international markets (Asness, Moskowitz & Pedersen, 2013; Chui, Titman & Wei, 2010; Fama and French, 2012; Griffin, Ji & Martin, 2003; Rouwenhorst, 1998). Rouwenhorst (1998) for example investigated twelve European countries and found that past winners outperformed past losers by one percent per month. Asness et al. (2013) also found excess returns through momentum in different countries and asset classes, such as corporate and governmental bonds. Additional support for momentum in different assets can be found in studies investigating currencies (Moskowitz, Ooi & Pedersen, 2012; Okunev & White, 2003), commodities (Erb & Harvey, 2006; Gorton, Hayashi & Rouwenhorst, 2013), industries (Moskowitz & Grinblatt, 1999), mutual funds (Carhart, 1997) and country indices (Bhojraj & Swaminathan, 2006; Chan, Hameed & Tong, 2000).

In contrast to these international findings, while Fama and French (2012) and Chui et al. (2000, 2010) found excess momentum returns in the regions of North America, Europe and Asia Pacific, both authors could not find significant evidence for momentum profits in Japan. In accordance with this result, Hameed and Kusnadi (2002) were unable to find momentum effects in six different Asian stock markets. They concluded that factors contributing to momentum profits are not present in their investigated markets as they potentially are in others such as the United States. This line of thought highlights another interesting debate in the literature, namely the one trying to explain the cause of abnormal returns from momentum strategies.

Following the findings by Jegadeesh and Titman (1993), researchers have proposed various explanations for the profitability of momentum strategies and vast focus has been centered around behavioral explanations. Chan, Jegadeesh and Lakonishok (1996) explain momentum profits by investors' underreaction to new firm-specific information. In a similar vein, Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Hong and Stein (1999) and Hong, Lim and Stein (2000) present behavioral models that explain the momentum effect by a delayed overreaction to information that put pressure on the stock prices, causing them to deviate from their long-term values. Furthermore, the behavioral models predict that the effect will eventually reverse, and stock prices will over time go back to their fundamental values. These models are consistent with the findings in the literature, presenting evidence that the profitability of momentum portfolios will turn negative 13 to 60 months following the formation period (Jegadeesh & Titman, 1993, 2001; Moskowitz et al., 2012). In addition to that, profitability is also found to be driven by intermediate horizons of past performance ranging from 7 to 12 months, instead of recent past performance (Novy-Marx, 2012).

Other explanations proposed by the literature for abnormal returns derived from momentum strategies are risk-based, suggesting that the momentum premium is due to a compensation for risk under rationality. The risk-based models boil down to two main explanations, namely that of riskier growth prospects and compensation for beta risk. With regards to the former explanation, Johnson (2002) found that there is a correlation between past realized returns and current expected returns. Firms that have experienced a period of high returns signal to investors that the long-term growth prospects have improved. This provides an increase in future expected returns and therefore also to momentum. With respect to the latter explanation, Zhang (2004) proposes a model demonstrating that time-varying risk factors potentially drive momentum. Firms with strong past performance will experience greater beta risk for which an investor is compensated with an increase in future expected returns (Ahn, Conrad & Dittmar, 2003; Chordia & Shivakumar, 2002; Grundy & Martin, 2001; Ruenzi & Weigert, 2018).

2.3 Momentum Crashes

Whilst previous research has demonstrated that a price momentum strategy can provide significant abnormal returns, this type of strategy has also received a considerable amount of critique. The main point of criticism involves what is referred to as "momentum crashes", where the momentum strategy experiences an abrupt and persistent sequence of negative returns. These crashes commonly transpire during periods of market panic and high volatility. Daniel and Moskowitz (2016) showed in their momentum study on U.S. equities from 1927 to 2013 that their loser decile portfolio returned 232% in July and August 1932, while the winner decile only gained 32%. Additionally, from March to May 2009 during the Global Financial Crisis, the past winners during the formation period merely returned 8%, whereas the past losers returned 163%. Findings of these momentum crashes are consistent with the results from other scholars in the literature discussing the relatively extreme drawdowns of momentum strategies during turbulent market states (Barroso & Santa-Clara, 2015; Cooper, Gutierrez & Hameed, 2004; Daniel, Jagannathan & Kim, 2012; Grundy & Martin, 2001).

A common interpretation with regards to the reasoning behind these momentum crashes comprises of the momentum strategy's dynamic exposure to systematic risk factors (Blitz et al., 2020; Daniel & Moskowitz, 2016; Grundy & Martin, 2001). Due to the strategy's nature of buying past winners and selling past losers, the momentum portfolio obtains increased (decreased) exposure to high beta (low beta) stocks in bull markets and vice versa in bear markets. This consequently creates substantial vulnerability to negative returns for momentum portfolios during market trend reversals. Kothari and Shanken (1992) were one of the first authors to suggest this time-varying exposure to systematic risk factors, which was later verified by both Daniel and Moskowitz (2016) and Grundy and Martin (2001) as a partial explanation for momentum crashes. Moreover, Daniel and Moskowitz (2016) emphasize that these crashes mainly occur due to the strong performance of the loser portfolio during market rebounds, rather than the poor performance of the winner's portfolio.

As a consequence, different hedging strategies have been proposed over time to manage the risk that a momentum strategy carries. Grundy and Martin (2001) demonstrated through their study that with the aid of dynamically hedging the strategy's market and size factors, one can reduce volatility without sacrificing average returns. Notwithstanding the improved performance, Daniel and Moskowitz (2016) criticized the findings because the results were based on the utilization of forward-looking betas to hedge the aforementioned factor exposures. This makes the strategy inexecutable and induces a strong bias in estimated returns. Furthermore, the authors demonstrate that a similar hedging strategy utilizing ex ante betas does not lead to an improvement in performance.

Nevertheless, several scholars in the literature state that the risk with reference to the momentum strategy is highly predictable and can therefore be managed accordingly (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Moreira & Muir, 2017). For example, Moreira and Muir (2017) construct a volatility-managed momentum portfolio that applies the inverse of the most recent month's realized variance to scale monthly returns, leading to improved performance. Barroso and Santa-Clara (2015) scale their momentum portfolio based on the realized volatility in the previous six months, targeting a constant level of volatility over time. Consistent with the findings of Moreira and Muir (2017), their results indicate a substantial increase in the Sharpe ratio and reduction in momentum risk with the maximum drawdown decreasing from -96.69% to -45.20%. The authors' findings are also found to be robust across different subsamples and international markets.

Despite its improved performance, Daniel and Moskowitz (2016) constructed a dynamic momentum strategy that has been shown to outperform the constant volatility approach suggested by Barroso and Santa-Clara (2015). This dynamic momentum strategy can be seen as an extension of the constant volatility scale approach, where forecasts on both the portfolio's returns and volatility are utilized to apply dynamic weights to the WML portfolio. In addition to reducing the momentum strategy's volatility, the dynamic approach also exploits the predictability of the momentum premium. In conclusion, while traditional price momentum strategies contain considerable risks, literature has suggested numerous ways on how a momentum strategy can be risk-adjusted to account for its volatile nature.

2.4 Momentum Strategy Adaptations

Apart from risk-adjustments, literature also mentions momentum strategy adaptations that are said to reduce exposure to systematic risk factors. The two alternative strategies that will be discussed in this thesis are the idiosyncratic (residual) and alpha momentum strategies.

2.4.1 Idiosyncratic Momentum

To overcome the previously mentioned crash risks associated with the traditional price momentum strategy, new and enhanced momentum strategies have been proposed by literature. One such strategy is the so-called idiosyncratic momentum strategy, introduced by Blitz et al. (2011). This strategy is based on the stocks' idiosyncratic returns, estimated using the Fama-French three-factor model:

$$r_{i,t} = a_i + \beta_{i,M} R^e + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t}$$

where R_t^e is the excess return on the market, while SMB (Small Minus Big) and HML (High Minus Low) are the size and value factors. These factors are used to explain the sensitivity of stock returns with R_M^e describing how much of the returns are derived from taking additional market risk. SMB describes the returns obtained from the market capitalization of companies and HML from the book-to-market value of the stock (Fama & French, 1993). Furthermore, α_i and ε_{it} are the alpha and idiosyncratic returns. Hence, the stock returns can be divided into stock-specific excess returns (α_i and ε_{it}) and factor-related returns, ($\beta_{iM} R_M^e + \beta_{iSMB} SMB_t + \beta_{iHML} HML_i$). The traditional price momentum approach displays significant time-varying exposure to the Fama-French factors. As a consequence, the ranking of returns is highly dependent on the factor realizations. In contrast, the idiosyncratic momentum approach is by construction less prone to time-varying factor exposures, which results in reduced stock return volatility. Due to less exposure to the aforementioned factors, the idiosyncratic momentum strategy is close to market-neutral, meaning not dependent on general market movements, and can deliver positive returns during both expansions and recessions. Furthermore, the excess returns achieved by price momentum are sometimes explained by concentration on small cap stocks (Jegadeesh & Titman 1993). This is not the case for idiosyncratic momentum, as the strategy is neutral to the Fama-French size factor.

The idiosyncratic momentum strategy follows Jegadeesh and Titman (1993) with the exception that the forming is based on idiosyncratic returns rather than past total returns. Blitz et al. (2011, 2020) construct the idiosyncratic momentum strategy in several stages. As a starting point, the model mentioned above is estimated over the past 36-months for all available stocks in their trading universe and require stocks to have a full 36 month return history to be included in the estimation. The idiosyncratic momentum is then defined as the sum of the past 12 months idiosyncratic returns, while skipping the most previous month to account for short-term reversals. This short-term reversal is a well-documented stock market anomaly that describes how stocks that have performed strongly in the past month reverse in the following month and vice versa (Jegadeesh, 1990; Lehman, 1990). By skipping the most recent month the results from the momentum strategy ignore delayed reaction effects. The authors then form equally weighted portfolios and exclude micro-caps, which are stocks with exceptionally low market capitalizations, to address some of the concerns regarding equal weighting. The rest of the process in forming the winner minus loser portfolio follows the traditional price momentum strategy originated by Jegadeesh and Titman (1993).

Findings by Blitz et al. (2011, 2020) show that forming portfolios based on idiosyncratic returns yields similar profits as for price momentum but with half the volatility in returns, resulting in a higher Sharpe ratio, which measures the risk-adjusted returns of the portfolio. Furthermore, idiosyncratic momentum profits are present in both bull and bear markets, which goes against the behavioral based explanations for the momentum anomaly concerning over- and underreactions. Moreover, lower beta risk exposure associated with idiosyncratic momentum is presented, confirming that the idiosyncratic approach is less sensitive to market price movements. This result goes directly against the risk-based explanation for momentum profits mentioned before, suggesting that the excess returns are achieved as a consequence of taking greater beta risk.

Evidence regarding the superior performance of idiosyncratic momentum compared to the original price momentum is documented several times in the literature. Chang et al. (2018) find that the idiosyncratic momentum strategy is profitable in Japan, while Lin (2019) finds similar results in the Chinese equity market. Hanauer and Windmüller (2019) show that idiosyncratic momentum outperforms both normal and the previously mentioned volatility adjusted price momentum, whereas Zaremba, Umutlu and Maydybura (2018) find that the idiosyncratic momentum strategy outperforms standard momentum in international equities, achieving Sharpe ratios that are two to three times higher.

2.4.2 Alpha Momentum

Another strategy that utilizes the benefits of stock-specific returns is the alpha momentum strategy. Similar to Blitz et al. (2011, 2020) who disregard the factor-related returns in their momentum strategy and use the idiosyncratic returns, Hühn and Scholz (2018) use the other stock-specific return, alpha (α_i), following a regression estimated by the Fama-French three-factor model. Further contrast to earlier studies on stock-specific momentum returns is that the authors estimate alpha using daily stock returns during the formation period only. This is done to achieve more accurate estimates following a higher number of return observations and to ensure that the ranking of stocks is not affected by potential differences between the factor exposures of stocks before and after the formation period. This approach also makes no restriction on the stock sample because 36 months of return history is not needed. The process of forming the winner minus loser portfolio follows Jegadeesh and Titman (1993), except that the formation is based on past alphas.

Hühn and Scholz (2018) compare the common price momentum with their alpha momentum and find that the alpha momentum strategy yields higher returns in the U.S. whereas in Europe there is no clear dominance of either strategy. Moreover, the profits following alpha momentum are less volatile in both the U.S. and Europe. Zaremba, Umutlu and Karathanasopoulos (2019) also found support for the alpha momentum strategy on country and industry indices in their research. In contrast to Hühn and Scholz (2018), the authors used monthly returns to estimate the alphas instead of daily. They argue that this approach deals better with microstructural issues, different session timings in a global context and efficiency when handling large datasets. Alpha momentum is shown to be robust in many settings, for instance when using different weighting techniques, including trading costs and estimating the alphas based on other models, such as the capital asset pricing model (CAPM).

3. Methodology

The aim of the thesis is to investigate the previously reviewed momentum strategies and compare their performances with each other. This section will firstly highlight the data that has been utilized to conduct the thesis, followed by an elaboration on the sample design including the argumentations behind the choices we made. Secondly, the section will provide further details on the technical aspects concerning the construction of the momentum portfolios and the discussed momentum strategies. Third and lastly, several performance measures that will be used for the empirical analysis are presented and explained.

3.1 Data

This subsection is concerned with the applied data and sample design of the thesis. First, we will elaborate on the sources and types of data used, followed by the chosen markets and time period for this study. Afterwards we will present our filtering process, including the reasonings behind the decisions we made, and the final sample result.

3.1.1 Datatypes

The data regarding individual securities has been extracted through Thomson Reuters Datastream. The Datastream database is provided by Gothenburg University's Centre for Finance and has also been utilized by several scholars in the literature with regards to momentum strategies, thus providing reliability of its usage (Asness et al., 2013; Barroso & Santa-Clara, 2015; Chan et al., 2000; Hühn & Scholz, 2018; Zaremba et al., 2018, 2019). The specific datatypes obtained from Datastream are adjusted unpadded stock prices (P#T) and market values (MV#T). Unpadded simply means that delisted equities will not continue with their last known values. The adjusted stock prices account for events such as issued dividends, stock splits and spin-offs, whereas the market value is calculated by multiplying the amount of outstanding shares with the price per share. Both datatypes are also extracted on a monthly basis, which is consistent with the literature. In addition to that, adjusted prices are also extracted on a daily basis. This is done to test the alpha momentum strategy based on daily values similar to Hühn and Scholz (2018).

Our data sample includes countries with multiple unique currencies. In order to achieve a combined international sample, both previously mentioned datatypes have been converted to U.S. dollars (USD) using the exchange conversion in Datastream (~U$). The utilization of a common currency is consistent with previous literature focused on international markets and has been shown to have no significant impact on the outcome for momentum profits (Chan et al., 2000; Chui et al., 2010; Grobys & Huhta-Halkola, 2019; Hameed & Kusndad, 2002; Rouwenhorst, 1998). Furthermore, to remain consistent with the chosen currency, the one-month U.S. treasury bill rate is chosen to calculate monthly excess returns (Fama & French, 2012; Zaremba et al., 2018). Both the monthly U.S. treasury bill and the time series of factors required for the Fama-French three-factor model are obtained from Applied Quantitative Research (AQR), which is a commonly used source by scholars in the academic literature (Asness et al., 2013, Hühn & Scholz, 2018). AQR provides factors for each country in our sample individually. While these factors are utilized to conduct tests on the countries in isolation, dynamic factors are constructed on a monthly basis to comply with the Nordic sample. This construction is simply done by assigning weights to the individual factors based on the percentage of stocks from the specific country over that of the total sample. This method has been chosen in favor of utilizing market values because this research follows an equally weighted approach, which will be elaborated upon in the section discussing momentum construction. AQR data, including daily momentum portfolio returns, has also been utilized to conduct volatility scaling, which is required for the volatility-adjusted price momentum strategy developed by Barroso and Santa-Clara (2015).

3.1.2 Sample Design

The focus of this study is on the Nordic market, which includes the following countries: Denmark, Finland, Iceland, Norway and Sweden. Iceland has been excluded from this study due to limited output, low trading volumes and insignificant historic data. As a consequence, the study comprises of stocks traded on the OMX Nordic Exchange Copenhagen (CSE), Helsinki Stock Exchange (HSE), Oslo Stock Exchange (OSE) and the Stockholm Stock Exchange (SSE). The reasoning behind the choice of the Nordic market is derived from the limited amount of research in the literature focused on this market in isolation. Grobys and Huhta-Halkola (2019) state to be the first article to explore momentum combined with value in the Nordics. Nevertheless, additional research appears to be non-existent according to our knowledge, especially regarding momentum strategy adaptations such as alpha and idiosyncratic momentum. Hence, results from this study can provide additional robust evidence to the findings of scholars such as Jegadeesh and Titman (1993) and demonstrate that the momentum anomaly also holds for Nordic countries.

A 25-year time period is chosen for the sample that ranges from January 1995 until December 2020. This implies that the extracted stock data starts at December 1991, due to the 36-month backward-looking period required for the idiosyncratic momentum strategy and the aforementioned one-month gap to avoid short-term reversals. The 25-year time period is selected because it provides us with a substantial amount of data regarding Nordic equities from which statistically relevant results can be derived. In addition to that, the chosen time period also consists of three notable market downturns, namely the Dot-Com Bubble (2000), Global Financial Crisis (2008) and the Coronavirus Crash (2020). The latter can especially be considered of serious interest because literature has not yet provided supplementary insights concerning momentum strategies in this time period due to its nascence. Therefore, it becomes intriguing to investigate whether momentum strategies experience a similar "momentum crash" in 2020 as it has previously been demonstrated for other crises (Daniel & Moskowitz, 2016). Aside from the previously mentioned reasoning, the 25-year length of the time period allows us to examine multiple sub periods, consequently further enhancing the robustness of the study.

By using the previously mentioned market and time period, our initial sample provides 5594 observations of historic data from Datastream. However, through applying numerous filters and exclusions, our final sample consists of 2155 stocks (see Table 1). The first step in the filtering process was to solely focus on the equity security type, thereby excluding data from close-end-funds, preference shares, exchange traded funds, warrants and exchange traded notes. Both listed and delisted equities are included in the sample. Delisted equities, labeled as "dead" in Datastream, can disappear for numerous reasons such as bankruptcies or mergers and acquisitions (M&A). The inclusion of delisted equities is vital for the study in order to control for a so-called "delisting" or "survivor" bias, meaning that results can become skewed by removing those that have performed poorly (Carhart, 1997; Griffin et al., 2003; Grobys & Huhta-Halkola, 2019).

The second step included selecting the "major" Datastream item, which for firms with multiple securities only includes the one with the largest market value and liquidity. Liquidity represents the ability for an investor to either buy or sell an asset. The third step concerned filtering to "primary" items to avoid cross-listings, meaning that stocks are excluded if their main listing is different from the chosen Nordic exchanges. The fourth step involved filtering out certain sectors, more specifically the sectors of "equity investment instruments", "non-equity investments instruments", "real-estate investments and services" and "real-estate investment trusts (REITs)". Since investment instruments commonly invest in other equities included in the Nordic market sample, these sectors have been excluded to avoid high levels of correlation in the portfolio results. The exclusion of real-estate is based on only including firms with ordinary common equity, which is consistent with previous literature (Asness et al., 2013; Blitz et al., 2011; Fama & French, 1996; Griffin et al., 2003). After applying the filters, we also had to delete all error outputs supplied by Datastream.

The final step in constructing the data sample was to remove micro-caps, which are stocks with extremely low market value, and other stocks with potentially low liquidity. Similar to the currency choice, the reasoning behind this removal is to create a realistic trading universe from the perspective of an international investor. Additionally, this process is performed to ascertain that the end-results are not derived from small and illiquid stocks, who's exclusion was conducted two-folded. Firstly, we excluded all stocks with a market capitalization under 10 million USD at the beginning of the month, following Hühn and Scholz (2018). Secondly, we ruled out stocks with share prices under 1 USD from the calculations, which is another common approach found in the literature to remove illiquid or so-called "penny stocks" (Asness et al., 2013; Blitz et al., 2011; Hühn & Scholz, 2018). An overview of the filtering process and the final sample result can be found in Table 1 below. Every row indicates the number of equities that are left after the mentioned filtering step in the first column. The sample in Table 1 represents the study's trading universe and will be used as a foundation for the momentum portfolios. Furthermore, all equities within the trading universe will constitute an equally weighted benchmark for comparison purposes when discussing the empirical results.

Table 1. Stock sampling and filtering approach for the Nordic countries, excluding Iceland. The numbers represent the amount of equities left after each step in the filtering process. The derived total represents the study's trading universe for equities and constitutes a benchmark for comparison purposes.

	Sweden	Denmark	Norway	Finland	**Total**
Start	3188	822	954	630	**5594**
-Filtered	1491	571	744	358	**3164**
-Errors	1296	351	667	286	**2600**
-Illiquid	961	330	602	262	**2155**

The computer program MATLAB has been utilized to conduct the empirical tests on the dataset mentioned above. In order to confirm the validity of the written codes, we ran the scripts on data samples with already known results and conclusions. For example, running our codes on a sample consisting of equities from the Tokyo Stock Exchange (TSE) also demonstrated the absence of momentum profits in the Japanese stock market (see Figure 11 in the Appendix). This result is similar to previous findings in the literature, hence provides an assurance for the quality of our self-developed scripts (Chui et al., 2010; Fama & French, 2012).

3.2 Momentum Strategies

In this subsection we will firstly explain parts of the construction process that are common to all momentum strategies, covering topics such as return calculations, formation and holding periods and overlapping portfolios. The subsection then continues with describing the specific details regarding the chosen momentum strategies that will be compared in the analysis later on.

3.2.1 Momentum Construction

The methodology to construct the momentum portfolios is consistent with the general approach first implemented by Jegadeesh and Titman (1993) and later used by several scholars in studies of momentum (Blitz et al., 2011, 2020; Daniel & Moskowitz, 2016; Hühn & Scholz, 2018). Monthly returns for stock *i* at time *t* are calculated in the following way:

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$$

where $P_{i,t}$ is the adjusted closing price of stock *i* at the end of month *t*. The monthly return of a portfolio *p* consisting of $n_t^{(p)}$ different stocks at the end of month *t* is calculated as:

$$r_t^{(p)} = \sum_{i=1}^{n} w_{i,t} * r_{i,t}$$

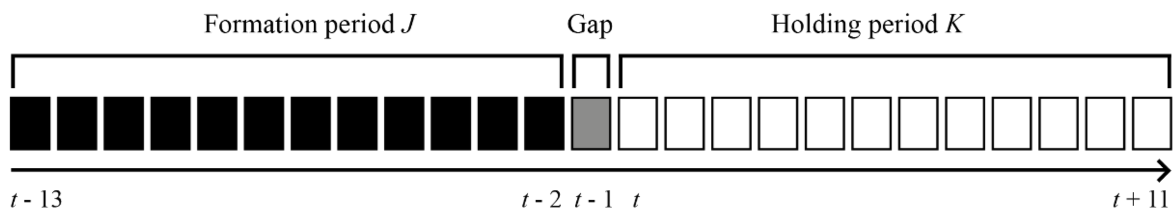
where $r_{i,t}$ is the return for stock *i* in month *t*. The weight $w_{i,t}$ is in our case determined by the number of available stocks each month as we choose to use equally weighted portfolios. The weight is determined by how many stocks that are available during the selected period and sorted into each decile. For example, if there are 200 available stocks during the selected period, the winner portfolio will have 20 stocks with a weight of $\frac{1}{20}$ on each stock, while the same applies to the other decile portfolios and their holdings. Thereby, the weight $w_{i,t}$ for stock *i* in month *t* will always be defined as:

$$w_{i,t} = \frac{1}{n_t^{(p)}}$$

where $n_t^{(p)}$ is the number of available stocks in month *t* sorted into portfolio p. The reasoning behind choosing equally weighted portfolios is two-folded; first, it is in line with most of the literature, see for example Jegadeesh and Titman (1993), Blitz et al. (2011, 2020) and Hühn and Scholz (2018). Second, during the Dot-Com Bubble, stocks such as Nokia and Ericsson had abnormally large market values relative to others in the Nordic stock market. A value weighted approach in this case would yield substantially different results versus an equal weighted approach. Since we want to reflect the entire trading universe, in our case the Nordic stock market, we chose to invest in each stock with an equal weight.

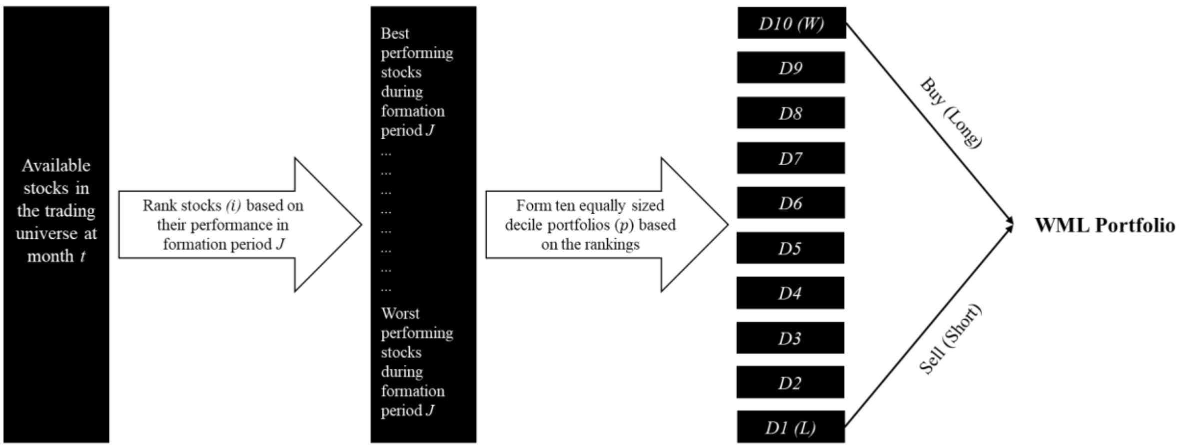
Following the calculations of individual stock returns, the next step for the construction of the momentum portfolios is to rank all available stocks in descending order based on their performance during a past time period, also known as the formation period *J*. The most commonly implemented and rewarding formation period in the literature is that of 12 months, hence also used in this study. The usage of this formation period follows the statement made by Novy-Marx (2012) that momentum is primarily driven by intermediate horizon past performance, rather than recent past performance. Therefore, for a stock to be included in the ranking it must have available monthly returns for the full period *t*-13 to *t*. To account for short-term reversals, we do not include the most recent month (*t*-1) (Jegadeesh, 1990; Lehman, 1990). Thus, the formation period starts at month *t*-13 and ends at *t*-2 (see Figure 1). The number of eligible stocks included per country over time can be found in Figure 12 in the Appendix.

Figure 1. Construction of momentum portfolios based on holding period *K* and formation period *J*, including a one-month gap period to account for short-term reversals.



After ranking all the available stocks on their performance in the formation period *J*, ten equally weighted decile portfolios are formed with the best performing stocks going into portfolio 10 (Winners) and the worst in portfolio 1 (Losers), see Figure 2. Note that the way performance is measured depends on the type of momentum strategy, which will be further elaborated later on. An overview of the whole construction process for the momentum portfolios can be found in Figure 2 below. The construction process is conducted repeatedly at the end of every month for the entire time period.

Figure 2. Construction of momentum portfolios (p) for month *t* based on the performance of individual stocks in formation period *J*. This process is repeated throughout the entire sample period at the end of every month, resulting in a time series of WML portfolio returns.



After constructing the ten decile portfolios based on the stock performances in the formation period *J*, the strategy is to buy the top decile (W) and sell the bottom (L) decile portfolio, while D2 to D9 are ignored. This results in a zero-cost portfolio, meaning an equal amount of asset value is bought and sold. The winner minus loser (WML) portfolio is therefore calculated by subtracting the bottom decile from the top decile:

$$r_{WML,t} = r_t^{(W)} - r_t^{(L)}$$

where $r_{WML,t}$ is the return from the winner minus loser portfolio in month *t*, $r_t^{(W)}$ is the return from the top decile in month *t* and $r_t^{(L)}$ is the return from the bottom decile in month *t*. The WML portfolio is then held during the holding period *K* and rebalanced after its final month. This procedure is repeated throughout the available years with a one-month rolling window, resulting in a time series of monthly portfolio returns. It is important to be aware that these portfolio returns do not include trading expenses, such as transactions costs and borrowing fees.

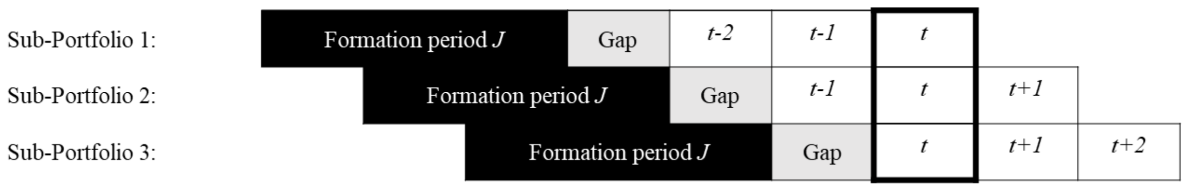
The reasoning behind the exclusion of trading expenses is that the aim of the thesis is to compare the relative performance between momentum strategies that have similar cost structures. Therefore, the inclusion of trading expenses falls outside the scope of this thesis but should be kept in mind when comparing a momentum strategy with a benchmark or different holding periods. Despite that, the benchmark is still included in tables and figures as a reference point and comparison for performance measures beside returns.

Following Jegadeesh and Titman (1993), when momentum strategies contain holding periods that exceed the one-month time period (K>1), monthly returns are calculated using the overlapping portfolio approach (see Figure 3). The reasoning behind this is to obtain a larger number of observations which in return increases the robustness of the test results, as well as aids the avoidance of any seasonality effects. The consequence of seasonality can be observed from Figure 13 in the Appendix, where each sub portfolio has different performance over time depending on which month the portfolio is initiated. At each month t, the total amount of overlapping sub-portfolios held equals the holding period K, where the first constructed sub-portfolio starts at month t-K+1. Through an equally weighted approach, all sub-portfolios are given 1/K weights to produce their respective monthly returns. The total monthly return for the momentum strategy at month t is then calculated by the summation of these weighted sub-portfolio returns, as can be seen in the equation below:

$$r_t^{(p)} = \frac{1}{K}\sum_{i=1}^{K} r_{i,t}^{(sp)}$$

where $r_{i,t}^{(sp)}$ is the monthly return of sub-portfolio i at month t.

Figure 3. Construction of overlapping portfolios for momentum strategies. The illustration demonstrates an example for a three-month holding period (K=3). The momentum portfolio's return $r_t^{(p)}$ is calculated by the sum of the sub-portfolios' returns $r_{i,t}^{(sp)}$ at time t multiplied by 1/K.



3.2.2 Price Momentum

For price momentum we closely follow the methodology of Jegadeesh and Titman (1993), where the formation of the decile portfolios in month *t* is based on the cumulative returns for the available stocks during the formation period. That is, in month *t*, all available stocks are ranked in descending order based on their cumulative returns during the formation period, that is:

$$cr_{i,t} = \prod_{\tau=t-13}^{t-2} (1 + r_{i,\tau})$$

where $cr_{i,t}$ is the cumulative return for stock i at time t, based on the formation period *t*-13 to *t*-2. With the available stocks ranked in descending order, we buy the top decile (winners) and sell the bottom decile (losers), resulting in our WML (Winners Minus Losers) portfolio. In both the winner and loser portfolio each stock is assigned an equal weight, resulting in an equally weighted zero-cost portfolio (see Figure 2).

3.2.3 Idiosyncratic Momentum

In idiosyncratic momentum we form our portfolios based on idiosyncratic returns. We follow the same methodology as Gutierrez and Prinsky (2007), Blitz et al. (2011, 2020) and Chang et al. (2018) where we start in month *t* by estimating a regression on month t-36 to t using the Fama-French three-factor model given by:

$$r_{i,t} = \alpha_i + \beta_{i,M} R_t^e + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t}$$

where R_t^e is the excess return on the market, SMB and HML are the size and value factors and α_i and ε_{it} are the alpha and idiosyncratic returns. Hence, the stock returns can be divided into stock-specific excess returns, (α_i and ε_{it}) and factor related returns, ($\beta_{i,M} R_t^e + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t$). To be included in the regression, we require the stock to have available returns throughout the entire past 36-months' time period. Next, the idiosyncratic returns are calculated as:

$$\varepsilon_{i,t} = r_{i,t} - \alpha_i - \beta_{i,M} R_t^e - \beta_{i,SMB} SMB_t - \beta_{i,HML} HML_t$$

Finally, we take the mean for all stock specific idiosyncratic returns from *t*-13 to *t*-2 and adjust for volatility to obtain the so-called idiosyncratic momentum score (IMS_i) used in our rankings, that is

$$IMS_{i,t} = \frac{\sum_{t-13}^{t-2} \varepsilon_{i,t}}{\sqrt{\sum_{t-13}^{t-2}\left(\varepsilon_{i,t} - \bar{\varepsilon}_i\right)^2}}$$

where $\varepsilon_{i,t}$ is the idiosyncratic return for stock *i* at time *t* and $\bar{\varepsilon}_i$ is the average idiosyncratic return for stock *I* during the formation period *J*. To form the portfolio for month *t*, all stocks are ranked in descending order based on IMS_i and divided into deciles. As before, an equally weighted portfolio is created for the top and bottom decile where the former is bought and the latter sold, resulting in a zero-cost WML portfolio.

3.2.4 Alpha Momentum

Regarding alpha momentum, we follow both Hühn and Scholz (2018) and Zaremba et al. (2019) by means of constructing the portfolios in a similar way as with price momentum. Instead of creating a portfolio in month *t* based on cumulative returns, we create a portfolio based on the alpha values for each stock following a regression on the formation period. Hence, to obtain stock specific alphas in month *t*, we run a regression on all available monthly stock returns during the formation period using the Fama-French three-factor model, given by

$$\alpha_i = r_{i,t} - \beta_{i,M} R_t^e - \beta_{i,SMB} SMB_t - \beta_{i,HML} HML_t - \varepsilon_{i,t}$$

where α_i is the stock's specific alpha. Note that we utilize monthly stock returns for the regression due to the fact that it deals with structural issues and differences, as mentioned before by Zaremba et al. (2019). We also tested the utilization of daily values and although results did not differ significantly, we achieved more robust results with monthly returns (see Figure 14 in the Appendix). Stocks in month *t* are subsequently ranked in descending order based on the alpha values obtained from the regression. Consistent with the price momentum approach, we construct an equally weighted top and bottom decile which are bought and sold respectively, resulting in a WML portfolio for month *t*.

3.2.5 Volatility-Adjusted Price Momentum

To enhance the price momentum strategy and avoid potential crashes, the WML portfolio is risk managed with a volatility adjusted approach. We adopt the constant-volatility scaling method designed by Barroso & Santa-Clara (2015), where the risk-managed WML portfolio is constructed by scaling it with the exposure to the strategy every month. The exposure to the momentum strategy is determined by forecasting volatility using past six months variances in returns. For each month in the sample, a variance forecast $\hat{\sigma}_t^2$ is created by computing the realized variance from the WML portfolio using the previous six months (126 days) daily returns:

$$\hat{\sigma}_t^2 = RV_{t-1} = \frac{21 \sum_{j=0}^{125} r_{WML,d_{t-1}-j}^2}{126}$$

where $r_{WML,d}^2$ is the daily returns from the winner minus loser portfolio. A constant volatility target σ_{target} is then used together with the variance forecast to scale the portfolio returns:

$$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t^2} r_{WML,t}$$

where $r_{WML,t}$ is the standard monthly WML returns and $r_{WML^*,t}$ is the scaled version of the monthly WML returns. The target volatility is selected to coincide with an annualized volatility of 12%, which is consistent with the approach conducted by Barroso and Santa-Clara (2015).

3.3 Performance Measures

This subsection will explain and outline the performance measures that will be practiced comparing the previously discussed momentum strategies in the analysis part.

3.3.1 Returns & Jensen's Alpha

In order to measure the average monthly return, we calculate the geometric mean instead of the arithmetic mean. The reasoning behind this is because the geometric mean takes the compounding effect into account which occurs during the time series. Hence, the geometric mean provides a more accurate estimation of the momentum strategies' monthly returns. The average monthly return μ_p is therefore calculated as follows:

$$\mu_p = \prod_{t=1}^{m} \left(r_t^{(p)} + 1 \right)^{\frac{1}{m}} - 1$$

where $r_t^{(p)}$ represents the monthly portfolio return at month t, and m is the total number of months. Similar to this calculation, the average monthly excess return (μ_p^e) of the portfolio compared to the associated risk-free rate is defined as:

$$\mu_p^e = \prod_{t=1}^{m} \left(\left(r_t^{(p)} - rf_t \right) + 1 \right)^{\frac{1}{m}} - 1$$

where rf_t represents the risk-free rate at month t, which as mentioned before comprises of the U.S. one-month treasury bill. In addition to average monthly and excess returns, it is also of interest to calculate the average abnormal return, also known as Jensen's Alpha (Jensen, 1968). This metric provides greater insight on the achieved excess returns in relation the portfolio's benchmark and risk. A positive Jensen's Alpha implies overcompensation for the risk taken, while vice versa for a negative value. Jensen's Alpha (α) is defined as:

$$\alpha = r^{(p)} - (rf + \beta(r_b - rf))$$

where rf is the risk-free rate, β is the portfolio's beta with respect to the benchmark, and r_b and $r^{(p)}$ represent the benchmark and portfolio returns respectively.

3.3.2 Sharpe Ratio

A common metric used in the literature to assess portfolio performance is the so-called Sharpe Ratio. The Sharpe Ratio is a relatively simple but also meaningful performance measure that considers both returns and risk by also taking the portfolio's volatility into account (Sharpe, 1966). The Sharpe Ratio is calculated as:

$$SR = \frac{\mu_p^e}{\sigma_p}$$

where μ_p^e is the portfolio's average excess monthly return and σ_p is the standard deviation of the portfolio's returns. The portfolio's risk-adjusted return can be considered greater when its Sharpe Ratio is higher than that of another.

3.3.3 Maximum Drawdown

The maximum drawdown (*MDD*) is another measure commonly used in literature to assess the downside risk of the momentum portfolio (e.g. Blitz et al., 2011). This measure is simply calculated by comparing current cumulative returns to the all-time high up until that point in time, which can be seen in the following equations:

$$D(\tau) = \left[\max_{t\in(0,\tau)} r^{(p)}(t) - r^{(p)}(\tau)\right]$$

$$MDD(T) = \max_{\tau\in(0,T)} D(\tau)$$

where $\max_{t\in(0,\tau)} r^{(p)}(t)$ and $r^{(p)}(\tau)$ represent the peak cumulative returns over period t and cumulative returns at time τ respectively. Consequently, the maximum drawdown measures the largest cumulative loss of the momentum portfolio and will either be a negative number or 0.

3.3.4 Skewness & Kurtosis

Both skewness and kurtosis are performance measures commonly used in the literature that provide further insights on the distribution of the obtained results (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016). Skewness describes the asymmetry of the data from a distribution. A negative skewness implies a longer left-tail with the mean being on the left side of the peak, while a positive skewness insinuates the opposite. Kurtosis describes whether the results are fat- or light-tailed relative to the distribution. A high kurtosis indicates that the distribution has a fat-tail with more extreme outliers and vice versa for a low kurtosis. As mentioned by Barroso and Santa-Clara (2015), the combination of a high kurtosis and negative skewness poses a severe risk to investors, especially with regards to momentum strategies. The reasoning is because this combination indicates an exceptionally fat left-tail, which implies a considerable crash risk for the portfolio that can swiftly erase long periods of positive returns. Therefore, it can be considered beneficial to compare the aforementioned performance measures among different momentum strategies to assert potential tail risks.

3.3.5 T-statistics

The portfolio returns for each strategy are tested using a two-sided t-test to assess if the obtained returns are statistically different from zero. Consistent with literature, the Newey and West (1987) standard errors are used to obtain t-statistics that are robust to both autocorrelation and heteroscedasticity (Jegadeesh & Titman,1993; Chang et al., 2018). This is used to account for the fact that the time series of portfolio returns are by construction autocorrelated and possibly also heteroscedastic. In addition to these tests, a normal t-test is used to determine if there is a significant difference between the average monthly returns among the chosen momentum strategies. The higher a result from the t-statistic test is, the lower the probability of the result being derived from chance.

4. Empirical Results & Analysis

In this section we will both present and discuss the findings regarding the different momentum strategies in the Nordics. Firstly, a detailed overview and analysis will be presented on the momentum strategies in our Nordic sample, discussing various subjects such as returns, volatility and factor exposures. Secondly, a more in-depth examination will be made on the chosen momentum strategies in different time periods, such as times of economic expansion and contraction. Thirdly, the momentum strategies will be analyzed on the Nordic countries in isolation in order to find meaningful commonalties or differences. Fourth and lastly, the volatility-adjusted price momentum will be introduced for comparison purposes.

4.1 Momentum Strategies Nordics

Results from the different momentum strategies tested on our Nordic trading universe between 1995 and 2020 can be found in Table 2 below. The first observation that stands out from the results is that momentum profits appear to exist in the Nordic stock market. All momentum strategies demonstrate statistically significant returns that are different from zero. Furthermore, up until a six-month holding period *K*, all strategies provided higher monthly returns than the trading universe's benchmark, which as said before includes all available stocks with equal weights. This result of abnormal returns represents a robust contradiction to the EMH in our self-constructed Nordic context. The largest difference from the benchmark can be found from the original price momentum strategy with a one-month holding period *K*. This strategy presents a monthly return of 1.93%, whereas the benchmark exhibits a significantly lower return of 0.86% per month, indicating that the price momentum strategy produces considerable abnormal returns. As mentioned before, it is important to note that the momentum strategies include higher trading costs than a benchmark. Therefore, the difference in returns would be smaller if implemented in practice. Nevertheless, the aim of this thesis is to mainly compare the relative performance between momentum strategies, which can be assumed to have similar cost structures.

Similar to previous findings in the literature, monthly momentum returns deteriorate when the length of the holding period increases (Jegadeesh & Titman, 1993, 2001; Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al, 2003). Taking the price momentum strategy as an example, it becomes observable that monthly returns decrease substantially from 1.93% per month to a mere 0.72% when using a twelve-month holding period *K*, leading to underperformance compared to the benchmark (see Figure 15 in the Appendix). Deteriorated returns following increased holding periods suggest additional evidence on behavioral explanations brought up by literature, signifying a potential delay in overreaction on information causing stock prices to increase substantially (Barberis et al., 1998; Chan et al., 1996; Daniel et al., 1998; Hong & Stein, 1999; Hong et al., 2000). Nevertheless, the results also demonstrate the reversal of this phenomenon with decreasing returns, suggesting the stocks reverting to their fundamental values over time. Despite the lower returns, all momentum strategies present positive Jensen's alphas, implying an overcompensation for the risk taken compared to the benchmark and risk-free rate.

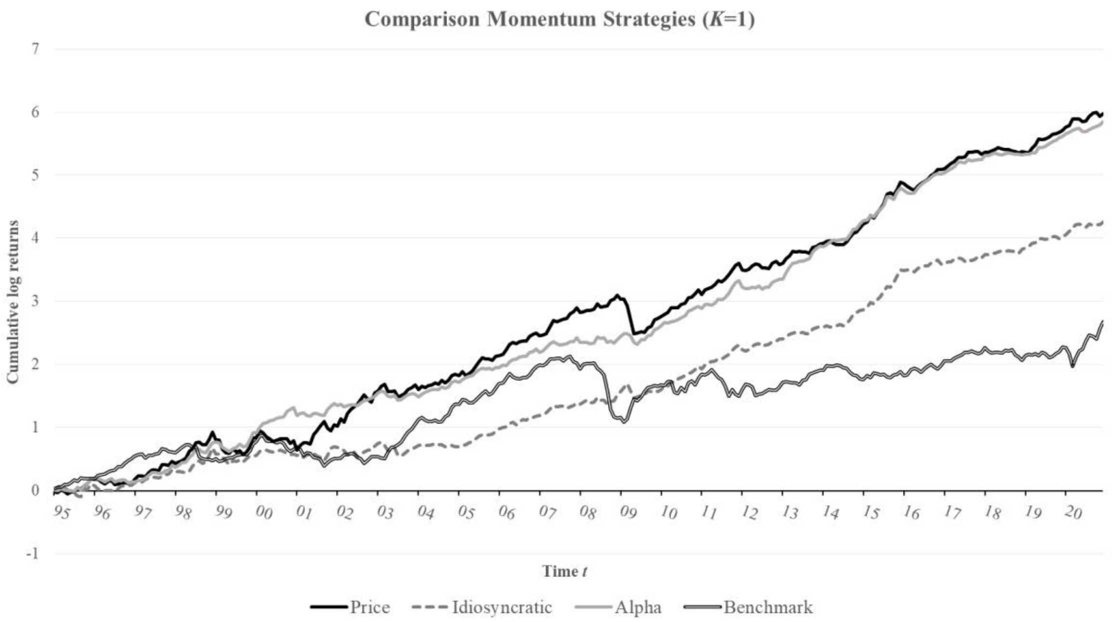
Table 2. Nordic performance measures regarding the discussed momentum strategies for different holding periods *K* and a twelve-month formation period *J,* where μ_p represents the average monthly return, σ_p the portfolio's standard deviation, *SR* the Sharpe Ratio, α Jensen's Alpha and *MDD* maximum drawdown. The final column exhibits the relative performance of the benchmark for the created Nordic trading universe. All results are derived from the time period 1995-2020.

J = 12	**Price momentum**				**Idiosyncratic Momentum**				**Alpha Momentum**				**Benchmark**
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0193	0.0168	0.0127	0.0072	0.0134	0.0126	0.0102	0.0052	0.0192	0.0154	0.0118	0.0069	0.0086
α	0.0203	0.0160	0.0113	0.0055	0.0129	0.0110	0.0083	0.0034	0.0181	0.0140	0.0101	0.0052	0
σ_p	0.0532	0.0503	0.0483	0.0470	0.0379	0.0382	0.0377	0.0375	0.0386	0.0379	0.0382	0.0384	0.0568
SR	0.3280	0.2960	0.2249	0.1130	0.3048	0.2793	0.2186	0.0894	0.4488	0.3573	0.2605	0.1322	0.1186
MDD	-0.4550	-0.3757	-0.3427	-0.3373	-0.2332	-0.1612	-0.2394	-0.3868	-0.1580	-0.1330	-0.1620	-0.3446	-0.6468
Skewness	-0.4929	-0.8218	-0.7432	-0.6873	-0.1378	-0.2860	-0.3682	-0.5217	-0.0355	0.0745	-0.0636	-0.2398	-0.5690
Kurtosis	4.6111	6.2453	4.5689	3.2334	3.8975	4.1317	3.5733	2.7399	3.9155	3.7297	3.1189	3.2288	5.6755
t-stat	6.8866	9.7331	10.4484	7.4585	6.5908	9.4969	10.3464	6.3271	9.1204	11.7632	12.3376	9.0818	3.1885

Comparing across the chosen momentum strategies during the sample period, the following observations can be made from Table 2. Alpha momentum provides the best risk-based strategy across all holding periods. With a holding period of one month (*K*=1), the alpha momentum strategy posseses a Sharpe ratio of 0.4488, which is considerably higher compared to price and idiosyncratic momentum with Sharpe ratios of 0.3280 and 0.3048 respectively. The superior Sharpe ratio inherent in the alpha strategy is derived from similar returns as price momentum and slightly better returns than idiosyncratic momentum, but a significantly lower standard deviation. This result is aligned with findings in the literature on the alpha momentum strategy in Europe, demonstrating that the strategy provides comparable returns to price momentum yet with lower levels of volatility (Hühn & Scholz, 2018).

Nevertheless, while idiosyncratic returns also exhibit less volatily than price momentum, the risk-adjusted profits do not appear to be superior. Both the Sharpe ratio and Jensen's alpha for price momentum are slightly higher than those for idiosyncratic momentum, mainly due to the particular higher returns of the former strategy. This outcome stands in contrast to findings in other markets provided by Blitz et al. (2011, 2020), who found that idiosyncratic momentum generated similar returns as price momentum but with half the volatility. Notwithstanding the strategy's underperformance in comparison with price and alpha momentum, idiosyncratic momentum still shows greater performance results than the Nordic benchmark. A time series of cumulative returns for the momentum startegies and benchmark over the chosen 25-year time period can be found in Figure 4 below, which more clearly visualizes the performances of the momentum strategies over time.

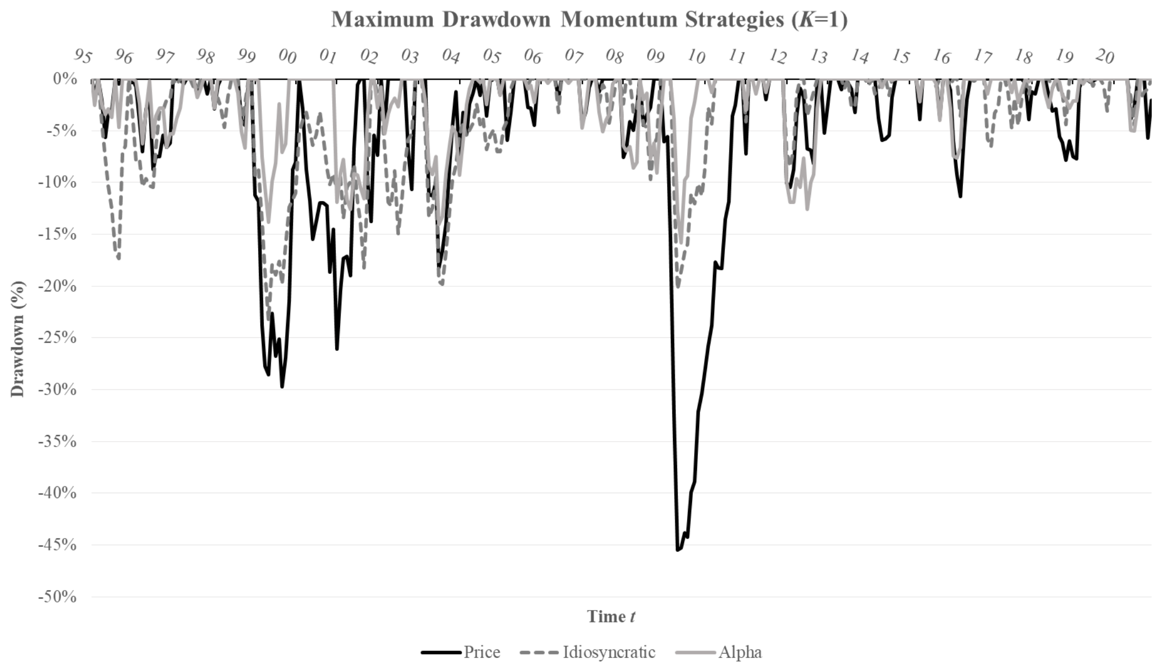
Figure 4. Comparison of the different momentum strategies on the Nordic trading universe between 1995-2020. Strategies are based on a one-month holding period *K* and a twelve-month formation period *J*.



As mentioned before, all three momentum strategies result in returns that are statistically different from zero. Considering the statistical differences between each momentum strategy and the benchmark, we find that the differences in average returns are statistically different from zero when comparing the benchmark with price and alpha momentum but not when comparing the benchmark with idiosyncratic momentum (see Table 7 in Appendix). This suggests that even though there is an economical difference between the benchmark and the idiosyncratic strategy, we cannot rule out that the strategy gives different returns than the benchmark by chance. Moreover, when doing the comparison among the different strategies the findings are similar to those of Hühn and Scholz (2018). That is, the difference in average returns between price and alpha momentum are not statisically significant different from zero. However, we find that the average returns for both price and alpha momentum are statistically different from zero when comparing the two strategies with idiosyncratic momentum (see Table 8 in Appendix).

Apart from differences in returns and monthly volatility, all three momentum strategies also differ with regards to their crash risks. Increased volatility for price momentum becomes even more apparent when examining its maximum drawdown (*MDD*) compared to those of idiosyncratic and alpha momentum (see Figure 5 below). For almost every period of sustained negative returns, the drawdowns for price momentum are meaningfully larger. Especially during the period of the Global Financial Crisis, the price momentum strategy experienced a significantly larger maximum drawdown of approximately -45% compared to idiosyncratic and alpha momentum who decreased -23% and -16% respectively. This result provides further confirmation of the purpose for both idiosyncratic and alpha momentum, namely to reduce exposure to systematic risk factors (Blitz et al., 2011, 2020; Hühn & Scholz, 2018).

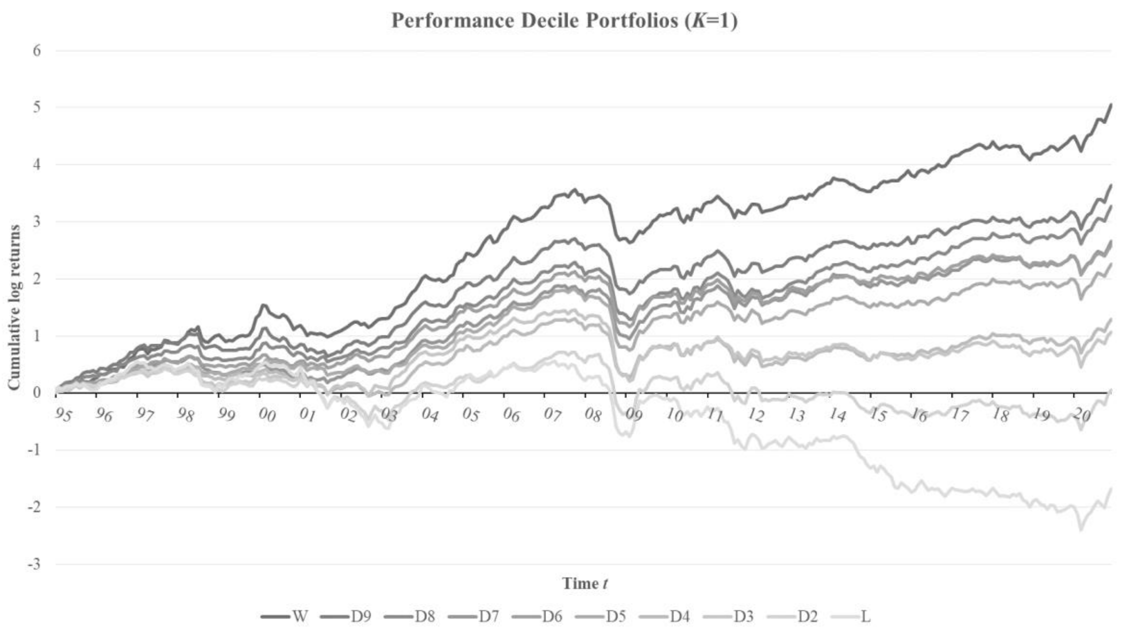
Figure 5. Comparison of the maximum drawdowns (*MDD*) from the chosen momentum strategies, based on a one-month holding period *K* and a twelve-month formation period *J*.



The possibility of the price momentum's crash risk can furthermore be derived from the skewness and kurtosis values in Table 2, which shows that the skewness value is more negative for price momentum, while its kurtosis value is higher than those of idiosyncratic and alpha momentum. As mentioned before, this combination implies a fatter left-tail for the distribution of price momentum returns, hence an increased tail-risk that can wipe out previously made gains (Barroso & Santa-Clara, 2015).

Although price momentum demonstrates the greatest crash risk of all three momentum strategies, it's still below that of the Nordic benchmark. This finding stands in contrast to the outcomes of literature studies conducted on the U.S. stock market, where price momentum signifcantly underperformed during periods of large sustained drawdowns (Barroso & Santa-Clara, 2015; Daniel & Moskowtiz, 2016). The reasoning as to why this might be evident for our Nordic sample stems from the performances of our winner and loser portfolios during times of market turbulances. Similar to the results of other momentum studies, momentum crashes in our sample occur due to the strong performance of the loser portfolio during market rebounds. However, the loser portfolio's returns are not that signficantly higher than those of the winner's during market rebounds, hence the WML portfolios do not crash to a similar degree as in other markets studied in the literature. This phenomenon becomes further evident from Figure 6 below.

Figure 6. Comparison of the decile portfolios from the Nordic sample for the standard price momentum strategy, based on a one-month holding period *K* and a twelve-month formation period *J*, where W and L represent the winner and loser portfolio respectively.



The performance of the different decile portfolios as seen in Figure 6 follow a similar pattern across all the discussed momentum startegies and holding periods. The winner portfolio provides the highest returns, which gradually decreases throughout the lower deciles. As mentioned before, the lower deciles experience larger returns during market rebounds, consequently causing the momentum crashes. These findings are consistent with the results from other authors in the literature (Daniel & Moskowitz, 2016; Hühn & Scholz, 2018; Jegadeesh & Titman, 1993; Rouwenhorst, 1998).

However, a noteworthy difference between our results and those found in the literature is the extend of the relatively poor performance of the loser portfolio. While the pattern appears to be similar, other studies commonly find that the loser portfolios still provide positive monthly returns over the investigated time period (e.g. Jegadeesh & Titman, 1993). In contrast to that, our results are more in line with the findings of Daniel and Moskowitz (2016), who also found sizeable negative monthly returns for their loser portfolio. The signficant impact of the loser portfolio on the performance of the WML portfolio is furthermore also applicable for the earlier mentioned lower returns found for the idiosyncratic momentum strategy. As can be seen in Figure 16 in the Apendix, the returns for the winner portfolio of the idiosyncratic momentum strategy are only slighty below those of price and alpha momentum. Nevertheless, Figure 16 also shows that the performance of the loser portfolio for the idiosyncratic momentum strategy is substantially better than those of price and alpha momentum, partially explaining the lower returns of the WML portfolio for this strategy. Thus, the performances of the WML portfolios are shown to be firmly dependent on both the results of the winner and loser portfolios in our trading universe.

In addition to examining the momentum strategies' results through the lenses of returns and volatility, it is also of interest to investigate their exposure to the Fama-French three factor model. From this investigation one can potentially derive explanations for the abnormal results found earlier. As can be seen from Table 9 in the Appendix, the returns from the WML portfolios do not appear to have significant exposure to the Fama-French factors based on the significant alpha and low adjusted R-squared values, which is in line with previous findings on momentum and holds across all three momentum strategies and different holding periods (Blitz et al., 2020; Fama & French, 1996, 2016; Lin, 2019). Consequently, the Fama-French factors of market, size and value do not provide explanatory reasonings for the derived abnormal returns.

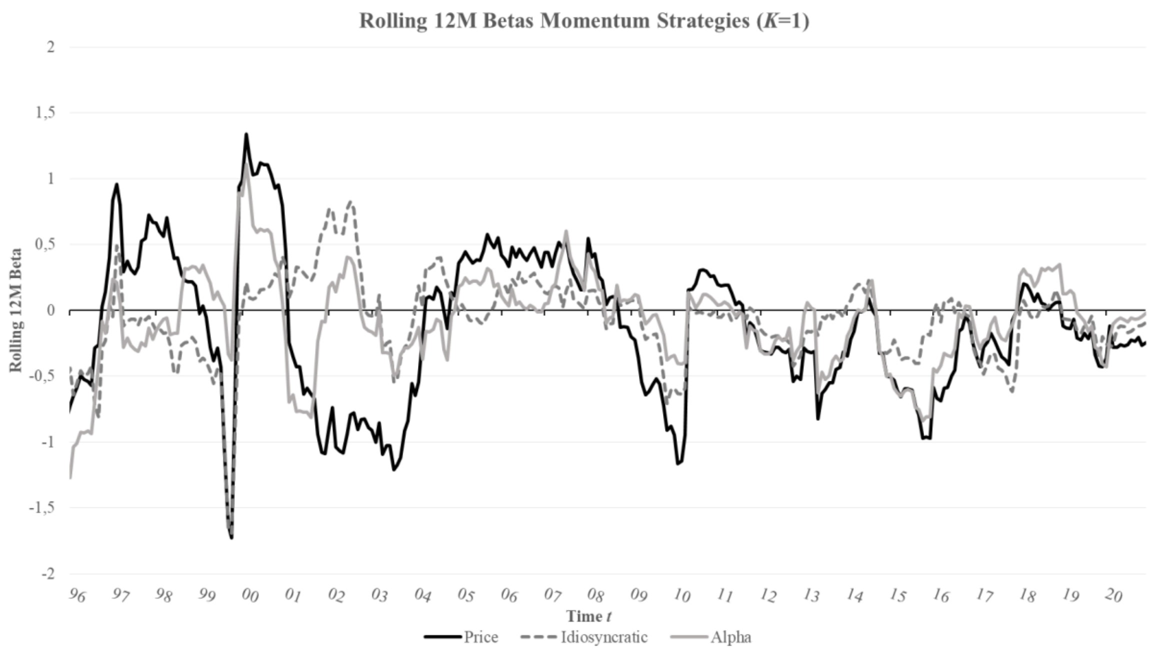
Nevertheless, examining the decile portfolios of the momentum strategies in isolation provide more valuable insights with regards to factor exposures. Outcomes of the regressions utilizing the Fama-French three factor model on the decile portfolios can be found in Table 3 below. In contrast to the results from the WML portfolio, the deciles present a strong increase in adjusted R-squared values, rising from a range of 0%-9% to 79%-93%. Similar to the findings of Jegadeesh and Titman (1993), both the loser and winner portfolio for price momentum exhibit higher market betas and volatility levels. Additionally, as can be seen in Table 3, the market beta for the loser portfolio is larger than the winner's, hence leading to a negative market beta for the WML portfolio, which also applies to idosyncratic and alpha momentum. Moreover, both the WML portfolios for idiosyncratic and alpha momentum demonstrate lower levels of market betas in comparison with price momentum, illustrating lower exposure to market risks. The reduced exposure to market factors is consistent with the findings of Blitz et al. (2011, 2020) and with the fact that idiosyncratic and alpha momentum by construction are less prone to market risk compared to price momentum.

Table 3. Overview of the beta coefficients regarding factor exposures for the different decile portfolios across all three chosen momentum strategies, where σ represents the portfolio's standard deviation, *SR* the Sharpe Ratio, α the alpha factor, R_M^e the market factor, *SMB* the size factor, HML the value factor and $adj.R^2$ the adjusted R-squared value. Results are derived from a twelve-month formation period *J* and a one-month holding period *K*.

	σ	SR	α	R^e	SMB	HML	$adj.R^2$
PANEL A: Price Momentum							
D1 (L)	0.0778	-0.0933	-0.0140	1.1979	0.1204	-0.1159	0.789
D2	0.0656	-0.0259	-0.0086	1.0693	-0.0874	-0.0353	0.853
D3	0.0597	0.0260	-0.0050	1.0016	0.0174	0.0279	0.910
D4	0.0533	0.0427	-0.0040	0.9107	-0.0246	0.1295	0.931
D5	0.0541	0.0997	-0.0011	0.9269	-0.0541	0.1841	0.933
D6	0.0528	0.1223	8.4e-05	0.9083	-0.0790	0.1578	0.935
D7	0.0524	0.1275	0.0003	0.8972	-0.0976	0.1602	0.923
D8	0.0544	0.1590	0.0022	0.9235	-0.1116	0.0833	0.908
D9	0.0579	0.1700	0.0033	0.9699	-0.0842	-0.0034	0.897
D10 (W)	0.0646	0.2236	0.0079	1.0369	0.0560	-0.1412	0.850
WML	0.0532	0.3280	0.0201	-0.1593	-0.1117	-0.0239	0.0245
PANEL B: Idiosyncratic Momentum							
D1 (L)	0.0638	-0.0447	-0.0094	1.0352	0.0518	0.2339	0.855
D2	0.0573	-0.0148	-0.0071	0.9549	-0.0396	0.1545	0.885
D3	0.0555	0.0296	-0.0045	0.92843	0.0079	0.1896	0.898
D4	0.0552	0.0736	-0.0021	0.9407	-0.0771	0.1875	0.920
D5	0.0565	0.0743	-0.0021	0.9612	-0.0768	0.2147	0.918
D6	0.0564	0.0798	-0.0018	0.9612	-0.0361	0.1509	0.924
D7	0.0555	0.1249	6.7-e04	0.9452	-0.1341	0.07215	0.913
D8	0.0543	0.1157	1.26e-04	0.9287	-0.1436	0.0784	0.919
D9	0.5068	0.1325	0.0011	0.9694	-0.1622	0.0236	0.919
D10 (W)	0.0579	0.2016	0.0054	0.95442	-0.0875	-0.0709	0.875
WML	0.0379	0.3048	0.0129	-0.0798	-0.13615	-0.3034	0.0868
PANEL C: Alpha Momentum							
D1 (L)	0.0711	-0.1058	-0.0143	1.1355	0.1298	-0.0273	0.843
D2	0.0602	-0.0014	-0.0067	1.0150	0.0749	0.0711	0.923
D3	0.0560	0.0592	-0.0031	0.9518	0.0020	0.0350	0.929
D4	0.0539	0.0659	-0.0030	0.9306	-0.1469	0.1352	0.937
D5	0.0545	0.0895	-0.0016	0.9318	-0.0349	0.1920	0.932
D6	0.0517	0.0999	-0.0011	0.8865	-0.1151	0.1521	0.925
D7	0.0556	0.1412	0.0011	0.9587	-0.1740	0.1465	0.931
D8	0.0562	0.1490	0.0018	0.9585	-0.0749	0.0547	0.925
D9	0.0579	0.1595	0.0026	0.9879	-0.1238	-0.0507	0.930
D10 (W)	0.0662	0.1924	0.0061	1.0862	0.0743	-0.2494	0.916
WML	0.0386	0.4488	0.0185	-0.0476	-0.0523	-0.2208	0.0338

Further evidence of market exposure can be found in Figure 7 below, illustrating the twelve-months rolling betas for the discussed momentum strategies. As can be seen in Figure 7, the concentration in large beta stocks appear to be the highest ahead of market drawdowns (e.g. Dot-Com and Global Finanical Crisis) for all three strategies. The betas crash with the market and become negative, which cause extended periods of negative portfolio returns. The magnitude of the negative portfolio returns are positively correlated with the time-variance in the strategies' market betas. Price momentum with the highest time-varying beta also has the most severe crashes with a maximum drawdown of -45%. Meanwhile, idiosyncratic and alpha momentum, who have lower time-varying betas and thus lower market exposure, have a maximum drawdown of only -23% and -16% respectively. Therefore, the higher market exposure of price momentum can be suggested as a reasoning for its larger drawdowns, volatility levels and returns. The higher market exposure furthermore aligns with the risk-based explanations found in the literature, suggesting that momentum profits are partially driven by time-varying risk exposure (Ahn et al., 2003, Chordia & Shivakumar, 2002; Grundy & Martin, 2001; Ruenzi & Weigert, 2018; Zhang, 2004).

Figure 7. Comparison of twelve-months rolling Betas for all three momentum strategies, based on a one-month holding period *K* and a twelve-month formation period *J*.



With regards to the size and value factors, two interesting observations can be derived from Table 3. Firstly, both price and alpha momentum appear to have higher exposure to small-cap stocks in their winner and loser portfolios, which is consistent with findings in the literature (Blitz et al., 2015; Jegadeesh & Titman, 1993). Secondly, the winner portfolios of all three strategies seem skewed towards growth stocks, whereas the loser portfolio of idiosyncratic momentum opposes this with a skewness towards value. Nevertheless, these observations need to be taken into careful consideration as the correlations do not necessarily explain the variation in portfolio returns. Removing the market factor decreases the adjusted R-square values signficantly to around 5%, while the alpha values are all statistically significant, indicating the model fails to explain the variation in momentum returns. As a consequence, the derived factor exposures do not provide a robust explanation for the momentum returns, which is in line with the earlier mentioned results of Fama and French (1996, 2016).

4.2 Momentum Strategies Across Time

In addition to analyzing our chosen momentum strategies over the 25-year sample length, it also of interest to examine their performance under specific time-periods and during different phases of the business cycle. More specifically, we have divided the timeframe into two parts, namely expansion and contraction periods. Contraction periods include timeframes of decreases in economic activities, as defined by the Organisation for Economic Cooperation and Development (OECD, n.d.). This mostly includes recession periods, such as the Dot-Com Bubble, Global Financial Crisis and more recently the Coronavirus Crash. Time periods outside of these timeframes with economic growth were labeled as expansion periods. The three contraction periods are cut out from the original time series and put together to create a hypothetical timeframe with only contractions periods. The same process has been applied for expansion periods. The hypothetical timeframes are created to investigate how the momentum strategies perform during different economic environments. Table 4 below provides an overview of the chosen momentum strategies and their performance in both contraction and expansion periods.

Table 4. Nordic performance measures regarding the discussed momentum strategies for different holding periods K and a twelve-month formation period J, where AR represents the average monthly return, σ_p the portfolio's standard deviation, SR the Sharpe Ratio, α Jensen's Alpha and MDD maximum drawdown. Panel A represents the time periods of economic expansion, whereas Panel B constitutes results of periods with economic contraction.

PANEL A (Expansion)

J = 12	Price momentum				Idiosyncratic Momentum				Alpha Momentum				Benchmark
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0221	0.0193	0.0148	0.0069	0.0151	0.0139	0.0120	0.0069	0.0217	0.0167	0.0127	0.0068	0.0133
α	0.0197	0.0173	0.0132	0.0049	0.0144	0.0124	0.0104	0.0054	0.0201	0.0149	0.0110	0.0049	0
σ_p	0.0464	0.0443	0.0432	0.0436	0.0358	0.0351	0.0362	0.0367	0.0360	0.0363	0.0375	0.0375	0.0440
SR	0.4294	0.3877	0.2924	0.1074	0.3613	0.3346	0.2709	0.1272	0.5416	0.4006	0.2795	0.1236	0.2540
MDD	-0.2973	-0.2311	-0.1303	-0.3229	-0.2333	-0.1538	-0.1463	-0.2707	-0.1356	-0.1330	-0.1620	-0.3446	-0.2277
Skewness	-0.0177	-0.3229	-0.3713	-0.6317	0.0847	-0.0165	-0.4369	-0.3895	0.3500	0.1260	-0.1169	-0.3953	-0.2127
Kurtosis	3.5592	4.8126	3.3540	3.3238	3.9735	3.9289	4.3664	2.7844	3.6622	3.3959	3.0740	3.0950	4.0146
t-stat	7.3879	10.8645	11.5394	6.9819	6.5098	9.7437	10.3488	7.3367	9.1693	10.8880	10.5282	7.5795	4.8128

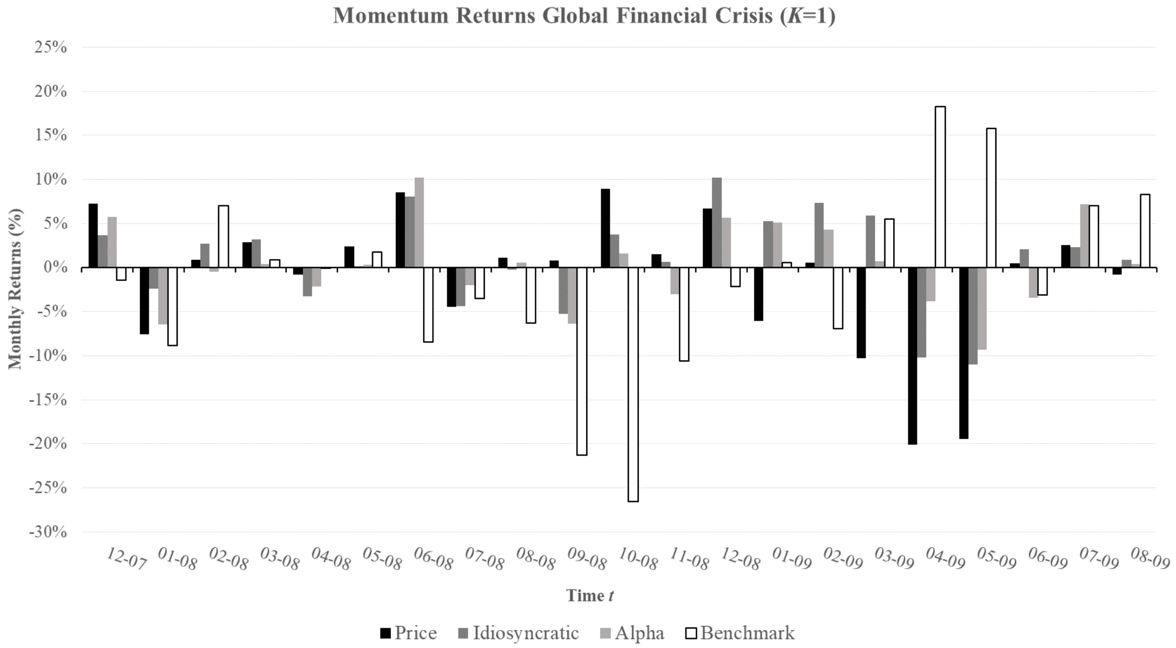
PANEL B (Contraction)

J = 12	Price momentum				Idiosyncratic Momentum				Alpha Momentum				Benchmark
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0128	0.0107	0.0079	0.0080	0.0095	0.0093	0.0059	0.0014	0.0133	0.0124	0.0099	0.0073	-0.0024
α	0.0137	0.0103	0.0071	0.0071	0.0092	0.0086	0.0049	4.1e-04	0.0131	0.0115	0.0088	0.0062	0
σ_p	0.0665	0.0621	0.0583	0.0538	0.0425	0.0447	0.0406	0.0387	0.0437	0.0416	0.0395	0.0407	0.0788
SR	0.1753	0.1537	0.1152	0.1263	0.1962	0.1822	0.1163	0.0063	0.2781	0.2708	0.2205	0.1501	-0.0457
MDD	-0.4549	-0.3757	-0.2894	-0.2846	-0.2015	-0.1612	-0.2394	-0.3606	-0.1580	-0.1091	-0.0723	-0.1082	-0.6452
Skewness	-0.7101	-0.9109	-0.7948	-0.7221	-0.3756	-0.4070	-0.2326	-0.5836	-0.4251	0.0194	-0.0361	0.0684	-0.3853
Kurtosis	4.1296	5.3304	4.1660	2.5554	3.4388	3.5866	2.0586	2.1694	3.6136	4.2910	2.9406	3.4281	4.0358
t-stat	2.1823	2.8039	2.9606	3.5282	2.3595	3.2769	3.3122	0.9121	3.1459	4.9815	6.5185	4.9808	0.0913

The first observation that stands out from Table 4 is the unsurprising difference in returns between periods of expansion and contraction. Logically, stocks provide higher returns in periods of economic expansion and decline during recessions. However, it can be considered noteworthy that even in periods of contraction the momentum strategies provide positive monthly returns, which is in line with findings by Griffin et al. (2003). Meanwhile, the benchmark demonstrates negative monthly returns in contraction periods. The ranking of return performances also changes between the different time periods, as can be seen in Table 4. While price momentum provides the highest monthly returns in expansion periods, alpha momentum outperforms price momentum in contraction periods for one-, three- and six-months holding periods. Furthermore, idiosyncratic momentum experiences the lowest relative decline in monthly returns compared to the other two strategies. This even leads to idiosyncratic momentum obtaining a superior Sharpe Ratio in comparison to price momentum in periods of contraction. This once again demonstrates the design of idiosyncratic momentum being less sensitive to the market, as mentioned by Blitz et al. (2011, 2020).

With regards to volatility, we can observe from Table 4 that all strategies and the benchmark experience higher levels of standard deviations in contraction periods. This also does not come as a surprise since stocks behave more volatile in periods of crisis. Despite increased volatility, alpha momentum remains the best performing strategy based on risk-adjusted returns. Similar to the previously discussed change in returns, the relative delta for volatility levels regarding both idiosyncratic and alpha momentum are particularly lower between the different time periods than for price momentum. As mentioned before, the reasoning behind this is that both idiosyncratic and alpha momentum are designed to have lower time-varying exposure to systematic risk factors than price momentum (Daniel & Moskowitz, 2016; Grundy & Martin 2001; Blitz et al., 2011, 2020; Hühn & Scholz, 2018). The difference in exposure becomes furthermore evident from comparing the maximum drawdowns, whereas price momentum experiences more significant declines than its peer strategies for both expansion and contraction periods. Figure 8 below provides a simplistic overview of the differences in drawdowns during the Global Financial Crisis, showing the increased negative returns of price momentum in comparison to other strategies and the benchmark. Moreover, Figure 8 presents an additional illustration of the lagged crash risk for momentum strategies, with extensive drawdowns occurring during market rebounds (Daniel & Moskowitz, 2016). While the benchmark crashes from June 2008 until December 2008, the momentum strategies experience positive returns due to their short positions. Nevertheless, as the benchmark bounces back from March 2009, the momentum strategies start to crash.

Figure 8. Momentum returns during the Global Financial Crisis for all three momentum strategies, based on a one-month holding period *K* and a twelve-month formation period *J*.



Apart from the variance in expansion and contraction periods, a notable difference in performance can be observed in Table 10 (see Appendix) between the period prior to the Global Financial Crisis in 2009 and after. All momentum strategies produce more significant abnormal returns after 2009. Monthly returns doubled while volatility levels decreased, which consequently led to substantial increases in Sharpe ratios. Especially idiosyncratic momentum experienced a large increase in performance. A possible explanation can be derived from Figure 16 in the Appendix, demonstrating the increasingly poor performance of the loser portfolios for all three strategies. In addition to that, the period after 2009 mainly consisted of a bull market until the Coronavirus crash in 2020, hence lacking periods of subsequent negative returns. Furthermore, the Coronavirus crash occurred extremely fast and the momentum strategies appear to be barely affected, potentially due to the lagging factor for momentum crashes. A possible explanation for the abnormal momentum returns can therefore also be connected to a compensation for beta risk in a bull market, as suggested by literature (Ahn et al., 2003; Chordia & Shivakumar, 2002; Johnson, 2002; Ruenzi & Weigert, 2018; Zhang, 2004). In conclusion, the momentum strategies appear to perform remarkably well during both expansion periods and the time period after the Global Financial Crisis.

4.3 Momentum Strategies per Country

Table 5 below provides a comprehensive overview of the performance measures per Nordic country regarding the chosen momentum strategies with a one-month holding period *K*. Apart from a few exceptions, the results per country mostly align with the findings on the Nordic sample as a whole. As can be seen from Table 5, all three momentum strategies outperform the benchmark and create alphas that are statistically significantly different from zero. Similar to the findings on the Nordic market, alpha momentum appears to be the superior strategy for each country based on risk-adjusted returns, except for Finland. Although price momentum experiences more volatility in Finland, it is the only country where this strategy provides the best Sharpe ratio. In Sweden and Denmark, the superior performance of alpha stems not only from lower volatility, but also from higher returns, whereas for Norway we find similar returns yet lower levels of volatility between alpha and price momentum. Despite lower volatility levels, idiosyncratic momentum appears to also be the most inferior strategy for individual countries, with the exception of Denmark where it comes second after alpha momentum.

Another commonality between the results of the Nordic market (see Table 2) and the countries individually (see Table 5) is that idiosyncratic and alpha momentum exhibit lower levels of volatility than price momentum. Once again, this is due to their construction being less exposed to systematic risk factors (Blitz et al., 2011, 2020; Hühn & Scholz, 2018). The standard deviation for price momentum in Norway is the highest with 0.0888, while Norway's idiosyncratic and alpha momentum have standard deviations of 0.0713 and 0.0792 respectively. Similar patterns can be observed in the other countries.

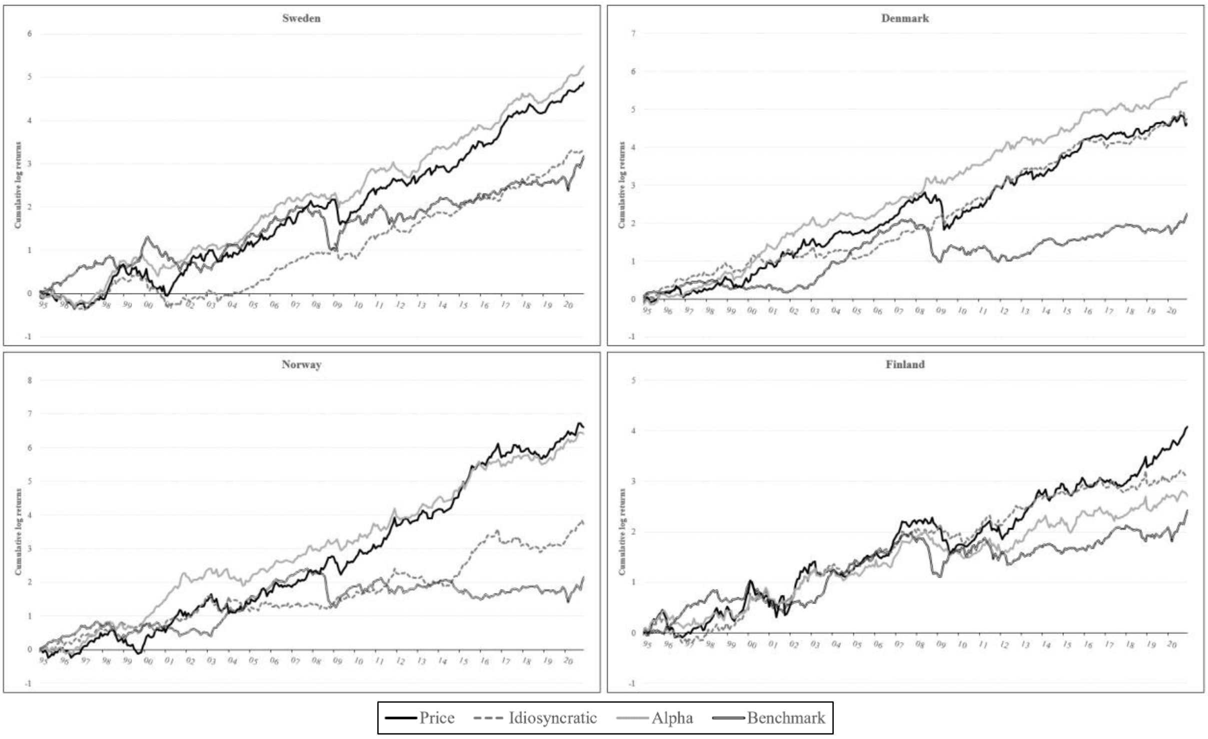
Examining the maximum drawdowns between strategies in the Nordic countries, a few things stand out in Table 5. In general, maximum drawdowns for price momentum are higher than for the other two strategies, however one exception can be found in Sweden where idiosyncratic momentum decreases more than price. Another noteworthy point is the difference in spreads between the maximum drawdowns per country. The maximum drawdowns in Denmark for both idiosyncratic and alpha momentum are more than 30 percent lower than for price momentum, whereas the spread in the other countries lies more around five to ten percent. Alpha momentum being the superior strategy is further strengthened when observing the skewness and kurtosis values for the chosen momentum strategies. The skewness for alpha momentum is the lowest compared to idiosyncratic and price momentum for each individual country. The same holds true for kurtosis, indicating that alpha momentum substantially lowers the crash risk, especially compared to price momentum (Daniel & Moskowitz, 2016; Barroso & Santa-Clara, 2015). This can be seen as a partial explanation for the lower maximum drawdowns mentioned earlier. For more detailed results regarding the momentum strategies, including different holding periods (see Table 11 in the Appendix).

Table 5. Nordic performance measures regarding the discussed momentum strategies for a one-month holding period *K* and a twelve-month formation period *J*, where μ_p represents the average monthly return, σ_p the portfolio's standard deviation, *SR* the Sharpe Ratio, α Jensen's Alpha and *MDD* maximum drawdown. *P* stands for price momentum, *I* for idiosyncratic momentum and *A* for alpha momentum.

J = 12	Sweden			Norway			Denmark			Finland		
K =1	*P*	*I*	*A*	*P*	*I*	*A*	*P*	*I*	*A*	*P*	*I*	*A*
μ_p	0.0157	0.0107	0.0170	0.0214	0.0120	0.0208	0.0149	0.0153	0.0186	0.0132	0.0100	0.0087
α	0.0175	0.0109	0.0166	0.0256	0.0139	0.0189	0.0173	0.0163	0.0167	0.0149	0.0106	0.0068
σ_p	0.0667	0.0502	0.0553	0.0888	0.0713	0.0792	0.0694	0.0547	0.0568	0.0743	0.0632	0.0601
SR	0.2077	0.1759	0.2732	0.2199	0.1414	0.2388	0.1880	0.2461	0.2947	0.1521	0.1285	0.1141
MDD	-0.5146	-0.5394	-0.3936	-0.5021	-0.4916	-0.4070	-0.6214	-0.2785	-0.2319	-0.5158	-0.4156	-0.4112
Skewness	-0.5483	-0.7124	-0.0008	-0.1930	-0.3811	0.0105	-1.1439	-0.7078	-0.0457	-0.4325	0.4438	-0.0647
Kurtosis	4.1229	5.8174	3.3517	3.1080	4.3226	3.4503	9.0138	6.0397	3.5146	4.9139	7.7790	3.8868
t-stat	4.7634	4.2193	5.9061	5.0386	3.6007	5.3211	4.4446	5.4419	6.2804	3.7981	3.3395	3.0931

Comparing the countries with one another in Table 5, we can state that the highest momentum returns are derived from Norway, whereas the lowest are derived from Finland. These two countries also demonstrate the highest volatility levels. Norway's outperformance experiences a strong acceleration in 2014, which can be seen from Figure 9 below. This acceleration stems mostly from substantial declines in Norway's loser portfolios, consequently creating large momentum profits for the WML portfolios. A potential explanation could be the significant drop in oil prices around this time period, which would severely affect Norway due to its higher exposure to the energy sector. Another observation that stands out is the poor performance of idiosyncratic momentum in Sweden until 2004, prior to which it still provided negative cumulative log returns.

Figure 9. Performance graphs of the different momentum strategies and benchmarks for the individual Nordic countries. All visualized strategies are based on a one-month holding period *K* and a twelve-month formation period *J*.



4.4 Volatility-Adjusted Price Momentum

Literature has introduced and discussed volatility scaling as an alternative adaptation of the price momentum strategy in order to improve performance (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016). Therefore, it can be considered interesting to investigate if this type of strategy leads to enhanced results in our unexplored Nordic sample. Furthermore, comparing the volatility-adjusted price momentum with the previously discussed momentum strategies provides further insights into the possibility of producing abnormal returns in the Nordic stock market. As mentioned before, we follow the methodology of Barroso and Santa-Clara (2015) with constant volatility scaling. We believe that the practical implementation of this strategy appears more reasonable than for example the dynamic volatility scaling proposed by Daniel and Moskowitz (2016). According to Daniel and Moskowitz (2016), the amount of leverage with dynamic volatility scaling is 3.6 times more volatile than for constant volatility scaling. Moreover, dynamic volatility scaling reaches impracticable levels of leverage, such as weights that are negative and above five.

The levels of leverage, also referred to as the weight on the WML portfolio, applied to the price momentum strategy can be found in Figure 10 below. The degree of leverage ranges between 0.5 and 2.5, implying much more realistic levels than the dynamic volatility scaling of Daniel and Moskowitz (2016). Similar to the findings of other authors applying volatility scaling, the weight decreases significantly in times of economic contraction and higher volatility (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Moreira & Muir, 2017). As Moreira and Muir (2017) mention, decreasing leverage in recessions goes against common belief indicating one should increase their risk-taking during bad times. Nevertheless, as will be presented in the next paragraph, the utilization of volatility scaling provides improved risk-adjusted returns. As a consequence, the abnormal returns cannot be described by the earlier mentioned risk-based explanations.

Figure 10. Constant volatility-adjusted weights on the WML portfolio between 1995-2020.

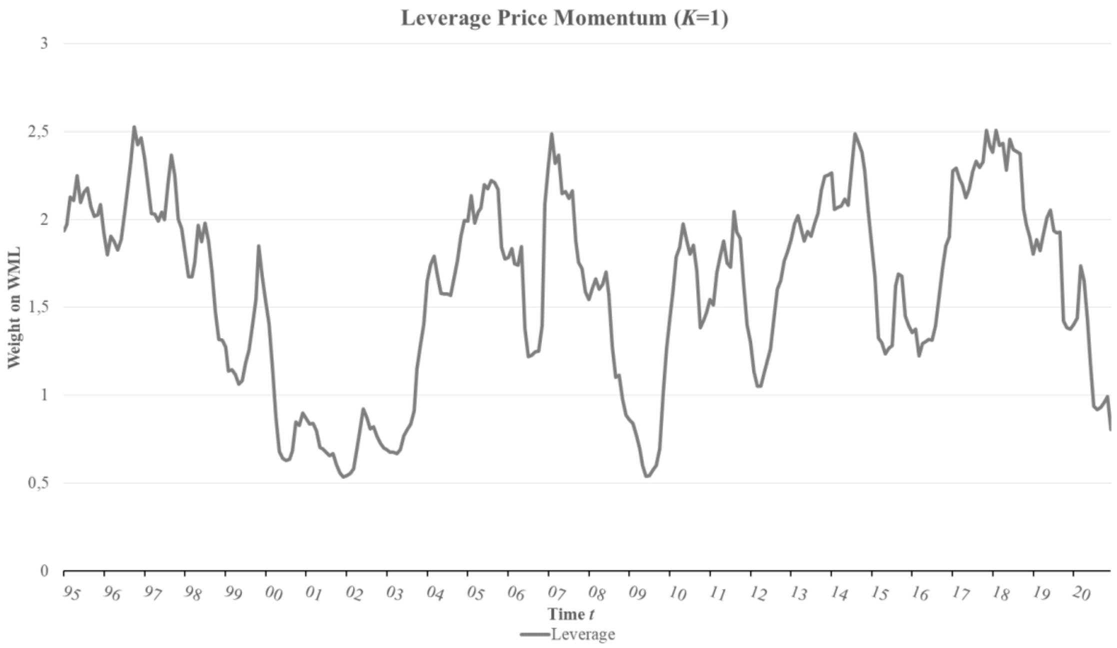


Table 6 below illustrates the performance measures of the volatility-adjusted price momentum strategy (VAPM) in comparison with the other momentum strategies. Comparing VAPM with the original price momentum strategy, one can observe both a strong increase in monthly returns and standard deviation (see also Figure 17 in the Appendix). This results in a slight improvement of the Sharpe ratio, which is in line with the findings of Barroso and Santa-Clara (2015) in the United Kingdom. VAPM demonstrates to be especially good at reducing the crash risk related to high-order moments. Price momentum has a skewness of -0.4550 whereas

VAPM has positive skewness of 0.2860. In addition to this, the kurtosis is halved from 4.6111 to 2.2876 when using the volatility-adjusted approach and thus further reduces the probability of large negative returns. Hence, the combination of a positive skewness and a halving of kurtosis makes the VAPM strategy less exposed to significant drawdowns or so-called momentum crashes. This becomes furthermore evident from the maximum drawdown results in Table 6, showcasing a decrease from -45.5% to -33.5%. These results are in line with the findings of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), who demonstrate reduced crash risk through their volatility scaling. Additionally, these results follow the reasoning of utilizing idiosyncratic and alpha momentum, namely to achieve enhanced risk-adjusted returns. Hence, it is of considerable interest to also compare the VAPM with both idiosyncratic and alpha momentum.

While VAPM outperforms idiosyncratic momentum in our Nordic sample, the same cannot be said for alpha momentum. Although monthly returns appear higher for VAPM, alpha momentum demonstrates close to half the level of volatility, hence resulting in a superior Sharpe ratio. In addition to this, the maximum drawdowns for both idiosyncratic and alpha momentum are significantly lower than for VAPM, exhibiting a greater ability to deal with crash risks. On top of these results, one has to also take the additional transaction costs associated with volatility scaling into consideration. This paper does not include the influence of transaction costs on momentum profits, as all momentum strategies would incur approximately similar cost structures. However, this does not apply to volatility scaling, meaning that increased risk-adjusted returns compared to regular price momentum can potentially be offset by transaction costs.

In conclusion, VAPM seems to provide improved performance compared to both regular price momentum and idiosyncratic momentum, although this is suspect to change after including transaction costs. Nevertheless, alpha momentum appears once again to be the superior risk-adjusted momentum strategy. Additionally, the implementation of constant volatility scaling is much more difficult than the implementation of the other momentum strategies.

Table 6. Comparison between volatility-adjusted price momentum (VAPM), as suggested by Barroso and Santa-Clara (2015), and the other momentum strategies. All results are based on a one-month holding period *K* and a twelve-month formation period *J*.

J = 12 / *K* =1	**Price Momentum**	**VAPM**	**Idiosyncratic Momentum**	**Alpha Momentum**
μ_p	0.0193	0.0332	0.0134	0.0192
α	0.0203	0.0352	0.0129	0.0181
σ_p	0.0532	0.0766	0.0379	0.0386
SR	0.3280	0.4008	0.3048	0.4488
MDD	-0.4550	-0.3348	-0.2332	-0.1580
Skewness	-0.4929	0.2860	-0.1378	-0.0355
Kurtosis	4.6111	2.2876	3.8975	3.9155
t-stat	6.8866	8.3010	6.5908	9.1204

5. Conclusion

The purpose of this thesis was to investigate the momentum anomaly in the Nordics, while also comparing the different adaptations of the original price momentum strategy firstly introduced by Jegadeesh and Titman (1993). Our results suggest that the momentum anomaly exists in the Nordic stock market providing abnormal returns that are statistically significant, hence challenging the EMH theory (Fama, 1970). All analyzed momentum strategies outperform the benchmark with enhanced risk-adjusted returns. Momentum profits are derived from both the strong performance of the winner deciles and the poor performance of the loser deciles. However, performance has been shown to deteriorate with longer holding periods, supporting the behavioral explanations made by literature (Barberis et al., 1998; Chan et al., 1996; Daniel et al., 1998; Hong & Stein, 1999; Hong et al., 2000).

Comparing the different momentum strategies amongst each other, alpha momentum appears to be the superior risk-adjusted strategy in our Nordic sample. Consistent with the suggestions made by literature (Blitz et al., 2011, 2020; Hühn & Scholz, 2018), both idiosyncratic and alpha momentum reduce crash risks. This can be seen from the results in volatility, maximum drawdowns, skewness and kurtosis. Moreover, reduced crash risk can be derived from the differences in time-varying betas and exposure to the Fama-French market factor, consequently supporting the risk-based explanations of momentum profits (Ahn et al., 2003, Chordia & Shivakumar, 2002; Johnson, 2002; Ruenzi & Weigert, 2018; Zhang, 2004). Nevertheless, the remaining factors of *SMB* and *HML* were not found to be statistically significant, which is in line with the findings of Fama and French (1996, 2016).

Contrary to studies in other markets, price momentum did not experience more extreme drawdowns than the benchmark, due to the loser deciles not rebounding in a similar degree. However consistent with other studies, all momentum strategies demonstrate a lag in their crashes compared to the benchmark. Nevertheless, while the benchmark provides negative returns over the contraction period, all momentum startegies exhibit positive returns. The delta in performance between contraction and expansion periods is most notable for price momentum, once again highlighting its higher exposure to the market. This consequently enables especially idiosyncratic momentum to outperform price momentum in contraction periods, whereas alpha momentum already outperformed price momentum over the whole time period. Furthermore, the majority of momentum profits are derived from the period after the

Global Financial Crisis with in particular idiosyncratic momentum exhibiting a prominent increase in performance, which can be partially explained by the greater returns obtained from the loser decile.

Examining the Nordic countries in isolation, multiple commonalities can be found. Alpha momentum provides the best risk-adjusted returns in all countries except Finland. Idiosyncratic momentum demonstrates at the same time to be the most inferior strategy in Sweden and Norway. Furthermore, in line with previous findings, both idiosyncratic and alpha momentum express lower volatility levels than price momentum. With regards to differences, Norway exhibits the highest abnormal returns for both price and alpha momentum, whereas idiosyncratic appears to be superior in Denmark. Sweden in particular displays a considerably poor performance for idiosyncratic momentum during the first ten years of the sample period. In general, momentum profits are the lowest in Finland.

Introducing the constant volatility scaling approach of Barroso and Santa-Clara (2015) signficantly reduces the crash risk of the price momentum strategy. Even though volatility increases, both drawdowns and kurtosis decrease substantially while the skewness turns positive. The volatility-adjusted price momentum provides enhanced performance in terms of risk-adjusted returns compared to both regular price momentum and idiosyncratic momentum. Although alpha momentum exhibits lower monthly returns, it remains superior on a risk-adjusted basis. In addition to this, the implementation of volatility scaling is much more complicated than for the other momentum strategies and also includes additional transaction costs that could potentially influence the outcomes.

All in all, this thesis contributes to the literature by showcasing the existence of momentum in the Nordic stock market. Support for both behavioral- and risk-based explanations have been found through deteriorating returns and exposure to systematic risk factors. Furthermore, this thesis provides an unprecedented comparison of different momentum strategy adaptations. The results from this advocate the suggestions of Blitz et al. (2011, 2020) and Hühn and Scholz (2018) that idiosyncratic and alpha momentum reduce the momentum strategy’s volatility and crash risk. However, only alpha momentum consistently demonstrated superior risk-adjusted returns. Moreover, the results affirm the suggestion of constant volatility scaling proposed by Barroso and Santa-Clara (2015), but highlights its inferiority compared to alpha momentum and emphasizes potential problems regarding practical implementation.

6. Limitations & Future Research

As with every research, this study contains several limitations that need to be taken into consideration when interpreting the results. Firstly, this thesis is conducted on the Nordic stock market consisting of stocks from Denmark, Finland, Norway and Sweden. Hence, results from this sample are not applicable to other regions or countries. Additionally, the Nordic region might have a bias towards certain industries where momentum effects are more common. On top of this, numerous filters have been applied to the data sample, such as the exclusion of micro-caps and penny stocks, which potentially affect the outcomes. While we attempted to create a realistic Nordic trading universe, it does not necessarily represent reality or indicate similar results in practice.

Secondly, the thesis is limited by the chosen time periods. Momentum might not have existed prior to 1995 in the Nordics. Furthermore, the results are also no guarantee for its persistence in the future. Thirdly, this thesis does not include the impact of trading costs, as the main purpose of the thesis was to compare different momentum strategies with similar cost structures, apart from VAPM. Trading costs will however in practice have an influence on the net returns between different holding periods and the volatility scaling approach. Fourth and lastly, our research is dependent on various data sources, such as Datastream and AQR. Although their validity is confirmed through literature, it does not imply the sources to be faultless.

Aside from limitations, several areas for future research are identified. Firstly, future studies could consider the inclusion of trading costs, such as transaction, borrowing and margin expenses. More specifically, the difference between holding periods and the volatility scaling approach after these trading costs would provide a more comprehensive comparison. Besides trading costs, future studies could also explore and compare the aforementioned strategies in different regions or countries. It could be considered interesting to examine whether the alpha momentum's superiority holds in other international markets. Lastly, subsequent studies could indulge deeper into the reasonings behind momentum profits, potentially utilizing new or existing models aside from CAPM or the Fama-French three factor model.

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Appendix

Figure 11. Comparison between the price momentum strategy and the benchmark of the Tokyo Stock Exchange (TSE) for 1995-2020.

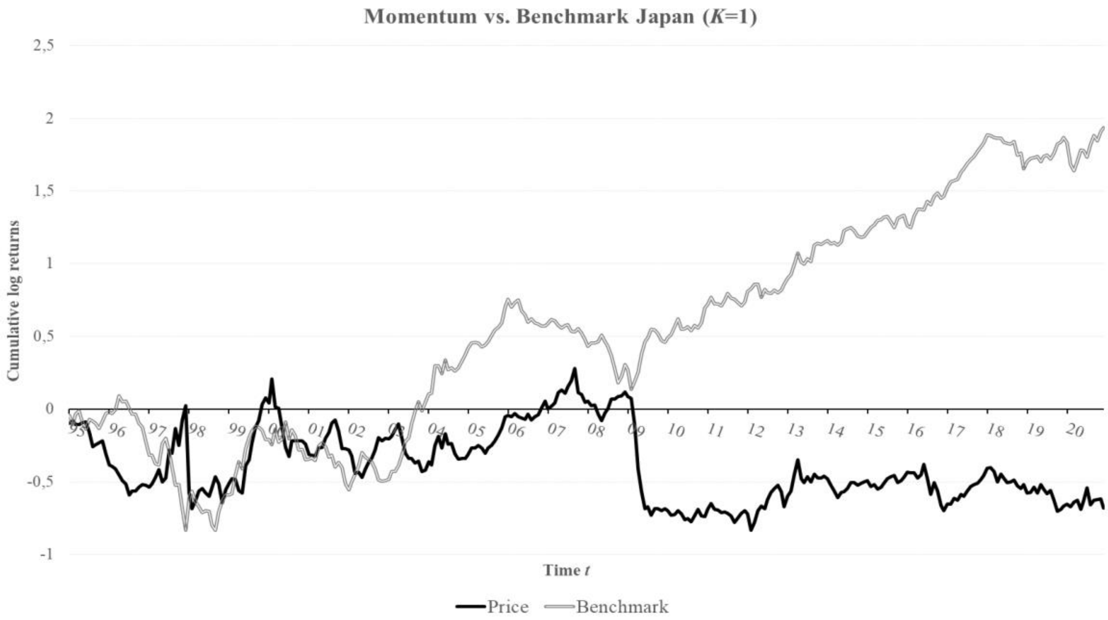

Figure 12. Overview regarding the number of eligible stocks per country in our Nordic sample as a result of our filtering process. This also includes pre-requisites for being eligible for the momentum strategies, such as having at least one year of past returns.

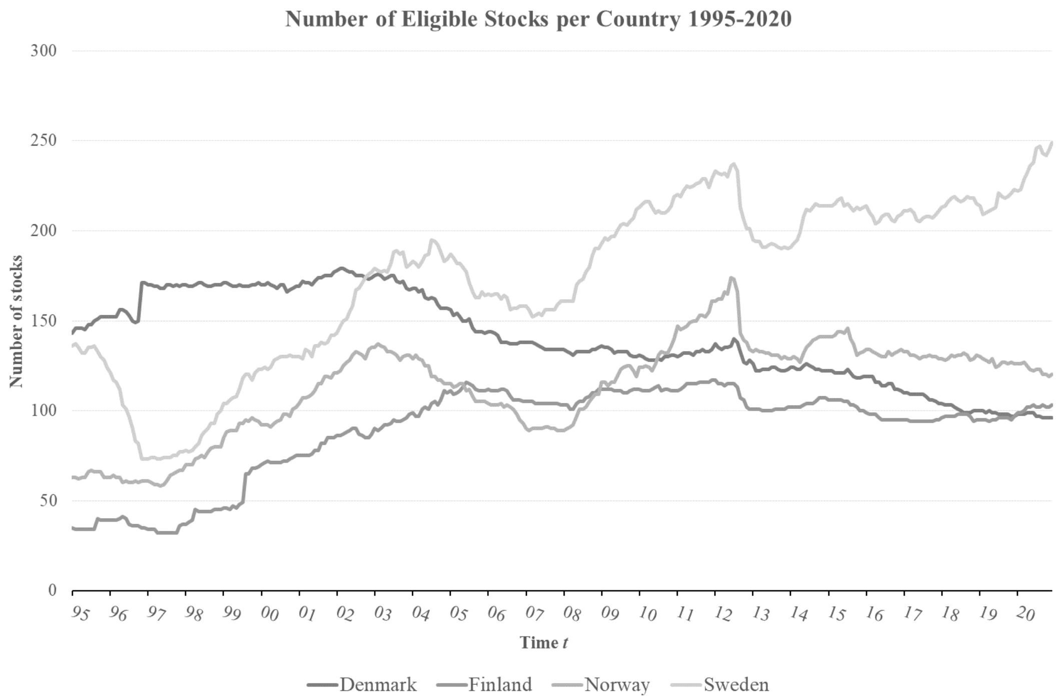

Figure 13. Comparison between the different sub-portfolios from original price momentum strategy with a three-month holding period *K* to display seasonality effects.

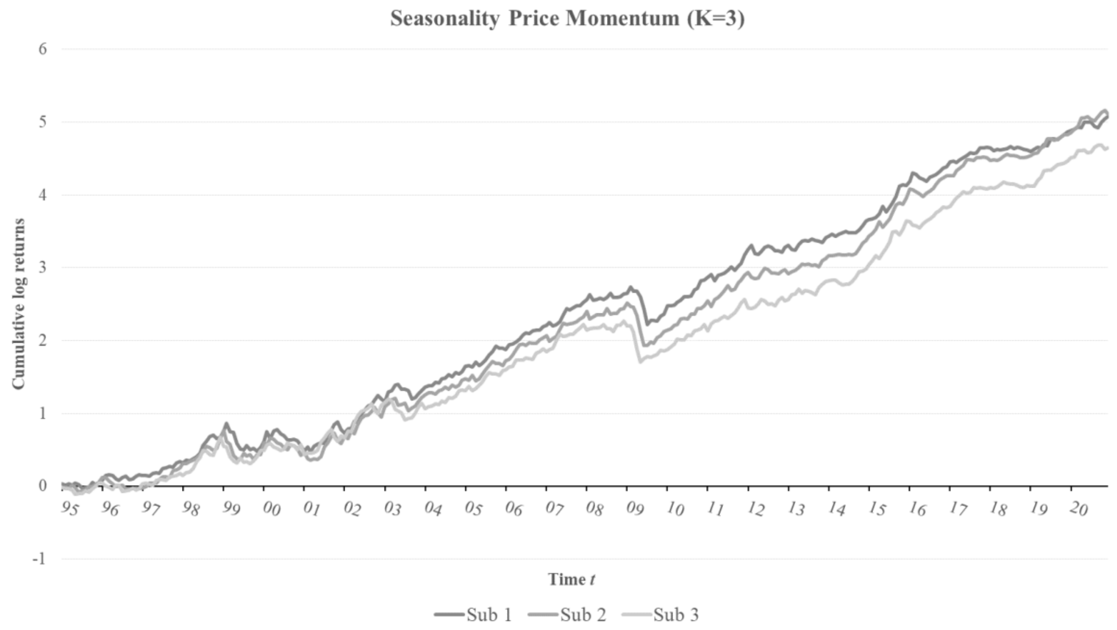

Figure 14. Comparison of the results between alpha momentum strategies using past daily and monthly returns for the estimation of the alpha from the Fama-French three-factor model.

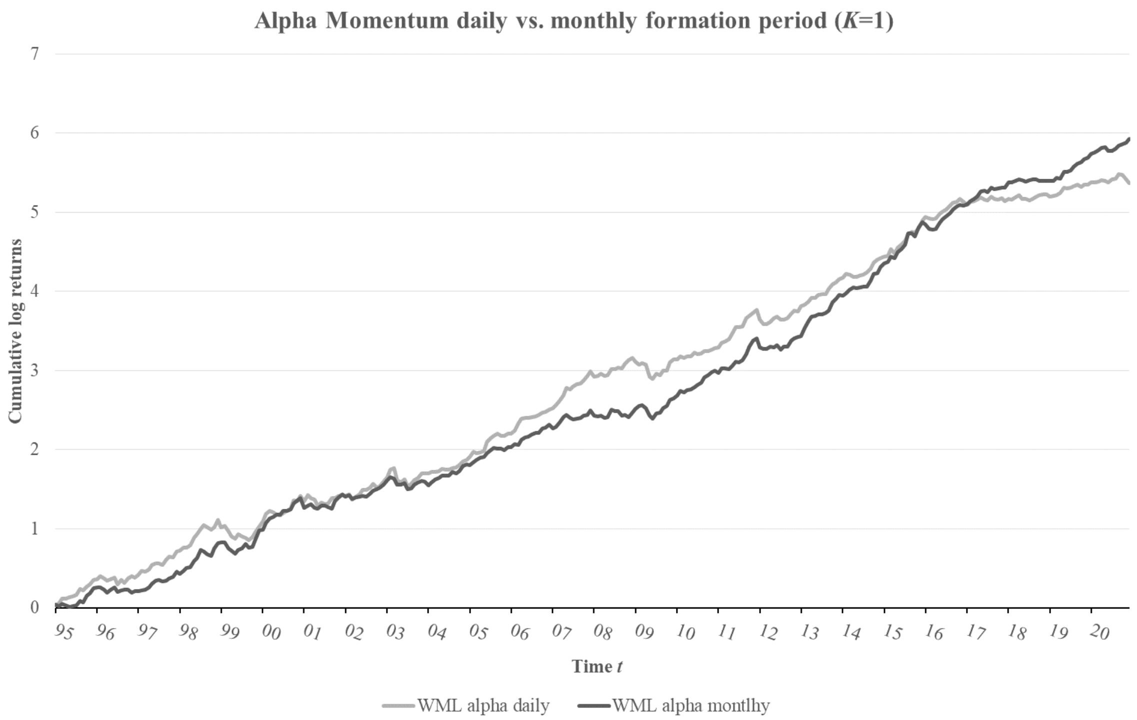

Figure 15. Comparison of price momentum strategies with different holding periods *K* to demonstrate deteriorating returns, following the behavioral-based explanations for momentum mentioned by the literature.

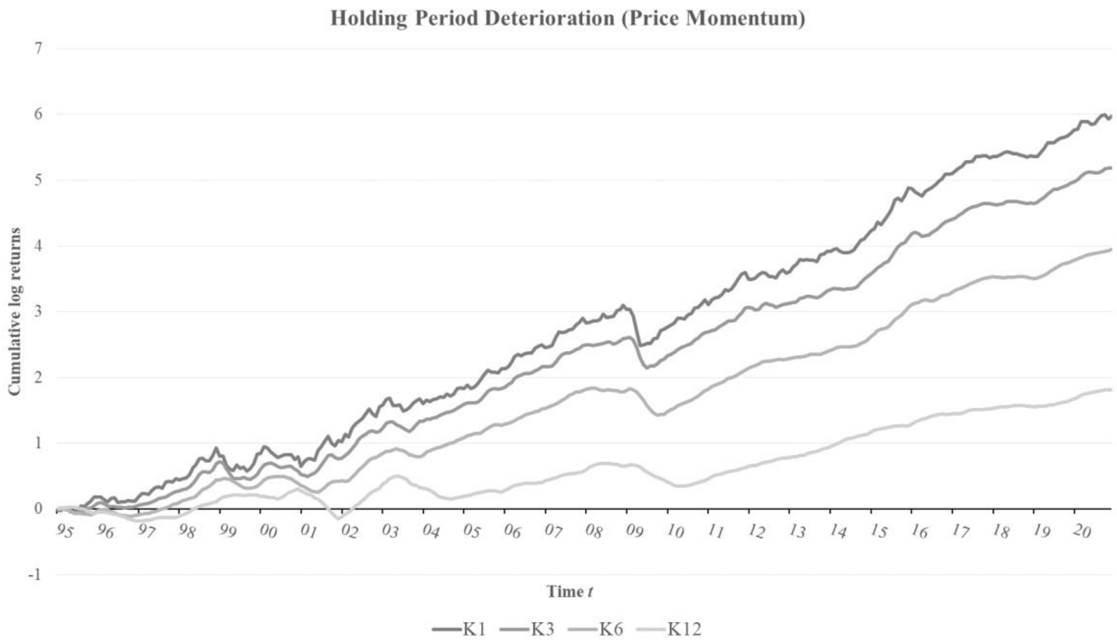

Figure 16. Comparison of the winner (W) and loser (L) portfolios of the three discussed momentum strategies with a one-moth holding period *K*.

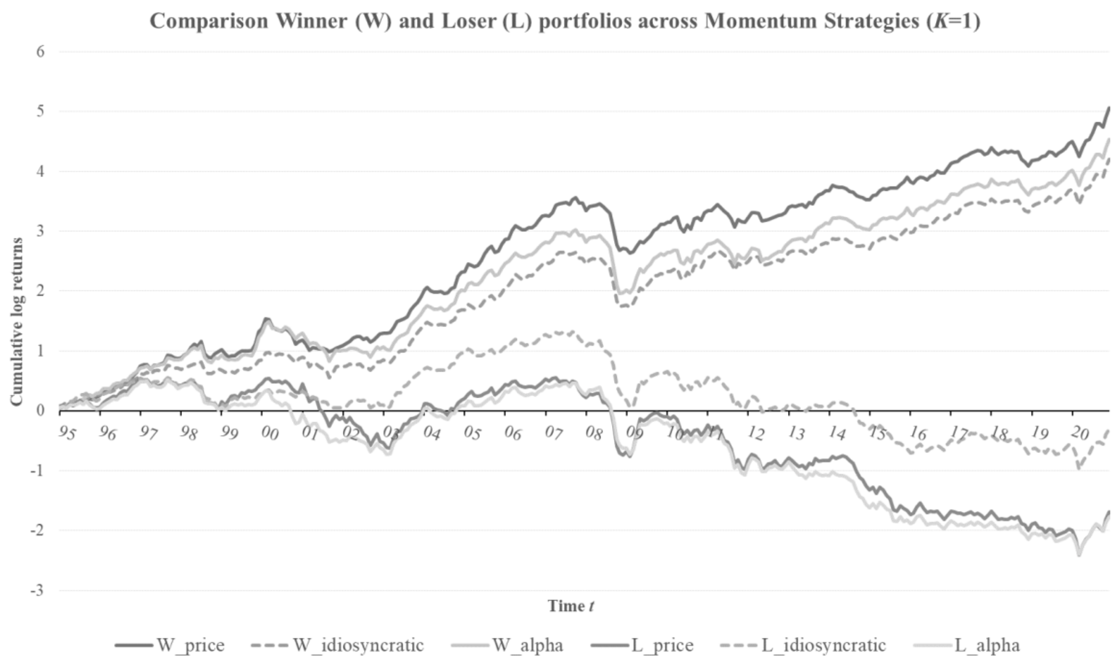

Figure 17. Comparison between the price momentum strategy and the volatility-adjusted price momentum approach, using constant-volatility scaling with a one-moth holding period *K*.

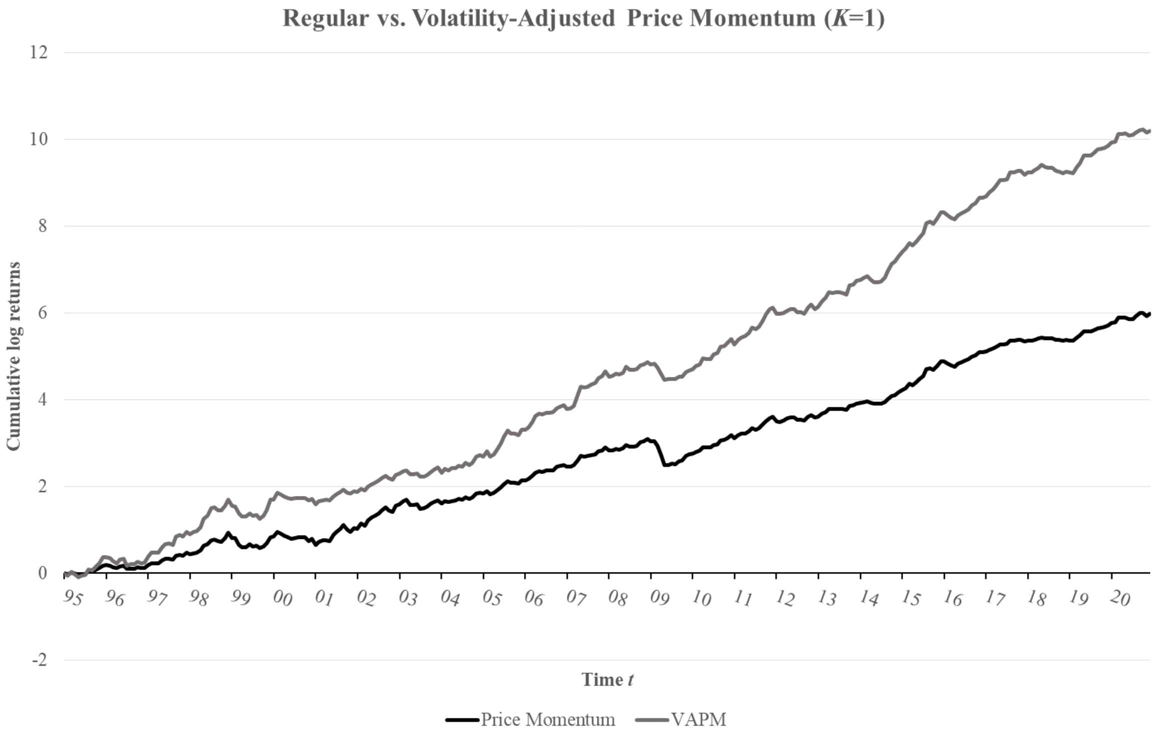

Table 7. Statistical tests on the average returns of the momentum strategies against the benchmark for a one-month holding period *K* and a twelve-month formation period *J*. * implies statistical significance at a 95% confidence level.

J = 12 / *K=1*	**Price momentum**	**Idiosyncratic Momentum**	**Alpha Momentum**
t-stat	2.188*	0.955	2.414*

Table 8. Statistical tests on the average returns of the momentum strategies against each other for a one-month holding period *K* and a twelve-month formation period *J*. * implies statistical significance at a 95% confidence level.

J = 12 / *K=1*	**Price against Alpha**	**Alpha against Idiosyncratic**	**Idiosyncratic against Price**
t-stat	0.368	3.145*	-2.567*

Table 9. Overview of the Fama-French three-factor exposures for the WML portfolios of the chosen momentum strategies, where SR represents the Sharpe Ratio, α the alpha factor, R_M^e the market factor, SMB the size factor, HML the value factor and $adj.R^2$ the adjusted R-squared value. Results are derived from a twelve-month formation period J and a one-month holding period K.

J = 12	Price momentum				Idiosyncratic Momentum				Alpha Momentum			
K	1	3	6	12	1	3	6	12	1	3	6	12
SR	0.3280	0.2960	0.2249	0.1130	0.3048	0.2793	0.2186	0.0894	0.4488	0.3573	0.2605	0.1357
α	0.0201	0.0161	0.0116	0.0043	0.0130	0.0112	0.0085	0.0035	0.0185	0.0141	0.0104	0.0053
R_M^e	-0.1593	-0.0767	-0.0362	-0.0165	-0.0791	-0.0147	0.0032	-0.0016	-0.0476	-0.0237	-0.0161	-0.0055
SMB	-0.1165	0.0066	0.1038	-0.0106	-0.1362	-0.0064	0.0472	0.0415	-0.0523	0.0461	0.0814	0.0499
HML	-0.0238	-0.0599	-0.0838	0.0107	-0.3034	-0.1644	-0.1123	-0.0345	-0.2208	-0.0992	-0.0873	0.0360
$adj.R^2$	0.0245	0.0120	0.0191	-0.0061	0.0868	0.0450	0.0385	-0.0001	0.0338	0.0127	0.0278	0.0043

Table 10. Overview of the performances of the chosen momentum strategies and the benchmark until the Global Financial Crisis and the period after. Panel A displays the results of the time period 1995-2009, whereas Panel B showcases the performances from 2010-2020.

PANEL A (1995-2009)

J = 12	Price momentum				Idiosyncratic Momentum				Alpha Momentum				Benchmark
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0152	0.0127	0.0080	0.0029	0.0088	0.0071	0.0045	-0.0011	0.0143	0.0120	0.0079	0.0027	0.0092
α	0.0154	0.0111	0.0113	2.4e-04	0.0070	0.0045	0.0017	-0.0040	0.0122	0.0095	0.0053	-4.7e-06	0
σ_p	0.0595	0.0556	0.0536	0.0469	0.0408	0.0417	0.0407	0.0391	0.0394	0.0394	0.0403	0.0399	0.0550
SR	0.2083	0.1769	0.0959	5.6e-04	0.1443	0.1008	0.0401	-0.1022	0.2917	0.2321	0.1246	-0.0040	0.1156
MDD	-0.4549	-0.3757	-0.3427	-0.3229	-0.2333	-0.1601	-0.2394	-0.3868	-0.1580	-0.1330	-0.1620	-0.3469	-0.6468
Skewness	-0.5445	-0.8507	-0.5950	-0.3054	-0.1150	-0.2957	-0.2776	-0.1582	-0.1751	0.0286	0.0810	0.2107	-0.9755
Kurtosis	4.3100	5.7016	3.6933	2.4937	3.9347	3.8441	2.6913	2.3785	3.5657	3.9962	3.1327	3.2380	7.4721
t-stat	3.8510	5.0717	4.5038	2.1181	3.1624	3.8956	3.3974	-0.8833	5.1647	6.8434	6.0748	2.4285	2.6407

PANEL B (2010-2020)

J = 12	Price momentum				Idiosyncratic Momentum				Alpha Momentum				Benchmark
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0248	0.0223	0.0192	0.0130	0.0205	0.0201	0.0179	0.0139	0.0252	0.0201	0.0172	0.0129	0.0077
α	0.0269	0.0226	0.0113	0.0127	0.0217	0.0200	0.0174	0.0136	0.0263	0.0200	0.0168	0.0126	0
σ_p	0.0428	0.0416	0.0394	0.0341	0.0326	0.0320	0.0315	0.0332	0.0368	0.0354	0.0345	0.0360	0.0594
SR	0.5695	0.5248	0.4762	0.3685	0.6150	0.6138	0.5528	0.4055	0.6719	0.4974	0.4840	0.3462	0.1223
MDD	-0.1138	-0.0590	-0.0355	-0.0427	-0.0846	-0.0363	-0.0179	-0.0259	-0.1261	-0.0710	-0.0542	-0.0246	-0.3415
Skewness	0.0812	0.1703	0.3249	-0.5765	0.1098	0.5159	0.8097	-0.2363	0.2520	0.2945	0.0766	0.1672	-0.1190
Kurtosis	3.2224	3.0570	3.1775	3.8669	3.0414	3.0419	4.6304	2.9354	4.1814	3.0322	2.9551	3.8517	3.8349
t-stat	6.9044	10.8595	14.6528	13.4810	7.4087	12.229	16.2032	16.8258	8.0671	10.5988	13.6026	15.2558	1.8331

Table 11. Performance measures for the Nordic countries in isolation regarding the discussed momentum strategies for different holding periods *K* and a twelve-month formation period *J*, where μ_p represents the average monthly return, σ_p the portfolio's standard deviation, *SR* the Sharpe Ratio, α Jensen's Alpha and *MDD* maximum drawdown. The final column exhibits the relative performance of the benchmark for the created Nordic trading universe. All results are derived from the time period 1995-2020.

Sweden

J = 12	**Price momentum**				**Idiosyncratic Momentum**				**Alpha Momentum**				**Benchmark**
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0157	0.0141	0.0116	0.0080	0.0107	0.0111	0.0097	0.0062	0.0170	0.0143	0.0107	0.0066	0.0102
α	0.0175	0.0138	0.0104	0.0064	0.0109	0.0099	0.0077	0.0044	0.0166	0.0128	0.0089	0.0049	0
σ_p	0.0667	0.0646	0.0625	0.0598	0.0502	0.0489	0.0483	0.0472	0.0553	0.0541	0.0534	0.0532	0.0662
SR	0.2077	0.1897	0.1561	0.1022	0.1759	0.1880	0.1617	0.0915	0.2732	0.2291	0.1660	0.0880	0.1256
MDD	-0.5146	-0.4508	-0.4457	-0.4224	-0.5394	-0.4536	-0.3978	-0.4277	-0.3936	-0.2902	-0.2652	-0.3252	-0.6461
Skewness	-0.5483	-0.5776	-0.2415	-0.2698	-0.7124	-0.6104	-0.7594	-0.4581	-0.0008	-0.3263	0.0921	0.1579	-0.2000
Kurtosis	4.1229	5.1891	3.9328	3.1958	5.8174	4.0924	3.6314	3.0795	3.3517	4.0690	3.5833	3.5930	4.5793
t-stat	4.7634	6.6636	7.5352	6.9575	4.2193	6.7389	3.3974	7.0684	5.9061	8.3681	6.0748	6.7288	3.3052

Norway

J = 12	**Price momentum**				**Idiosyncratic Momentum**				**Alpha Momentum**				**Benchmark**
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0214	0.0193	0.0150	0.0089	0.0120	0.0104	0.0085	0.0037	0.0208	0.0200	0.0158	0.0098	0.0069
α	0.0256	0.0196	0.0142	0.0075	0.0139	0.0096	0.0072	0.0022	0.0189	0.0197	0.0146	0.0082	0
σ_p	0.0888	0.0828	0.0807	0.0808	0.0713	0.0673	0.0682	0.0698	0.0792	0.0762	0.0753	0.0743	0.0680
SR	0.2199	0.2105	0.1633	0.0874	0.1414	0.1263	0.0976	0.0262	0.2388	0.2384	0.1855	0.1069	0.0738
MDD	-0.5021	-0.4304	-0.2432	-0.2654	-0.4916	-0.3460	-0.2922	-0.5182	-0.4070	-0.3182	-0.3024	-0.2441	-0.6823
Skewness	-0.1930	-0.1715	0.0715	0.1106	-0.3811	0.1200	0.1247	-0.1412	0.0105	0.2535	0.1640	0.2042	-0.5320
Kurtosis	3.1080	3.7539	3.0933	2.4760	4.3226	2.8562	2.7163	3.0365	3.4503	2.9829	2.6948	2.8460	5.3306
t-stat	5.0386	7.6147	8.7927	7.1200	3.6007	5.0733	5.2339	3.0552	5.3211	8.4454	9.0873	7.6049	2.4041

Denmark

J = 12	**Price momentum**				**Idiosyncratic Momentum**				**Alpha Momentum**				**Benchmark**
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0149	0.0148	0.0118	0.0052	0.0153	0.0140	0.0116	0.0046	0.0186	0.0145	0.0110	0.0075	0.0072
α	0.0173	0.0145	0.0107	0.0034	0.0163	0.0133	0.0102	0.0029	0.0167	0.0135	0.0096	0.0056	0
σ_p	0.0694	0.0669	0.0647	0.0626	0.0547	0.0557	0.0550	0.0536	0.0568	0.0590	0.0587	0.0573	0.0492
SR	0.1880	0.1932	0.1535	0.0524	0.2461	0.2180	0.1770	0.0512	0.2947	0.2136	0.1563	0.0978	0.1081
MDD	-0.6214	-0.4639	-0.3969	-0.4556	-0.2785	-0.2367	-0.2224	-0.2117	-0.2319	-0.1789	-0.1470	-0.1856	-0.6779
Skewness	-1.1439	-0.7386	-0.6649	-0.2361	-0.7078	-0.3794	-0.2843	-0.1692	-0.0457	-0.1231	0.2334	-0.0966	-0.5327
Kurtosis	9.0138	5.6849	4.0392	3.2666	6.0397	4.9137	4.4894	2.7230	3.5146	4.1403	4.1302	3.1766	6.5229
t-stat	4.4446	7.2001	7.9166	4.7997	5.4419	7.6993	8.8139	-4.9811	6.2804	8.0621	8.7819	7.3601	3.0223

Finland

J = 12	**Price momentum**				**Idiosyncratic Momentum**				**Alpha Momentum**				**Benchmark**
K	1	3	6	12	1	3	6	12	1	3	6	12	
μ_p	0.0132	0.0124	0.0091	0.0032	0.0100	0.0116	0.0087	0.0039	0.0087	0.0096	0.0065	0.0024	0.0078
α	0.0149	0.0113	0.0078	0.0017	0.0106	0.0101	0.0072	0.0022	0.0068	0.0082	0.0050	6.5e-04	0
σ_p	0.0743	0.0722	0.0722	0.0711	0.0632	0.0596	0.0578	0.0561	0.0601	0.0608	0.0600	0.0576	0.0576
SR	0.1521	0.1458	0.1007	0.0190	0.1285	0.1626	0.1184	0.0362	0.1141	0.1277	0.0778	0.0093	0.1023
MDD	-0.5158	-0.4532	-0.4877	-0.5598	-0.4156	-0.2821	-0.3084	-0.3466	-0.4112	-0.3446	-0.3167	-0.3022	-0.5841
Skewness	-0.4325	-0.1529	-0.2950	-0.8920	0.4438	-0.2092	-0.3546	-0.3519	-0.0647	-0.2716	-0.3155	-0.3301	-0.2400
Kurtosis	4.9139	3.5542	4.2728	4.8328	7.7790	4.5332	3.6768	3.0833	3.8868	4.6456	2.9902	3.3328	4.1675
t-stat	3.7981	5.3559	5.1393	2.4598	3.3395	6.4178	6.6484	3.8307	3.0931	5.0969	5.0263	2.4573	2.8926