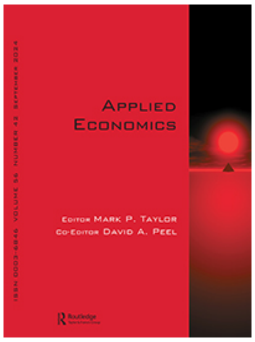

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Combining low-volatility and momentum: recent evidence from the Nordic equities

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ABSTRACT

This paper investigates the profitability of combined low-volatility and momentum investment strategies in the Nordic stock markets from January 1999 to September 2022. Confirming earlier studies, our results first indicate that both the volatility and momentum effects persist as pure-play strategies. Further, we explore combined strategies using 50/50, double screening, and ranking strategies. Among the long-only portfolios, the momentum-first strategy generates the best Sharpe ratio using the double screening method–slightly outperforming the ranking method. Additionally, all long-only combination portfolios outperform the market in terms of risk-adjusted returns. Combination long-short strategies produce significantly higher risk-adjusted returns than pure-play strategies. Surprisingly, novel evidence suggests that none of the combination long-short strategies outperforms the pure momentum strategy after risk-adjusting the returns using the Fama and French five-factor model, implying that while momentum may enhance the returns from the low-volatility strategy, the reverse is not true for the Nordic stock markets.

KEYWORDS

Efficient markets; volatility effect; momentum; stock markets; asset pricing

JEL CLASSIFICATION

G10; G11; G14; G15

I. Introduction

The low-volatility effect, also known as the low-risk effect, refers to the asset pricing anomaly where – contrary to the theorized relationship between risk and return – low-risk portfolios outperform both the market index and high-risk portfolios. Interest in low-volatility investing has rekindled in recent years following periods of high volatility – especially after the 2007–08 financial crisis. Aside from being documented in developed and emerging markets worldwide (Ang et al. 2006; Blitz, Pang, and van Vliet 2013; Blitz and van Vliet 2007; Dutt and Humphery-Jenner 2013), the low-volatility effect has also been shown to enhance the returns on the popular momentum strategy (Bornholt and Malin 2011). Extending earlier literature, this study explores the persistence of the low-volatility and momentum anomalies in Nordic stock markets. In doing so, our goal is to determine whether a combination of these strategies can outperform the pure-play low-volatility and momentum portfolios or the market index, respectively.

Evidence for the low-volatility effect has been documented already in the early 1970's, when it was argued that the actual relationship between stock beta and returns may not be as steep as predicted by the Capital Asset Pricing Model (CAPM) (Black, Jensen, and Scholes 1972; Fama and Macbeth 1973; Haugen and Heins 1975). That is, the expected returns on low-volatility stocks would lie above the capital market line (CML), and vice versa, the expected returns of high-volatility stocks would lie below it. Consistent with this argument, Blitz and van Vliet (2007) find that stocks with low past volatility generate significant excess returns as measured by the Sharpe Ratio and the CAPM alpha. They conclude that this effect is similar to that of other well-known anomalies, including size, value, and momentum. The low-volatility effect, which is also shown to be significant in the U.S., the European, and the Japanese markets throughout the 1986–2006 period, has lower maximum drawdowns and considerably higher performance in bear markets than in bull markets. Furthermore, Blitz

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and van Vliet (2007) note that the strategy is particularly beneficial to risk-averse investors, such as pension funds.

Tests of the CAPM in emerging markets yield even more surprising results. In particular, Blitz Pang, and van Vliet (2013) find that contrary to the predictions of the CAPM, portfolios sorted on past volatility exhibit a flat or even a negative relationship between risk and return. This effect is robust among large-cap stocks, holds when controlling for the size, value and momentum factors, and appears to increase over time. While this finding is consistent with previous evidence documented by Blitz and van Vliet (2007) for the U.S., the European and Japanese equity markets, the low-volatility effect is in fact shown to be uncorrelated between the two markets.

There is some literature arguing that the low-volatility effect may be explained by behavioural theories and factors related to limits of arbitrage. For instance, Baker, Bradley and Wurgler (2011) argue that the CML – the slope between risk and expected returns – flattens as irrational investors push up the demand for high-volatility stocks, whereas expected returns remain capped by fixed benchmarks and access to leverage. This could suggest the profitability from the low-volatility strategy may be driven primarily by its short leg.

Low-volatility strategies tend to not require significant trading activity – performing efficiently with a turnover of about 30% only (van Vliet 2018). They also include stocks that are larger and more liquid than average, reducing trading costs. However, there is conflicting evidence regarding the robustness of the low-volatility strategy's alphas when controlling for additional standard risk factors. Specifically, the value factor model has been shown to explain the low-volatility or minimum variance alpha in one instance (Chow et al. 2011), but not in others (Blitz, Pang, and van Vliet 2013; Blitz and van Vliet 2007). Upon further investigation, Blitz (2016) conclude that the value factor is only useful in explaining the low-volatility alpha in the specific sub-sample period from 1963 to 1984, and only among large-cap stocks.

Meanwhile, the momentum strategy, which involves buying past high performers (winners) and selling past low performers (losers), is one of the many anomalies that has enjoyed a prolonged persistence in global financial markets (Drew et al. 2007; Okunev and White 2003). It has been extensively studied in finance literature (Jegadeesh and Titman 1993; Moskowitz and Grinblatt 1999; George and Hwang 2004; Jannen and Pham 2009; Novy-Marx 2012, etc.), and has been shown to suffer from occasional crashes (Daniel and Moskowitz 2016; Grobys, Ruotsalainen, and Äijö 2018). Due to its features and ongoing prominence as an investment vehicle, it is an ideal strategy to test alongside and in combination with the low-volatility strategy.

Among U.S. stocks, the momentum strategy has been shown to produce significant positive returns of approximately 1% per month, or 12% per annum (Jegadeesh and Titman 1993; Rouwenhorst 1998), which is in excess of the 8% per annum earned by the S&P 500 from 1957–2018. However, momentum crashes can wipe away as much as 91% of the strategy's value, and affect returns for an extended period. Barroso and Santa-Clara (2015) find that a risk-managed momentum portfolio, constructed by scaling on past return information to keep volatility fixed, can significantly alleviate the momentum crash risk.

Just as combinations of the momentum and value strategies have been shown to outperform pure-play portfolios (Asness et al. 2013; Grobys and Huhta-Halkola 2019; Leivo 2012), momentum returns may be increased by combining it with a low-risk or low-volatility strategy, and vice-versa, the returns from low-volatility strategy may be amplified if combined with momentum (Bornholt and Malin 2011; van Vliet 2018). It is therefore interesting to examine whether a combination of these two strategies can produce persistent alphas and higher risk-adjusted returns, across distinct asset markets.

In this article, we investigate the performance of the low-volatility strategy, the momentum strategy, and combinations of the low-volatility and momentum strategies in the Nordic stock markets, which consist of stock markets in Denmark, Finland, Norway, and Sweden.[1] Covering a sample period of 20 years, from 2002–2022, we determine whether the strategies produced returns and Sharpe Ratios in

[1]Owing to the considerably smaller size of the Icelandic stock market, we follow the precedent study of Grobys and Huhta-Halkola (2019) by excluding Icelandic stocks from this study.

excess of the market, and whether they produce significant alphas after controlling for standard risk factors included in the capital asset pricing model (CAPM), the Fama and French three-factor model (FF3), and the Fama and French five- factor model (FF5). For the purpose of this study, prices of stocks from the Swedish, Norwegian and Danish markets are converted using the corresponding exchange rates into Euros.

Our study contributes to the existing body of literature on market anomalies in several important ways. Grobys and Huhta-Halkola (2019) highlight that compared to the US equity market, the Nordic stock market is relatively new, yet developed equity market. Foreign ownership of the Nordic stock markets has undergone some dramatic changes and started to increase from the early 1990s, as the Nordic economies have developed, and the equity markets have become more actively traded. An interesting feature of Nordic equity markets is that, at times, they experience high levels of volatility as in times of distress–especially institutional investors tend to withdraw their investment from these markets first–a phenomenon often regarded the "flight to safety effect." Hence, it is interesting to explore the profitability of the low-volatility strategy or its combinations with the popular momentum strategy in this special market environment. As pointed out in Grobys and Huhta-Halkola (2019), it is important to study stock market anomalies across samples with differing features, such as size or liquidity (Fama and French 2008; Hou, Xue, and Zhang 2020). Hence, our study adds to the growing body of literature exploring the profitability of investment strategies in Nordic equity market settings (e.g. Grobys and Huhta-Halkola 2019; Jokipii and Vähämaa 2006; Leivo 2012; Leivo and Pätäri 2009; Nikkinen et al. 2009; Rinne and Vähämaa 2011; Silvasti, Grobys, and Äijö 2021). Next, our study adds to the body of literature testing the often-analysed efficient market hypothesis (Fama 1970). In doing so, we contribute to this strand of literature by employing portfolio approaches involving combined signals derived from portfolio sorts on low-volatility and momentum implemented in a market environment known for providing investors a high-level of information-flow-efficiency (Silvasti, Grobys, and Äijö 2021). Further, given the potential crash risk associated with momentum strategy, the performance of risk-adjusted returns of a combination of low-volatility and momentum strategies is studied, which to the best of our knowledge, is a novel feature in this relatively new, yet developed equity market. Finally, due to contradicting evidence regarding the robustness of the low-volatility strategy's alphas when controlling for additional standard risk factors (Blitz 2016; Blitz, Pang, and van Vliet 2013; Blitz and van Vliet 2007; Chow et al. 2011) it is important to shed new light on this issue using novel data which exhibit perhaps very different features than data samples used in earlier studies.

The findings of this paper indicate that while the low-volatility effect can be found in the Nordic stock markets, earning average monthly excess returns of 0.84% compared to the market's 0.69%, the low-volatility alpha only remains significantly positive after using the CAPM (Sharpe 1964) or FF3 models (Fama and French 1993) for risk adjustments. Employing the FF5 model for risk adjustment (Fama and French 2015), the profitability factor appears to wipe away the low-volatility alpha. The low-volatility effect is therefore likely explained by existing risk-factors. Meanwhile, in the Nordic stock markets, the momentum strategy produces positive and significant alphas in all factor models, suggesting that it persists as an unresolved anomaly. The combination of low-volatility and momentum strategies may reward the investor with average excess returns as high as 1.13%–depending on the portfolio construction–yet it too can mostly be explained by the profitability and investment factors.

The rest of the paper is organized as follows. Chapter 2 explains the data and methodology. Chapter 3 describes the statistical models used in this study. Chapter 4 presents the empirical findings of the OLS regressions for the low-volatility and momentum pure-play and combination strategies, and sub-sample tests. Chapter 5 provides a summary and some concluding remarks.

II. Data and methodology

Data

Weekly and monthly stock price data for the Finnish, Swedish, Danish, and Norwegian stock markets is obtained from January 1999–September 2022. Following Grobys and Huhta-Halkola (2019), the Icelandic market is excluded because of its small size. The stock market data includes all stocks that have been actively traded at some point during the sample period, and excludes delisted stocks at the time of delisting to avoid survivorship bias. After generating volatility and combination portfolios using data from prior 36 months, and excluding financial stocks and nano-stocks (e.g. stocks with a maximum market value lower than €20 million), the final sample consists of 1645 stocks, sorted into various portfolios from January 2002–September 2022.

Portfolio sorts

Following prior literature (Grobys and Huhta-Halkola 2019; Leivo 2012; Leivo and Pätäri 2009; Silvasti, Grobys, and Äijö 2021) and owing to the low number of large-capitalization firms, stocks are sorted into equally-weighted portfolios for both the low-volatility and momentum strategy. In this regard, we would like to refer to Grobys and Huhta-Halkola (2019), who documented that in the early 2000s, Nokia's market cap was more than 25% of the total market value of all stocks in the Nordic stock market. Employing value-weighted portfolios would result in investment vehicles where one stock's weight is more than half of the long or short leg portfolio, implying that the portfolio performance would be almost solely driven by one stock. From a practical point of view, this is not a realistic representation of an implementable strategy. Therefore, we choose to follow earlier literature and focus solely on equal-weighted returns because it provides according to Grobys and Huhta-Halkola (2019, 2877) "the best representation of the returns that could actually have been achieved."[2] Furthermore, each month, non-active or delisted stocks are removed from the sample and the portfolios are rebalanced. Pure strategy portfolios for volatility and momentum are formed using only the top third largest stocks. The low-volatility, momentum and combination strategies are evaluated using long-only and long-short portfolios.

Using terciles sorts, stocks are sorted into momentum portfolios, rebalanced monthly based on their returns over the previous 12 months, excluding the most recent month. Stocks with the highest cumulative past returns are allocated to the winner stock portfolio (winners), whereas stocks with the lowest cumulative past returns are allocated to the loser stock portfolio (losers). Average returns in the one-month holding period are the winners-minus-losers (WML).

Further, using tercile sorts, low-volatility portfolios are created using weekly stock return data over the past 36 months for each stock, following the methodology of earlier studies on the low-volatility effect (Blitz and van Vliet 2018; Van Vliet 2018). The standard deviation is used as the measure of return volatility, and stocks with the lowest return standard deviations over the previous 36 months are allocated to the low-volatility portfolio of stocks, whereas stocks with the highest return standard deviations over the previous 36 months are allocated to the high-volatility portfolio of stocks. The long-short low-volatility portfolio returns are defined as the returns obtained by taking a long position on low volatility stocks and a short position on high volatility stocks. Pure-play and combination portfolios of low-volatility and momentum are rebalanced monthly to aid in comparison.[3]

Next, we explore the payoffs of eight different combination portfolios using a holding period of one month. These portfolios are also equally weighted, and employ long-only and long-short strategies. In the first instance, the portfolios use a 50/50 combination of the volatility and momentum strategy. In the long-only strategy, low-

[2] However, future studies could take a more theoretical perspective and explore this issue for value-weighted portfolios even though such highly concentrated portfolios might be irrelevant from a practical point of view.

[3] Whereas we follow the literature and employ a 36-month formation period for sorting stocks into terciles based on their past volatility, in Table A1 in the Appendix, we report the average payoffs for the low-volatility strategy using various formation periods, ranging between 60- and 12-months. Our findings indicate that the well-established formation period of 36-months produces indeed the highest payoffs.

volatility stocks are combined with winner stocks (high momentum), and high-volatility stocks are combined with loser (low momentum) stocks. Similarly, the low-volatility long-short portfolio is combined with the momentum long-short portfolio.

Secondly, combination portfolios are created by double-screening stocks by volatility and momentum, and using both volatility-first and momentum-first sorting. For example, in the volatility-first double-screened combination portfolio, stocks are first sorted into two halves by volatility, and then by momentum. This process generates two portfolios, winner stocks from the low volatility universe, and loser stocks from the high-volatility universe. This allocation procedure is repeated vice versa for the momentum-first double-screened combination portfolios.

Lastly, combination portfolios are created for the average rank of stocks on both of their characteristics, volatility and momentum. High-rank combination portfolios then include stocks within the highest tenth rankings (i.e. by the lowest volatility and highest momentum average), and low-rank combination portfolios include stocks within the lowest tenth rankings (i.e. by the highest volatility and the lowest momentum average). The long-short combination portfolio takes a long position on high-rank stocks and a short position on low-rank stocks.

The low-volatility and momentum strategies are tested using ordinary least squares (OLS) regressions of the excess portfolio returns on the capital asset pricing model (CAPM), the Fama French three-factor model, and the Fama French five-factor model to determine whether the excess returns from these strategies in pure play or combination are statistically significant (as measured by the *t*-statistic) after controlling for standard asset pricing risk factors often used for risk adjustments.

The implications of various dependency structures in financial time-series data has been explored in recent literature. For example, in the context of this study, momentum strategies are prone to crashes, increasing the number of outliers and extreme events in the return series of portfolios sorted on momentum. Similar issues may persist in the return series for low-volatility and combination portfolios. In addition, based on Godfrey's (2009) findings, traditional *t*-statistics may suffer from severe size distortions if the dataset is small, fat-tailed, and highly skewed. Although the Newey and West (1987) covariance matrix accounts for autocorrelation and heteroskedasticity, it has been proposed that more accurate and robust covariance matrices can be achieved through bootstrapping techniques. For instance, Liu et al. (2019) find that bootstrapped-based testing may produce more reliable estimates than standard tests. Note that Huang et al. (2020) find that the *t*-statistics of excess returns may increase but do not exceed critical values when applying more robust statistical tests via bootstrapping.

Therefore, in this study, we use Grobys and Junttila's (2021) blocks-bootstrapping procedure, which does not preclude specific information about the dependency structure of the data unlike more standard bootstrapping methods. These blocks-bootstrapped *t*-statistics are marked as HAC-robust *t*-statistics in the results. In addition, due to varying market conditions over the sample period, sub-sample tests are performed for robustness by splitting the sample in two periods, from 2002–2012, and 2012–2022 respectively.

III. Empirical Findings

This section further describes statistically the data and presents the empirical findings regarding the excess returns on the pure-play and combination portfolios.

Descriptive Statistics and Correlation Coefficients

Table 1 reports the descriptive statistics of the low-volatility, winner and combination portfolio returns, specifically, the monthly excess returns (portfolio returns less the risk-free rate) over the period January 2002 until September 2022, the monthly minimum and maximum returns, the annualized excess returns, the annualized standard deviation, the Sharpe Ratio, and the beta. The reported *t*-statistics are calculated using the blocks-bootstrapping method introduced by Grobys and Junttila (2021), and are HAC-robust. We also report the blocks bootstrapped Sharpe ratios employing the blocks-bootstrapping method proposed by Grobys and Junttila (2021).

Table 1. Descriptive Statistics.

	Low Vol	High Vol	LMH	Winners	Losers	WML	Market
Panel A: All Nordic stocks equally weighted							
Mean	**0.84%**	0.74%	0.10%	**1.92%**	−0.35%	**2.27%**	**0.69%**
(HAC robust t-statistic)	(−2.60)	(−1.07)	(−0.20)	(−3.49)	(−0.55)	(−6.29)	(−1.76)
Min	−15.49%	−25.41%	−35.53%	−19.62%	−31.97%	−21.44%	−19.05%
Max	9.63%	38.85%	26.17%	35.46%	29.47%	28.62%	21.96%
Annualized mean return	10.55%	9.31%	1.15%	25.70%	−4.11%	30.96%	8.56%
Annualized STDEV	11.99%	30.76%	24.99%	22.27%	31.42%	21.48%	18.36%
Sharpe ratio (SR)	0.88	0.30	0.05	1.15	−0.13	1.44	0.47
Bootstrapped SR	0.16	0.07	0.01	0.22	−0.03	0.40	0.11
Beta	0.56	1.11	−0.55	0.96	1.31	−0.35	–
Panel B: Top third Nordic stocks by market capitalization equally weighted							
Mean	**0.86%**	0.38%	0.48%	**1.27%**	−0.22%	**1.49%**	**0.69%**
(HAC robust *t*-statistic)	(2.52)	(0.55)	(0.94)	(2.40)	(−0.35)	(3.30)	(1.76)
Min	−14.04%	−32.57%	−27.81%	−25.67%	−36.78%	−18.58%	−19.05%
Max	10.96%	30.45%	22.69%	17.70%	21.60%	22.14%	21.96%
Annualized mean return	10.82%	4.66%	5.91%	16.36%	−2.60%	19.43%	8.56%
Annualized STDEV	13.46%	34.44%	27.51%	22.75%	32.52%	25.03%	18.36%
Sharpe ratio (SR)	0.80	0.14	0.21	0.72	−0.08	0.78	0.47
Bootstrapped SR	0.16	0.03	0.06	0.15	−0.02	0.21	0.11
Beta	0.62	1.49	−0.87	1.06	1.45	−0.39	–

	Long-Only Combination				Long-Short Combination				
	50/50	DS Vol First	DS Mom First	Ranking	50/50	DS Vol First	DS Mom First	Ranking	Market
Mean	**1.02%**	**1.13%**	**1.08%**	**1.11%**	**0.87%**	**1.24%**	**0.93%**	**1.21%**	**0.69%**
(HAC robust *t*-statistic)	(2.43)	(2.59)	(3.08)	(2.89)	(1.90)	(2.32)	(1.79)	(2.21)	(1.76)
Min	−17.64%	−18.73%	−17.43%	−16.67%	−32.48%	−50.04%	−29.39%	−40.04%	−19.05%
Max	14.32%	13.92%	11.02%	10.37%	23.86%	27.96%	22.74%	26.84%	21.96%
Annualized mean return	13.00%	14.42%	13.76%	14.20%	10.92%	15.91%	11.76%	15.54%	8.56%
Annualized STDEV	16.99%	17.66%	15.12%	15.89%	23.89%	28.35%	27.13%	29.17%	18.36%
Sharpe ratio (SR)	0.76	0.82	0.91	0.89	0.46	0.56	0.43	0.53	0.47
Bootstrapped SR	0.15	0.16	0.20	0.18	0.12	0.15	0.11	0.11	0.11
Beta	0.82	0.82	0.68	0.71	−0.70	−0.77	−0.82	−0.88	–

This table presents the descriptive statistics of the six equally-weighted pure-play portfolios (Panel A), the equally-weighted pure-play portfolios by top tercile of market capitalization (Panel B), the eight volatility and momentum combination portfolios (Panel C), and the market index. Mean is the monthly average return over the time period January 2002–September 2022. HAC-robust *t*-statistics are *t*-statistics that account for various dependency structures in the return data, and based on blocks-bootstrapping methodology developed by Grobys and Junttila (2021), and all mean returns with HAC-robust *t*-statistics significant on at least a 10% level are stated in **bold**. Min and Max are the monthly minimum and the monthly maximum returns. Annualized mean and standard deviation are the annualized values for the monthly average returns and standard deviations. All returns are measured as excess returns, i.e. raw returns less the risk-free rate. Thus, the Sharpe Ratio is the annualized mean divided by the annualized standard deviation. To account for heavy tails, this table reports also bootstrapped Sharpe ratios using the blocks bootstraps approach outlined in Grobys and Junttila (2021).

Panel A reports the descriptive statistics of the pure-play volatility portfolios in columns 1 to 3, and momentum portfolios in columns 4 to 6 for all equally weighted Nordic stocks. Comparable statistics for the market portfolio are reported in column 7. The low-volatility portfolio produces statistically significant average monthly excess returns of 0.84%, however, the average excess returns for the LMH portfolio are not only insignificant but lower than the market excess return (0.69%). Meanwhile, the high momentum or winner portfolio earns a significant average monthly excess return of 1.92%, and the WML portfolio earns an even higher significant excess return of 2.27%. This suggests that while the low-volatility effect exists in the Nordic markets, it is significantly weaker than the momentum effect.

Panel B reports the descriptive statistics of the pure-play volatility portfolios in columns 1 to 3, and momentum portfolios in columns 4 to 6, for Nordic stocks that fall within the top tertile of market capitalization. The average excess returns over the sample period is 0.86% for the low-volatility portfolio, and 1.27% for the high momentum (winner) portfolio, compared to 0.69% for the market portfolio. These returns indicate that the low-volatility and momentum strategies persist among large cap stocks. Interestingly, the low-volatility portfolio produces the smallest maximum monthly returns out of all portfolios, across both the equally-weighted and the largest tercile sample.

Panel C of Table 1 reports the descriptive statistics of long-only combination portfolios in columns 1–4, and long-short combination portfolios in columns 5–8 of the low-volatility and momentum strategies. Columns 1 and 5 present the statistics for portfolios constructed using the 50/50 long-only and 50/50 long-short combination strategies respectively. While the average excess returns are the lowest out of the three combination portfolios, the 50/50 combination yields 1.02% in the long-only portfolios, significant at a 5% level, and 0.87% in the long-short portfolios, significant at a 10% level. The respective average excess returns for the double-sorted (DS) volatility-first portfolios, reported in columns 2 and 6 for the long-only and long-short strategies, are 1.13% and 1.24%, significant at 5%. Meanwhile, the DS momentum-first portfolios earn an average excess return of 1.08%, significant at a 1% level in the long-only strategy, compared to 0.93%, significant at only a 10% level, in the long-short strategy. Overall, these descriptive statistics provide a rough view on the earning potential of various portfolio combinations of the low-volatility and momentum strategies in the Nordic markets.

Figure 1 presents the cumulative average excess returns of the pure volatility, pure momentum, the long-only combination portfolio and the long-short combination portfolio, respectively. While the low-volatility portfolio significantly outperforms the market after the 2007–08 financial crash, the difference in the excess returns between the low- and high-volatility portfolios does not. This is indicative of the success of a long-only strategy with regards to the low-volatility effect in the Nordic markets. On the other hand, not only does the high-momentum (winner) portfolio consistently outperform the market since the start of the sample period, the low-momentum (loser) portfolio appears to consistently underperform it, leading to significant excess returns for the WML portfolio that grew substantially higher than the market returns in the ex-post 2010 period.

All the combination long-only portfolios of the low-volatility and momentum strategies comparably outperform the market portfolio over the entire sample period studied, with the DS volatility-first, DS momentum-first, and the ranking portfolios also noticeably outperformed the 50/50 long-only portfolio over the recent years. Meanwhile, among the combination long-short portfolios, the DS volatility-first and the ranking portfolios appear to significantly outperform the 50/50 and the DS momentum-first portfolios and the market portfolio over the entire sample period. A sharp decline in the cumulative average excess returns of all long-short combination portfolios can be seen during the first quarter of 2021, possibly coinciding with a momentum crash brought on by the reversal in returns on loser stocks.

Furthermore, we observe from Figures 1 and 2 sharp declines in the cumulative returns of the low-volatility pure-play portfolios and combination long-only portfolios arriving in the beginning of 2020 – coinciding with the arrival of the worldwide COVID-19 outbreak. The arrival of this event was unforeseen by market

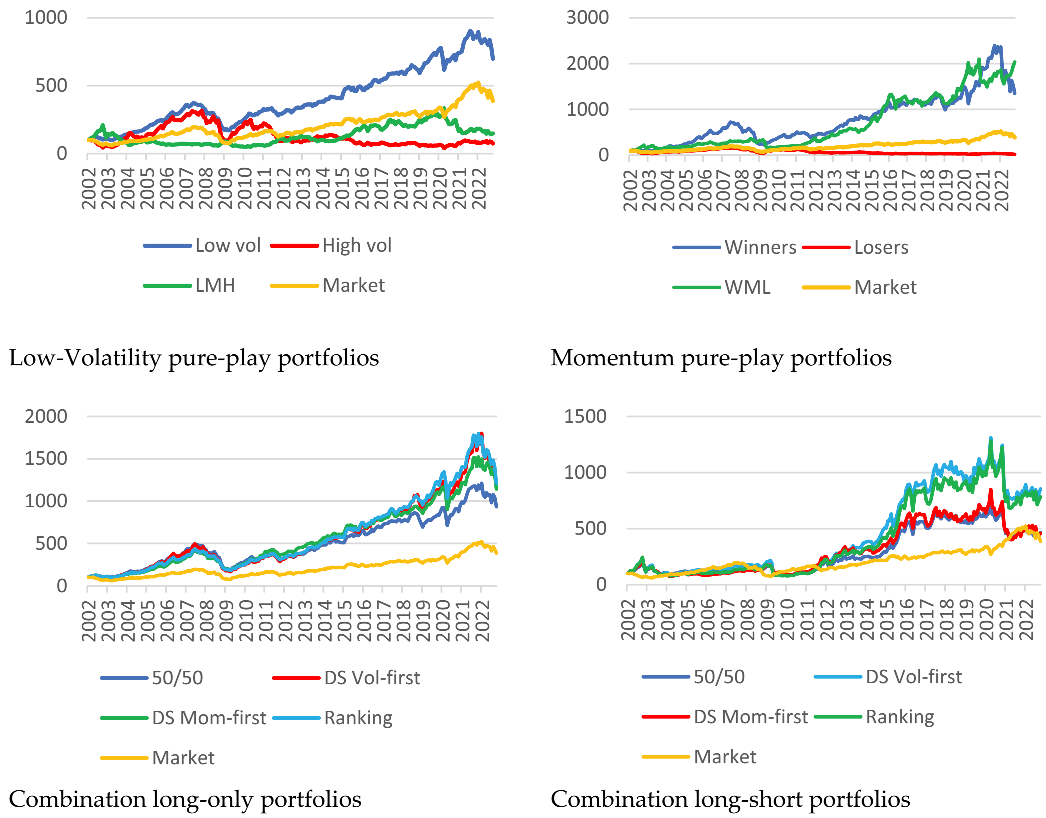


Figure 1. Cumulative excess returns for each portfolio.

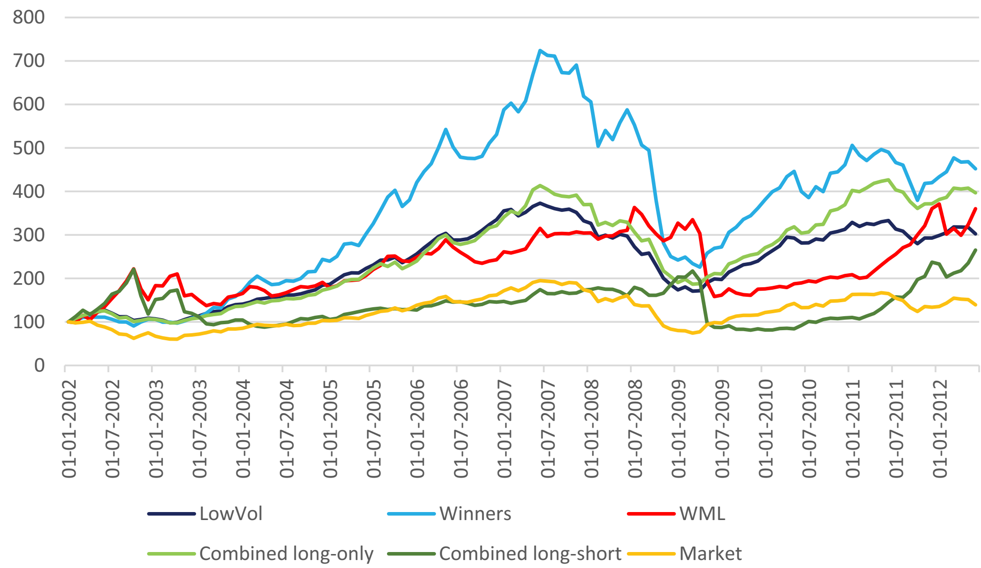
participants, and hence, came as a surprise. Even some well-known "hedges" didn't seem to workout. For example, using a difference-indifferences setting, Grobys (2020) explores the dynamic correlation between Bitcoin and stocks. Whereas earlier studies argued that Bitcoin serves as a hedge for equities, Grobys' (2020) finds that Bitcoin performed poorly in hedging the tail risk that arose from the COVID-19 outbreak. On the other hand, Grobys' (2020) findings show that gold serves indeed as a safe haven as the correlation between gold and US stocks is in the early wake of the COVID-19 outbreak statistically not different from the before-the-event sample average. This suggests that investors could diversify certain tail risks by adding gold to their portfolios. Developing a strategy incorporating gold on top of low-volatility pure-play portfolios or combination long-only portfolios exceeds, however, the scope of this study and is therefore left for future research.

The correlation coefficients presented in Table 2 provide additional perspective on the relationship between the returns of the low-volatility and momentum pure-play portfolios. The winner and low-volatility portfolio returns are highly positively correlated, with a coefficient of 0.81, and both of these portfolios are also highly positively correlated with the market index, with coefficients of 0.86 and 0.82 respectively. Surprisingly the long-short portfolios LMH and WML are negatively correlated with almost every long portfolio and the market index, but are positively correlated with each other with a coefficient of 0.5.

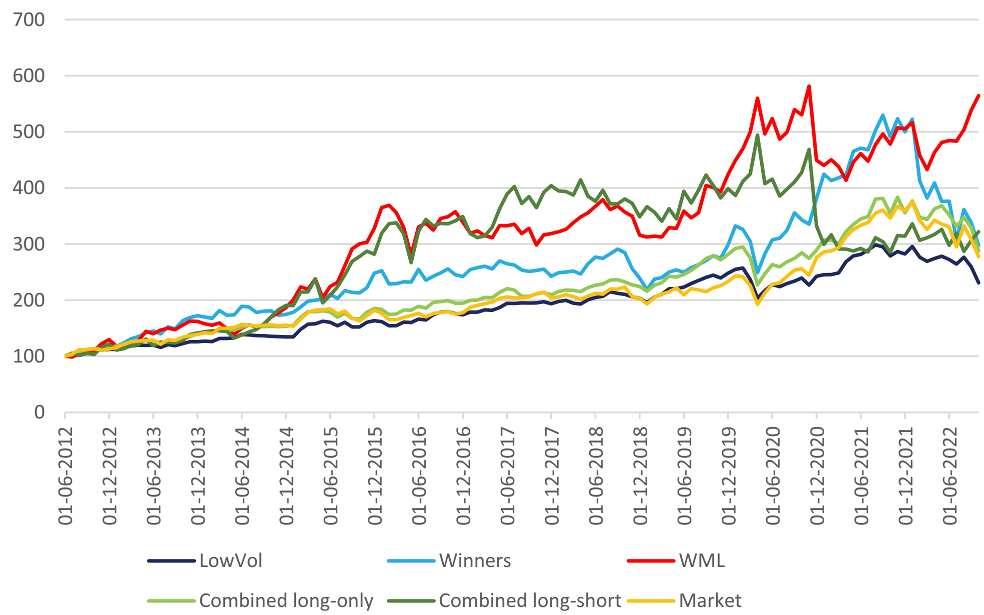
Regression Results

In this section, we further investigate portfolio returns corresponding to the low-volatility, momentum, and combination strategies for Nordic stocks by estimating factor loadings using the CAPM, the FF3, the FF5 models.

Table 3 reports the coefficients and the HAC-robust *t*-statistics obtained using OLS regressions for pure-play volatility portfolio excess returns for each of the factor models. Panels A, B and C of Table 3 report the coefficients for the low-volatility portfolio, high-



Panel A: Cumulative excess returns 2002-2012



Panel B: Cumulative excess returns 2012-2022

Figure 2. Cumulative excess returns for each subsample.

volatility portfolio, and the LMH portfolio respectively. The low-volatility portfolio generates a positive alpha of 0.44%, significant at a 5% level after controlling for market returns. Meanwhile, using the the same model, the high-volatility portfolio generates an insignificant alpha of −0.64%, and the LMH portfolio generates a positive alpha of 1.08%, significant at a 5% level. The LMH portfolio alpha (1.24%) also exceeds the low-volatility alpha (0.38%) when the size and value factors are added to the model, while the high-volatility portfolio generates a significant negative alpha of −0.86%.

However, including the profitability and investment factors, as shown in row 3, and additionally the momentum factor, as shown in row 4, removes the significance of the alphas generated from the low-volatility and LMH portfolios. Based on these findings, we argue that the low-volatility strategy

Table 2. Correlation Coefficients.

	Low vol	High vol	Winners	Losers	LMH	WML	Market
Low vol	1***						
High vol	0.66***	1***					
Winners	0.81***	0.72***	1***				
Losers	0.67***	0.85***	0.64***	1***			
LMH	−0.33***	−0.93***	−0.5***	−0.73***	1***		
WML	−0.14	−0.45***	0.08	−0.72***	0.5***	1***	
Market	0.84***	0.79***	0.86***	0.82***	−0.58***	−0.29***	1***

This table presents the correlation coefficients between the excess returns pure-play low-volatility and momentum portfolios. The low volatility portfolio consists of stocks in the top tercile by their standard deviation calculated over the past 36-month period derived from weekly return data. Similarly, the high volatility portfolio consists of stocks in the bottom tercile by their standard deviation. The winner portfolio consists of the top tercile of past high performing stocks, whereas the loser portfolio consists of the top tercile of past low performing stocks. LMH represent the low-minus-high portfolio, that is, the difference between low- and high-volatility stock returns, and WML represents the winner-minus-loser portfolio, that is, the difference between the returns of winner and loser stocks. Market represents the return on the market index. *** denotes statistical significance at the 1% level.

Table 3. OLS regressions of pure-volatility portfolios on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA
Panel A: Low volatility portfolio excess returns						
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***	0.20**	0.50***	0.20
(HAC robust *t*-statistic)	(0.86)	(22.4)	(2.96)	(2.04)	(3.65)	(1.43)
Panel B: High volatility portfolio excess returns						
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 portfolio excess returns						
Coefficient	1.08**	−0.87***				
(HAC robust *t*-statistic)	(2.20)	(−8.30)				
Coefficient	1.24**	−0.82***	−0.47	−0.60***		
(HAC robust *t*-statistic)	(2.55)	(−6.24)	(−1.46)	(−2.99)		
Coefficient	0.57	−0.71***	−0.60**	0.00	1.60**	0.26
(HAC robust *t*-statistic)	(1.03)	(−6.40)	(−2.32)	(0.00)	(2.38)	(0.58)

This table reports the results of the OLS regressions of the monthly average excess returns of pure-play volatility portfolios on theCAPM, which includes the excess market returns (MKT), the Fama French 3 factor model, which adds the size (SMB) and value (HML) factors, the Fama French 5 factor model, which adds the profitability (RMW) and investment (CMA) factors. HAC-robust *t*-statistics are *t*-statistics that account for unknown dependency structures in the return data, and are based on the blocks-bootstrapping methodology developed by Grobys and Junttila (2021). *, **, and *,**, or *** represent statistical significance at the 10%, the 5% or the 1% level, respectively.

returns are subsumed by other risk factors already present in the Fama French 5-factor model, that is, profitability and investment.

Table 4 reports the estimated coefficients and the HAC-robust *t*-statistics obtained from the OLS regressions for pure-play momentum portfolio excess returns in each of the three models: CAPM, FF3, and FF5. Once again, Panels A, B, and C of Table 4 report the coefficients for the high-momentum (winner) portfolios, low-momentum (loser) portfolios, and the WML portfolios, respectively. The winner portfolio generates a positive alpha of 0.54% significant at a 5% level in the CAPM regression. However, all other factor models capture the significance of the excess returns from the high-momentum portfolio. Specifically, the size factor in the FF3 and the FF5 model remains consistently significant, subsuming the effect of high momentum. Meanwhile, the loser (low momentum) portfolio produces significant negative alphas in all factor models; and hence, the profitability of the WML portfolio appears to be driven by the short leg.

Unlike the coefficient estimates of the momentum portfolios, the results obtained for the pure-

Table 4. OLS regressions of 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)	(−1.50)		
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	−0.90**	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)	(−0.70)	(1.46)	(1.66)

This table reports the results of the OLS regressions of the monthly average excess returns of pure-play momentum portfolios on the CAPM, which includes the market returns (MKT), the Fama French 3-factor model, which adds the size (SMB) and value (HML) factors, and the Fama French 5-factor model, which adds the profitability (RMW) and investment (CMA) factors. HAC-robust *t*-statistics are *t*-statistics that account for unknown dependency structures in the return data, and are based on blocks-bootstrapping methodology developed by Grobys and Junttila (2021). *, **, and *** represent statistical significance at the 10%, the 5% and the 1% level, respectively.

Table 5. OLS regressions of the long-only strategy 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)	(19.60)	(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)	(2.80)	(13.55)				
Coefficient	0.47**	0.82 ***	0.48***	−0.09		
(HAC robust t-statistic)	(2.55)	(14.40)	(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)
Panel C: Double screening 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)

This table reports the results of the OLS regressions of the monthly average excess returns of long-only volatility and momentum combination portfolios on the CAPM, which includes the market returns (MKT), the Fama French 3-factor model, which adds the size (SMB) and value (HML) factors, the Fama French 5-factor model, which adds the profitability (RMW) and investment (CMA) factors. Panels A, B, C, and D report the results for portfolios constructed using the 50/50, the double-screening volatility-first, the double-screening momentum-first, and the ranking methods respectively. HAC-robust *t*-statistics are *t*-statistics that account for unknown dependency structures in the return data, and are based on blocks-bootstrapping methodology developed by Grobys and Junttila (2021). *, **, and *** represent statistical significance at the 10%, the 5% and the 1% level, respectively.

Table 6. OLS regressions of the long-short strategy portfolios on standard risk factors.

	α	MKT	SMB	HML	RMW	CMA
Panel A: 50/50 long-short portfolio						
Coefficient	1.35***	−0.70***				
(HAC robust t-statistic)	(2.97)	(−5.15)				
Coefficient	1.40***	−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 portfolio						
Coefficient	1.77***	−0.77***				
(HAC robust t-statistic)	(3.31)	(−4.10)				
Coefficient	1.81***	−0.72***	0.11	−0.74***		
(HAC robust t-statistic)	(3.28)	(−3.60)	(0.27)	(−3.39)		
Coefficient	1.10*	−0.55***	0.05	−0.36	1.50	0.77
(HAC robust t-statistic)	(1.89)	(−3.10)	(0.15)	(−0.54)	(1.64)	(1.48)
Panel C: DS Mom first long-short portfolio						
Coefficient	1.49***	−0.82***				
(HAC robust t-statistic)	(2.99)	(−5.85)				
Coefficient	1.60***	−0.77***	−0.20	−0.63***		
(HAC robust t-statistic)	(3.27)	(−4.95)	(−0.58)	(−3.04)		
Coefficient	0.91*	−0.63***	−0.30	−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 portfolio						
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)	(3.40)	(−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)

This table reports the results of the OLS regressions of the monthly average excess returns of long-short volatility and momentum combination portfolios on the CAPM, which includes the market returns (MKT), the Fama French 3 factor model, which adds the size (SMB) and value (HML) factors, the Fama French 5 factor model, which adds the profitability (RMW) and investment (CMA) factors. Panels A, B, C, and D report the results for portfolios constructed using the 50/50, the double-screening volatility-first, the double-screening momentum-first, and the ranking methods, respectively. HAC-robust *t*-statistics are *t*-statistics that account for unknown dependency structures in the return data, and are based on blocks-bootstrapping methodology developed by Grobys and Junttila (2021). *, **, and *** represent statistical significance at the 10%, the 5% and the 1% level, respectively.

play volatility portfolios suggest that excess returns may be driven by long-only low-volatility strategies, which is also consistent with prior studies on the volatility effect (Blitz 2016; Chow et al. 2014). Therefore, we first construct long-only combination portfolios using four separate methods. The first combines the volatility and momentum strategies in a 50/50 strategy, where half of the portfolio consists of low-volatility stocks, and the other half consists of high-momentum (winner) stocks. In the second and third methods, portfolios are double-screened by volatility first, and momentum first, respectively. Finally, a ranking strategy is employed where all stocks are assigned a rank based on their volatility and momentum signals. The long-only ranking portfolio consists of the top 10 stocks ranked by low-volatility and high-momentum.

Table 5 presents the coefficient estimates of the OLS regressions for excess returns from the long-only combination portfolios in each of the four factor models. Panels A, B, C & D of Table 5 report the results for the regressions using the 50/50, the DS volatility-first, the DS momentum-first, and the ranking portfolios, respectively. In a simple 50/50 strategy, the volatility and momentum long-only portfolio generate a positive alpha of 0.46% (significant at a 5% level) using the CAPM, and a positive alpha of 0.34% (significant at a 5% level) using the FF3 model for risk adjustment. However, when controlling for the profitability and investment factors, and additionally the momentum factor, the alpha drops in magnitude and loses its statistical significance. Results for the remaining portfolio constructs are similar, with the DS momentum-first portfolio and the ranking portfolio earning the highest alphas, significant at 1%, in the CAPM (0.61% and 0.62%) and FF3 model (0.54% and 0.54%).

The long-short portfolios are next constructed by using the same four methods as the long-only portfolios and including a short position in the opposing strategy. The results for the OLS regressions of their excess returns on various factor models are reported in Table 6. While the long-short portfolios unsurprisingly earn significantly higher alphas than the long-only portfolios in the CAPM and the FF3 model, the 50/50 long-short portfolio still produces a smaller and statistically insignificant alpha in the FF5 and FF6 models, specifically when adding the profitability, investment, and momentum factors, respectively. Unlike the long-only portfolios, the DS volatility-first, DS momentum-first, and the ranking long-short combination portfolios also earn weakly statistically significant alphas in the FF5 factor model specification. Moreover, the long-short portfolio constructs that are the most likely to earn the highest alphas are the DS volatility first portfolio, with an alpha of 1.81% (significant at a 1% level) and the ranking portfolio, with an alpha of 1.88% (significant at a 1% level) in the FF3 factor model.

Additionally, in the FF3 factor model, the double-screening long-short portfolios have significant negative factor loadings on the excess market and value factors. Unlike the long-only portfolios, the long-short volatility-first double-screened portfolio also generates higher and more robust alphas than the momentum-first portfolios. The monthly minimums and volatilities suggest that all combination portfolios are riskier than the market index; however, long-short double-screening volatility-first and ranking portfolios can still outperform the market in terms of generating risk-adjusted returns. Nevertheless, while the volatility and momentum strategy combination portfolios may generate consistently high monthly excess returns, the returns on the long-only portfolios may be entirely explained by several existing and well-document risk factors, such as size, value and profitability, and the returns on the long-short portfolios may be at least partially explained by the profitability factor. Notably, the combination portfolios do not appear to outperform the pure-play momentum WML portfolio, which obtains the largest significant alpha of 1.12% in an FF5 model, i.e. after controlling for the profitability and investment factors.

Table 7. Sub-sample tests.

	Mean	Sharpe ratio	Bootstrapped Sharpe ratio	FF3 alpha
Panel A: 01/2002–05/2012				
LowVol	0.98%	0.84	0.11	0.54**
(HAC-robust *t*-statistic)	(1.69)			(2.36)
Winners	1.46%*	0.79	0.11	0.74**
(HAC-robust *t*-statistic)	(1.70)			(2.29)
WML	1.38%*	0.64	0.12	1.35*
(HAC-robust *t*-statistic)	(1.83)			(1.95)
Combination long-only	1.22%**	0.97	0.13	0.77***
(HAC-robust *t*-statistic)	(2.01)			(3.22)
Combination long-short	1.26%**	0.52	0.13	1.58*
(HAC-robust *t*-statistic)	(2.02)			(1.95)
Market	0.45%	0.26	0.04	–
(HAC-robust *t*-statistic)	(0.64)			–
Panel B: 06/2012–09/2022				
LowVol	0.74%***	0.77	0.18	0.12
(HAC-robust *t*-statistic)	(2.82)			(0.60)
Winners	1.08%**	0.64	0.14	−0.11
(HAC-robust *t*-statistic)	(2.16)			(−0.39)
WML	1.60%***	0.97	0.19	1.82***
(HAC-robust *t*-statistic)	(2.97)			(3.72)
Combination long-only	0.94%***	0.84	0.21	0.22
(HAC-robust *t*-statistic)	(3.25)			(0.96)
Combination long-short	1.21%**	0.63	0.14	1.80***
(HAC-robust *t*-statistic)	(2.22)			(3.57)
Market	0.92%***	0.77	0.18	–
(HAC-robust *t*-statistic)	(2.78)			–

This table reports the means (average monthly excess returns), Sharpe Ratios, and alphas obtained from Fama French 3 factor model regressions for low-volatility, winner (high-momentum), WML, volatility and momentum combination long-only and long-short portfolios, and the market index. Panel A reports the statistics for the first sub-sample, which spans the period 01/2002–05/2012, and Panel B reports the statistics for the second sub-sample, which spans the period 06/2012–09/2022. HAC-robust *t*-statistics are t-statistics that account for unkown dependency structures in the return data, and are based on blocks-bootstrapping methodology developed by Grobys and Junttila (2021). *, **, and *** represent statistical significance at the 10%, the 5% and the 1% level respectively. To account for heavy tails, this table reports also bootstrapped Sharpe ratios using the blocks bootstraps approach outlined in Grobys and Junttila (2021).

Sub-sample results

Figure 1 suggests that most volatility and momentum strategy portfolios have significantly different performance relative to the market index before and after the 2007–08 financial crisis. To further investigate variation in the excess returns and alphas of the pure-play and combination portfolios over the sample period, two subsamples are formed by dividing the studied period in two non-overlapping subsamples. Table 7 presents the results of the sub-sample tests, where column 1 reports the means – the average excess returns of the corresponding portfolio, column 2 reports the Sharpe Ratio of the portfolio, column 3 reports the bootstrapped Sharpe Ratio of the portfolio, whereas column 4 reports the alpha obtained through regressions performed using the FF3 factor model. Panels A and B of Table 7 report the results of the sub-sample tests for sample period 2002–2012, and 2012–2022 respectively.

The average monthly excess returns for all pure-play and combination portfolios are significantly different across the two sample periods. Specifically, while all pure-play and combination portfolios — with the exception of the WML portfolio which earns higher average monthly excess returns from 2002–2012—these returns have higher statistical significance in the later part of the sample, i.e. from 2012–2022. Similarly, the Sharpe ratios for all portfolios with the exception of the WML portfolio are higher from 2012–2022. This holds for the bootstrapped Sharpe ratios as well. Using bootstrapped Sharpe Ratios, however, the performances of our proposed strategies are less impressive as Sharpe Ratios decrease by substantial margins. This implies that accounting for the presence of heavy tails, the reward-to-risk relationship in terms of the Sharpe Ratio is penalized. On the other hand, the highest alphas are to be obtained from the WML (1.82%) and combination long-short portfolios (1.80%) in recent years. While these results may not be consistent with the cumulative excess returns portrayed in Figure 1, they may be explained in part by the significantly higher returns of the market index over the years 2012–2022. In line with the results from our previous tests, all portfolios – with the exception of the low-volatility pure-play strategy – outperform the market index in the later subsample.

The cumulative excess returns of the portfolios in the first and second sub-samples are displayed in Figure 2, Panels A and B respectively. Interestingly, the long-only portfolio outperforms the WML and combination long-short portfolios in cumulative excess returns in the first sub-sample, despite its lower monthly average excess returns. This is likely to be explained by the lower volatility of the long-only portfolio. In the second sub-sample, the cumulative excess returns of the WML portfolio seem to diverge from other portfolios — that is, considerably exceed the cumulative returns on the other portfolios — in the last two years of our sample.

IV. Conclusion

Earlier research proposed investment strategies that are designed to make quantitative investing easy for investors by using only historical stock price data which means no accounting for other data sources is required. Motivated by this research stream, we explored the profitability of combined low-volatility and momentum investment strategies in the Nordic stock markets from January 1999 to September 2022. Unlike other asset markets, the Nordic stock markets exhibit some appealing features such as a high level of information-flow-efficiency. Our results show that strategies incorporating both momentum and low volatility signals give simultaneous positive exposure to well-known factors such as value and profitability. The returns are consistent over time and even more pronounced in the later subsample, as indicated by higher robust Sharpe Ratios. Whereas our findings indicated that the plain momentum portfolio exhibits the highest robust Sharpe Ratio, for investors wishing to implement a long-only strategy, the DS strategy that first sorts stocks with respect to the momentum signal (e.g. winner stocks), and then sorts stocks with respect to the low-volatility signal appears to be superior to other strategies. Since our results showed evidence for that some strategies are subject to tail risks (e.g. global financial crisis, COVID-19 outbreak, etc.), future research is needed to develop strategies incorporating hedging instruments such as gold. This is, however, left for future research.

Disclosure statement

The authors declare that they have no interests to declare.

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Appendix

Table A1. Low-volatility strategy for various formation periods.

Formation period	60-months	48-months	24-months	12-months
Average payoff	0.30*	0.24	0.39	0.52**
(*t*-statistic)	(1.75)	(1.32)	(1.61)	(2.04)

This table reports the estimated payoffs for various formation periods. Whereas the main analysis employs a 36-month formation period for sorting stocks into terciles based on their past volatility, here we vary this formation period between 60- and 12-month. To ensure that point estimates are not driven by outliers, we trim the data such that we shrink the distribution and use the 2.50% to 97.50% percentiles. Note, *, **, or *** indicate statistical significance on the 10%, 5%, or 1% level.