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Combining idiosyncratic volatility and momentum

Evidence from the Nordic stock markets

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ABSTRACT:
Financial markets are full of anomalies where abnormal excess returns are documented using specific investment strategies over time. Many of these anomalies challenge the efficient market hypothesis, which states that past information and historical returns cannot be used to generate excess returns in the future. Moreover, some anomalies are more robust than others, and there is evidence that not all proposed anomalies can be replicated using slightly different methods and data. One of the well-known anomalies in the financial markets is the momentum strategy that takes a long position on stocks with the highest past returns and a short position on stocks with the lowest past returns. The momentum effect has been found to generate high absolute and risk-adjusted returns globally and across different asset classes. However, the strategy has a downside, often referred to as the momentum crash, which can negatively affect the strategy's profitability. Another effect related to past information is a low-volatility effect, where excess returns can be produced by taking an advance on the stocks with low historical volatility. Stocks with past low volatility are documented to generate abnormal excess risk-adjusted returns. Finally, earlier literature has proposed profitable investment strategies by combining anomalies. For instance, the combination of momentum and value has been studied extensively, and there is also positive evidence for the profitability of low volatility and momentum combinations.

Motivated by the earlier literature findings of combination strategies, this thesis investigates the combination investment strategy of low volatility and momentum using individual stock data from the Nordic stock markets from January 1999 until September 2022. First, the occurrence of both effects is studied individually, and second, the best way to combine the two strategies is examined. The combination methods include 50/50, double screening, and ranking strategies. This thesis contributes to the earlier literature by investigating the best ways to combine these two strategies and proposing multiple simple investment strategies using these effects.

The results show that first, by studying the pure strategies, it can be concluded that momentum effect is found in the Nordic stock market but the evidence for the low-volatility effect is not robust enough over the sample period. Considering the combinations among the long-only portfolios, the momentum-first double-screening method generated the best Sharpe ratio, slightly outperforming the ranking method. Moreover, all long-only combination portfolios outperformed the market by risk-adjusted returns, which indicates robust performance. Also, the combination of low volatility and momentum significantly increased risk-adjusted returns compared to pure-play strategies. However, the long-short portfolio formation is not that efficient. None of the combination long-short strategies outperform the simple pure WML momentum strategy, even measured by risk-adjusted returns. Robustness for the results is added by using blocks bootstrap t-statistics, and the data sample is divided into two sub-samples.

KEYWORDS: efficient markets, volatility effect, momentum, stock markets

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TIIVISTELMÄ:
Rahoitusmarkkinat ovat täynnä anomalioita, joita hyödyntämällä on saavutettu ylituottoja pitkällä aikavälillä. Monet näistä anomalioista haastavat tehokkaiden markkinoiden hypoteesin, jonka mukaan muun muassa tuottohistoriaa ei voi hyödyntää ylituottoihin tulevaisuudessa. Toiset anomaliat ovat vankempia kuin toiset, ja onkin näyttöä siitä, että kaikkia anomalioita ei voida todentaa toistamalla tutkimus käyttäen erilaisia menetelmiä tai dataa. Yksi tunnetuimmista anomalioista rahoitusmarkkinoilla on momentum-ilmiö, jossa sijoittaja ostaa osakkeita, jotka ovat tuottaneet parhaiten lähihistoriassa ja myy lyhyeksi osakkeita, jotka ovat tuottaneet heikoiten. Momentum-ilmiön on havaittu tuottavan korkeita absoluuttisia ja riskikorjattuja tuottoja maailmanlaajuisesti eri omaisuusluokissa. Strategialla on kuitenkin varjopuoli, jota usein kutsutaan momentum-romahdukseksi, ja se voi vaikuttaa negatiivisesti strategian kannattavuuteen. Toinen tuottohistoriaan liittyvä strategia on matalan volatiliteetin strategia, jossa ylituottoja voidaan saavuttaa ostamalla osakkeita, joilla on alhainen historiallinen volatiliteetti. Osakkeiden, joilla on alhainen historiallinen volatiliteetti, on todettu tuottavan poikkeuksellisia riskikorjattuja ylituottoja. Lisäksi aiempi kirjallisuus on tarjonnut kannattavia sijoitusstrategioita eri ilmiöitä yhdistämällä. Esimerkiksi momentum ja arvo -yhdistelmää on tutkittu laajasti, ja myös alhaisen volatiliteetin ja momentum -yhdistelmän kannattavuudesta on positiivista näyttöä.

Motivoituneena aikaisemman kirjallisuuden löydöksistä koskien yhdistelmästrategioista tämä tutkielma tarkastelee alhaisen volatiliteetin ja momentumin yhdistelmästrategiaa käyttäen yksittäisiä osakkeita pohjoismaisilta osakemarkkinoilta tammikuusta 1999 syyskuuhun 2022. Ensiksi tutkitaan kummankin ilmiön olemassaoloa, ja sen jälkeen kartoitetaan parhaat menetelmät yhdistää kyseiset kaksi strategiaa. Yhdistelmämenetelmiin kuuluvat 50/50-, kaksoisseulonta- ja ranking -menetelmät. Tämä tutkielma tuo uutta tietoa aikaisempaan aihetta koskevaan kirjallisuuteen tutkimalla parhaita menetelmiä yhdistää nämä kaksi strategiaa ja tarjoamalla yksinkertaisia sijoitusstrategioita näiden ilmiöiden hyödyntämiseksi rahoitusmarkkinoiden osapuolille.

Tutkielman tulokset osoittavat, että momentum-ilmiö esiintyy pohjoismaiden osakemarkkinoilla, mutta löydökset volatiliteetti-ilmiölle eivät ole tarpeeksi riittävät. Ainoastaan ostopositioita sisältävien yhdistelmästrategioiden suhteen momentum-ensin-kaksoisseulontamenetelmä tuottaa parhaan Sharpen luvun suoriutuen hieman paremmin kuin ranking-menetelmä. Kaikki ainoastaan ostopositioita sisältävät yhdistelmästrategiat voittavat markkinaindeksin riskikorjattujen tuottojen perusteella, mikä osoittaa niiden vahvaa suorituskykyä. Lisäksi alhaisen volatiliteetin ja momentumin yhdistelmä lisää merkittävästi riskikorjattuja tuottoja verrattuna strategioihin, jotka eivät sisällä ilmiöiden yhdistelyä. Yksikään sekä osto- että lyhyeksimyyntiposition sisältävistä yhdistelmästrategioista ei kuitenkaan ylitä yksinkertaisen momentum-strategian riskikorjattua tuottoa. Tulosten luotettavuutta lisätään laskemalla t-arvot lohkoihin perustuvaa bootstrap -menetelmää käyttäen sekä jakamalla aineiston ajanjakso kahteen osaan.

AVAINSANAT: markkinoiden tehokkuus, volatiliteetti-ilmiö, momentum, osakemarkkinat

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1 Introduction

Participants in the stock investment world can be roughly divided into active and passive investors, although it is not black and white. Active investors seek excess returns for their portfolios and usually try somehow to beat the market index or some other comparing index. Active investors modify and adjust their portfolios daily, weekly or monthly. Passive investors rarely change their position if adding more capital does not count, and the investment is mostly some index. Beating the market could be achieved with higher absolute returns, higher returns with the same risk, the same returns with lower risk, or higher returns with even risk. Risk is often measured by the level of price fluctuation, which is called volatility. A highly volatile stock's price fluctuates more and is more sensitive to firm-specific and macroeconomic news, whereas low volatile stock prices are more stable.

Fama (1970) presents the Efficient Market Hypothesis (EFH). According to the hypothesis, no excess returns could be generated by using past information about the stocks as all that information should be priced correctly in the stock price. However, since 1970, many different anomalies in financial markets have been established, others more robust than others. On the other hand, different Factor models have been proposed to capture the excess returns of stock market anomalies. One of the first factor models proposed to capture the excess returns of a stock or portfolio is the Capital Asset pricing model (CAPM). Later more advanced and complex asset pricing models were founded that include, for instance, Fama and French (1993) three-factor model, Carhart (1996) four-factor model, and Fama and French five (2015) and six (2018) factor models.

This thesis touches on all of the issues mentioned as it dives into the stock market environment and investigates whether active investment strategies could be formed that outperform passive investors and challenges the efficient market hypothesis. To implement the strategy, two well-known anomalies, (low) idiosyncratic volatility and momentum, are used to examine if they can produce excess returns alone and combined.

Absolute and risk-adjusted terms measure the performance of different strategies. Finally, portfolio returns are regressed to the asset pricing models to see how well they perform.

1.1 Motivation

The well-known momentum anomaly is heavily studied in earlier literature, and momentum strategies have generated excess returns. However, momentum has a crash risk that can affect returns harmfully (Daniel & Moskowitz, 2016). The momentum effect has also been combined with other effects, for instance, value, resulting in positive returns (Asness, Moskowitz, and Pedersen, 2013; Fisher, Shah, and Titman, 2016). Moreover, the momentum strategy can be enhanced, and momentum crashes can be avoided with risk management based on past volatility (Barroso & Santa-Clara, 2015).

Evidence of the low idiosyncratic volatility effect is found across developed and emerging stock markets (Ang, Hodrick, Xing and Zhang, 2006; Blitz & van Vliet, 2007; Blitz, Pang, and van Vliet, 2013). Blitz (2016) concludes that low-volatility effect is an independent effect. However, it is also proposed that low volatility can be controlled with some other factors (Novy-Marx, 2014; Fama & French, 2015). Motivation arises to investigate more the low-volatility effect. There is also evidence of combined strategies, as Blitz and van Vliet (2018) propose a conservative formula where low historical stock return volatility is combined with price momentum and net payout yield. The strategy generates excess returns and thus provides evidence for possible excess returns of the combination.

According to the efficient market hypothesis and capital asset pricing model, neither of the strategies should provide excess returns as all past information is priced on stocks, and lower risk (volatility) results in lower returns. However, as mentioned earlier, both strategies and the combination strategy (conservative formula) have generated excess returns. Motivation arises to investigate if an investment strategy where momentum is combined with a low-volatility generates excess returns and outperforms pure low-volatility or momentum strategies. Questions arise whether a portfolio consisting of low-volatility and momentum stocks can provide similar or better results than risk-managed momentum strategies that use past volatility in a different way. Moreover, an additional aspect of the study is that during the long periods of zero interest rates, it could be proposed that a low-risk stock investment strategy could play the role of bond investments in addition to the riskier stock investments. The suitability of the low volatility strategy for this is interesting.

1.2 Purpose of the study

The thesis aims to investigate whether low-volatility and momentum anomalies exist in the Nordic stock markets. The low-volatility effect or strategy in this thesis refers to the idiosyncratic (company specific) volatility studied by Ang et. al. (2006) and Blitz and van Vliet (2007) among others. Moreover, this study examines if abnormal risk-adjusted returns can be generated by combining low volatility and momentum strategies. Different kinds of combinations are investigated to find out which is the best way to combine these strategies. Finally, this thesis compares the combination strategies to pure low-volatility and momentum strategies and examines whether the combination strategy generates similar results as value momentum. This thesis contributes to previous literature by studying volatility and momentum together in the Nordic stock market environment.

1.3 Hypotheses development

The hypotheses of this study are related to market efficiency. First, this study investigates whether the volatility effect and the momentum effect exist in the Nordic stock market environment. The first part of the thesis includes the following hypotheses:

$H1_1$: Past stock return volatility will affect future stock returns.

$H2_1$: Past stock return will affect future stock return.

It is assumed that hypotheses H1 and H2 are accepted as there are evidence in the earlier literature to support both hypotheses. Second, the combination of these two strategies is studied more in-depth by creating combined long-short and long-only portfolios. The aim is to find the best method to combine the two strategies. The second part of the thesis includes the following hypotheses:

$H3_1$: Portfolio that is allocated 50/50 between low volatility strategy and momentum strategy generates higher risk-adjusted returns than pure play strategies and the market.

$H4_1$: Portfolio combining low volatility and momentum generates higher risk-adjusted returns than the pure-play strategies and the market.

It is assumed that at least one of the hypotheses H4 and H5 is accepted.

1.4 Structure of the study

The thesis includes a theoretical part as well as an empirical part. The structure of the study is as follows. After the introduction chapter, the second chapter presents the theoretical background of the topic. The theoretical framework starts with a discussion of the efficient market hypothesis (EMH). The second subchapter presents standard stock pricing models. The focus is on the capital asset pricing model and other factor models as they are used in the thesis. The third subchapter presents different portfolio performance measures.

Chapter three includes the literature review, presenting and discussing relevant earlier literature. First, the volatility effect and studies related to low volatility are discussed. Second, the momentum anomaly is demonstrated by presenting different momentum strategies, returns of the strategies, and drawbacks of the momentum strategy, momentum crash. Finally, combinations of anomalies are discussed.

The empirical part first includes a chapter about data and methodology. Chapter four presents the data and methodology used in this study. The chapter discusses the methods for testing the hypotheses and answering the research question. Also, assumptions and other possible issues related to the empirical study are discussed. Chapter five presents the results of the empirical part of the thesis. Results are divided into subchapters by different strategies. Finally, chapter six concludes the thesis and presents ideas for future research.

2 Theoretical background

This chapter presents the theoretical framework of this study. The chapter discusses theoretical issues and models related to this thesis. The first subchapter focuses on efficient markets as the efficient market hypothesis is presented, and the overall market efficiency is discussed. Volatility and momentum effects are in contrast with the Efficient market hypothesis, as the excess returns of both anomalies are based on historical information only. The second subchapter presents standard stock pricing models that are widely used in previous literature and this thesis. The third subchapter includes a presentation and discussion about a standard portfolio performance measure, Sharpe ratio.

2.1 Efficient market hypothesis

According to the efficient market hypothesis by Eugene Fama (1970), stock prices include all information, and new information is priced immediately. No information asymmetry could be used to make profits. The core of the efficient market hypothesis is that investors cannot generate excess returns compared to market returns by taking advantage of historical, public, or private information. All the information is priced in stocks and cannot be exploited.

When the market is efficient, no abnormal returns can be generated. Abnormal returns can be measured by subtracting the expected return of the stock or portfolio from the realized return of the stock or portfolio. Formulas to express abnormal returns are below.

$$E(z_{i,t+1}) = 0 \tag{1}$$

$$z_{i,t+1} = r_{i,t+1} - E(r_{i,t+1}) \tag{2}$$

where $E(z_{i,t+1})$ is the expected abnormal return for stock i at time t + 1. $E(z_{i,t+1})$ can be calculated as a difference of realized return $r_{i,t+1}$ and expected return of stock $E(r_{i,t+1})$ (Fama, 1970).

Fama (1970) divides market efficiency into three levels: weak form, semi-strong form, and strong form. Forms of efficiency are modeled in figure 1 below.

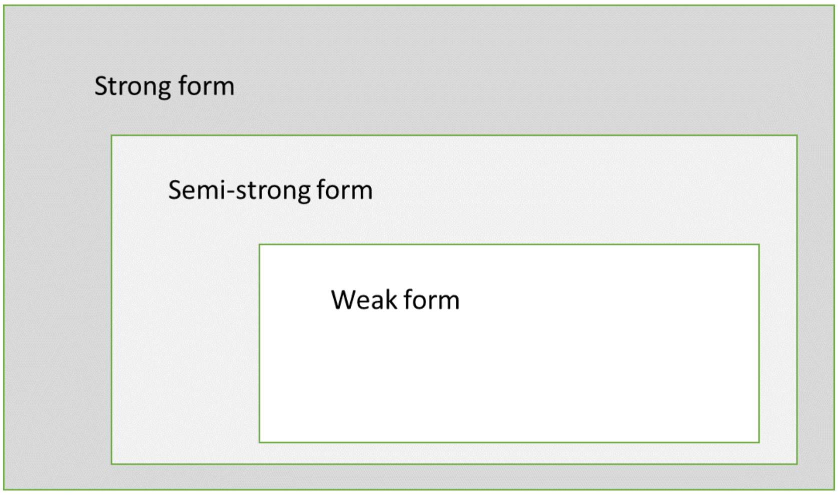


Figure 1. Forms of market efficiency

In weak form, according to Fama (1970), all past information is priced in the stock. In addition, returns are not autocorrelated. Thus, technical analysis and other methods using past stock return data should not provide any consistent abnormal returns. Past trends, volumes, or volatilities of stock returns are thus irrelevant to future prices.

In semi-strong form, all essential information about the company and its business is available to investors and priced. In other words, all public information is priced in stocks. Public information could include financial reports and other announcements about relevant information to stock prices. In addition to technical analysis, fundamental analysis cannot be used to generate abnormal returns. Furthermore, when new public information affecting the company's value arises, a semi-strong form suggests that it is priced in stock immediately. Only private information is the possibility to produce abnormal returns.

Fama (1970) argues that in strong form, all possible information, including inside information, is priced and available. The strong form is a helpful benchmark for efficient capital markets, and it means investors can generate no abnormal returns as the stock prices include all possible information. Thus, no matter what kind of new information arises, no investors can earn higher returns than market returns. However, Fama (1991) states that the strong form of the efficient market hypothesis may only sometimes hold in practice.

When considering momentum and low volatility strategy from an efficient market perspective, no excess returns should be possible to generate. Even in the case of weak-form efficiency, all past information is priced in the stocks. As both strategies, low volatility and momentum, are based on past stock information, profiting with these strategies should not be possible.

2.2 Stock pricing models

Stock market participants try continuously to find excess returns and mispriced assets. When possible excess returns or abnormal returns are investigated, stock pricing models come into consideration. Next, a few asset valuation methods that can be used, for example, to find excess returns, are presented.

2.2.1 Capital Asset Pricing Model

The capital asset pricing model (CAPM), developed by William Sharpe (1964) and John Lintner (1965), is the cornerstone and first asset pricing model dated back to the 1960s. CAPM includes three components to calculate excess returns: risk-free rate, stock beta, and market excess return. With CAPM, one can regress the portfolio's returns to market returns. Using the standard OLS model, it can be calculated whether the portfolio generates significant alpha when the market factor is controlled. The formula of the Capital asset pricing model is below.

$$E(r_i) = \beta_i[E(r_m) - r_f] \tag{3}$$

where $E(r_i)$ is expected excess return of portfolio i, r_f is the risk-free rate, $E(r_m)$ is expected return of the market portfolio, and β_1 is the beta of the portfolio i.

2.2.2 Fama and French three-factor model

Fama and French (1993) propose a three-factor model to extend the CAPM. The model adds the size factor and value factor to the CAPM. The size factor, small minus big (SMB), captures size premium as the small stocks are expected to have higher returns and risk. Value factor, high minus low (HML), tries to capture value stock risk. Value stocks (high book-to-market ratio) are expected to carry more risk. Together, small-value stocks should generate higher returns and risk than the market. (Fama & French, 1992, 1996). The formula of the three-factor model is below.

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML \tag{4}$$

where $E(r_i) - r_f$ is the expected excess return of portfolio i, MKT is the excess return of the market portfolio, SMB is the excess return of the size factor, HML is the excess return of the value factor, β_1 is the factor loading market factor, β_2 is the factor loading on size factor, and β_3 is the factor loading on value factor.

2.2.3 Carhart four-factor model

Carhart (1997) suggests that a four-factor model captures risk premiums better than earlier models. The model adds momentum factor to the earlier three factors, market, size, and value. The momentum factor, winners-minus-losers (WML), measures the return difference of high momentum stocks and low-momentum stocks, and momentum anomaly should thus be captured. The formula of the four-factor model is below.

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 UMD \tag{5}$$

where all other variables are same as in the three-factor model and UMD is the excess return of the momentum factor and β_4 is the factor loading on momentum factor.

2.2.4 Fama and French five-factor model

Fama and French (2015) develop their earlier three-factor model by adding two more factors, profitability, and investment. The profitability factor, robust minus weak (RMW), measures the difference in returns between highly profitable and low profitable firms. The conservative minus aggressive (CMA) investment factor measures the difference between low and high-investment firms. The formula of the five-factor model is below.

$$E(r_i) - r_f = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA \tag{6}$$

where RMW is the excess return of the profitability factor, CMA is the excess return of the investment factor $\beta_4$is the factor loading on profitability factor, β_5 is the factor loading on investment factor and all other variables are the same as in three-factor model.

2.2.5 Fama and French six-factor model

Furthermore, Fama and French (2018) also consider the sixth factor, momentum, in the model as they compare nested models. Momentum factor, winners minus losers (WML), captures momentum anomaly. Formula of the six-factor model is below.

$$\begin{aligned} E(r_i) - r_f = {} & \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA \\ & + \beta_6 UMD \end{aligned} \tag{7}$$

where UMD is the excess return of the momentum factor and β_6 is the factor loading on momentum factor and all other variables are the same as in the five-factor model.

In this chapter, standard stock portfolio performance measures are presented and discussed. Measures include the Sharpe ratio, Treynor ratio, and Jensen’s alpha.

2.3 Portfolio performance

William Sharpe (1966) presents the Sharpe ratio that measures portfolios' performance by evaluating the excess return to risk. The portfolio's excess return is calculated by subtracting a risk-free rate from the portfolio's return. The higher the portfolio excess return and the lower the standard deviation of the excess return, the higher the Sharpe ratio. Sharpe ratio is used, for example, to compare investment managers' performance. Sharpe ratio is highly used in the finance literature. However, Sharpe (1994) considers the Sharpe ratio has some disadvantages. The ratio only considers the excess return and does not consider the correlations between other securities in the portfolio. The formula of the Sharpe ratio is below.

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p} \tag{8}$$

Where r_p is the return of portfolio, r_f is the risk-free return and σ_p is the standard deviation of the excess return (Sharpe, 1966). Other portfolio performance measures have also been developed, but this thesis focuses on measuring the performance of portfolios only by Sharpe ratio.

3 Literature review

According to the efficient market hypothesis, no excess returns should be possible to generate using past information and other available stock data. Literature considering using past information on stock returns is reviewed. Results from previous literature related to idiosyncratic volatility effect, momentum, and anomaly combinations are discussed. Earlier literature regarding the volatility effect is presented in the first sub-chapter. Momentum anomaly, including the presentation of returns, strategies, and crashes, is discussed in the second sub-chapter. Finally, the third sub-chapter presents the combinations of relevant anomalies and their performance in the earlier literature.

3.1 Idiosyncratic volatility

Considering Capital Asset Pricing Model, a firm's risk can be divided into systematic risk or market risk and unsystematic risk or firm-specific risk (Lintner, 1965; Sharpe, 1963; Sharpe, 1964). In CAPM, beta is a measure of systematic risk. Firm-specific risk, which can also be referred to as idiosyncratic risk, and stock returns are studied by Ang et. al. (2006) and Blitz and van Vliet (2007). This thesis studies idiosyncratic volatility and uses historical stock return volatility as a measure to sort the stocks of the sample. However, it is also relevant to go through other kinds of volatility measures that are used in earlier literature.

Evidence for the low-volatility effect or low-volatility anomaly has been found already in the 1970s. Several studies such as (Black, Jensen, and Scholes, 1972; Fama & MacBeth, 1973; Haugen & Heins, 1975) conclude that the actual relationship between stock beta and return is not as steep as Capital Asset Pricing Model (CAPM) predicts. Meaning stocks that have lower volatility have higher returns than the model predicts and vice versa. Moreover, Fama and French (1992) find that the beta in CAPM is not priced when the size factor is controlled.

Ang et. al. (2006) examine idiosyncratic volatility using a sorting of test assets based on short-term historical volatility, and find that stocks with higher volatility generate lower average returns. Ang et. al. (2006) also conclude that value, size and momentum, among other effects cannot explain the low returns of the stocks with high idiosyncratic volatility.

Blitz and van Vliet (2007) study the (idiosyncratic) volatility effect focusing on long-term past volatility (over three years) in a global stock market setting. They find that stocks with past low volatility generate excess returns measured by the Sharpe ratio and CAPM alpha. They conclude that the effect is similar to other anomalies, for instance, size, value, and momentum. Low volatility strategy has lower maximum drawdowns and exemplary performance in bear markets, but on the other hand, the strategy underperforms in bull market conditions. Blitz and van Vliet (2007) suggest that investors that benefit from this strategy are, for example, pension funds, as they could replace part of bond investments with low-volatility stocks. They find that the low-volatility effect is significant in the US, European, and Japanese markets in the 1986-2006 period.

Blitz, Pang, and van Vliet (2013) investigate the relationship between risk and return in emerging markets. They find opposite results considering financial theories such as CAPM, where the relationship between risk and return should be positive. Blitz et al. (2013) find that portfolios sorted based on past volatility form a flat or even negative relationship between risk and return. Thus, the evidence is consistent with earlier findings from Blitz and van Vliet (2007) from the US, European, and Japanese markets and confirms the low-volatility effect in emerging markets. The effect is robust among large-cap stocks and holds when controlling the size, value, and momentum factors. Furthermore, according to the authors, the low-volatility effect has developed more robust over time. However, Blitz et al. (2013) conclude that the low-volatility effect is not correlated between the emerging and developed markets, which indicates that low-volatility is not a common factor.

Baker, Bradley, and Wurgler (2011) argue that the reasons behind the high returns of low volatility strategy are behavioral and related to limits to arbitrage. They conclude that the capital market line flattens as irrational investors demand higher volatility and fund managers have fixed benchmarks and no leverage. That means higher volatility stocks have lower returns.

Van Vliet (2018) examines the amount of trading needed to create a low-volatility portfolio. Van Vliet (2018) finds there is no need for high-volume trading to create an efficient low volatility strategy. The paper concludes that 30 percent is a sufficient turnover for low volatility portfolios. Moreover, the low volatility strategy includes stocks that are larger than average, thus making the trading cheaper (low trading costs, 11 basis points) and stocks more liquid. With a low 30 percent turnover and low trading costs at 11 bps, the number of costs per year is seven basis points making the low volatility strategy cheap overall. Van Vliet (2018) points out that one reason to justify a higher turnover in a low-volatility portfolio could be to generate higher excess returns by adding other factors, such as value or momentum. Van Vliet (2018) concludes that the combination of low volatility and value or low volatility and momentum is a cost-effective way to improve the alpha.

Considering low volatility and other anomalies, Chow, Hsu, Kalesnik, and Little (2011) find that value anomaly explains the alpha of the low-volatility or minimum variance strategy when the Fama-French 3-factor model is tested. In other words, the alpha is not significant after the high-minus-low (HML) factor is controlled. On the other hand, Blitz and van Vliet (2007) and Blitz et al. (2013) find that that the value factor cannot explain the low volatility alpha. Low volatility is related to the value effect and the low beta effect. However, both the studies mentioned above, Blitz and van Vliet (2007) and Blitz et al. (2013), find that the alpha of low volatility is not explained by the value factor when it is controlled.

Blitz (2016) also studies this relation of the value factor explaining low volatility excess returns and finds that the value factor only explains the alpha of the low volatility strategy during the specific sub-period 1963-1984 and only among large-cap stocks. Furthermore, Blitz (2016) summarizes that after using Fama-MacBeth regressions, the low-volatility alpha is significant even during the sub-period mentioned above, when the value factor was found to explain the excess returns. Finally, Blitz (2016) argues that the reasons behind the value and the low-volatility effects are different and concludes that low volatility is an independent effect. There is as much evidence for low volatility as for the value effect.

Other views against the low-volatility effect come from Novy-Marx (2014). He confirms that defensive stocks have outperformed aggressive stocks and defensive strategies based on low volatility have generated excess returns when Fama and French three-factor model is controlled. However, Novy-Marx (2014) argues that these excess returns are not generated from the low-volatility effect after controlling size, relative valuations, and profitability. Novy-Marx (2014) concludes that high profitability and large market capitalization are the main factors to drive low volatility. In addition, defensive portfolios tend to have high profitability characteristics.

3.2 Momentum

Momentum is an investment strategy established in 1993 by Jegadeesh and Titman. Jegadeesh and Titman (1993) find that buying stocks that have performed well in the recent past and selling stocks that have performed poorly in the recent past creates positive returns. These findings are contrary to the efficient market hypothesis, concluding that all past information is priced in stocks (Fama, 1970).

There are multiple types of momentum strategies, but they all have the same idea of taking advantage of recent winners and losers. One type of strategy is the momentum strategy studied by Jegadeesh and Titman (1993), which includes buying stocks that have the highest past returns and short-selling stocks that have the lowest past returns .

Another strategy built on momentum anomaly is the 52-week high momentum strategy, introduced by George and Hwang (2004). They use the 52-week high prices of each stock and rank the stocks based on their current prices. They buy stocks that are closest to their 52-week highs and sell stocks that are far from their 52-week highs. The third example of momentum strategy is the industry momentum strategy presented by Moskowitz and Grinblatt (1999). In the industry momentum strategy, an investor buys stocks from the industry that has performed well and sells stocks from the industry that has performed poorly. Moskowitz and Grinblatt (1999) find that the industry momentum strategy is highly profitable.

Jannen and Pham (2009) compare the previous three momentum strategies using the same data on each strategy. They find that the industry momentum strategy is the most profitable of these strategies, and the 52-week high strategy is the worst of the three but still provides small positive monthly returns.

Novy-Marx (2012) studies the standard momentum strategy more in-depth. He finds that the momentum strategy of buying stocks that have performed well in the last twelve to seven months creates better returns than the strategy where more recent past winners are bought. Moreover, Novy-Marx (2012) finds that these positive returns are strong among large companies.

Momentum has been a topic of many scientific papers, so there is broad evidence of momentum strategies from different countries and asset classes. Rouwenhorst (1998) studies momentum using international data of 2190 stocks from 12 European countries. He finds that an internationally diversified portfolio, including recently well-performed stocks, beat poorly performed stocks by 1% per month. Moreover, Rouwenhorst (1998) finds that momentum returns are higher among small companies, and momentum strategy works similarly in Europe compared to the United States.

Moskowitz and Grinblatt (1999) study industry momentum. They find that buying stocks from winning industries and selling stocks from loser industries generates positive monthly returns. Okunev and White (2003) find positive evidence from currency markets. They conclude that the momentum strategy provides positive returns in currencies. Erb and Harvey (2006) study commodity futures and find that momentum strategies applied to commodity investing can produce positive returns.

Asness, Moskowitz, and Pedersen (2013) study momentum strategy globally across asset classes. Their paper completes the earlier mentioned results as they find that momentum returns are strongly correlated between asset classes. Their study concludes that the momentum strategy provides positive returns among different asset classes and countries. All in all, there is evidence that the momentum strategy, which was first found in the stock market, can also be used to produce positive returns elsewhere.

When studying investment strategies and their profitability, there is a motive to investigate the size of the possible positive returns. Jegadeesh and Titman (1993) conclude that the momentum strategy produces a 12.01% annual return. They confirm similar positive results also in their paper from 2001. As mentioned earlier in this paper, Rouwenhorst (1998) finds positive returns of 1% per month. Moreover, Fuertes, Miffre, and Fernandez-Perez (2014) conclude that the momentum strategy returns 11.42% yearly.

Previous studies show that the momentum strategy has provided high positive excess returns. The average return of the S&P 500 stock index from 1957 to 2018 is approximately 8% per year (Maverick, 2020). The S&P 500 stock index contains 500 large stocks from the United States of America and is a relevant benchmark index. Momentum strategy porvides high excess returns when considering the overall stock market returns.

However, not all evidence praises momentum returns. Huang, Li, Wang, and Zhou (2020) investigate the standard time-series momentum returns across different asset classes. They find that the t-statistics of the returns are high but not over the critical values when applying more robust statistical test using bootstrapping. Huang et. al. (2020) conclude that time-series momentum is weak and fails to deliver statistically significant results across all asset classes, not being everywhere.

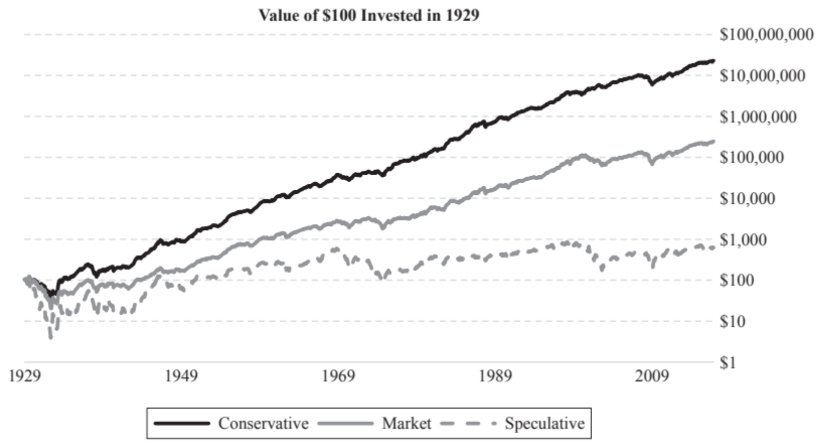
Even though the momentum strategy can produce abnormal positive returns, the strategy has a risky downside. Daniel and Moskowitz (2016) call it a momentum crash. They investigate the reasons behind the crashes and can these crashes be predictable. They find that these momentum crashes tend to occur after a bear market period. That is because after the bear market, stocks that have plunged the most tend to recover more, so the “loser” stocks perform better than “winner” stocks. The momentum strategy buys the winner stocks and sells the loser stocks, which results in significant negative returns. In these cases, the strategy should be another way around. Stocks that have plunged the most should be bought when the market recovers from a significant drop.

Barroso and Santa-Clara (2015) also study momentum crashes and find a risk-managed momentum strategy to avoid these crashes. Furthermore, their strategy increases the positive returns of the momentum strategy also. Grobys, Ruotsalainen, and Äijö (2018) present further evidence that risk-managed momentum, introduced by Barroso and Santa-Clara (2015), provides more stable positive returns.

3.3 Combining anomalies

The low-volatility effect has been combined with other effects in earlier literature. Combining strategies have generated excess returns. For instance, Blitz and van Vliet (2018) propose a quantitative formula called the conservative formula, where stocks are sorted by low volatility, price momentum, and net payout yield. Using 1000 liquid stocks, they select the top 100 stocks in their portfolio. Although the strategy is simple and easy to form, the returns of the conservative formula are significant. The strategy produced a 15.1% annual return from 1929 to 2016. Conservative formula generates consistent returns internationally in the United States across both large and mid-size stocks, Europe, Japan, and emerging markets. The figure below presents the cumulative returns of the conservative strategy by Blitz and van Vliet (2018), the market, and the opposite speculative strategy.

EXHIBIT 3
Development of Dollar Value over Time



Notes: This exhibit shows the dollar development over time for the conservative and speculative portfolios. The active portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. For comparison, we also show the U.S. stock market portfolio (CRSP value-weighted). The results are gross of implementation costs and before taxes.

Figure 2. The returns of the conservative formula investment strategy (Blitz and van Vliet, 2018).

Asness, Moskowitz, and Pedersen (2013) examine the value and momentum effects jointly globally and across asset classes. In their equity value investment strategy, stocks with a high book-to-market ratio are bought, and stocks with a low book-to-market ratio are sold. Asness et al. use past 12-month returns skipping the most recent month as their momentum measure. Among other asset classes, similar value and momentum measures are used. The most important result of the study is that the authors find evidence of excess returns of combining value and momentum strategy in all markets and different asset classes, such as stocks and government bonds. Asness et al. (2013) find that value and momentum are negatively correlated among the same and different asset classes. In addition, momentum and value strategy returns are positively correlated with other momentum and value strategy returns across different markets.

Fisher, Shah, and Titman (2016) find similar results when combining value and momentum, focusing on long-only portfolios. They first find that a pure long-only value strategy outperforms the market even after reducing transaction costs. However, the pure momentum strategy generates a high Sharpe ratio but underperforms the market occasionally when transaction costs are considered because of high turnover. Fisher et al. find that other more complex combinations of value and momentum outperform simple 50/50 combinations, and all combination strategies outperform pure value and momentum strategies.

Bird & Whitaker (2004) study value and momentum investing in the European markets in 1990-2002. They find positive evidence of the combination strategy overall in all markets and individually across most markets. The authors also raise the question of whether the value and momentum combination performance can be enhanced with more complex combination methods than their simple ranking method.

Grobys and Huhta-halkola (2019) complete value and momentum combination findings as they conclude that risk-adjusted returns are higher when combining the two strategies in the Nordic stock markets. They also find that momentum excess returns are robust even after controlling size, but the value effect decreases as the size factor is controlled in the Nordic markets. Grobys and Huhta-halkola (2019) conclude that all kinds of combination methods of value and momentum enhanced the risk-adjusted returns of pure strategies. The most excess returns are generated with a ranking-scheme combination portfolio.

Momentum has also been combined with low volatility in earlier literature. As discussed, Blitz and van Vliet (2018) find strong positive results with their conservative formula, including price momentum, low historical stock volatility, and positive NPY. They use 36-month past weekly volatility as a volatility measure and simple price momentum as a momentum measure. Moreover, Van Vliet (2018) concludes that adding value or momentum factor to the low volatility strategy is a cost-effective way to improve the alpha.

4 Data and methodology

In this chapter, the data and methodology of the thesis are presented. As the stock market data comes from the Nordic stock market, all data must be fitted to the Nordic environment and its features.

The Nordic stock market includes five countries: Finland, Sweden, Norway, Denmark, and Iceland. In the financial literature, Iceland is usually left out of the sample as the market is small. The Nordic stock market is relatively small in market capitalization and trading volume but has grown significantly over the last 30 years. Nowadays, the market is liquid and comprehensive from an industry perspective. Moreover, foreign investment capital has also grown over the years. However, like the geographical location of the Nordic countries, the Nordic stock market is also a bit remote from the main markets in Europe. This might result in more volatile markets, at least in the financial distress periods, as the foreign money might withdraw first from the Nordic markets compared to, for example, the US and central Europe’s larger markets.

Unlike countries in the emerging markets, the Nordic countries are developed welfare countries with far smaller risk profiles, which generates an interesting investment environment. The Nordic stock market is rarely included in financial research and has received less attention in earlier literature, which makes it a more interesting and important environment to study. Investigating a developed, growing, liquid, and less studied market environment such as the Nordic stock market this thesis contributes to earlier literature as the anomalies and stock market returns could be sample specific.

4.1 Data

As this study focuses on quantitative investment strategy using past stock price information, stock price data is the central data for this study. The stock market data for this study is gathered from Thomson Reuters Datastream. The time period of the stock market data for this study is from January 1999 to September 2022. However, the generated portfolio return period is from January 2002 to September 2022, as the volatility portfolio and combination portfolios need the prior 36 months data to be created. A total of 285 months is included in the portfolio formation time series, which results in 249 holding period months for the portfolios as the first holding period is January 2002. Stock market data for this thesis is gathered from the Finnish, Swedish, Danish, and Norwegian main stock markets. Similar to earlier studies on Nordic stock markets (Grobys & Huhta-Halkola, 2019), the Icelandic market is left out because of its small size.

Moreover, non-main lists such as First North are left out as the market capitalization of the firms is small. Financial companies are also left out of the sample. Finally, nano-size stocks with a maximum market value lower than 20 million in the 1999 – 2021 period are left out. The stock market data includes all stocks that have been active at some point in the time period. Delisted companies are left out of the data at the point of delisting. This helps to avoid survival bias, which would affect the portfolio returns if only stocks that have survived over the last 22 years were in the sample. Stock returns are measured as total shareholder returns. Total shareholder return takes account dividend payments avoiding biases to large dividend payments as the price of the stock should drop the same amount. This way, companies that pay large dividends are not avoided as easily when the returns of the stocks are compared for the momentum portfolios. Table 1 below presents the descriptive statistics for the Nordic stock market.

Table 1. Descriptive statistics for Nordic stocks.

	Min	**Max**	**Average**	**Total**
Finland	116	154	131	214
Sweden	267	417	345	757
Denmark	100	185	138	251
Norway	143	216	170	423
Combined	709	853	781	1645

Table 1 shows that, in total, there are 1645 stocks in the sample. Almost half of the stocks are from the Stockholm stock market, about a fourth of the stocks are from the Oslo stock market, and the final fourth is from Helsinki and Copenhagen, divided relatively equally. As stocks are constantly listed and delisted, the number of stocks varies over time. The minimum number of stocks in the monthly period is 709 stocks in total, and the maximum number is 853 stocks. On average, there are 781 active stocks in the sample.

As the Nordic firms are relatively small on average, this thesis primarily studies the investment strategies using the top third largest firms by market capitalization like earlier studies (Grobys & Huhta-Halkola, 2019). This makes the results more implacable for real life as the smallest Nordic stocks are not liquid and inconvenient to short-sell. A data set of the Nordic stocks market capitalizations is needed to select the largest firms in each period. The set includes the same stocks suitable for this study and their monthly market values from January 1999 to September 2022.

When investigating excess or risk-adjusted returns of the generated portfolio, market return and the risk-free rate must be considered as well as other risk factors. This study uses the average market return from the four above-mentioned Nordic countries' indexes. This way, the comparison is relevant, and the index demonstrates investing in the whole Nordic market as well as possible. To create the market index, a value-weighted average of the all-share indexes of each country is calculated. The weights of each country are roughly estimated using the starting and ending market values and taking the average. This method results in the following weights: Sweden 52.40%, Denmark 19.08%, Finland 14.42%, and Norway 14.10%. All returns in this thesis are reported as excess returns where the risk-free interest rate has been subtracted from the raw returns. The Nordic market index generated a monthly excess return of 0.69% over the sample period resulting in 8.56% per year. The market index has a monthly minimum return of -19.05% and a maximum of 21.96%. The annual volatility is 18.36%, resulting in a Sharpe ratio of 0.47. Figure 4 below presents the cumulative return graph of the Nordic stock market's value-weighted total excess return index.

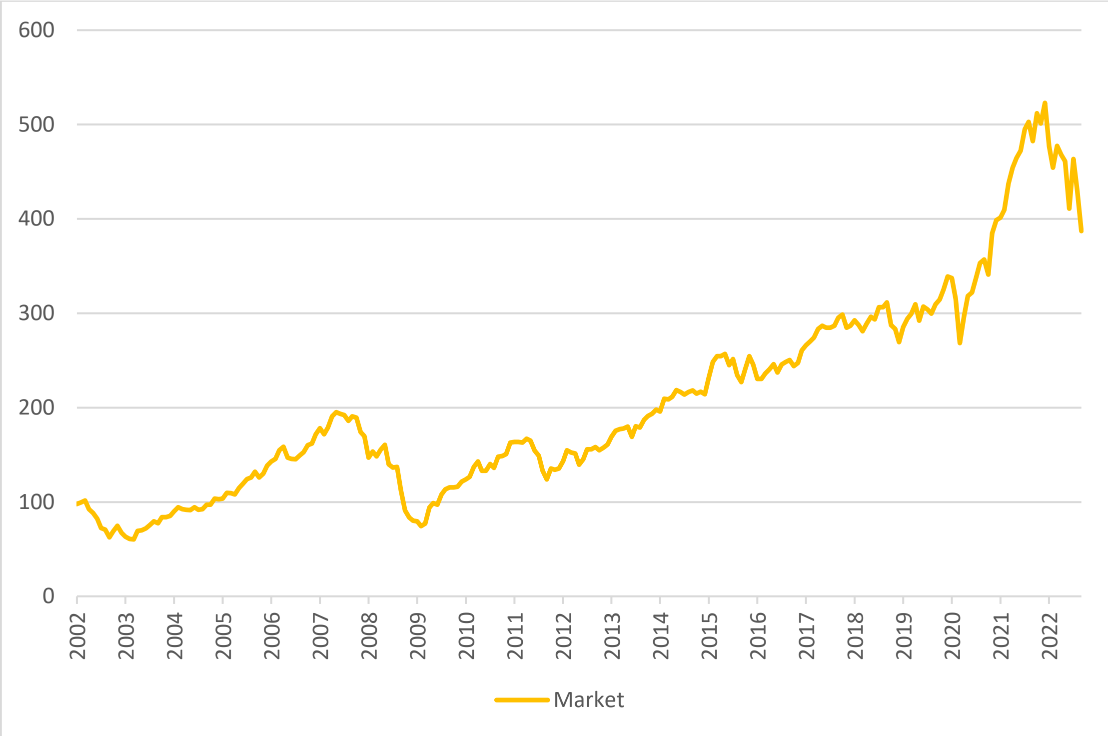


Figure 3. Cumulative excess returns of the value weighted Nordic total return index.

The risk-free rate will be gathered in the same manner as the market return from the four countries and is then the average six-month interest from Eurobor, Stibor, Nibor, and Cibor. Figure 5 below shows that the interest rates have fluctuated quite similarly over the sample period in the Nordic countries. However, there is quite a significant difference in the Norwegian risk-free rate compared to Finnish, Swedish, and Danish rates, as the Nibor six-month rate is significantly higher than other rates.

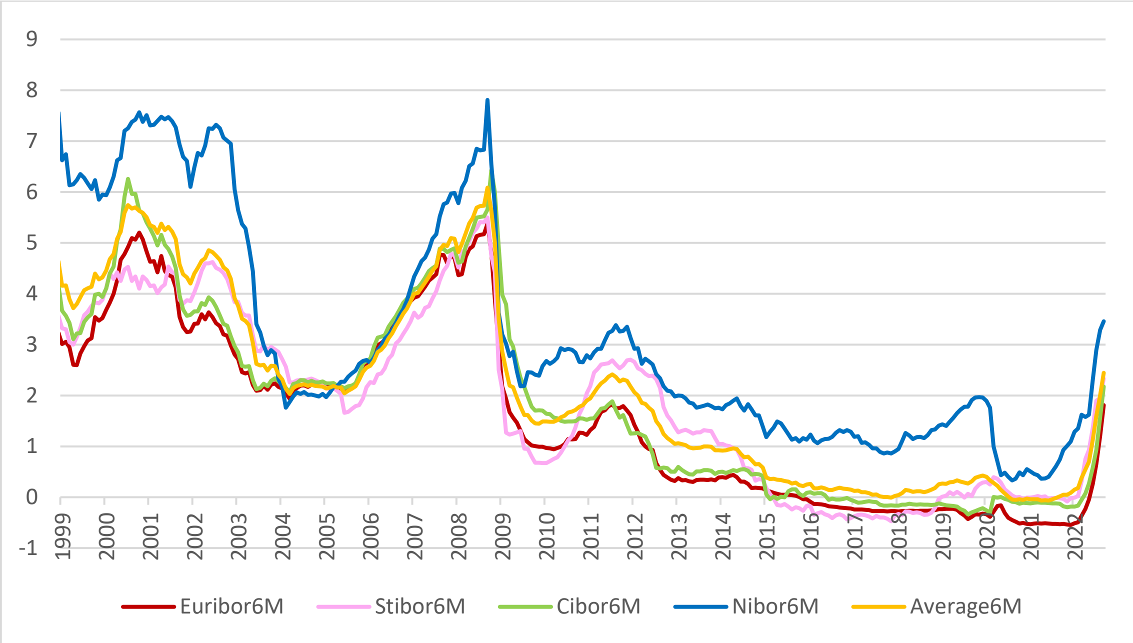


Figure 4. Nordic interest rates.

Furthermore, as all four Nordic countries have different currencies, exchange rates must be considered when examining the returns. The returns from Sweden, Norway, and Denmark will be converted to Euros at the current rate. Figure 6 below presents the exchange rates over the sample period. SEK/EUR rate and NOK/EUR rate fluctuate a bit over time, but there is not a significant change in the rates that would turn the returns around, but they affect at least somehow the EUR-measured returns. If the Euro gets stronger than SEK or NOK over a period, the returns in SEK/NOK are higher than in euros over the period and vice versa. The Danish crone is tied to Euro, so there are not any differences in the rate over time.

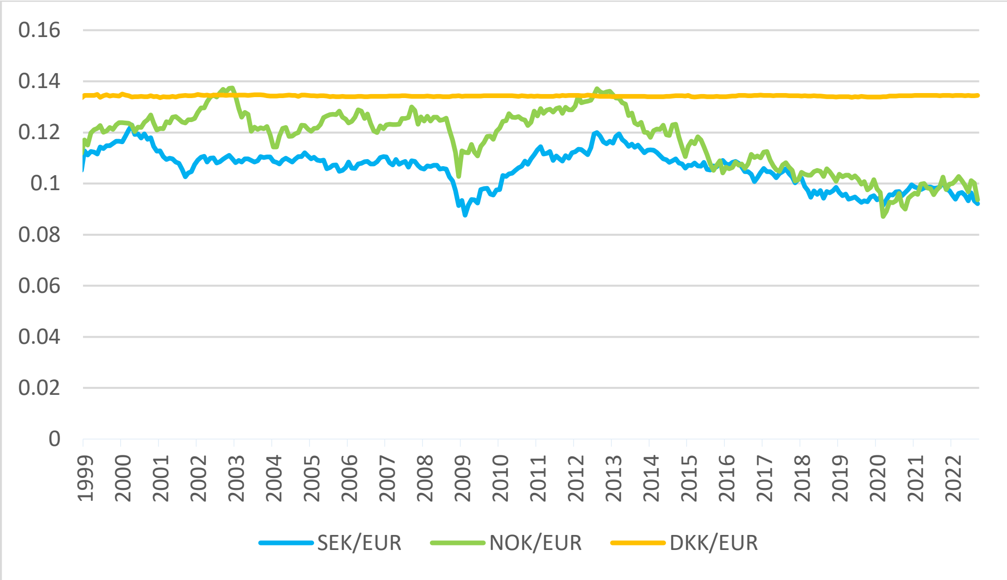


Figure 5. Nordic exchange rates.

After the absolute and risk-adjusted returns have been calculated, the exposures to the commonly used risk factors will be measured. This study uses the value-weighted Nordic total return index minus the risk-free rate as the market factor but and the rest factor data is gathered from the Kenneth and French's website. As there is no risk factor data for Nordic countries only, European risk factor data are used. This solution is convenient, although not the most accurate. However, all four Nordic countries are included in the European risk factor data. Other countries are Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Switzerland, and the United Kingdom.

4.2 Methodology

This study examines two different effects or strategies and their combinations. It is relevant to start by investigating the performance of pure-play strategies of momentum and low volatility. In this subchapter, first, the methodology of low volatility and momentum pure play strategies is presented, including the methods of how different portfolios are formatted. Second, a combination strategy methodology is presented, including a discussion of the combined portfolio formation. Third, portfolio performance measures and portfolio factor-controlling methods are presented.

4.2.1 Pure play strategy methodology

Past stock price data is used in both the volatility and momentum effect. Portfolios are equally weighted, similar to the earlier literature on Nordic Stock market research due to a low number of large-capitalization firms (Grobys & Huhta-Halkola, 2019; Leivo, 2012). During each point of time, non-active stocks are sorted out from the sample. Non-active stock is a stock that does not have returns every 36 prior months or the next month. Moreover, both pure strategies are formed using all active stocks and the top third of active stocks by market capitalization. All strategies are evaluated in a long-only and long-short manner. Long-only strategies will be used as there might be difficulties short-selling some of the smallest stocks and as the low-volatility effect is used in long-only portfolios in the earlier studies.

Momentum portfolios are created using the standard momentum strategy by sorting the stocks by the previous 12-month returns skipping the most recent month. The holding period is one month, so the portfolio is adjusted monthly. Winner stocks are the ones with the highest average returns in the above period, and loser stocks are the ones with the lowest returns in that period. Returns are measured in the winner portfolio, loser portfolio, and a long-short portfolio consisting of taking a long position on winner stocks and a short position on loser stocks.

Volatility portfolio creation uses past 36-month weekly stock return data similar to earlier studies of the low-volatility effect (Blitz & Van Vliet, 2018; Van Vliet ,2006). Standard deviation, a square root of the variance, is used as a measure of stock return volatility. Stocks with the lowest volatility during the past 36-month period are considered low-volatility stocks. In long-short portfolios, stocks with the highest 36-month volatility are considered high-volatility stocks. A long position is taken on stocks with the lowest volatility, and a short position is taken on stocks with the highest past volatility. The volatility portfolios are also adjusted monthly, although van Vliet (2018) suggests that there is no need to adjust low-volatility portfolios that often. A monthly adjustment is made for pure-play results of low volatility strategy to be comparable with combination strategies results as in these strategies, and portfolios are adjusted monthly because of the momentum strategy. However, if the stocks with the highest or lowest volatility stay the same in the rolling month period to the next one, there is no need to sell or buy stocks. In the volatility strategy, we are interested in the performance of the long-only and long-short portfolios.

4.2.2 Combination strategy methodology

After both pure strategies are investigated, the two strategies are combined. Combination portfolios are created with different methods. However, every combination includes a volatility measure and a momentum measure. As a volatility measure, past 36-month weekly volatility is still used, and as the momentum measure, past 12-month returns skipping the most recent month are used. Both low volatility and momentum strategies and combination portfolios have the same one-month holding period to make portfolio formation simple.

Moreover, combination portfolios are created similarly to pure portfolios using top and bottom tenths. The combination strategies use only the top third largest Nordic stocks. Combination portfolios are equally weighted like pure portfolios, and all strategies are evaluated in a long-only and long-short manner. Long-only strategies will be used as there might be difficulties short-selling some of the smallest stocks, and the low-volatility effect is used in long-only portfolios in the earlier studies.

The first method is a simple 50/50 combination where half of the portfolio is invested in a volatility strategy and the other half according to the momentum strategy. Low-volatility stocks are combined with (momentum) winner stocks. High-volatility stocks are then combined with loser stocks. Finally, the low-volatility long-short portfolio is combined with the momentum long-short portfolio.

The second combination method is double screening, where stocks are sorted by both low volatility and momentum into one portfolio. Two kinds of double-screening portfolios are created: volatility-first sorting and momentum-first screening. In the volatility-first portfolio, all active stocks are sorted by volatility and divided into two halves, the other with the highest volatility stocks and the other with the lowest volatility stocks. Then, from the low volatility half, stocks are sorted by momentum, and the stocks with the highest returns are included in the long portfolio. Similarly, from the highest volatility half, stocks are sorted by momentum, and the stocks with the lowest returns are included in the short portfolio. This procedure generates two portfolios, winner stocks from the low volatility universe and loser stocks from the high volatility universe. In the momentum-first portfolio, the above procedure is done other ways by first sorting all active stocks by momentum into two halves. Then the long portfolio includes stocks from the top momentum half with the lowest volatility, and the short portfolio vice versa.

The third combination method is the average ranking method, where stocks are ranked based on momentum and volatility, and the combined portfolio is created based on average ranks. The average ranking method is proposed by Fisher et. al. (2016) as they study a long-only value and momentum combination portfolios. Their method creates separate rankings for value and momentum using percentiles from 0 to 1 and then calculates the average. Grobys and Huhta-Halkola (2019) use the same ranking method and they add a short portfolio in addition to Fisher et. al. (2016).

This thesis uses a similar ranking method, but the ranks are given in a slightly different way as this study creates separate ranks for volatility and momentum using the number of stocks currently in the sample. In other words, if there are 500 active stocks at time t, the highest momentum and volatility rank is number one and the lowest rank is 500. Furthermore, to create the portfolio, all active stocks in the corresponding 36-month period will be sorted first according to their past 36-month weekly volatility so that the stock with the lowest volatility is ranked as number one and the highest volatility as the highest active number. Similarly, past 36-month active stocks are sorted with the standard 12-1 momentum method. Stock with the highest returns during the past twelve months, skipping the most recent month, is ranked number one and vice versa. After all active stocks have a volatility rank and a momentum rank, the average rank of those two is calculated for all stocks. High-rank portfolio includes stocks with the highest tenth rank and low-rank portfolio with the bottom tenth rank meaning the high-rank portfolio thus includes stocks with the lowest volatility and highest momentum average and the low-rank portfolio vice versa. The long-short strategy takes a long position on high-rank stocks and a short position on low-rank stocks.

4.2.3 Portfolio performance measures

Portfolio performance is analyzed in three ways:

1. A descriptive statistics table for each portfolio is reported, including the results of the portfolio's performance.
2. Cumulative return graphs are presented where the portfolio returns are compared to the market index.
3. The corresponding portfolio's factor loadings against the most common factor models are investigated.

Descriptive statistics tables include the monthly mean return of the portfolio and the corresponding t-statistic, minimum monthly return, maximum monthly return, annualized mean return, annualized standard deviation, Sharpe ratio of the portfolio, and a beta of the portfolio. Monthly and annualized returns are reported as excess returns where the risk-free rate has been deducted from the raw monthly return. The corresponding t-statistics are calculated to investigate whether the returns are statistically significant at ten, five, or one percent significance levels. Annualized standard deviation is simply calculated from the standard deviation of monthly returns. Sharpe ratio measures the risk-adjusted returns of the portfolio. The formula for the Sharpe ratio is below.

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p} \tag{11}$$

where r_p is the return of portfolio, r_f is the risk-free return and σ_p is the standard deviation of the excess return (Sharpe, 1966).

The capital Asset Pricing Model (CAPM) is first used to measure whether any of the strategies generate excess returns. After controlling for the CAPM, other factor exposures against Fama and French (1993; 2015; 2018) models are controlled. These factor models include Fama and French three-factor model (FF3), and five-factor model (FF5). Regressions are run via the ordinary least squares model (OLS). Formulas for the OLS regressions of the portfolios on standard factor models are below in the following order: CAPM, FF3, and FF5.

$$r_{i,t}^{ex} = \alpha_{i,t} + \beta_{1,t}MKT + \varepsilon_{i,t} \tag{12}$$

$$r_{i,t}^{ex} = \alpha_{i,t} + \beta_{1,t}MKT + \beta_{2,t}SMB + \beta_{3,t}HML + \varepsilon_{i,t} \tag{13}$$

$$r_{i,t}^{ex} = \alpha_{i,t} + \beta_{1,\mathrm{t}}MKT + \beta_{2,\mathrm{t}}SMB + \beta_{3,\mathrm{t}}HML + \beta_{4,\mathrm{t}}RMW + \beta_{5,\mathrm{t}}CMA + \varepsilon_{i,t} \tag{14}$$

where $r_{i,t}^{ex}$ is the expected excess return of portfolio i at time t, α_i is the intercept term of portfolio i, MKT is the excess return of the market portfolio, SMB is the excess return of the size factor, HML is the excess return of the value factor, RMW is the excess return of the profitability factor, CMA is the excess return of the investment factor, β_1 is the factor loading market factor, β_2 is the factor loading on size factor, β_3 is the factor loading on value factor, β_4 is the factor loading on profitability factor, β_5 is the factor loading on investment factor, and $\varepsilon_{i,t}$ is the error term of portfolio i at time t.

To interpret the Capital Asset Pricing model, factor loadings give the alpha and the beta of the corresponding investment strategy related to Nordic markets' returns. From the alpha, we can investigate whether the corresponding strategy generates excess returns (positive alpha), and from the t-statistics of the alpha, it can be seen whether the alpha is statistically significant at ten, five, or one percent significance level. From beta, it can be investigated how the corresponding strategy behaves related to the market returns. The beta of one tells us that the corresponding strategy moves similarly to the market portfolio, the beta over one tells us that the strategy returns fluctuate stronger than the market, and the beta under one tells us that the corresponding strategy portfolio fluctuates lower than the market portfolio. A negative beta means that the strategy is negatively correlated with the market returns meaning that as the Nordic stock market goes up, the corresponding strategy goes down and vice versa. CAPM is thus a relevant tool to investigate the absolute returns more in-depth and provides new helpful information about the corresponding strategy. However, as there are more factors than the market factor presented in the finance literature, it is natural to control for these added factors also.

Continuing to the Fama and French three-factor model (FF3), the monthly returns of the corresponding strategy's exposure to the three factors, market, size, and value are measured. As a result, the alpha and three betas are generated. Similar to the CAPM, positive alpha means excess returns, and betas tell the sensitivity of the strategy to the corresponding factor. After Fama and French three-factor model, Fama and French five-factor model are used to control the returns of the corresponding strategy. The Five-factor model adds investment and profitability factors to the three-factor model. FF5 controls result in an alpha and four betas that can be interpreted similarly to CAPM and FF3 models.

4.2.4 Statistical significance

The statistical inference of the monthly returns and factor loadings is measured by t-statistics. For all portfolio monthly return means and corresponding factor loadings of the standard models, the corresponding t-statistics are calculated to analyze the statistical significance of the values. All t-statistics in this thesis for returns and factor exposures are calculated using a blocks bootstrap method proposed by Grobys and Junttila (2021) with a block length of ten.

It is well-known that there are different dependency structures in the financial time series data. Bootstrapping methodology is one way that can help to get more robust t-statistics. However, when using standard bootstrapping methods, the kind of dependency structure in the data must be known. Grobys and Junttila's (2021) blocks bootstrapping schema accounts for all kinds of dependency structures, so it does not need to be examined which exact dependency structures there might be in the data to find a suitable methodology. This is convenient for this study as it has many portfolios that are formed in different ways. For example, momentum strategies are prone to crashes that might bring more outliers and extreme events in the return series, possibly making it fat-tailed and the low-volatility and combination portfolios might have other or same issues.

Although the popular Newey and West (1980) covariance matrix accounts for autocorrelation and heteroskedasticity, it has been proposed that more accurate and robust estimates can be achieved using bootstrapping techniques. Liu et al. (2019) find that their bootstrap-based offer better performance than the standard test as they test out-of-sample stock return predictability. Huang et al. (2020) investigate the statistical significance of time-series momentum returns. They find that the t-statistics of the returns are high but not over the critical values when applying more robust statistical tests using bootstrapping. Godfrey (2009) states that if the data set is small, fat-tailed, and highly skewed, there might be severe size distortions in the standard t-statistics. These findings also support the use of bootstrapped t-statistics in this thesis as the data set is relatively small, including 249 time series observations, and it is likely that at least some of the return series are fat-tailed and highly skewed.

The blocks bootstrapped t-statistics that are robust for heteroskedasticity, and autocorrelation are marked as (HAC-robust t-statistics) in the result tables. In addition to the robust t-statistics, sub-sample tests are performed on the top-performing portfolios to add robustness to the results. Sub-samples are generated by dividing the time period into two parts, the first starting from 2002 and ending in 2012, and the other starting from 2012 and ending in 2022. Investigating the performance of the portfolios over the separate sub-periods gives a better overall view of the profitability of the strategies, as the market conditions may vary a lot.

5 Results

In this chapter, the results of the empirical study are presented and discussed. Results include descriptive portfolio statistics, cumulative return graphs, and risk factor regression tables. Also, a correlation matrix is created that shows the correlations between pure portfolios, combination portfolios, and the market index.

Tables of descriptive portfolio statistics of the strategies include monthly excess return where the risk-free rate has been deducted, monthly minimum and maximum, annualized excess return, annualized standard deviation, Sharpe ratio, and beta. In addition, the t-statistics of the monthly returns are reported in brackets. The t-statistics are calculated using the blocks bootstrap method proposed by Grobys and Junttila (2021). These t-statistics are HAC-robust which means they account for all kinds of dependency structures that might exist in the return data, such as heteroscedasticity and autocorrelation. Significance levels of one, five, and ten percent are marked with stars (***, **, and *, respectively). The cumulative return graphs demonstrate the excess returns in the whole sample period, giving more perspective and comparison between the strategies. The regression tables present the factor loadings of the corresponding portfolio on standard factor models. Risk factor tables include the corresponding factor loadings and the HAC-robust t-statistics.

It is expected that both pure low volatility and momentum strategies outperform the market index in pure returns. Absolute excess returns of the momentum strategy are expected to be higher, but when considering risk-adjusted returns, low volatility is expected to outperform momentum because of the lower volatility. It is also expected that all combination strategies can outperform pure strategies, as the combinations should increase the absolute returns compared to low-volatility strategies and decrease the standard deviation compared to momentum strategies. However, it is still being determined which combination strategies will produce the highest risk-adjusted returns. Moreover, it needs to be clarified how the long-only combinations and long-short combinations perform related to each other.

This chapter includes results of the pure strategies of low-volatility and momentum as well as long-only and long-short combination portfolios' returns. Combination portfolios include a 50/50 strategy, two double-screening strategies, and a ranking strategy. Finally, top-performing portfolios are compared across the whole sample and sub-sample time periods.

5.1 Pure volatility strategy

First, it is examined whether the pure low idiosyncratic volatility portfolio can produce excess returns and outperform the market index as well as the high volatility portfolio. Portfolios are formed using the past 36-month weekly stock volatilities. The low volatility portfolio includes the top ten percent stocks with the lowest volatility, and the high volatility portfolio includes the top ten percent highest volatility stocks. LMH is the long-short portfolio that is long on low-volatility stocks and short on high-volatility stocks. Table 2 below shows the results of pure volatility portfolios. The table includes results for portfolios created using all Nordic stocks and top-third market capitalization stocks.

Table 2. Descriptive statistics for pure volatility portfolios.

	Low Vol	High Vol	LMH	Market
Panel A: All Nordic stocks equally weighted				
Mean	0.84 %***	0.74 %	0.10 %	0.69 %*
(HAC robust t-statistic)	(2.60)	(1.07)	(0.20)	(1.76)
Min	-15.49 %	-25.41 %	-35.53 %	-19 %
Max	9.63 %	38.85 %	26.17 %	22 %
Annualized mean return	10.55 %	9.31 %	1.15 %	9 %
Annualized STDEV	11.99 %	30.76 %	24.99 %	18 %
Sharpe ratio	0.88	0.3	0.05	0.47
Beta	0.56	1.11	-0.55	-
Panel B: Top third Nordic stocks by market capitalization equally weighted				
Mean	0.86 %**	0.38 %	0.48 %	0.69 %*
(HAC robust t-statistic)	(2.52)	(0.55)	(0.94)	(1.76)
Min	-14.04 %	-32.57 %	-27.81 %	-19 %
Max	10.96 %	30.45 %	22.69 %	22 %
Annualized mean return	10.82 %	4.66 %	5.91 %	9 %
Annualized STDEV	13.46 %	34.44 %	27.51 %	18 %
Sharpe ratio	0.8	0.14	0.21	0.47
Beta	0.62	1.49	-0.87	-

Mean is the monthly average return over the time period of January 2002 until September 2022. HAC-robust t-statistic is robust t-statistic measure that accounts for all kinds of dependency structures in the return data and is based on a blocks bootstrap methodology proposed by Grobys and Junttila (2021). Min and Max are the monthly minimum and maximum returns. Annualized mean and standard deviation are simply an annualized value of monthly average return and standard deviation. All returns are measured as excess returns where the monthly risk-free rate is deducted from the monthly raw returns. Thus, Sharpe ratio is simply then Annualized mean divided by Annualized standard deviation.
Low Vol refers to a low volatility portfolio that buys top ten percent stocks with the lowest past 36-month weekly volatilities. All returns are excess returns where the risk-free rate has been deducted from the raw returns and all measures in the table are same as in the earlier return tables. High Vol refers to an opposite portfolio that includes stocks with the highest past volatility. LMH is a long-short portfolio consisting of a long position on Low Vol and a short position on High Vol.

Low volatility (Low Vol) portfolio produces the highest absolute excess return and the highest Sharpe ratio. Monthly returns of 0.84% (all stocks) and 0.86% (top third market cap) are significant at a one percent level. The high volatility portfolio and the long-short portfolio LMH (low volatility minus high volatility) also generate positive excess returns, but neither are statistically significant. Moreover, Panel B shows that when only top-third market cap stocks are used, both High Vol and LMH lose to the market index. Low Vol portfolio performance is persistent across all stocks and top market cap stock samples.

Low Vol portfolio generates higher excess returns than the market index with lower volatility, proving that there is some evidence that volatility effect might exists in the Nordic stock market. Moreover, the Low Vol portfolio has the lowest minimum monthly return among volatility portfolios and the market index. Figure 7 below presents the cumulative excess returns of the volatility portfolios.

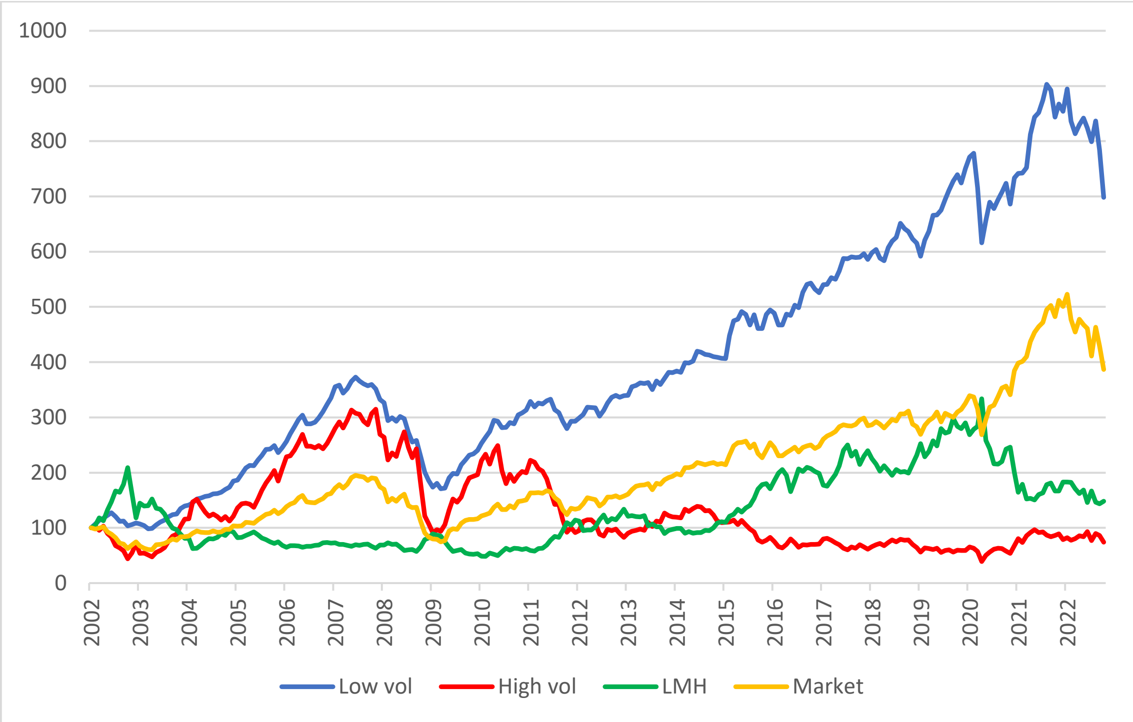


Figure 6. Cumulative excess returns of the pure volatility portfolios.

In addition to the descriptive statistics, factor loadings on common risk factors are investigated. Factor models used in this study include the Capital Asset Pricing Model (CAPM), Fama and French three-factor model (FF3), and Fama and French five-factor model (FF5). Table 3 below presents factor loadings for volatility portfolios.

Table 3. Regressing pure volatility portfolios on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA
Panel A: Low volatility						
Coefficient	0.44**	0.62***				
(HAC robust t-statistic)	(2.43)	(17.34)				
Coefficient	0.38**	0.61***	0.24***	0.05		
(HAC robust t-statistic)	(2.28)	(17.52)	(2.71)	(0.82)		
Coefficient	0.15	0.66***	0.21***	0.2**	0.5***	0.20
(HAC robust t-statistic)	(0.86)	(22.40)	(2.96)	(2.04)	(3.65)	(1.43)
Panel B: High volatility						
Coefficient	-0.64	1.49***				
(HAC robust t-statistic)	(-1.42)	(16.36)				
Coefficient	-0.86**	1.43***	0.71***	0.65***		
(HAC robust t-statistic)	(-2.12)	(13.46)	(2.75)	(3.81)		
Coefficient	-0.43	1.37***	0.81***	0.20	-1.09*	-0.06
(HAC robust t-statistic)	(-0.87)	(14.00)	(3.42)	(0.55)	(-1.77)	(-0.16)
Panel C: LMH						
Coefficient	1.08**	-0.87***				
(HAC robust t-statistic)	(2.20)	(-8.30)				
Coefficient	1.24**	-0.82***	-0.47	-0.6***		
(HAC robust t-statistic)	(2.55)	(-6.24)	(-1.46)	(-2.99)		
Coefficient	0.57	-0.71***	-0.6**	0.00	1.60**	0.26
(HAC robust t-statistic)	(1.03)	(-6.40)	(-2.32)	(-0.00)	(2.38)	(0.58)

In Table 3, α refers to the alpha or the intercept term of the corresponding regression model. MKT refers to the market factor, SMB to the size factor, HML to the value factor, RMW to the profitability factor and CMA to the investment factor. The coefficients give the corresponding factor loadings for the corresponding model. In all panels the used regression models are CAPM, FF3 and FF5. HAC-robust t-statistics are given in brackets.
In Panel A, Low Volatility refers to a low volatility portfolio that buys top ten percent stocks with the lowest past 36-month weekly volatilities. In Panel B, High Volatility refers to an opposite portfolio that includes stocks with the highest past volatility. In Panel C, LMH is a long-short portfolio consisting of a long position on Low Vol and a short position on High Vol.

Low Vol portfolio generates significant positive alpha when CAPM and FF3 are controlled. However, the alpha decreases and becomes insignificant when FF5 is controlled. Low Vol portfolio also has significant positive loadings on the market, size, value (FF5) and profitability (FF5) factors. Particularly the robust minus weak (RMB) factor seems to capture the returns of the Low Vol portfolio, which indicates that stock with low past volatility tends to be profitable.

When considering volatility strategies, it can be concluded that there is some evidence of the volatility effect in the Nordic stock market, but the effect is not robust. The long-only low-volatility portfolio generates significant returns and outperforms the market index and produces a positive significant alpha when FF3 is controlled. However, the excess returns are insignificant when the FF5 is controlled. Moreover, the long-short volatility strategy does not produce significant returns.

5.2 Pure momentum strategy

Next, the pure momentum strategy is investigated. This thesis uses a standard 12-1-1 momentum, where stocks are sorted based on their past 12-month returns. The top ten percent of stocks with the highest returns are considered winners, and the bottom ten percent are losers. Long-short strategy (WML) includes buying the Winner stocks and shorting the loser stocks. Table 4 below shows the results of pure momentum portfolios.

Table 4. Descriptive statistics for pure momentum portfolios.

	Winners	Losers	WML	Market
Panel A: All Nordic stocks equally weighted				
Mean	1.92 %***	-0.35 %	2.27 %***	0.69 %*
(HAC robust t-statistic)	(3.49)	(-0.55)	(6.29)	(1.76)
Min	-19.62 %	-31.97 %	-21.44 %	-19.05 %
Max	35.46 %	29.47 %	28.62 %	21.96 %
Annualized mean return	25.70 %	-4.11 %	30.96 %	8.56 %
Annualized STDEV	22.27 %	31.42 %	21.48 %	18.36 %
Sharpe ratio	1.15	-0.13	1.44	0.47
Beta	0.96	1.31	-0.35	-
Panel B: Top third Nordic stocks by market capitalization equally weighted				
Mean	1.27 %**	-0.22 %	1.49 %***	0.69 %*
(HAC robust t-statistic)	(2.40)	(-0.35)	(3.30)	(1.76)
Min	-25.67 %	-36.78 %	-18.58 %	-19.05 %
Max	17.70 %	21.60 %	22.14 %	21.96 %
Annualized mean return	16.36 %	-2.60 %	19.43 %	8.56 %
Annualized STDEV	22.75 %	32.52 %	25.03 %	18.36 %
Sharpe ratio	0.72	-0.08	0.78	0.47
Beta	1.06	1.45	-0.39	-

Winners refers to a long-only portfolio that buys the top ten percent stocks with the highest returns in the past 12-month period skipping the most recent month. Losers-portfolio refers to similar long-only portfolio but buying the bottom ten percent stocks. WML refers to a long-short portfolio that is long on Winners and short on Losers. All returns are excess returns where the risk-free rate has been deducted from the raw returns and all measures in the table are same as in table 2.

From table 4, it can be concluded that when using a sample of all Nordic stocks, both Winners and WML portfolios create excess returns significant at a one percent level. WML has slightly higher absolute returns and a higher Sharpe ratio than the Winners portfolio. These results are also persistent when the highest third market capitalization stocks are considered, and this shows that the momentum effect is present even among the largest stocks. However, the absolute returns are lower than in all stocks sample, but they are still statistically significant on a one percent level. Sharpe ratios of Winners and WML portfolios are also lower than among all stocks but still higher than the market portfolio's Sharpe ratio. Cumulative excess returns of the third top Winners and WML portfolios are significantly higher than market portfolios, as shown in figure 8 below.

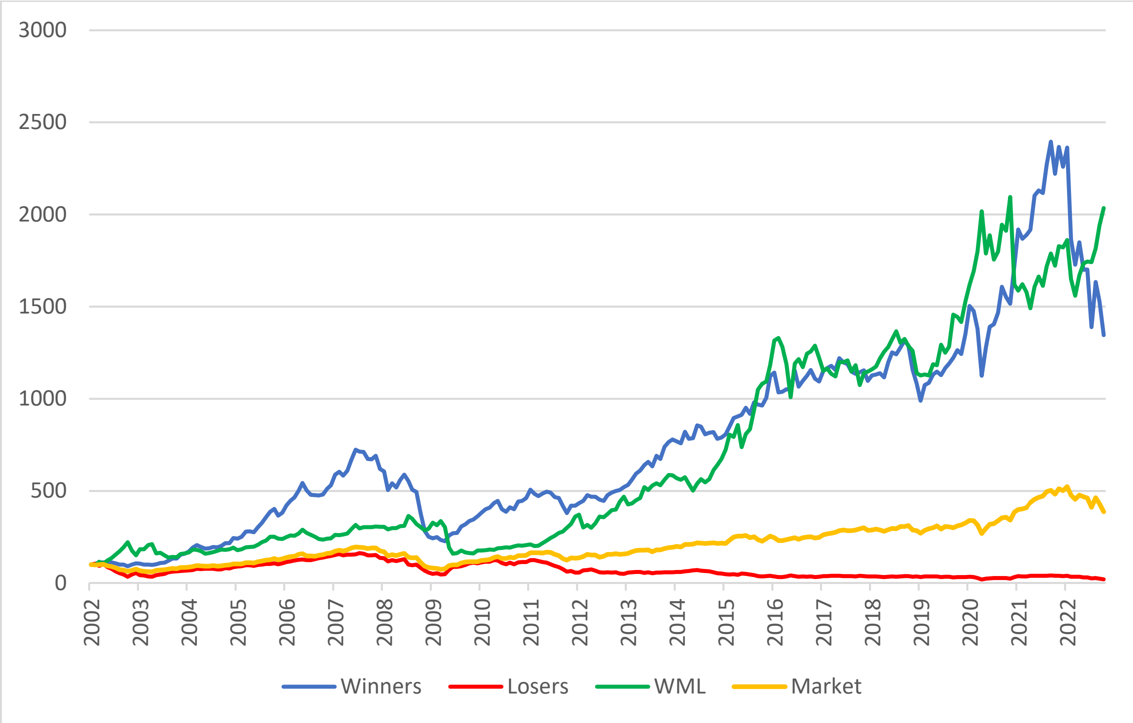


Figure 7. Cumulative excess returns of the pure momentum portfolios.

When regressing momentum portfolios on standard risk factors, the Winners portfolio only creates a statistically significant alpha on CAPM. Both Fama and French factor models can capture excess returns. On the other hand, the WML portfolio generates a significant alpha on CAPM, FF3, and even FF5. Regression results are presented below in Table 5.

Table 5. Regressing pure momentum portfolios on standard risk factors.

	α	**MKT**	**SMB**	**HML**	**RMW**	**CMA**
Panel A: Winners						
Coefficient	0.54**	1.06***				
(HAC robust t-statistic)	(1.98)	(13.61)				
Coefficient	0.37	1.06***	0.83***	-0.17		
(HAC robust t-statistic)	(1.56)	(17.37)	(6.94)	(-1.5)		
Coefficient	0.22	1.10***	0.82***	-0.11	0.30	0.20
(HAC robust t-statistic)	(0.99)	(18.36)	(6.99)	(-0.56)	(1.51)	(0.87)
Panel B: Losers						
Coefficient	-1.22***	1.45***				
(HAC robust t-statistic)	(-3.36)	(11.46)				
Coefficient	-1.34***	1.41***	0.36	0.48***		
(HAC robust t-statistic)	(-3.66)	(10.41)	(1.12)	(2.87)		
Coefficient	-0.9**	1.29***	0.37	0.32	-0.89	-0.64*
(HAC robust t-statistic)	(-2.1)	(10.02)	(1.39)	(0.69)	(-1.31)	(-1.87)
Panel C: WML						
Coefficient	1.76***	-0.39**				
(HAC robust t-statistic)	(3.68)	(-2.15)				
Coefficient	1.71***	-0.35**	0.47	-0.65***		
(HAC robust t-statistic)	(3.80)	(-1.93)	(1.23)	(-2.72)		
Coefficient	1.12**	-0.19	0.45	-0.43	1.19	0.84*
(HAC robust t-statistic)	(2.41)	(-1.11)	(1.33)	(-0.7)	(1.46)	(1.66)

In Table 5, Winners refers to a long-only portfolio that buys the top ten percent stocks with the highest returns in the past 12-month period skipping the most recent month. Losers refers to similar long-only portfolio but buying the bottom ten percent stocks. WML refers to a long-short portfolio that is long on Winners and short on Losers. The coefficients and risk factors are measured similarly as in table 3.

All in all, momentum anomaly exists in the Nordic stock market, and excess returns can be generated by investing in either long-only Winners portfolio or long-short WML portfolio.

5.3 Long-only combination strategies

After the pure volatility and momentum portfolios are investigated, combination portfolios are formed, and the aim is to find the best method to combine volatility and momentum. First, Long-only strategies are investigated as earlier studies, and pure volatility results give evidence that low volatility works well in long-only strategies. This sub-chapter presents long-only combination portfolio results, and the long-short strategies are examined in the next sub-chapter.

To get some perspective on the relationship between momentum and volatility portfolios' returns, table 6 below presents the correlation matrix of the volatility portfolios, momentum portfolios, and the market index.

Table 6. Correlation matrix of volatility and momentum portfolios.

	Low vol	High vol	Winners	Losers	LMH	WML	Market
Low vol	1.00						
High vol	0.66	1.00					
Winners	0.81	0.72	1.00				
Losers	0.67	0.85	0.64	1.00			
LMH	-0.33	-0.93	-0.50	-0.73	1.00		
WML	-0.14	-0.45	0.08	-0.72	0.50	1.00	
Market	0.84	0.79	0.86	0.82	-0.58	-0.29	1.00

In Table 6, Low vol refers to a low volatility portfolio that buys top ten percent stocks with the lowest past 36-month weekly volatilities. All returns are excess returns where the risk-free rate has been deducted from the raw returns and all measures in the table are same as in the earlier return tables. High Vol refers to an opposite portfolio that includes stocks with the highest past volatility. LMH is a long-short portfolio consisting of a long position on Low Vol and a short position on High Vol. Winners refers to a long-only portfolio that buys the top ten percent stocks with the highest returns in the past 12-month period skipping the most recent month. Losers refers to similar long-only portfolio but buying the bottom ten percent stocks. LMH is a long-short portfolio consisting of a long position on Low Vol and a short position on High Vol. WML refers to a long-short portfolio that is long on Winners and short on Losers.

Winners and low-volatility portfolios are highly correlated. Also, Winners and low-volatility portfolios are highly correlated with the market index. The long-short portfolios LMH and WML are negatively correlated with almost every long portfolio, but they are positively correlated with each other, which is surprising. Moreover, both LMH and WML are negatively correlated with the market index.

The first method to combine the two strategies is a simple 50/50 strategy where half of the portfolio is invested in one strategy and half in another. As a long-only portfolio, the other half of the portfolio is invested in low-volatility stocks and the other in momentum-winner stocks. The methodology of portfolio forming is the same as in pure strategies.

The second method to form the combination portfolios is a double screening method (DS). In the strategy, portfolios are formed by screening stocks first by another method and then by another. In this study, two kinds of double-screening methods are used. Portfolios are formed first by sorting volatility and then momentum and first by sorting momentum and then volatility. First, sorting divides the universe of stocks into halves, and then second, sorting selects stock from the wanted half. The lowest volatility half is combined with the winner stocks and vice versa. Then the winners half is combined with the lowest volatility stocks and vice versa. The long-only strategies of double screening include two portfolios, low volatility half and then winners and winners half and then low volatility. Double screening methods use top quintiles instead of top tenths because the active stocks are first divided into halves, so the total number of stocks invested is the same as in other strategies where tenths are used.

The third method to combine volatility and momentum is a ranking strategy where all stocks are given a rank based on volatility and momentum. Stock with the lowest past 36-month volatility is given rank one on volatility, and stock with the highest 12-1 momentum is given rank one on momentum, and so on. Then, an average rank is calculated for every stock, and the long-only ranking portfolio includes the top ten percent of the highest-ranking stocks. Table 7 below shows the descriptive statistics for the long-only combination portfolios and the market index.

Table 7. Descriptive statistics for long-only combination portfolios.

	50/50	DS Vol First	DS Mom First	Ranking	Market
Mean	1.02 %**	1.13%**	1.08%***	1.11 %***	0.69 %*
(HAC robust t-statistic)	(2.43)	(2.59)	(3.08)	(2.89)	(1.76)
Min	-17.64 %	-18.73 %	-17.43 %	-16.67 %	-19.05 %
Max	14.32 %	13.92 %	11.02 %	10.37 %	21.96 %
Annualized mean return	13.00 %	14.42 %	13.76 %	14.20 %	8.56 %
Annualized STDEV	16.99 %	17.66 %	15.12 %	15.89 %	18.36 %
Sharpe ratio	0.76	0.82	0.91	0.89	0.47
Beta	0.82	0.82	0.68	0.71	-

In table 7, 50/50 stands for the 50/50 combination portfolio including the low volatility stocks in the half of the portfolio and winner stocks in the other half of the portfolio. DS Vol first stands for the double screening portfolio where the stocks are first divided into a half based on the lowest volatility and then sorted by momentum. DS Mom first is the same but other way around as momentum is first and the lowest volatility. Ranking stands for the ranking portfolio including stocks with the highest ranks. All returns are excess returns where the risk-free rate has been deducted from the raw returns and all measures in the table are same as in tables 2 and 4.

The double screening volatility-first method generates the highest monthly return of 1.13%. The ranking method and momentum-first methods are close behind. 50/50 is the last one of the combination portfolios on monthly returns generating a 1.02% return. Moreover, all combination portfolios beat the market index and are statistically significant, at least at a five percent level.

All combination portfolios beat the market index on monthly minimum returns as the market index has the lowest minimum return. The ranking portfolio avoids the monthly decrease best, having -16.67% minimum. On the other hand, all portfolios lose to the market index on monthly maximums. The ranking portfolio is the last, with only a 10.37% monthly maxim compared to markets at 21.96%. Like the minimums, all portfolios outperform the market index on volatility measured as standard deviation. Volatility-first double screening portfolio has the lowest volatility of 15.12% per year.

Moreover, all portfolios outperform the market index on risk-adjusted returns measured by the Sharpe ratio. DS Vol First and ranking portfolio generate the highest Sharpe ratios of 0.91 and 0.89, respectively. Finally, all portfolios have a beta of less than one, as can be expected with low volatility.

The long-only double screening portfolios generate similar results whether volatility or momentum are sorted first. Volatility-first portfolio generates a higher monthly excess return, but a momentum-first portfolio produces a higher Sharpe ratio (0.91 versus 0.82). The ranking long-only portfolio generates the second-highest Sharpe ratio of 0.89 and the second-highest monthly return. 50/50 portfolio is in the last place of the four measured by both monthly returns and Sharpe ratios. Next, the cumulative excess returns of the portfolios are compared in Figure 8 below.

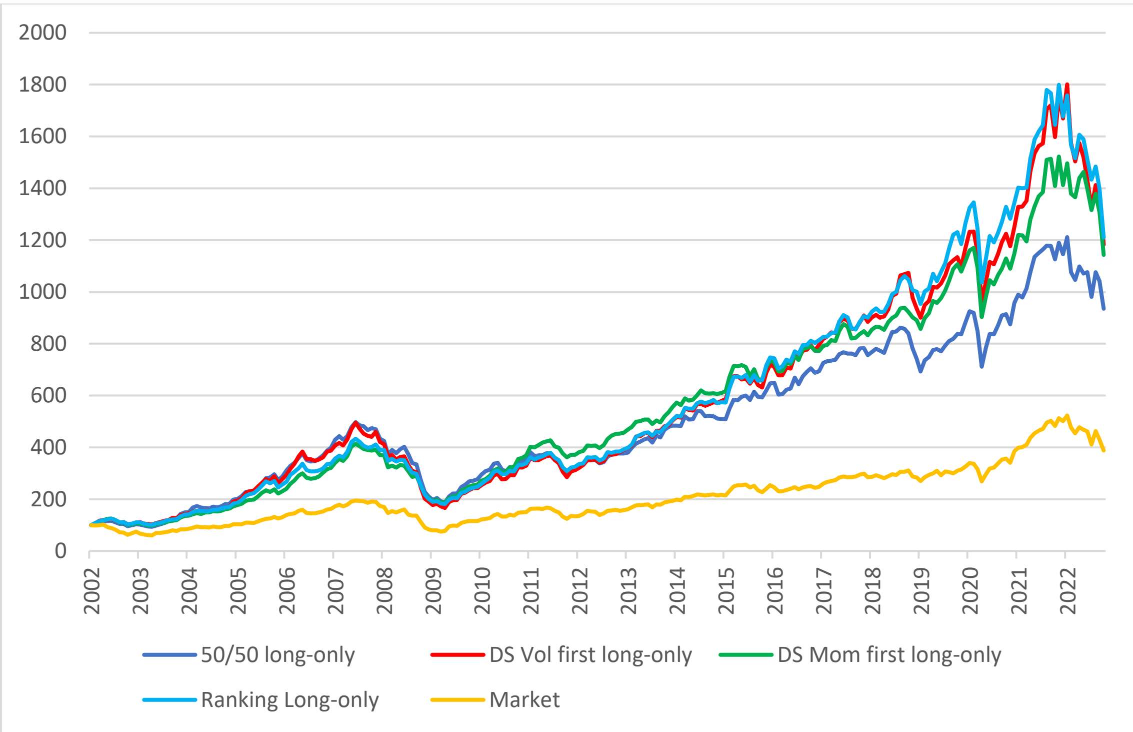


Figure 8. Cumulative excess returns of the long only combination portfolios.

Figure 8 shows that all four combination portfolios outperform the market index over the sample period by a far margin. Both double screening portfolios and the ranking portfolio generate similar cumulative returns, and the graphs mostly overlap with each other. 50/50 portfolio leaves behind, particularly in the second half of the sample period.

During the last two years of the sample period, all combination portfolios experience a large crash that wipes out significant returns. However, the bear market period can be seen in the market index. Next, the excess returns of the combination long-only portfolios are investigated further by regressing the portfolios on standard risk factors models. Table 8 below presents the regression results.

Table 8. Regressing the long-only combination portfolios on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA
Panel A: 50/50 long-only						
Coefficient	0.46**	0.82***				
(HAC robust t-statistic)	(2.36)	(15.67)				
Coefficient	0.34**	0.81***	0.53***	0.04		
(HAC robust t-statistic)	(2.25)	(19.6)	(5.14)	(0.53)		
Coefficient	-0.13	0.87***	0.53***	0.09	0.39**	0.34**
(HAC robust t-statistic)	-0.88	(23.65)	(5.75)	(0.66)	(2.49)	(2.14)
Panel B: DS Vol first long-only						
Coefficient	0.57***	0.82***				
(HAC robust t-statistic)	(2.8)	(13.55)				
Coefficient	0.47**	0.82***	0.48***	-0.09		
(HAC robust t-statistic)	(2.55)	(14.4)	(4.14)	(-1.06)		
Coefficient	0.18	0.87***	0.43***	0.13	0.65***	0.18
(HAC robust t-statistic)	(1.05)	(17.69)	(5.16)	(0.71)	(3.24)	(1.01)
	α	**MKT**	**SMB**	**HML**	**RMW**	**CMA**
Panel C: DS Mom first long-only						
Coefficient	0.61***	0.68***				
(HAC robust t-statistic)	(3.74)	(13.66)				
Coefficient	0.54***	0.68***	0.32***	-0.04		
(HAC robust t-statistic)	(3.36)	(14.45)	(3.47)	(-0.49)		
Coefficient	0.26	0.75***	0.30***	0.09	0.58***	0.35**
(HAC robust t-statistic)	(1.49)	(18.17)	(4.19)	(0.67)	(3.68)	(2.18)
Panel D: Ranking long-only						
Coefficient	0.62***	0.71***				
(HAC robust t-statistic)	(3.40)	(13.59)				
Coefficient	0.54***	0.71***	0.39***	-0.10		
(HAC robust t-statistic)	(3.19)	(14.26)	(3.76)	(-1.23)		
Coefficient	0.26	0.78***	0.36***	0.07	0.62***	0.28*
(HAC robust t-statistic)	(1.43)	(18.68)	(4.91)	(0.47)	(3.47)	(1.66)

In Table 8, portfolios 50/50 long-only, DS Vol first long-only, DS Mom first long-only and ranking long-only are same as in table 7. The coefficients and risk factors are measured similarly as in table 3 and 5.

The 50/50 portfolio produces a positive statistically significant alpha when CAPM and FF3 are controlled. Both alphas are statistically significant at a five percent level. However, the alphas turn slightly negative and insignificant after FF5 is controlled. As seen earlier in the descriptive statistics table, the market beta is positive and lower than one. Moreover, the 50/50 portfolio has significant positive loading on the size factor, indicating that the stocks in the sample are relatively small. Although the sample is the top third largest Nordic stocks, this makes sense as the overall size of the Nordic market stocks is relatively small. Also, the 50/50 portfolio has significant positive factor loadings on profitability and investment factors when FF5 is controlled. These findings conclude that the stocks in the 50/50 portfolio are profitable firms with conservative investments.

Both double-screening portfolios generate quite similar factor loadings compared to the 50/50 portfolio. Double screening portfolios produce significant alphas when CAPM and FF3 are controlled but not anymore when FF5 is controlled. Double screening portfolios also have significant positive factor loadings on the market, size, value (only when FF5 is controlled), profitability, and momentum factors. Momentum-first portfolio has positive loading on investment factor but only when FF5 is controlled. Overall, the momentum-first portfolio generates higher and more robust alphas compared to the volatility-first portfolio.

Regression results for the ranking portfolios are again similar to the other combination portfolios. Alphas are positive and significant when CAPM and FF3 are controlled but insignificant when FF5 is controlled. Like the DS Mom-first strategy, the FF5 alpha is 0.26 and very close to being significant at a ten percent level, as the HAC-robust t-statistic is 1.43. The ranking portfolio also has positive loadings on the market, size, value (only FF5), profitability, and momentum factors. The largest and most significant alphas are generated by momentum-first double screening portfolio and ranking portfolio. These results are in line with the Sharpe ratios.

All in all, long-only portfolios generate a relatively good return and risk-adjusted-performance. The low volatility part is shown in the results as all combinations have a lower risk profile than the market measured by monthly minimums and volatility. However, they can still outperform the market index by returns and risk-adjusted returns.

5.4 Long-short combination portfolios

This sub-chapter analyzes the performance of the long-short combination portfolios. Long-short portfolios are formed in the same manner as the long-only portfolios, so a total of four combination portfolios, 50/50, volatility-first double screening, momentum-first double screening, and ranking portfolio, are formed. The only difference between long-short and long-only portfolios is that long-short portfolios also include a short position in an opposite strategy.

The 50/50 long-short strategy is a simple combination of basic long-short strategies, as half of the portfolio is invested in LMH and the other half in WML. This method is identical to the combination of low-volatility stocks and winner stocks minus the combination of high-volatility stocks and loser stocks strategy; thus, these are not reported separately. Double screening long-short portfolios are formed by taking similar long positions as in long-only strategies and, in addition, short positions on the high volatility and loser stocks. In other words, the double screening volatility first strategy (DS Vol first) divides the stocks into two halves based on volatility. The long position is formed by investing in the winner-stocks from the low volatility half, and a short position is by shorting the loser stocks from the high volatility half. Double screening momentum-first strategy (DS Mom first) is formed in the same way except for volatility, and momentum sorting is done in a different order. The long-short ranking portfolio takes a long position on high-rank stocks and a short position on low-rank stocks. The ranking is done similarly to the long-only ranking strategy. The results of the four long-short combination portfolios are below in table 9.

Table 9. Descriptive statistics for the long-short combination portfolios.

	50/50	DS Vol First	DS Mom First	Ranking	Market
Mean	0.87 %*	1.24%**	0.93%*	1.21 %**	0.69 %*
(HAC robust t-statistic)	(1.90)	(2.32)	(1.79)	(2.21)	(1.76)
Min	-32.48 %	-50.04 %	-29.39 %	-40.04 %	-19.05 %
Max	23.86 %	27.96 %	22.74 %	26.84 %	21.96 %
Annualized mean return	10.92 %	15.91 %	11.76 %	15.54 %	8.56 %
Annualized STDEV	23.89 %	28.35 %	27.13 %	29.17 %	18.36 %
Sharpe ratio	0.46	0.56	0.43	0.53	0.47
Beta	-0.7	-0.77	-0.82	-0.88	-

In table 9, 50/50 stands for the long-short 50/50 combination portfolio including a long position half on low volatility stocks and half on winner stocks as well as a short position half on high volatility stocks and half on loser stocks. DS Vol first stands for the double screening portfolio where the stocks are first divided into a half based on the lowest volatility and then sorted by momentum. Long position includes winner stocks from low-volatility half and short position loser stocks from the high volatility half. DS Mom first is formed in the same manner but other way around as momentum is screened first and then volatility. Ranking stands for the long-short ranking portfolio including long position on stocks with the highest ranks and short position on stocks with the lowest ranks. All returns are excess returns where the risk-free rate has been deducted from the raw returns and all measures in the table are same as in tables 2 and 4.

The double screening volatility-first method generates the highest monthly return of 1.24%. The ranking method is close behind, with a monthly return of 1.21%. Both returns are statistically significant at a five percent level. Momentum first and 50/50 portfolios are far behind, generating 0.93% and 0.87% monthly returns, respectively. Both returns are statistically significant only at a ten percent significance level. However, all combination portfolios beat the market index on monthly returns.

All combination portfolios lose the market index on monthly minimum returns as the market index has the highest minimum return. DS Vol First has the worst, -50.04% monthly return minimum, which means that half of the portfolio value diminishes in the worst month. DS Mom-first portfolio avoids the monthly decrease best, having -29.39% minimum. On the other hand, all portfolios beat the market index on monthly maximums. DS Mom-first portfolio is the last, with only a 10.37% monthly maxim compared to the market's 22.74%. All portfolios lose to the market index on volatility measured as standard deviation. Volatility-first double screening portfolio has the lowest volatility of 23.89% per year, which is still relatively high. Moreover, only DS Vol first and ranking portfolios outperform the market index on risk-adjusted returns measured by the Sharpe ratio generating Sharpe ratios of 0.91 and 0.89, respectively. Finally, all portfolios have a negative beta.

Unlike long-only portfolios, the double screening method generates higher return and Sharpe ratio when volatility is sorted first compared to momentum. Volatility first portfolio generates the highest monthly return and Sharpe ratio. The ranking long-only portfolio generates the second-highest Sharpe ratio of 0.53 and the second-highest monthly return. 50/50 portfolio is at the last place of the four measured by monthly returns, and the momentum first portfolio is at the last place measured by the Sharpe ratio. Next, cumulative excess returns of the long-short portfolios are compared in Figure 9 below.

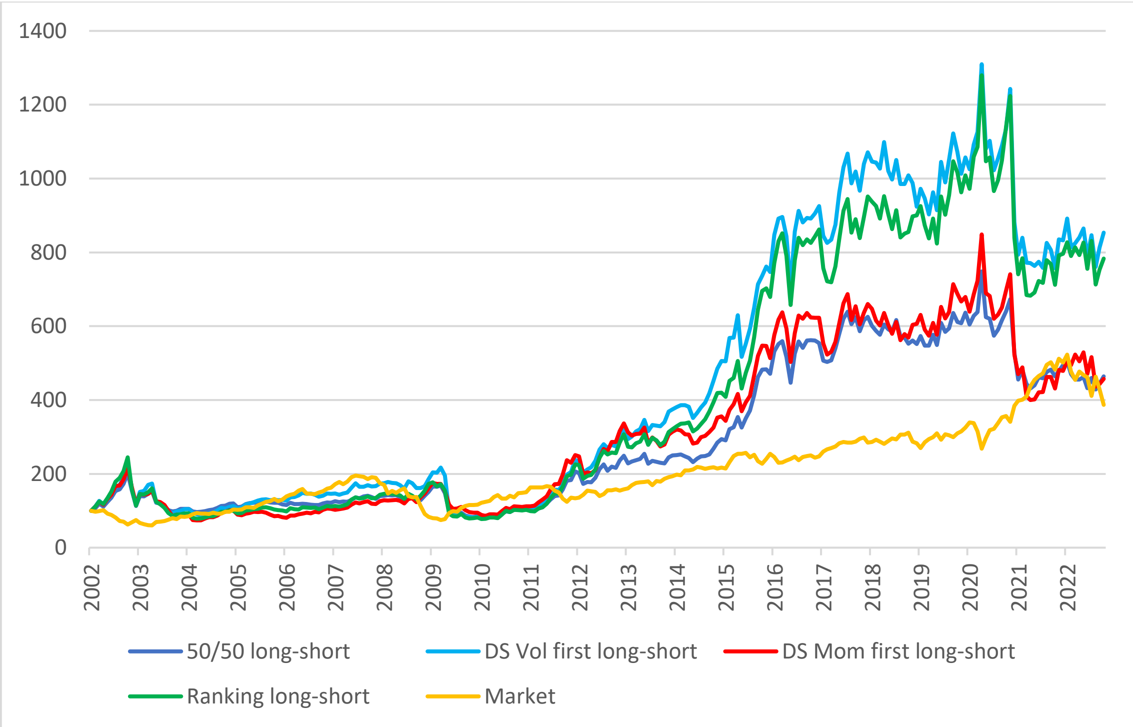


Figure 9. Cumulative excess returns of the long-short combination portfolios.

Figure 9 shows that all four combination portfolios outperform the market index over the sample period. However, momentum-first and 50/50 are practically at the same point as the market index at the end of the sample period. Similar to the long-only strategies, double screening portfolios and the ranking portfolio graphs mostly overlap with each other, generating similar returns. All long-short portfolios have a significant return crash during the first quarter of 2021 when the market index is steadily climbing. The timing for the crash is interesting and might be related to the momentum crashes as it happens after an extensive market index crash, possibly created by the excellent performance of loser stocks. To look more in-depth at the risk-adjusted returns, table 10 below presents the regression results of the long-short combination portfolios on common risk factors.

Table 10. Regressing the long-short combination portfolios on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA
Panel A: 50/50 long-short						
Coefficient	1.35***	-0.7***				
(HAC robust t-statistic)	(2.97)	(-5.15)				
Coefficient	1.4***	-0.65***	0.02	-0.63***		
(HAC robust t-statistic)	(3.03)	(-4.36)	(0.05)	(-3.63)		
Coefficient	0.78	-0.50***	-0.04	-0.29	1.33*	0.67
(HAC robust t-statistic)	(1.54)	(-3.82)	(-0.14)	(-0.57)	(1.69)	(1.87)
Panel B: DS Vol first long-short						
Coefficient	1.77***	-0.77***				
(HAC robust t-statistic)	(3.31)	(-4.1)				
Coefficient	1.81***	-0.72***	0.11	-0.74***		
(HAC robust t-statistic)	(3.28)	(-3.6)	(0.27)	(-3.39)		
Coefficient	1.10*	-0.55***	0.05	-0.36	1.50	0.77
(HAC robust t-statistic)	(1.89)	(-3.1)	(0.15)	(-0.54)	(1.64)	(1.48)
	α	**MKT**	**SMB**	**HML**	**RMW**	**CMA**
Panel C: DS Mom first long-short						
Coefficient	1.49***	-0.82***				
(HAC robust t-statistic)	(2.99)	(-5.85)				
Coefficient	1.6***	-0.77***	-0.2	-0.63***		
(HAC robust t-statistic)	(3.27)	(-4.95)	(-0.58)	(-3.04)		
Coefficient	0.91*	-0.63***	-0.3	-0.14	1.56**	0.53
(HAC robust t-statistic)	(1.67)	(-4.48)	(-1.05)	(-0.29)	(2.03)	(1.25)
Panel D: Ranking long-short						
Coefficient	1.81***	-0.88***				
(HAC robust t-statistic)	(3.34)	(-5.45)				
Coefficient	1.88***	-0.82***	-0.02	-0.72***		
(HAC robust t-statistic)	(3.4)	(-4.54)	(-0.04)	(-3.31)		
Coefficient	1.07*	-0.66***	-0.13	-0.14	1.83**	0.60
(HAC robust t-statistic)	(1.73)	(-4.24)	(-0.38)	(-0.23)	(2.11)	(1.42)

In Table 10, the portfolios 50/50 long-short, DS Vol First long-short, DS Mom First long-short and ranking long-short are same as in table 9. The coefficients and risk factors are measured similarly as in table 3 and 5.

The 50/50 portfolio produces a positive statistically significant alpha when CAPM and FF3 are controlled. Both alphas are statistically significant at a one percent level. However, the alpha is insignificant after FF5 is controlled. As seen in the descriptive statistics table, the market beta is negative. Moreover, the 50/50 portfolio does not have significant loading on size factor as the long-only portfolios have. Also, the 50/50 portfolio has significant negative factor loadings on the value factor only when FF3 is controlled, positive loading on the profitability factor only when FF5 is controlled.

Both double-screening portfolios generate quite similar factor loadings compared to the 50/50 portfolio. Double screening portfolios produce significant alphas when CAPM, FF3, and even when FF5 is controlled. Double-screening portfolios also have significant negative factor loadings on the market, and value (only when FF3 is controlled), profitability, and momentum factors. Momentum-first portfolio has negative loading on size factor but only when FF5 is controlled and positive loading on investment factor when FF5 is controlled. Opposite to the long-only portfolios, the volatility-first portfolio generates higher and more robust alphas than the momentum-first portfolio.

Regression results for the ranking portfolios are again similar to the other long-short combination portfolios. Alphas are positive and significant when CAPM (1%), FF3 (1%), and FF5 (10%) are controlled. The ranking portfolio also has negative loadings on market factor and value factor(only FF3), and positive loading on profitability factor. The volatility-first double screening portfolio and ranking portfolio generate the largest and most significant alphas of the long-short combination portfolios. These results are in line with the Sharpe ratios.

Overall, long-short portfolios generate good monthly returns but not risk-adjusted performance. All combinations have a higher risk profile than the market measured by monthly minimums and volatility. However, double screening volatility-first and ranking long-short strategies can still outperform the market index by risk-adjusted returns. Long-short strategies are less attractive investment strategies than similar long-only strategies.

5.5 Summary and robustness

This chapter summarizes the results of the investment strategies and portfolios used in this study. The aim is to answer the research questions of whether the volatility effect and momentum effect can be found in the Nordic stock market and whether the combination of the two can generate excess returns and outperform the market index and the pure strategies in risk-adjusted returns.

5.5.1 Portfolio performance summary

For this summary, pure volatility and momentum long-only and momentum long-short portfolios, the best combination long-only portfolio, the best combination long-short portfolio, and the market index are chosen, making a total of six portfolios. The best combination portfolios are selected based on the Sharpe ratio. Selected portfolios are low volatility, winners, WML, combination long-only portfolio (double screening momentum-first), combination long-short portfolio (double screening volatility-first), and the market index. Table 11 below compares monthly excess return, Sharpe ratio, and Fama and French three-factor model alpha.

Table 11. Comparison of the pure-play, combination, and market portfolios.

	Mean	Sharpe ratio	FF3 alpha
Low Vol	0.86%** (2.52)	0.80	0.38%** (2.28)
Winners	1.27%** (2.40)	0.72	0.37% (1.56)
WML	1.49%*** (3.30)	0.78	1.71%*** (3.80)
Combination long-only	1.08%*** (3.08)	0.91	0.54%*** (3.36)
Combination long-short	1.24%** (2.32)	0.56	1.81%*** (3.28)
Market	0.69%* (1.76)	0.47	- -

In the table 11, Low Vol stands for the long-only low-volatility portfolio, Winners stands for the long-only momentum portfolio, WML stands for the long-short momentum portfolio, Combination long-only refers to the best performing long-only combination portfolio (DS momentum first) and Combination long-short refers to the best performing long-short combination portfolio (DS Volatility first). Mean is the monthly average return over the time period of January 2002 until September 2022. HAC-robust t-statistic is given in parentheses. Mean returns are measured as excess returns where the monthly risk-free rate is deducted from the monthly raw returns. Sharpe ratio is calculated as annualized mean divided by annualized standard deviation. FF3 alpha is the intercept term of OLS regression of portfolio's monthly mean return series on the Fama and French three factor model.

The standard momentum strategy generates the highest monthly excess return of 1.49%. The return is significant at a one percent level. The long-only Winners portfolio has the second highest monthly return, concluding that the pure momentum strategy provides the highest absolute returns, and the combination strategies cannot enhance momentum portfolio return. This makes sense, as a low volatility strategy does not provide that high absolute return. However, the other way around, the combination long-only strategy increases the absolute returns of a low volatility portfolio. This means that the added momentum can enhance a low-volatility portfolio's absolute returns. Moreover, all selected portfolios outperform the market index in monthly returns.

When moving from monthly returns to the risk-adjusted returns measured by the Sharpe ratio, the best performers change. Firstly, low volatility long-only portfolio outperforms both momentum portfolios. Second, the combination long-only outperforms all pure portfolios with a Sharpe ratio of 0.91. On the other hand, the combination of long-short portfolios loses to every portfolio except the market. This concludes that using long-only portfolios, the combination of low volatility and momentum generates high risk-adjusted returns and outperforms the pure portfolios.

When comparing the FF3 alphas, the combination portfolios produce the highest and most significant alphas. Interestingly, from pure portfolios, the low volatility portfolio generates the highest alpha and is significant at a five percent level. All in all, the results are mixed as momentum portfolios generate the highest absolute returns. However, the low volatility portfolio outperforms momentum in risk-adjusted returns, and finally, the combination portfolio outperforms all pure portfolios in risk-adjusted returns. Figure 10 below presents the cumulative excess returns of the selected portfolios.

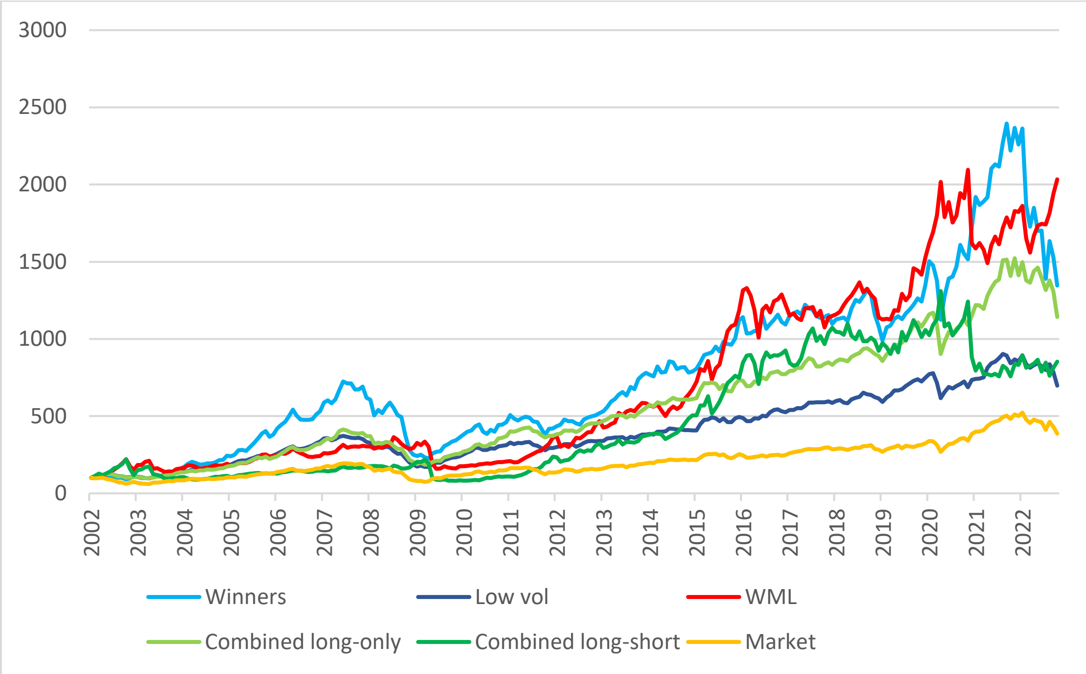


Figure 10. Comparison of the cumulative excess returns of pure, combination and market portfolios.

Figure 10 shows that the standard momentum strategy WML generates the highest cumulative excess returns. Pure momentum long-only Winners portfolio is second, and the long-only combined strategy is third. All portfolios outperform the market index. When cumulative returns are considered, the low volatility and momentum combination does not add value to the pure momentum strategy, either long-only or long-short portfolios.

5.5.2 HAC-robust t-statistics vs standard t-statistics

As the t-statistics used in this study are HAC-robust bootstrapped following Grobys and Junttila (2021), it is interesting to compare the results to the standard t-statistics. Table 12 below compares the t-statistics using five portfolios: low volatility, winners, WML, combination long-only, and combination long-short.

Table 12. Comparison of the bootstrapped HAC robust t-statistics and standard t-statistics

	Mean	α (CAPM)	α (FF3)	α (FF5)
Panel A: Low Vol				
Coefficient	0.86%	0.44%	0.38%	0.15%
(HAC robust t-statistic)	**(2.52)****	**(2.43)****	**(2.28)****	(0.86)
(Standard t-statistic)	**(3.49)*****	**(3.25)*****	**(2.85)*****	(1.12)
Panel B: Winners				
Coefficient	1.27%	0.54%	0.37%	0.22%
(HAC robust t-statistic)	**(2.4)****	(1.98)**	**(1.56)**	(0.99)
(Standard t-statistic)	**(3.05)*****	(2.49)**	**(1.91)***	(1.08)
Panel C: WML				
Coefficient	1.49%	1.76	1.71%	1.12
(HAC robust t-statistic)	(3.3)***	(3.68)***	(3.8)***	(2.41)**
(Standard t-statistic)	(3.26)***	(3.96)***	(3.96)***	(2.51)**
Panel D: Combination long-only				
Coefficient	1.08%	0.61%	0.54%	0.26%
(HAC robust t-statistic)	(3.08)***	(3.74)***	(3.36)***	**(1.49)**
(Standard t-statistic)	(3.91)***	(3.90)***	(3.54)***	**(1.71)***
Panel E: Combination long-short				
Coefficient	1.24%	1.77%	1.81%	1.10%
(HAC robust t-statistic)	(2.32)**	(3.31)***	(3.28)***	**(1.89)***
(Standard t-statistic)	(2.39)**	(3.88)***	(4.09)***	**(2.45)****

In table 12, Low Vol stands for the long-only low-volatility portfolio, Winners stands for the long-only momentum portfolio, WML stands for the long-short momentum portfolio, Combination long-only refers to the best performing long-only combination portfolio (DS momentum first) and Combination long-short refers to the best performing long-short combination portfolio (DS Volatility first). Table 12 provides coefficients of mean, CAPM alpha, FF3 alpha and FF5 alpha for all portfolios as well as HAC-robust and standard t-statistics.

Table 12 shows several differences between the standard t-statistics and HAC robust t-statistics. The standard t-statistics show higher significance than the HAC robust t-statistics across every portfolio and coefficient. In five cases, the difference affects the significance level (1%, 5%, or 10%), but both measures show significance at least at a ten percent significance level. Moreover, in two cases (FF3 alpha of the Winners portfolio and FF5 alpha of the Combination long-only portfolio), the coefficients are significant at a ten percent level if standard t-statistics were used but not significant when HAC-robust t-statistics are used. This is an important observation as it would change the core results of this study.

5.5.3 Sub-sample test

To investigate the robustness of the portfolio performance more in-depth, two sub-samples are formed. Table 13 below shows the monthly returns, Sharpe ratios, and FF3 alphas of the compared portfolios divided into two sub-samples.

Table 13. Monthly returns, Sharpe ratios and FF3 alphas of the sub-sample portfolios.

	Mean (HAC-robust t-statistic)	Sharpe ratio	FF3 alpha (HAC-robust t-statistic)
Panel A: 01/2002 - 05/2012			
Low Vol	0.98%* (1.69)	0.84	0.54** (2.36)
Winners	1.46%* (1.70)	0.79	0.74** (2.29)
WML	1.38%* (1.83)	0.64	1.35* (1.95)
Combination long-only	1.22%** (2.01)	0.97	0.77*** (3.22)
Combination long-short	1.26%** (2.02)	0.52	1.58* (1.95)
Market	0.45% (0.64)	0.26	- -
Panel B: 06/2012 - 09/2022			
Low Vol	0.74%*** (2.82)	0.77	0.12 (0.60)
Winners	1.08%** (2.16)	0.64	-0.11 (-0.39)
WML	1.60%*** (2.97)	0.97	1.82*** (3.72)
Combination long-only	0.94%*** (3.25)	0.84	0.22 (0.96)
Combination long-short	1.21%** (2.22)	0.63	1.80*** (3.57)
Market	0.92%*** (2.78)	0.77	- -

In table 13, Low Vol stands for the long-only low-volatility portfolio, Winners stands for the long-only momentum portfolio, WML stands for the long-short momentum portfolio, Combination long-only refers to the best performing long-only combination portfolio (DS momentum first) and Combination long-short refers to the best performing long-short combination portfolio (DS Volatility first). Mean is the monthly average return over the time period of January 2002 until September 2022. HAC-robust t-statistic is given in parentheses. Mean returns are measured as excess returns where the monthly risk-free rate is deducted from the monthly raw returns. Sharpe ratio is calculated as annualized mean divided by annualized standard deviation. FF3 alpha is the intercept term of OLS regression of portfolio’s monthly mean return series on the Fama and French three factor model. Panel A presents the results of the first sub-sample period and Panel B the results of the second sub-sample period.

The results over the two sub-sample periods are very different. From the market returns, over the first sub-sample, 1/2002 to 5/2012, the overall stock market performance is not high as the market portfolio returns 0.46% monthly excess returns. On the other hand, over the second sub-sample period from 6/2012 to 9/2022, the market returns 0.92% monthly excess return, which is over two times more than during the first period.

During the first period, the Winners portfolio generated the highest monthly return of 1.46%. The return is only significant at a ten percent level when calculated using HAC-robust t-statistics. Moreover, all pure and combination portfolios outperform the market index in monthly return, where the risk-free rate is deducted. However, only the returns of the combination portfolios are significant at the five percent level. The combination long-only portfolio generates the highest Sharpe ratio of 0.97 over the first sub-period and the low volatility portfolio second with 0.84. These findings are in line with the full sample results, and they are impressive as the market Sharpe ratio is only 0.26 in the first sub-sample. Finally, the combination long-only portfolio also generates the most significant FF3 alpha of 0.77% significant at a one percent level in the first sub-sample. Both pure and combination long-short strategies produce higher alphas, but they are significant only at a ten percent level.

In the second sub-sample, when the stock market performs better, the WML portfolio generates the highest monthly return of 1.60%, significant at a one percent level. The combination long-short portfolio comes second with 1.21% monthly return. All portfolios except low volatility outperform the market index. WML portfolio produces the highest Sharpe ratio of 0.97 in the second sub-sample. The combination long-only portfolio is second with 0.84. Winners and combination long-short portfolios lose to the market index in the Sharpe ratio in the second subsample. The low volatility portfolio generates the same Sharpe ratio as the market index, although having a lower monthly return. The results of the low volatility portfolio across the two sub-samples are in line with the finding from Blitz and van Vliet (2007), as they conclude that the low-volatility effect is stronger in bear market conditions. When looking at the FF3 alphas in the second sub-sample, only the long-short portfolios WML and combination generate significant positive alphas of 1.82% and 1.80%, respectively, both significant at one percent level.

Overall, the combination long-only portfolio performs best measured by the risk-adjusted returns by Sharpe ratio over both sub-periods, beating the market portfolio in both periods. In the first sub-sample, the combination long-only portfolio is the best, and in the second, second best. On the other hand, the combination portfolio's monthly return in the second sample outperforms the market index by only 0.02% and is not thus that impressive. The WML portfolio also performs well, but the Sharpe ratio of 0.64 in the first period is low. Figures 11 and 12 below demonstrate the cumulative excess returns of the portfolios in the first and second sub-samples, respectively.

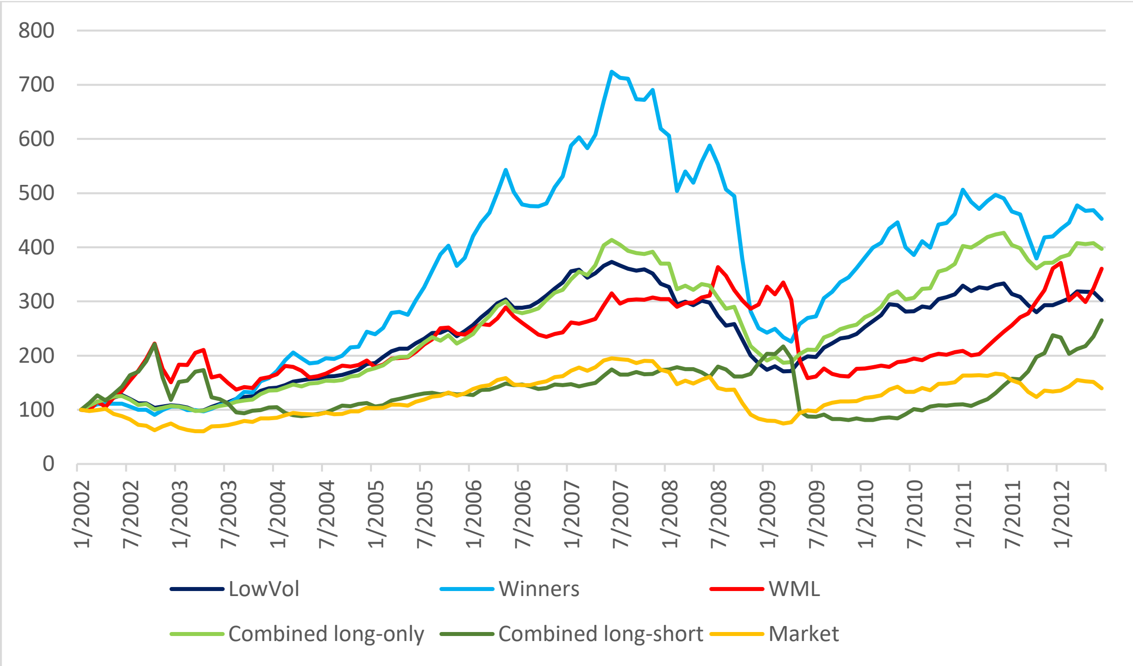


Figure 11. Cumulative excess returns of the first sub-sample period.

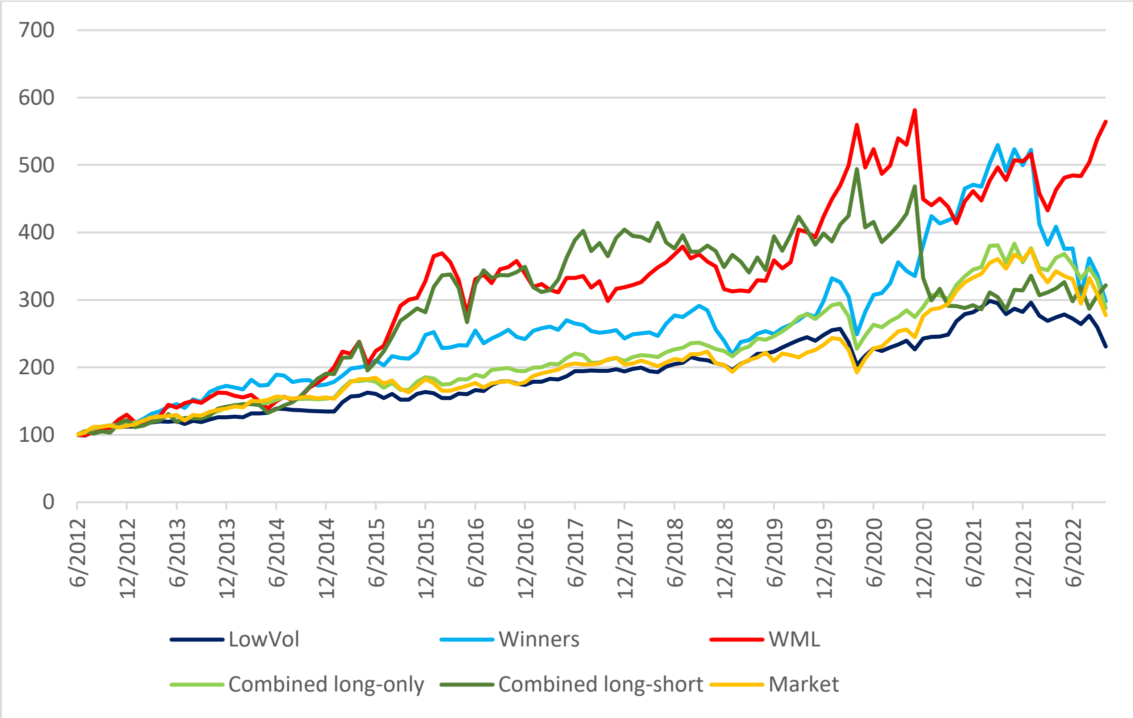


Figure 12. Cumulative excess returns of the second sub-sample period.

Interestingly, the combination long-only portfolio outperforms the WML and combination long-short portfolios in cumulative returns in the first sub-sample, although it has a lower monthly return. The lower volatility of the long-only portfolio probably explains this. In the second sub-sample, the WML portfolio's cumulative returns are highest by a margin, but the rest are almost at the same level at the end of the time period.

6 Conclusions

The core of this study is to investigate stock market efficiency. According to the efficient market hypothesis no excess returns can be generated using past stock return information. Motivated by many different studies, including Blitz and Van Vliet (2007, 2016) and Grobys and Huhta-Halkola (2019), this thesis examines whether the combination of past information about stock returns and return volatility can help to generate excess returns. Similar to Grobys and Huhta-halkola (2019), this study gathers evidence from the Nordic stock market.

First, this thesis investigates whether the momentum and idiosyncratic volatility effects are found in the Nordic stock market over the sample period from January 1999 until September 2022, including a return period from January 2002 to September 2022. Second, it investigates combined investment strategies of volatility and momentum and focuses on finding whether combining the two effects can enhance the pure strategies. Combination and pure strategies are compared to find the best ways to invest using basic measures of momentum and volatility. Both long-only and long-short strategies are included in the study.

First, by studying the pure strategies, it can be concluded that momentum effect exists in the Nordic stock market over the sample period. A portfolio including stocks with the highest past 12-month (skipping the most recent month) return outperforms the portfolio with the lowest past 12-month return and the market index measured by absolute and risk-adjusted returns. Moreover, long-short portfolio WML generates significant positive returns and a positive alpha when CAPM, FF3 and FF5 are controlled. However, there is not enough robust evidence for the low-volatility effect in the Nordic stock market. Although a portfolio consisting of stocks with the lowest past 36-month volatility outperforms the portfolio consisting of stocks with the highest past 36-month volatility and the market index by absolute and risk-adjusted returns, the alpha of the low-volatility portfolio is not significant when the FF5 is controlled. Moreover, the LMH portfolio does not produce returns statistically different from zero.

Volatility and momentum combination portfolios are formed using 50/50, double screening, and ranking. Among the long-only portfolios, the momentum-first double screening method generated the best Sharpe ratio of 0.91, slightly outperforming the ranking method (0.89). The combination of low volatility and momentum significantly increases risk-adjusted returns compared to pure strategies. However, the long-short portfolio formation is not that efficient. None of the combination long-short strategies outperform the simple, pure WML momentum strategy, even measured by risk-adjusted returns. The correlation between Winners and low volatility and Losers and High volatility might explain this. When the positive correlation of combining items is relatively high, the portfolio's volatility stays the same and could even increase.

When the sample period is divided into two sub-samples, the results show that only the standard long-short WML and long-only combination strategies can outperform the market index in risk-adjusted returns in both samples separately. The combination strategy is more consistent from the two, recording Sharpe ratios of 0.97 and 0.84 for the corresponding sub-periods compared to the WML portfolio's Sharpe ratios of 0.64 and 0.97. Moreover, the monthly return of the WML portfolio over the first sub-sample is statistically significant only at a ten percent level and a one percent level in the second sub-sample. In contrast, the returns of the combination long-only portfolio are significant at five and one percent levels, respectively. The long-only combination of low volatility and momentum is the most robust strategy in risk-adjusted returns. Also, the long-only low volatility portfolio performs solidly in both sub-samples outperforming the market in the first sample in both absolute and risk-adjusted returns. Over the second sub-period, it generates the same Sharpe ratio as the market portfolio but loses in absolute returns.

When the returns of the portfolios are regressed on the standard risk factor models, the WML portfolio and combination long-short portfolio are the only ones to generate positive alphas when the FF5 is controlled, significant at five and ten percent levels, respectively. The long-only combination portfolio generates a significant alpha when the CAPM and the FF3 are controlled, but the FF5 can capture the portfolio's excess returns.

Particularly the added profitability factor RMW in the FF5 captures the returns as the factor loading is positive and significant at a one percent level when FF5 is controlled. This is in line with earlier studies, such as Novy-Marx (2014), who argues that defensive low volatility portfolios can generate excess returns when FF3 is controlled, but when adding the profitability factor, excess returns can be captured. Moreover, this finding contradicts the conclusions from Blitz (2016), who argue that low-volatility effect is an independent effect. The explanation for the finding that profitability captures low volatility returns could be related to the lower net profit volatility of the high profitability firms. If a firm can maintain a steady profit generation over time, it is likely that the stock volatility is also lower than average.

As stock return volatility is often expressed as risk, it can be concluded that a low volatility strategy generates higher returns with lower risk. In addition, the momentum effect shows that stocks that performed well in the past tend to continue performing well. Furthermore, the combination-long-only strategy of low volatility and momentum generates higher risk-adjusted returns than the market and the pure-play strategies. All these observations are against the Efficient market hypothesis. This study contributes to the previous literature by investigating the low-volatility effect in the Nordic stock markets and the combination of volatility and momentum strategies. Moreover, this study contributes by adding more robustness to the conservative formula proposed by Blitz and van Vliet (2016) as this study uses a similar but not identical portfolio model, a different time period, and different markets as Hou, Xue, and Zhang (2020) suggest in their paper to study replication of anomalies.

The results of this study can be practically implied broadly in the financial markets. The findings of this study point out that high returns can also be achieved without taking a significant amount of risk, although there are always risks in the stock market. Retail investors, as well as asset managers, could find a useful strategy to allocate at least a part of their portfolio to the lower volatile stocks. The low volatility strategy could also be implemented as an alternative for fixed income investments, as the overall portfolio volatility is relatively low. Furthermore, the combination of low volatility and momentum is attractive, and this study proposes an interesting investment strategy for active stock market participants that seek to outperform the market.

Further research could investigate the combination of volatility and value strategies. In addition, the combination of the volatility and the MAX effect (e.g., Bali, Cakici & Whitelaw, 2011) in the stock markets could be an exciting topic for future research.

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