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Low-risk anomalies: evidence from the Nordic equity markets

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ABSTRACT

This study examines the low-risk anomaly in Nordic equity markets, filling a gap in the literature compared to extensive research in U.S. markets. From February 2005 to March 2024, portfolios sorted by volatility, beta, and idiosyncratic volatility are analysed with rolling risk measurement periods of 36, 24, and 12 months. The study also assessed the anomaly's behaviour across large-cap and small-cap stocks and its persistence over extended holding periods. Results confirm that low-risk portfolios outperform high-risk portfolios, achieving superior raw and risk-adjusted returns. Idiosyncratic volatility-sorted portfolios showed the strongest results, while beta-sorted portfolios performed weakest. The largest return spreads occurred with 36-month measurement periods, while shorter periods yielded weaker spreads. The anomaly is largely driven by underperformance in the short legs. For large-cap stocks, return spreads were muted, with significance only for idiosyncratic volatility portfolios. Robustness for holding periods up to 12 months underscores the anomaly's persistence in Nordic markets.

KEYWORDS

Asset pricing; efficient markets; low volatility effects; Nordic stock markets

JEL CLASSIFICATION

G10; G11; G12; G14; G15

I. Introduction

Background and motivation



The efficient market hypothesis (EMH) posits that stock prices fully reflect all available information, implying that excess risk-adjusted returns should not persist in well-functioning markets (Fama 1970). This foundational principle of modern finance suggests a positive relationship between risk and expected returns, as predicted by the Capital Asset Pricing Model (CAPM) (Lintner 1965; Sharpe 1964). However, extensive empirical evidence challenges this theoretical assumption (Black, Jensen, and Scholes 1972). The low-risk anomaly, first documented by Blitz and van Vliet (2007), reveals that stocks with lower volatility tend to generate higher risk-adjusted returns than their high-risk counterparts – contradicting the CAPM's core prediction. This anomaly has been further substantiated by subsequent studies (M. Baker, Bradley, and Wurgler 2011; Blitz, Pang, and van Vliet 2021, 2013; Frazzini and Pedersen 2014), prompting a reassessment of traditional asset pricing models. This phenomenon has been observed across various


asset classes, including stocks, bonds, and commodities (Alquist et al. 2020; Blitz, van Vliet, and Baltussen 2020; Frazzini and Pedersen 2014).

While the low-risk anomaly has been extensively documented in the U.S. and global markets (e.g. Baker and Haugen 2012; Bradrania, Veron, and Wu 2023), evidence from Nordic equity markets remains scarce. This gap in the literature is important, as Nordic stock markets, though distinct in regulatory and institutional structures, are highly integrated with broader European financial markets (Grobys, Fatmy, and Rajalin 2024). Moreover, most existing studies predominantly focus on total volatility, with limited attention given to alternative risk measures such as idiosyncratic volatility and beta factor risk. Furthermore, the literature has largely overlooked the impact of different portfolio formation periods and the interaction between firm size and the low-risk effect, particularly in small-cap versus large-cap stocks.

Addressing the research gap

This study addresses these limitations by conducting a comprehensive investigation of the low-risk

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anomaly in Nordic stock markets. Specifically, it expands the existing literature in three key ways. First, whereas existing studies often rely on a single low risk metric and typically prioritize long-short portfolio returns (i.e. Baker, Bradley, and Wurgler 2011; Blitz, Hanauer, and van Vliet 2021; Blitz, Pang, and van Vliet 2013; Blitz and van Vliet 2007; Frazzini and Pedersen 2014), the present study examines the relationship between risk and return across multiple risk definitions, including idiosyncratic volatility, total volatility, and beta factor risk, offering a more nuanced perspective on the anomaly's underlying drivers. Second, the analysis of the present study explores the effect of portfolio formation periods, revealing that longer return measurement windows (e.g. 36 months) yield stronger risk-return spreads. Third, the study investigates the interaction between firm size and the low-risk effect, assessing whether the anomaly is more pronounced in small-cap or large-cap stocks. These innovations provide new insights into how the low-risk effect manifests in Nordic equity markets and how it compares to findings in other regions.¹

Methodological approach

The study employs a portfolio-sorting methodology to construct long-short zero-cost portfolios based on different risk measures. Stocks are ranked according to total volatility, idiosyncratic volatility, and beta exposure, and portfolios are formed within market capitalization groups to examine the interaction between size and risk. The risk-adjusted performance of these portfolios is evaluated using standard asset pricing models, including the Fama-French (FF) three-factor model (Fama and French 1993), the FF five-factor model (Fama and French 2015), and the FF six-factor model (Fama and French 2018). Additionally, the study tests whether the low-risk anomaly is time-consistent by examining performance over different portfolio formation periods (e.g. 12-month, 24-month, and 36-month return measurement windows). The use of European factor models as

benchmarks allows for a broader assessment of the systematic risk exposures of Nordic stocks, reflecting their integration into European financial markets.

Contribution to the literature

This study makes several important contributions to the literature on the low-risk anomaly. While previous research has primarily focused on U.S. and global equity markets, the Nordic region remains underexplored in this context. Unlike prior studies that have largely included Nordic stocks as part of broader European samples (e.g. Baker and Haugen 2012; Bradrania, Veron, and Wu 2023), this study provides a dedicated examination of the low-risk anomaly within the Nordic stock markets. Given the distinct institutional and structural characteristics of Nordic markets (Grobys and Huhta-Halkola 2019), this research enhances the understanding of how the anomaly manifests in regional settings with specific market conditions. Furthermore, while much of the existing literature (e.g. Blitz and van Vliet 2007; Blitz, Pang, and van Vliet 2013, 2021; Frazzini and Pedersen 2014) has focused on total volatility as the primary risk measure, this study expands the scope by considering multiple definitions of risk, including idiosyncratic volatility and beta risk. By doing so, it provides a more comprehensive perspective on the risk-return relationship beyond conventional volatility-based approaches. In addition, the study extends prior research by incorporating different portfolio formation periods and analysing their impact on the persistence and magnitude of the low-risk effect. While previous studies have generally focused on one-month rebalancing horizons, this research evaluates the effectiveness of longer risk measurement periods. Another key contribution lies in examining the role of firm size in the low-risk anomaly. The study investigates whether the anomaly is more pronounced among small-cap or large-cap stocks, addressing an area of debate in the literature (Blitz and van Vliet 2007; Blitz, Pang, and van Vliet 2013). This analysis

¹Earlier research on investment strategies and financial market anomalies in Nordic markets includes the studies of Grobys and Huhta-Halkola (2019), Leivo (2012), Silvasti, Grobys, and Äijö (2021), Jokipii and Vähämaa (2006), Leivo and Pätäri (2009), Nikkinen et al. (2009), and Rinne and Vähämaa (2011). However, these studies primarily examine different aspects of financial anomalies, such as momentum effects, value investing, or earnings-based strategies, rather than the low-risk anomaly investigated in the present research.

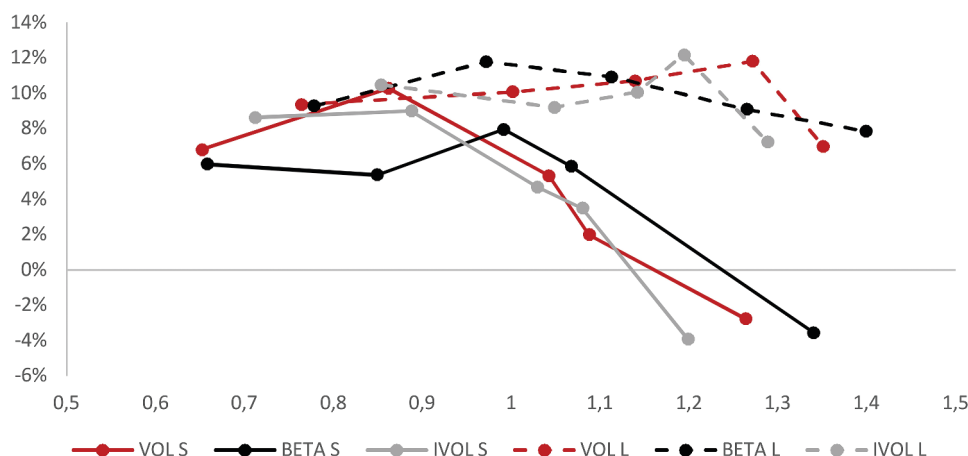


Figure 1. Annualized compounded return of long and short portfolios for various low risk strategies. This figure shows the annualized compounded return and beta relationship of each quintile portfolios sorted by 36-month volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL) for large-cap (L) and small-cap (S) stocks.

provides new insights into whether firm size conditions the low-risk effect in the Nordic context.

Summary of key findings

The results confirm the presence of a strong low-risk anomaly in Nordic stock markets, with idiosyncratic volatility-based portfolios consistently outperforming high-volatility portfolios in risk-adjusted terms. The anomaly persists across multiple risk measures, with the largest return spreads observed for longer portfolio formation periods (36 months). Additionally, the study finds that low-risk strategies exhibit significant exposures to European risk factors, reinforcing the argument that Nordic stocks are systematically linked to broader European equity markets. The analysis of size effects reveals that the low-risk effect is present in both small-cap and large-cap stocks, though the magnitude of the anomaly differs between these groups. These findings have important implications for fund managers, investors, and policymakers. Investors can enhance risk-adjusted returns by integrating low-risk factors into quantitative investment strategies, while policymakers can use the insights to assess market stability and potential mispricing. Moreover, the results suggest that European factor models provide an appropriate benchmark for pricing Nordic stocks, given their systematic integration with European financial markets.

II. Literature review

The low-volatility anomaly contradicts traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM) (Lintner 1965; Sharpe 1964), which predicts a positive risk-return relationship. Empirical evidence, however, consistently shows that low-volatility stocks tend to generate higher risk-adjusted returns than their high-volatility counterparts. The literature on this anomaly can be categorized into three primary research streams: (1) studies examining idiosyncratic volatility, (2) research focusing on beta exposure to the market factor, and (3) studies analysing plain stock return volatility. Each stream provides distinct insights into the anomaly's mechanisms and implications.²

Idiosyncratic volatility and the low-volatility effect

The first research stream investigates the low-volatility effect through idiosyncratic volatility, defined as the component of a stock's total risk that is uncorrelated with systematic market movements. The seminal work of Ang et al. (2006) documented a negative relationship between idiosyncratic volatility and future stock returns, challenging the conventional risk-return tradeoff. Their findings sparked further investigations into

²Supplementary Table S1 in the Appendix provides a summary of the results, methodologies, and sample characteristics from previous relevant studies on the low-volatility effect.

whether idiosyncratic volatility is mispriced or reflects systematic risk factors (Ang et al. 2009). Subsequent studies, such as those by Fu (2009) and Bali and Cakici (2008), have debated whether this effect is persistent across different markets and time periods. In particular, Fu (2009) argued that the negative relation between idiosyncratic volatility and returns could be driven by time-varying volatility rather than a true anomaly. More recent research has explored why idiosyncratic volatility might be linked to lower future returns. Stambaugh, Yu, and Yuan (2015) suggest that the underperformance of high-idiosyncratic-volatility stocks can be attributed to investor overconfidence and lottery-like preferences, where retail investors disproportionately favour speculative, high-risk stocks. Other studies, such as Blitz, Pang, and van Vliet (2013), have emphasized institutional constraints and leverage aversion, which may prevent sophisticated investors from exploiting the anomaly.

Beta exposure to the market factor and the low-volatility effect

A second research stream investigates low-volatility investing through the lens of beta exposure to the market factor. The work of Frazzini and Pedersen (2014) introduced the Betting Against Beta (BAB) factor, showing that low-beta stocks earn higher risk-adjusted returns than high-beta stocks. This finding suggests that investors leverage constraints force them to overweight high-beta stocks, leading to a relative underpricing of low-beta stocks. The BAB framework offers a theoretical explanation for why low-risk stocks outperform on a risk-adjusted basis despite their lower sensitivity to the market factor. Further research has expanded on this framework. Baker, Bradley, and Wurgler (2011) argue that behavioural biases, such as representativeness heuristics, contribute to investor overvaluation of high-beta stocks, which exacerbates the low-risk anomaly. Blitz, Pang, and van Vliet (2013, 2021) extend this discussion by analysing how fund manager constraints – such as benchmark-driven investing – lead to an overvaluation of high-beta stocks and a corresponding risk-adjusted premium for low-beta stocks.

Plain stock return volatility and the low-volatility effect

The third research stream examines plain stock return volatility, which refers to the total fluctuation in stock prices without decomposing risk into systematic and idiosyncratic components. Research in this category generally shows that stocks with lower total return volatility earn higher Sharpe ratios and risk-adjusted returns. Blitz and van Vliet (2007) provided some of the earliest empirical evidence supporting this view, demonstrating that low-volatility stocks tend to outperform high-volatility stocks across different market conditions. This result holds even when controlling for size and value effects, suggesting that the low-volatility effect is not entirely captured by traditional factor models. Further evidence from Baker, Bradley, and Wurgler (2011) and Baker and Haugen (2012) supports the notion that the low-volatility effect persists across global markets, reinforcing the idea that it is a widespread anomaly rather than a market-specific inefficiency. Additionally, Blitz, Pang, and van Vliet (2013) propose that this effect is driven by capital market frictions, including institutional constraints, behavioural biases, and leverage restrictions, which prevent rational arbitrage from eliminating the anomaly.

Enhancements and contributions of the present study

While these three research streams have significantly advanced the understanding of the low-volatility anomaly, several gaps remain. First, most studies have focused on U.S. and global markets, with little dedicated research on Nordic equity markets. Given the institutional differences and market structures in the Nordic region, it is unclear whether the low-volatility effect is equally pronounced. This study directly addresses this gap by providing a dedicated analysis of Nordic stock markets. Second, existing studies often limit their focus to one measure of volatility, whereas this research examines the low-volatility effect across idiosyncratic volatility, beta exposure, and total return volatility, offering a more comprehensive perspective. This approach aligns with prior studies

but introduces a comparative framework to assess whether different definitions of risk yield consistent or divergent results. Third, this study explores how the low-volatility anomaly interacts with portfolio formation periods and firm size, aspects that have received limited attention in the literature. By incorporating different return measurement horizons and size classifications, this research provides new insights into the persistence and variability of the anomaly. Finally, this study contributes by assessing whether European factor models provide an appropriate benchmark for pricing Nordic stocks, an area that remains underexplored. Given the integration of Nordic financial markets with broader European markets, the analysis of cross-country risk premia helps to contextualize the anomaly within a broader asset pricing framework.

In summary, this study extends prior research by applying a multi-dimensional approach to the low-volatility anomaly, focusing on a market that has received little dedicated attention, and introducing methodological enhancements that provide new insights into the risk-return relationship.

III. Data

The data for this study was primarily sourced from LSEG Datastream, with the exception of the Fama and French factors, which were obtained from Kenneth French's website. The sample period spans February 2005 to March 2024, encompassing 230 monthly return observations. Due to the 36-month portfolio formation period required for initial calculations, the complete dataset includes 266 monthly returns. This period captures a variety of market conditions, including the 2008 financial crisis, the COVID-19 market crash, and prolonged bull markets.

Equities

Data were collected from stocks listed on the Helsinki, Stockholm, Copenhagen, and Oslo stock exchanges. Following Grobys and Huhta-Halkola (2019), Iceland was excluded from the sample due to its limited number of stocks and small total market capitalization. The sample was restricted to main-listed stocks on the Helsinki (OMXH), Stockholm (OMXS), Copenhagen (OMXC), and

Oslo (OSEAX) stock exchanges, excluding less liquid and smaller stocks typically found on non-main lists such as First North. Consistent with Silvasti, Grobys, and Äijö (2021), the smallest 10% of stocks by market capitalization were removed monthly to address liquidity concerns.

Monthly index constituents were extracted from Datastream for the full sample period. Any gaps in data were filled by manually verifying index composition changes in LSEG Workspace. The dataset was further filtered to include only equity securities (Ince and Porter 2006). Following Fong, Holden, and Trzcinka (2017), primary quotations and major securities traded in local currency were retained, while residual cross-listings were excluded using country-specific listing identifiers (Landis and Skouras 2021). This ensured the sample included one primary security per company, eliminating secondary share classes and stocks listed primarily elsewhere. Such rigorous filtering is essential in the Nordic context, where companies often have multiple share classes and cross-listings (e.g. Nordea listed on OMXH, OMXC, and OMXS). Dynamic screens were applied to mitigate the influence of outliers and data errors. Following Schmidt et al. (2011), monthly observations exceeding 890% were excluded. Additionally, returns were omitted if either the return in one month or the preceding month exceeded 300%, and their cumulative return was below 50% (Ince and Porter 2006). Stocks were included in the portfolios only if they had 36 consecutive months of return data and remained continuously listed on the main exchanges. Monthly total return indices and market values were collected for each company, with all data converted to euros to ensure comparability across markets. To address rounding errors in return calculations due to Datastream's default two-decimal precision, total return indices were recorded with a minimum of five decimal places (Landis and Skouras 2021). Table 1 shows that the data set comprises a total of 1,113 unique stocks that were included in portfolios over the sample period. The portfolios held an average of 532 stocks monthly, ranging from 494 to 585. Sweden contributed approximately double the number of stocks compared to Finland, Denmark, and Norway. The average market capitalization was €2,042 million, with a median of

€274 million, reflecting the characteristic mix of small-cap and large-cap stocks in Nordic equity markets.

Market index and risk-free rate

The market index was constructed following Silvasti, Grobys, and Äijö (2021) as the equal-weighted average of excess returns from all-share indices in each sample market. Euro-denominated total return data were used to ensure consistency with individual stock returns. Due to limited availability of total return data for OMXS before 2003, price index data was utilized for that period.³ The risk-free rate was defined as the three-month Euribor offered rate, replacing the commonly used U.S. Treasury bill rate, as all data were denominated in euros. This ensured consistency in excess return calculations.

Fama and French factors

We follow Silvasti, Grobys, and Äijö (2021) and Grobys and Huhta-Halkola (2019) in constructing the Nordic stock market index using the total return indices of each country under study. Our market index is then the equal-weighted average of returns of each index. Furthermore, consistent with Grobys, Fatmy, and Rajalin (2024), the European factor dataset was sourced from Kenneth French's data library. We argue that the use of European Fama-French equity market factors in our study analysing investment strategies implemented with Nordic stocks is well-

justified on both empirical and theoretical grounds. Firstly, the Nordic stock markets, though distinct in some characteristics, are highly integrated with broader European financial markets. This integration implies that common risk factors, such as size and value effects, exert influence across European equity markets, including the Nordic region. Empirical evidence supports this connection. Risk-adjusting low-volatility strategies implemented among Nordic stocks, Grobys, Fatmy, and Rajalin (2024) shows that factor loadings on European equity market factors are typically highly statistically significant indicating that investment strategies based on Nordic stocks are systematically correlated with these broader European factors. This suggests that common cross-country risk premia drive stock returns, making European factor models an appropriate benchmark. Moreover, a portion of the European factor construction itself incorporates Nordic stocks, reinforcing their relevance. Since equity market risk factors, such as size and value, tend to co-move across countries, it follows that Nordic stocks share risk exposures with their broader European counterparts. This interconnectedness justifies the use of European factor models, as they accurately reflect systematic risks that impact Nordic stock performance.

Factor returns reported in U.S. dollars were converted to euros to mitigate currency fluctuations, following Glück, Hübel, and Scholz (2021):

$$LS_t^{EUR} = \frac{1}{(1 + r_{FX,t}^{USD/EUR})} LS_t^{USD},$$

Table 1. Descriptive statistics.

	Number of firms				Size (m)			
	Max	Min	Average	Total	Average	25th	50th	75th
Finland	110	83	96	164	1841	81	290	1174
Sweden	261	174	208	442	2157	100	344	1493
Denmark	143	87	110	219	2565	64	229	1346
Norway	137	99	117	288	1722	78	234	935
Combined	585	494	532	1113	2042	80	274	1220

Data were collected from stocks listed on the Helsinki, Stockholm, Copenhagen, and Oslo stock exchanges. Iceland was excluded from the sample due to its limited number of stocks and small total market capitalization. The sample was restricted to main-listed stocks on the Helsinki (OMXH), Stockholm (OMXS), Copenhagen (OMXC), and Oslo (OSEAX) stock exchanges, excluding less liquid and smaller stocks typically found on non-main lists such as First North. Furthermore, the smallest 10% of stocks by market capitalization were removed monthly to address liquidity concerns. This table reports the descriptive statistics for the number of firms and size.

³Supplementary Figure S1 in the Appendix shows the cumulative excess return of OMXH, OMXS, OMXC, OSEAX and Nordic market index over the sample period.

where LS_t^{EUR} is euro denominated long-short factor return, $r_{FX,t}^{USD/EUR}$ is exchange rate return between US dollar and euro and LS_t^{USD} is US dollar denoted return of long-short factor. This conversion was applied to all long-short factors, including SMB, HML, RMW, CMA, and MOM, ensuring uniformity across the dataset.

While European Fama-French factors serve as an appropriate benchmark given the high degree of financial integration between Nordic and broader European equity markets, we acknowledge that country- or region-specific factor models could potentially capture additional local risk premia. However, Nordic-specific factor datasets are not publicly available from standard sources, such as Kenneth French's data library, and constructing them would require extensive firm-level accounting data across multiple markets. Given these limitations, and consistent with prior research (e.g. Grobys, Fatmy, and Rajalin 2024), we rely on European factors, which have been shown to exhibit strong and statistically significant explanatory power for Nordic stock returns. We consider the development of Nordic-specific factor models a promising avenue for future research.

IV. Methodology

This section outlines the methodological framework employed in the study. It begins with a description of the risk measurement techniques, followed by a detailed explanation of the portfolio construction methodology. Lastly, alternative methodologies used for robustness checks are discussed.

Risk measures

This study examines the low-risk anomaly using three widely adopted risk measures to provide a comparative analysis. The first measure, *total volatility*, serves as a proxy for a company's overall risk and is calculated as the standard deviation of the company's excess returns over a rolling 36-month period. This aligns with the methodology of Blitz and van Vliet (2007), though their study

employed weekly returns, whereas this research uses monthly observations. Blitz, Pang, and van Vliet (2013) similarly used a three-year rolling window with monthly data. The second measure, *beta*, represents a company's systematic risk or sensitivity to broader market fluctuations. Beta is calculated by regressing a stock's excess returns against the excess returns of the Nordic market index. A rolling 36-month period is utilized for consistency. The third measure, *idiosyncratic volatility* (IVOL), captures company-specific risk independent of market movements. Following Ang et al. (2006), IVOL is derived from the residuals of the Fama-French three-factor model. Specifically, it is calculated as the standard deviation of the residuals from a 36, 24, or 12 months rolling regression of excess returns on the market (MKT), size (SMB), and value (HML) factors. Unlike Ang et al. (2006), who used one-month daily returns, this study adopts monthly returns, offering a more conservative approach consistent with Bali and Cakici (2008).⁴

Portfolio construction and regression analysis

At the beginning of each month, stocks are sorted into quintile portfolios based on their rolling risk measures over 36, 24, or 12 months. For each formation period, five long-only portfolios are constructed, along with a long-short, zero-cost portfolio that takes a long position in the lowest-risk quintile (P1) and a short position in the highest-risk quintile (P5). If a stock is delisted, it is liquidated at the closing price of its last trading day or its last recorded price. Following Silvasti, Grobys, and Äijö (2021) and Grobys and Huhta-Halkola (2019), equal-weighted portfolios are employed. This approach avoids undue influence from a small number of large-cap firms, which would distort results in value-weighted portfolios. For example, Novo Nordisk accounted for approximately 20% of the sample's total market value at the end of the observation period. Portfolio returns are subsequently regressed on the capital asset pricing model, the Fama-French (FF) factor models. The FF six-factor model is defined as:

⁴A more detailed comparison of low-volatility methodologies in Nordic stock markets is presented in Supplementary Table S2 in the Appendix.

$$R_{i,t}^{ex} = \alpha_i + \beta_{i,1}MKT_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + \beta_{i,6}UMD_t + u_{i,t},$$

where $R_{i,t}^{ex}$ denotes the excess return of some stock portfolio i at time t , MKT_t denotes the excess market factor at time t , SMB_t denotes the return on the size factor (small-minus-big) at time t , HML_t denotes the return on the value factor (high-minus-low book-to-market ratio) at time t , RMW_t denotes the return on the profitability factor (robust-minus-weak profitability) at time t , CMA_t denotes the return on the investment factor (conservative-minus-aggressive asset growth) at time t , and UMD_t denotes the return on the momentum factor (up-minus-down past performance) at time t , whereas $u_{i,t}$ is an white-noise error term of stock i at time t . Note that all other factor models used for risk adjustment in our study are nested in this model specification.

Impact of market conditions

To assess the performance of low-volatility strategies under different market conditions, we employ our primary strategies based on a 36-month formation period and implement a two-state Markov-Switching model defined as:

$$R_{i,t}^{ex} = \mu_{i,j} + \varepsilon_{i,t}, \text{ with } P_i = \begin{pmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{pmatrix}$$

where $R_{i,t}^{ex}$ denotes the return of zero-cost strategy i at time t , $\mu_{i,j}$ denotes the average payoff of zero-cost strategy i in state j , and $\varepsilon_{i,t}$ follows a Normal distribution with zero mean and variance $\sigma_{i,j}^2$. Note that for the model given here, the intercept and variance are switching states. Furthermore, P_i denotes the transition probability matrix for zero-cost strategy i , where $p_{1,1}$ ($p_{2,2}$) denotes the probability of remaining in state 1 (2) given that we are in state 1 (2), whereas $p_{1,2}$ ($p_{2,1}$) denotes the probability of transition into state 2 (1) given that we are in state 1 (2).

If we are in state $j = 1$, the value of $\mu_{i,1}$ represents the expected return on a bull market state, which implies a positive trend for financial prices,

whereas if we are in state $j = 2$, the value of $\mu_{i,2}$ represents the expected log return for the bear market state, which then implies a negative trend in prices. The different volatilities ($\sigma_{i,1}^2$ and $\sigma_{i,2}^2$) in each state represent the corresponding uncertainties in each given state. We examine this model for $i = \{1, 2, 3, 4\}$, where $i = 1$ represents the zero-cost low-volatility portfolio derived from total volatility, $i = 2$ represents the zero-cost low-volatility portfolio derived from beta factor exposure, $i = 3$ represents the zero-cost low-volatility portfolio derived from idiosyncratic volatility, and $i = 4$ represents the Nordic excess market factor.

V. Results

Main findings

Performance of low-risk portfolios

The results documented in Table 2–4 confirm that low-risk portfolios outperform high-risk portfolios in terms of both raw and risk-adjusted returns. Across all risk measurement methods – total volatility, beta, and idiosyncratic volatility (IVOL) – portfolios formed based on lower risk consistently achieved superior Sharpe ratios and excess returns. Among these, IVOL-sorted portfolios based on a 36-month formation period exhibited the strongest results with the highest return spreads between the lowest-risk (P1) and highest-risk (P5) quintiles (8.66% p.a.).⁵ Total volatility-sorted portfolios (Table 2) demonstrated that the lowest-risk quintiles (P1) achieved the highest Sharpe ratios, ranging between 0.61–0.69 with the largest return spreads observed in the 36-month formation period (5.64% p.a.). Furthermore, Beta-sorted portfolios (Table 3) exhibited weaker risk-adjusted performance compared to volatility and IVOL sorts (Table 4), aligning with prior findings by Blitz and van Vliet (2007) and Baker, Bradley, and Wurgler (2011), which suggest that beta alone does not adequately capture cross-sectional return differences. In contrast, IVOL-sorted portfolios

⁵A reader may question the impact of transaction costs on our results. Note that Van Vliet (2018) documents that low-volatility strategies typically require minimal trading and tend to include larger, more liquid stocks. The authors document an average turnover of 30% for such strategies. Additionally, Moreira and Muir (2017) provide a conservative estimate of trading costs at 14 basis points (bps) per transaction. Applying a 30% turnover rate and accounting for both buying and selling, the round-trip cost totals 28 bps (0.28%), yielding an annual impact of 8.4 bps (0.084%). Given this, we argue that trading costs are negligible.

showed the most significant return spreads, particularly in the 36-month formation period (8.66% p. a.), reinforcing prior evidence by Ang et al. (2006) and Blitz, Pang, and van Vliet (2013) that idiosyncratic risk provides strong predictive power for returns.⁶

Impact of portfolio formation periods

The choice of risk measurement window significantly influences return spreads, and this effect remains consistent across different lookback periods. We observe from Table 2–4 that longer formation periods, such as the 36-month rolling window, generate the most pronounced return differentials between low-risk and high-risk portfolios, whereas shorter formation periods, such as 12 months, produce weaker spreads. The robustness of this finding is further confirmed through alternative risk measurement periods, with portfolios formed using 24-month and 12-month rolling risk measures yielding similar, albeit weaker, results. The 36-month period consistently generates the strongest return spreads,

while the 24-month window produces slightly lower yet still significant return differences. Specifically, the largest spread (8.66% p.a.) is observed in 36-month sorts, with IVOL portfolios achieving the highest returns and lowest risk simultaneously. The 12-month window exhibits the weakest spreads across all strategies, suggesting that short-term risk measures are less effective in predicting future returns. These findings align with the observations of Blitz and van Vliet (2007), Bali and Cakici (2008), and Blitz, Hanauer, and van Vliet (2021), who emphasize that the persistence of the low-risk anomaly is best captured using longer-term risk measures. The results suggest that risk characteristics take time to materialize in market pricing, and shorter formation periods fail to capture the full effect of risk-adjusted return patterns.

Long-short portfolio alphas

The risk-adjusted performance of the portfolios is further analysed using alphas from different asset pricing models, including the CAPM, Fama-French three-factor (FF3), five-factor (FF5), and six-factor

Table 2. Descriptive statistics for volatility sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
Mean (compounded)	8.14%	10.57%	8.75%	8.26%	0.01%	4.55%
Mean (simple)	8.76%** (2.19)	11.65%** (2.40)	10.43%* (1.92)	10.46%* (1.81)	3.12% (0.48)	5.64% (1.51)
Standard deviation	13.32%	17.51%	19.93%	22.21%	24.79%	15.27%
Sharpe	0.61	0.60	0.44	0.37	0.00	0.30
Max drawdown	-59.68%	-62.92%	-65.50%	-65.96%	-73.22%	-44.12%
Panel B: 24-month						
Mean (compounded)	9.13%	9.32%	8.70%	6.79%	1.69%	3.73%
Mean (simple)	9.65%** (2.51)	10.53%** (2.15)	10.38%* (1.93)	9.05% (1.50)	4.80% (0.75)	4.85% (1.37)
Standard deviation	13.23%	17.57%	19.88%	22.04%	24.89%	15.27%
Sharpe	0.69	0.53	0.44	0.31	0.07	0.24
Max drawdown	-55.58%	-63.82%	-66.18%	-70.81%	-69.52%	-44.08%
Panel C: 12-month						
Mean (compounded)	9.01%	7.79%	9.35%	7.97%	1.63%	3.88%
Mean (simple)	9.58%** (2.33)	9.10%* (1.89)	10.92%** (2.10)	10.10%* (1.73)	4.71% (0.73)	4.88% (1.45)
Standard deviation	13.49%	17.60%	19.55%	21.82%	24.72%	14.54%
Sharpe	0.67	0.44	0.48	0.37	0.07	0.27
Max drawdown	-59.70%	-63.36%	-64.02%	-67.69%	-71.71%	-44.40%

The table reports compounded and simple annualized excess returns, standard deviations, Sharpe ratios and maximum drawdowns for volatility sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. All metrics, apart from maximum drawdown, are annualized and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

⁶The present study employs rolling windows of 36, 24, and 12 months to measure risk. A reader might question whether these fixed rolling windows effectively capture dynamic market conditions, as shorter windows may be more sensitive to recent market developments, whereas longer windows could smooth out short-term volatility. Notably, a recent study by Grobys, Fatmy, and Rajalin (2024), which also investigates the low-volatility strategy in Nordic equity markets, examines rolling windows up to 60 months. Although their results provide evidence of positive average payoffs for both shorter and longer windows, the conventional 36-month formation period consistently produced the highest payoffs.

Table 3. Descriptive statistics for beta sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
Mean (compounded)	7.01%	8.12%	9.89%	7.42%	3.17%	0.18%
Mean (simple)	7.73%* (1.89)	9.28%** (1.97)	11.40%** (2.14)	9.57%* (1.68)	6.42% (0.97)	1.31% (0.37)
Standard deviation	13.63%	16.89%	19.50%	21.66%	25.51%	14.94%
Sharpe	0.51	0.48	0.51	0.34	0.12	0.01
Max drawdown	-58.80%	-63.95%	-66.00%	-66.11%	-72.08%	-51.61%
Panel B: 24-month						
Mean (compounded)	7.67%	6.72%	8.85%	7.96%	4.39%	-0.21%
Mean (simple)	8.45%** (1.99)	8.01%* (1.66)	10.33%** (2.03)	10.02%* (1.74)	7.59% (1.16)	0.86% (0.26)
Standard deviation	14.34%	17.14%	18.92%	21.42%	25.48%	14.53%
Sharpe	0.53	0.39	0.47	0.37	0.17	-0.01
Max drawdown	-58.44%	-65.12%	-64.48%	-68.62%	-70.38%	-51.52%
Panel C: 12-month						
Mean (compounded)	5.93%	7.43%	9.12%	8.68%	4.56%	-1.37%
Mean (simple)	7.06% (1.55)	8.59%* (1.85)	10.55%** (2.07)	10.57%* (1.92)	7.63% (1.16)	-0.57% (-0.19)
Standard deviation	16.00%	16.63%	18.78%	20.90%	24.90%	12.73%
Sharpe	0.37	0.45	0.49	0.42	0.18	-0.11
Max drawdown	-64.04%	-62.09%	-63.30%	-65.74%	-71.68%	-43.46%

The table reports compounded and simple annualized excess returns, standard deviations, Sharpe ratios and maximum drawdowns for volatility sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio and. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. All metrics, apart from maximum drawdown, are annualized and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

Table 4. Descriptive statistics for idiosyncratic volatility sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
Mean (compounded)	10.04%	9.21%	9.47%	8.21%	-0.92%	7.98%
Mean (simple)	10.68%** (2.55)	10.50%** (2.06)	11.05%** (2.07)	10.17%* (1.81)	2.01% (0.32)	8.66%*** (2.65)
Standard deviation	14.56%	17.98%	19.67%	21.13%	24.11%	13.79%
Sharpe	0.69	0.51	0.48	0.39	-0.04	0.58
Max drawdown	-58.91%	-65.55%	-65.39%	-65.16%	-72.05%	-37.42%
Panel B: 24-month						
Mean (compounded)	10.37%	8.64%	8.48%	7.45%	0.93%	6.48%
Mean (simple)	10.96%*** (2.62)	9.98%** (2.03)	10.16%* (1.85)	9.51%* (1.66)	3.79% (0.62)	7.17%** (2.36)
Standard deviation	14.49%	18.03%	19.68%	21.36%	23.87%	13.22%
Sharpe	0.72	0.48	0.43	0.35	0.04	0.49
Max drawdown	-57.39%	-63.89%	-67.70%	-70.38%	-66.99%	-36.03%
Panel C: 12-month						
Mean (compounded)	8.96%	8.74%	8.50%	7.60%	2.09%	4.14%
Mean (simple)	9.76%** (2.25)	9.99%** (2.02)	10.18%* (1.93)	9.56%* (1.71)	4.90% (0.79)	4.86% (1.61)
Standard deviation	15.01%	17.58%	19.77%	20.90%	23.79%	12.53%
Sharpe	0.60	0.50	0.43	0.36	0.09	0.33
Max drawdown	-60.48%	-62.54%	-66.11%	-68.27%	-68.37%	-39.19%

The table reports compounded and simple annualized excess returns, standard deviations, Sharpe ratios and maximum drawdowns for volatility sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. All metrics, apart from maximum drawdown, are annualized and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

(FF6) models. The results documented in Table 5–8 confirm the robustness of the low-risk anomaly. Across all strategies, low-risk portfolios yield positive alphas, while high-risk portfolios generate mostly significantly negative alphas. Risk adjustments by means of FF3 and FF5 models (Table 5–7) indicate that the anomaly persists even after controlling for market, size, value, profitability, and

investment factors. When adjusting for the FF6 model (Table 8), which includes the momentum factor, the alphas remain significant, though some magnitudes are slightly reduced. Specifically, FF6 alphas reveal that a portion of returns remains unexplained, with annualized long-short portfolio alphas between 4.84% and 10.63%. These results support earlier research by Frazzini and Pedersen (2014),

Table 5. Alphas for volatility sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
CAPM alpha	1.68% (1.21)	2.23% (1.51)	-0.32% (-0.20)	-1.38% (-0.74)	-9.26%*** (-3.22)	10.94%*** (3.51)
FF3 alpha	1.90% (1.50)	2.58%** (2.07)	0.03% (0.02)	-0.88% (-0.54)	-8.34%*** (-3.35)	10.24%*** (3.40)
FF5 alpha	1.68% (1.14)	1.42% (0.97)	0.30% (0.18)	-0.67% (-0.40)	-7.72%*** (-2.85)	9.40%*** (2.76)
FF6 alpha	1.24% (0.80)	1.54% (0.93)	1.44% (0.89)	0.76% (0.45)	-7.07%** (-2.54)	8.31%** (2.36)
Panel B: 24-month						
CAPM alpha	2.64%** (2.04)	0.98% (0.70)	-0.32% (-0.21)	-2.75% (-1.54)	-7.63%*** (-2.64)	10.27%*** (3.50)
FF3 alpha	2.88%** (2.45)	1.30% (1.10)	0.02% (0.02)	-2.22% (-1.47)	-6.70%*** (-2.65)	9.58%*** (3.39)
FF5 alpha	2.55%* (1.85)	0.53% (0.38)	-0.29% (-0.19)	-1.22% (-0.79)	-6.57%** (-2.43)	9.11%*** (2.83)
FF6 alpha	2.00% (1.38)	0.75% (0.47)	0.43% (0.26)	0.23% (0.15)	-5.52%** (-1.97)	7.52%** (2.26)
Panel C: 12-month						
CAPM alpha	2.47%* (1.71)	-0.45% (-0.35)	0.40% (0.25)	-1.60% (-0.92)	-7.88%*** (-3.00)	10.34%*** (3.73)
FF3 alpha	2.75%** (2.18)	-0.16% (-0.14)	0.79% (0.57)	-1.13% (-0.73)	-6.97%*** (-3.11)	9.72%*** (3.59)
FF5 alpha	2.57%* (1.77)	-0.51% (-0.38)	0.40% (0.25)	-0.94% (-0.55)	-6.53%*** (-2.66)	9.10%*** (2.94)
FF6 alpha	1.98% (1.29)	-0.58% (-0.38)	1.28% (0.80)	0.39% (0.22)	-5.17%** (-2.06)	7.15%** (2.24)

The table reports annualized CAPM, FF3, FF5, and FF6 alphas for volatility sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

Table 6. Alphas for beta sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
CAPM alpha	0.82% (0.47)	0.31% (0.21)	1.02% (0.62)	-2.15% (-1.26)	-7.07%*** (-2.97)	7.88%*** (2.94)
FF3 alpha	1.18% (0.82)	0.64% (0.51)	1.41% (1.01)	-1.75% (-1.16)	-6.20%*** (-2.87)	7.38%*** (2.72)
FF5 alpha	0.97% (0.61)	0.24% (0.18)	1.49% (0.92)	-1.71% (-1.09)	-5.99%** (-2.54)	6.96%** (2.38)
FF6 alpha	0.54% (0.33)	0.25% (0.17)	2.06% (1.21)	-2.65% (-0.40)	-4.30%* (-1.81)	4.84%* (1.67)
Panel B: 24-month						
CAPM alpha	1.13% (0.67)	-1.11% (-0.75)	0.32% (0.19)	-1.58% (-1.00)	-5.82%** (-2.39)	6.96%*** (2.70)
FF3 alpha	1.52% (1.07)	-0.74% (-0.60)	0.69% (0.49)	-1.21% (-0.90)	-4.98%** (-2.21)	6.50%** (2.45)
FF5 alpha	1.30% (0.84)	-0.30% (-0.22)	-0.02% (-0.01)	-1.06% (-0.69)	-4.94%** (-2.05)	6.24%** (2.22)
FF6 alpha	0.75% (0.47)	0.35% (0.26)	0.06% (0.04)	-0.28% (-0.17)	-3.00% (-1.22)	3.74% (1.36)
Panel C: 12-month						
CAPM alpha	-1.12% (-0.65)	-0.20% (-0.14)	0.51% (0.33)	-0.64% (-0.36)	-5.62%*** (-2.62)	4.50%*** (2.00)
FF3 alpha	-0.71% (-0.46)	0.22% (0.19)	0.88% (0.68)	-0.27% (-0.17)	-4.84%*** (-2.61)	4.13%* (1.79)
FF5 alpha	-0.50% (-0.28)	0.39% (0.31)	0.46% (0.33)	-0.59% (-0.36)	-4.75%** (-2.35)	4.26%* (1.73)
FF6 alpha	-0.79% (-0.44)	0.87% (0.65)	1.17% (0.85)	-0.02% (-0.01)	-3.33% (-1.60)	2.55% (1.08)

The table reports annualized CAPM, FF3, FF5, and FF6 alphas for beta sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

Table 7. Alphas for idiosyncratic volatility sorted portfolios.

	P1	P2	P3	P4	P5	P1-P5
Panel A: 36-month						
CAPM alpha	2.71%** (2.31)	0.71% (0.51)	0.50% (0.30)	-1.07% (-0.59)	-9.92%*** (-3.58)	12.63%*** (4.43)
FF3 alpha	2.93%*** (2.71)	1.05% (0.93)	0.87% (0.60)	-0.46% (-0.28)	-9.10%*** (-3.83)	12.03%*** (4.47)
FF5 alpha	2.61%** (2.13)	0.69% (0.51)	0.39% (0.23)	-0.18% (-0.10)	-8.51%*** (-3.33)	11.12%*** (3.68)
FF6 alpha	2.51%* (1.95)	1.09% (0.73)	1.09% (0.60)	1.33% (0.79)	-8.12%*** (-3.07)	10.63%*** (3.46)
Panel B: 24-month						
CAPM alpha	3.06%*** (2.69)	0.15% (0.11)	-0.44% (-0.25)	-1.74% (-0.98)	-8.10%*** (-2.98)	11.17%*** (4.14)
FF3 alpha	3.31%*** (3.25)	0.45% (0.39)	-0.03% (-0.02)	-1.13% (-0.72)	-7.32%*** (-3.05)	10.63%*** (4.10)
FF5 alpha	2.98%*** (2.69)	0.07% (0.05)	-0.90% (-0.55)	-0.04% (-0.03)	-7.11%*** (-2.80)	10.09%*** (3.47)
FF6 alpha	2.95%** (2.44)	0.30% (0.19)	-0.40% (-0.22)	1.21% (0.74)	-6.17%** (-2.36)	9.12%*** (3.03)
Panel C: 12-month						
CAPM alpha	1.61% (1.38)	0.45% (0.30)	-0.48% (-0.30)	-1.59% (-0.96)	-7.05%*** (-2.63)	8.66%*** (3.22)
FF3 alpha	1.88%* (1.91)	0.76% (0.63)	-0.07% (-0.05)	-1.08% (-0.74)	-6.22%*** (-2.67)	8.10%*** (3.10)
FF5 alpha	1.60% (1.40)	0.26% (0.18)	-0.54% (-0.34)	-0.45% (-0.28)	-5.88%** (-2.37)	7.48%** (2.57)
FF6 alpha	1.55% (1.23)	0.17% (0.11)	-0.19% (-0.11)	0.79% (0.48)	-4.44%* (-1.74)	5.99%** (1.97)

The table reports annualized CAPM, FF3, FF5, and FF6 alphas for idiosyncratic volatility (IVOL) sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio. Panel A, panel B and panel C show the results for portfolios sorted based on 36-month, 24-month and 12-month volatility, respectively. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

Table 8. Six-factor regressions.

	VOL			BETA			IVOL		
	P1	P5	P1-P5	P1	P5	P1-P5	P1	P5	P1-P5
Alpha	1.24% (0.80)	-7.07%** (-2.54)	8.31%** (2.36)	0.54% (0.33)	-4.30%* (-1.81)	4.84%* (1.67)	2.51%* (1.95)	-8.12%*** (-3.07)	10.63%*** (3.46)
MKT	0.69*** (28.05)	1.16*** (21.16)	-0.47*** (-7.90)	0.66*** (21.41)	1.22*** (25.92)	-0.57*** (-10.15)	0.77*** (39.24)	1.12*** (20.61)	-0.35*** (-6.29)
SMB	0.26*** (5.01)	1.00*** (7.66)	-0.74*** (-5.06)	0.50*** (8.53)	0.83*** (8.29)	-0.33*** (-2.69)	0.23*** (5.11)	0.98*** (8.32)	-0.75*** (-5.82)
HML	0.11 (1.18)	-0.01 (-0.10)	0.12 (0.78)	0.08 (0.91)	0.13 (1.13)	-0.04 (-0.33)	0.12 (1.60)	-0.05 (-0.38)	0.17 (1.21)
RMW	0.04 (0.37)	-0.30 (-1.40)	0.34 (1.42)	0.01 (0.07)	-0.07 (-0.35)	0.08 (0.38)	0.08 (0.89)	-0.29 (-1.40)	0.37* (1.85)
CMA	-0.07 (-0.70)	0.04 (0.22)	-0.11 (-0.56)	-0.09 (-0.75)	-0.11 (-0.77)	0.02 (0.11)	-0.06 (-0.68)	0.02 (0.10)	-0.07 (-0.40)
MOM	0.04 (1.16)	-0.07 (-1.11)	0.11 (1.65)	0.04 (1.12)	-0.17*** (-3.89)	0.21*** (3.99)	0.01 (0.31)	-0.04 (-0.65)	0.05 (0.83)

The table reports the FF6 regression results for annualized 36-month volatility, beta and idiosyncratic volatility sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). MKT, SMB, HML, RMW, CMA, and MOM represent the market, size, value, profitability, investment, and momentum factors, respectively. P1 (P5) represents the low (high) risk portfolio. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

who documented similar risk-adjusted return differentials in low-volatility investing.

Robustness checks

Results for large and small stocks

The study further examines whether the low-risk anomaly is equally present in small-cap and large-cap stocks. The findings documented in Table 9

indicate that the anomaly is more pronounced in small-cap stocks with annualized excess average return spreads ranging from 6.55% to 9.81%. Raw return spreads as well as FF5 model alphas of large-cap portfolios are statistically not different from zero. This result aligns with Fama and French (2008), who found that anomalies tend to be more pronounced among small-cap stocks. The strong underperformance of high-risk small-cap

Table 9. Results for large and small stocks.

	VOL			BETA			IVOL		
	P1	P5	P1-P5	P1	P5	P1-P5	P1	P5	P1-P5
Panel A: Large									
Mean (compounded)	9.35%	6.98%	-1.08%	9.27%	7.84%	-2.03%	10.47%	7.24%	0.52%
Mean (simple)	9.98%** (2.56)	9.96% (1.57)	0.02% (0.01)	9.99%** (2.41)	10.91%* (1.67)	-0.92% (-0.26)	11.20%*** (2.70)	9.94% (1.64)	1.26% (0.44)
Standard deviation	14.13%	25.01%	14.80%	14.71%	25.67%	14.99%	15.40%	23.93%	12.18%
Sharpe	0.66	0.28	-0.07	0.63	0.31	-0.14	0.68	0.30	0.04
CAPM alpha	2.45%* (1.77)	-3.37%* (-1.66)	5.81%** (2.24)	2.31% (1.52)	-2.90% (-1.30)	5.21%* (1.85)	2.78%** (2.20)	-2.78% (-1.48)	5.56%** (2.50)
FF3 alpha	2.44%* (1.80)	-2.75% (-1.51)	5.19%** (2.12)	2.37%* (1.76)	-2.35% (-1.10)	4.72%* (1.71)	2.86%** (2.33)	-2.31% (-1.34)	5.17%** (2.43)
FF5 alpha	1.97% (1.18)	-2.13% (-1.12)	4.10% (1.45)	1.99% (1.23)	-2.52% (-1.10)	4.50% (1.42)	2.13% (1.59)	-2.03% (-1.12)	4.16%* (1.77)
Panel B: Small									
Mean (compounded)	6.79%	-2.78%	4.86%	5.98%	-3.56%	5.18%	8.61%	-3.93%	8.61%
Mean (simple)	7.48%* (1.80)	0.93% (0.13)	6.55% (1.48)	6.85% (1.53)	0.12% (0.02)	6.73% (1.65)	9.28%** (2.12)	-0.52% (-0.08)	9.81%** (2.49)
Standard deviation	13.22%	27.38%	18.69%	14.24%	27.30%	17.98%	14.01%	26.32%	17.23%
Sharpe	0.51	-0.10	0.26	0.42	-0.13	0.29	0.61	-0.15	0.50
CAPM alpha	1.05% (0.52)	-11.54%*** (-3.04)	12.59%*** (3.27)	0.36% (0.15)	-13.11%*** (-4.08)	13.47%*** (3.79)	2.26% (1.18)	-12.35%*** (-3.42)	14.61%*** (4.06)
FF3 alpha	1.58% (0.92)	-10.40%*** (-3.13)	11.98%*** (3.14)	0.93% (0.45)	-11.96%*** (-3.98)	12.89%*** (3.50)	2.80%* (1.74)	-11.41%*** (-3.63)	14.21%*** (3.98)
FF5 alpha	1.67% (0.91)	-10.05%*** (-2.79)	11.71%*** (2.82)	0.66% (0.31)	-11.16%*** (-3.44)	11.83%*** (3.17)	2.89%* (1.73)	-10.68%*** (-3.08)	13.57%*** (3.45)

The table reports compounded and simple annualized excess return, standard deviation, Sharpe ratio, CAPM alpha, FF3 alpha and FF5 alpha for 36-month volatility (VOL), beta (BETA) and idiosyncratic volatility (IVOL) sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio and. Panel A and panel B show the results for large and small stocks, respectively. All metrics are annualized, and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

stocks primarily drives this result, reinforcing the argument that anomalies are particularly prevalent in less efficient market segments, as also noted by Blitz, Pang, and van Vliet (2013). Furthermore, Figure 1 shows the annualized compounded return and beta relationship of each quintile portfolios sorted by 36-month volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL) for large-cap (L) and small-cap (S) stocks. The evidence shows that the annualized compounded returns across all strategies are considerably higher for S than for L.

Portfolio holding periods

To assess whether the anomaly persists beyond the standard one-month holding period, portfolios were constructed with 3-, 6-, and 12-month holding periods. The results documented in Table 10 demonstrate that low-risk portfolios maintain strong Sharpe ratios and excess returns across all holding periods. Specifically, long-short portfolios achieve statistically significant alphas across all models, with annualized CAPM alphas ranging from 7.88% to 12.63%. Figure 2 displays average monthly excess returns, confirming the persistence

of return differentials between low- and high-risk portfolios over 12 months. While return spreads decline slightly with longer holding periods, they remain statistically significant, reinforcing the persistence of the anomaly. Moreover, Figure 3 shows the rolling 12-month excess returns for the Nordic market index (MKT) and zero-cost long-short portfolios (P1-P5) formed based on 36-month rolling sorts of volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL). Visual inspection of Figure 3 suggests a high level of co-movement across various low volatility strategies.

Subsample analysis

To examine whether the anomaly has remained stable over time, the sample was divided into two subperiods: 2005–2014 and 2015–2024. The results documented in Table 11 indicate that the low-risk anomaly persisted across both periods, with IVOL-sorted portfolios consistently exhibiting the strongest results. Specifically, annualized alphas range between 11.02% (FF5) and 13.54% (CAPM). Interestingly, the anomaly appears to have strengthened in the latter period, particularly for long-short portfolios. This finding is

Table 10. Results for longer holding periods.

	VOL			BETA			IVOL		
	P1	P5	P1-P5	P1	P5	P1-P5	P1	P5	P1-P5
Panel A: 1-Month									
Mean (compounded)	8.14%	0.01%	4.55%	7.01%	3.17%	0.18%	10.04%	-0.92%	7.98%
Mean (simple)	8.76%** (2.19)	3.12% (0.48)	5.64% (1.51)	7.73%* (1.89)	6.42% (0.97)	1.31% (0.37)	10.68%** (2.55)	2.01% (0.32)	8.66%*** (2.65)
Standard deviation	13.32%	24.79%	15.27%	13.63%	25.51%	14.94%	14.56%	24.11%	13.79%
Sharpe	0.61	0.00	0.30	0.51	0.12	0.01	0.69	-0.04	0.58
CAPM alpha	1.68% (1.21)	-9.26%*** (-3.22)	10.94%*** (3.51)	0.82% (0.47)	-7.07%*** (-2.97)	7.88%*** (2.94)	2.71%** (2.31)	-9.92%*** (-3.58)	12.63%*** (4.43)
FF3 alpha	1.90% (1.50)	-8.34%*** (-3.35)	10.24%*** (3.40)	1.18% (0.82)	-6.20%*** (-2.87)	7.38%*** (2.72)	2.93%*** (2.71)	-9.10%*** (-3.83)	12.03%*** (4.47)
FF5 alpha	1.68% (1.14)	-7.72%*** (-2.85)	9.40%*** (2.76)	0.97% (0.61)	-5.99%** (-2.54)	6.96%** (2.38)	2.61%** (2.13)	-8.51%*** (-3.33)	11.12%*** (3.68)
Panel B: 3-Month									
Mean (compounded)	7.98%	0.82%	3.67%	7.22%	3.20%	0.44%	9.79%	-0.17%	6.94%
Mean (simple)	8.60%** (2.18)	3.86% (0.60)	4.74% (1.31)	7.94%* (1.94)	6.40% (0.97)	1.54% (0.43)	10.45%** (2.48)	2.77% (0.44)	7.68%** (2.41)
Standard deviation	13.30%	24.54%	14.92%	13.66%	25.33%	14.72%	14.61%	24.08%	13.75%
Sharpe	0.60	0.03	0.25	0.53	0.13	0.03	0.67	-0.01	0.50
CAPM alpha	1.52% (1.12)	-8.41%*** (-3.01)	9.94%*** (3.28)	0.95% (0.59)	-6.99%*** (-2.91)	7.94%*** (2.90)	2.47%** (2.09)	-9.17%*** (-3.43)	11.63%*** (4.15)
FF3 alpha	1.74% (1.40)	-7.51%*** (-3.08)	9.25%*** (3.16)	1.30% (0.95)	-6.13%*** (-2.81)	7.43%*** (2.70)	2.69%** (2.49)	-8.36%*** (-3.63)	11.05%*** (4.15)
FF5 alpha	1.50% (1.04)	-6.54%** (-2.45)	8.04%** (2.44)	1.06% (0.69)	-5.84%** (-2.51)	6.89%** (2.34)	2.36%* (1.93)	-7.35%*** (-2.89)	9.71%*** (3.24)
Panel C: 6-Month									
Mean (compounded)	7.84%	0.89%	3.43%	7.91%	3.17%	1.12%	9.68%	0.06%	6.53%
Mean (simple)	8.49%** (2.14)	3.97% (0.62)	4.51% (1.28)	8.59%** (2.10)	6.37% (0.97)	2.22% (0.62)	10.37%** (2.45)	3.06% (0.49)	7.31%** (2.27)
Standard deviation	13.40%	24.70%	14.96%	13.68%	25.34%	14.75%	14.70%	24.33%	13.87%
Sharpe	0.58	0.04	0.23	0.58	0.13	0.08	0.66	0.00	0.47
CAPM alpha	1.35% (1.01)	-8.34%*** (-3.03)	9.70%*** (3.27)	1.61% (0.98)	-6.99%*** (-2.91)	8.61%*** (3.13)	2.33%** (1.99)	-8.98%*** (-3.33)	11.31%*** (4.01)
FF3 alpha	1.59% (1.30)	-7.45%*** (-3.07)	9.04%*** (3.14)	1.97% (1.42)	-6.12%*** (-2.78)	8.09%*** (2.91)	2.57%** (2.41)	-8.18%*** (-3.51)	10.75%*** (4.00)
FF5 alpha	1.27% (0.90)	-6.23%** (-2.25)	7.50%*** (2.94)	1.83% (1.18)	-5.77%** (-2.43)	7.60%** (2.57)	2.22%* (1.86)	-6.85%** (-2.56)	9.07%*** (2.94)
Panel D: 12-Month									
Mean (compounded)	7.79%	0.86%	3.38%	8.07%	2.96%	1.59%	9.53%	0.43%	5.93%
Mean (simple)	8.46%** (2.13)	3.98% (0.63)	4.48% (1.29)	8.76%** (2.12)	6.12% (0.94)	2.64% (0.76)	10.25%** (2.41)	3.46% (0.55)	6.79%** (2.11)
Standard deviation	13.60%	24.83%	15.05%	13.88%	25.12%	14.46%	14.85%	24.46%	14.15%
Sharpe	0.57	0.03	0.22	0.58	0.12	0.11	0.64	0.02	0.42
CAPM alpha	1.21% (0.92)	-8.34%*** (-3.08)	9.54%*** (3.27)	1.73% (1.01)	-7.13%*** (-3.10)	8.86%*** (3.29)	2.13%* (1.80)	-8.56%*** (-3.19)	10.69%*** (3.77)
FF3 alpha	1.45% (1.21)	-7.46%*** (-3.14)	8.91%*** (3.15)	2.09% (1.49)	-6.29%*** (-2.97)	8.39%*** (3.09)	2.37%** (2.17)	-7.77%*** (-3.33)	10.14%*** (3.75)
FF5 alpha	1.05% (0.78)	-6.17%** (-2.19)	7.22%** (2.16)	1.80% (1.15)	-5.68%** (-2.36)	7.49%** (2.47)	2.00%* (1.66)	-6.39%** (-2.31)	8.39%*** (2.63)

The table reports compounded and simple annualized excess return, standard deviation, Sharpe ratio, CAPM alpha, FF3 alpha and FF5 alpha for 36-month volatility (VOL), beta (BETA) and idiosyncratic volatility (IVOL) sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio and. Panel A, Panel B, Panel C, and Panel D show the results for portfolios with 1-month, 3-month, 6-month, and 12-month holding periods, respectively. All metrics are annualized, and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) t-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

consistent with Blitz, van Vliet, and Baltussen (2020), who noted that the low-risk effect has become more pronounced in recent years, possibly due to increasing institutional adoption of low-volatility strategies.

Market state analysis

In this section, we analyse the performance of our low-volatility strategies under regime-switching conditions using a two-state Markov-Switching model,

calibrated via Hamilton's (1994) estimation method. For this robustness check, we focus on strategies employing a 36-month formation period and a one-month holding period. The results are presented in Table 12. The findings from Table 12 indicate that the average payoffs of low-volatility strategies are indeed regime-dependent, similar to the excess market factor. Specifically, in state 1 ('bull market state'), the average payoff ranges from 0.92% (IVOL) to 0.96% (BETA) per month, accompanied by an average

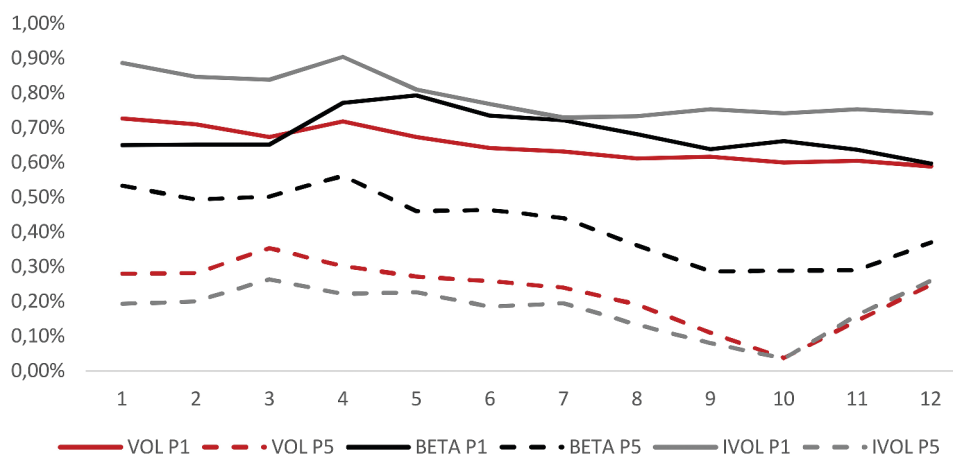


Figure 2. Average monthly excess returns. This figure shows the average monthly excess return of 36-month volatility (VOL), beta (BETA), idiosyncratic volatility (IVOL) sorted low-risk (P1) and high-risk (P5) portfolios each month after portfolio formation.

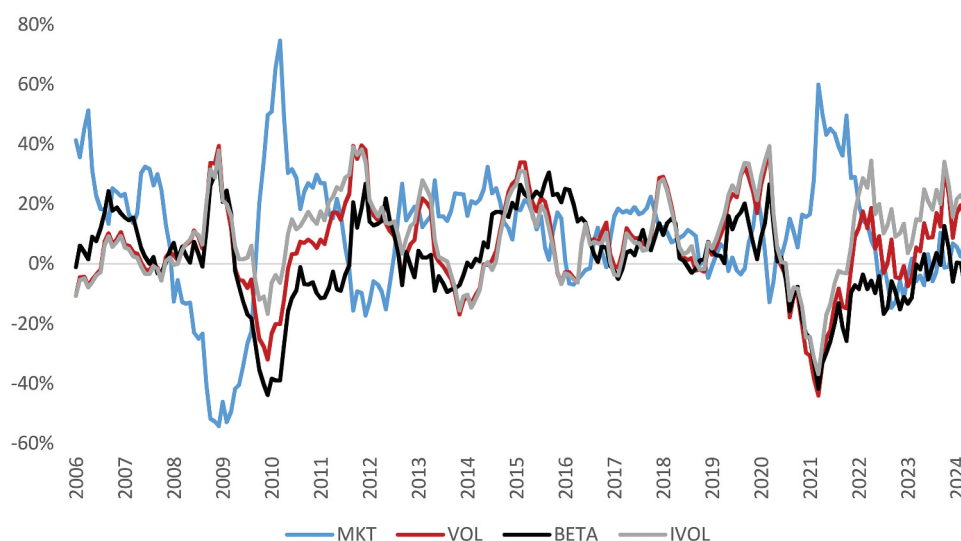


Figure 3. Rolling 12-month excess returns for various low risk strategies and the index. This figure shows the rolling 12-month excess returns for the Nordic market index (MKT) and zero-cost long-short portfolios (P1-P5) formed based on 36-month rolling sorts of volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL).

excess market return of 0.96% per month.⁷ Conversely, in state 2 ('bear market state'), the average payoff ranges from 0.09% (BETA) to 0.66% (IVOL) per month, with an average excess market return of 0.17% per month. The *t*-statistics suggest that, for most strategies and the excess market factor, the average payoffs are in bear market states not statistically different from zero at the conventional 5% significance level. As expected, variances are considerably higher in state 2 for both low-volatility

strategies and the excess market factor. Figure 4 illustrates the evolution of the smoothed state probabilities. A visual inspection of Figure 4 suggests a strong co-movement among the smoothed state probabilities, a relationship further supported by the correlation matrix reported in Supplementary Table S4 in the Appendix. Additionally, a principal component analysis (unreported) reveals that the smoothed state probabilities exhibit a single dominant eigenvalue, which explains 63% of the overall variation.⁸

⁷The transition probability matrices for our calibrated two-state Markov-Switching models are reported in Supplementary Table S3 in the Appendix.

⁸The standardized eigenvalues sorted from largest to smallest are 2.51, 0.88, 0.45, and 0.16.

Table 11. Results for subperiods.

	VOL			BETA			IVOL		
	P1	P5	P1-P5	P1	P5	P1-P5	P1	P5	P1-P5
Panel A: 2/2005–8/2014									
Mean (compounded)	6.35%	−0.38%	3.30%	5.06%	0.68%	0.55%	8.24%	−0.76%	6.23%
Mean (simple)	7.28%	2.98%	4.29%	6.02%	4.31%	1.72%	9.23%	2.33%	6.91%
	(1.04)	(0.27)	(0.79)	(0.86)	(0.38)	(0.30)	(1.26)	(0.22)	(1.53)
Standard deviation	14.75%	25.66%	14.45%	14.54%	26.77%	15.18%	16.01%	24.65%	12.99%
Sharpe	0.43	−0.01	0.23	0.35	0.03	0.04	0.51	−0.03	0.48
CAPM alpha	0.20%	−8.64%**	8.84%**	−0.63%	−8.52%**	7.90%*	1.37%	−8.70%	10.07%***
	(0.09)	(−2.21)	(2.11)	(−0.25)	(−2.57)	(1.90)	(0.77)	(0.98)	(2.70)
FF3 alpha	0.35%	−8.32%**	8.67%**	−0.41%	−8.27%***	7.86%*	1.53%	−8.41%***	9.94%***
	(0.19)	(−2.51)	(2.11)	(−0.18)	(−2.75)	(1.85)	(0.98)	(−2.68)	(2.74)
FF5 alpha	0.23%	−7.69%	7.92%	−0.64%	−7.73%*	7.09%	1.04%	−7.68%*	8.72%
	(0.09)	(−1.51)	(1.24)	(−0.24)	(−1.91)	(1.35)	(0.53)	(−1.66)	(1.60)
Panel B: 9/2014–3/2024									
Mean (compounded)	9.97%	0.40%	5.82%	8.99%	5.72%	−0.19%	11.87%	−1.08%	9.76%
Mean (simple)	10.24%***	3.26%	6.98%	9.45%**	8.53%	0.91%	12.12%***	1.70%	10.42%***
	(2.64)	(0.46)	(1.38)	(2.25)	(1.24)	(0.22)	(2.99)	(0.24)	(2.22)
Standard deviation	11.77%	23.99%	16.11%	12.71%	24.28%	14.76%	13.01%	23.67%	14.58%
Sharpe	0.85	0.02	0.36	0.71	0.24	−0.01	0.91	−0.05	0.67
CAPM alpha	3.15%*	−10.40%**	13.54%***	2.07%	−6.05%*	8.13%**	3.98%**	−11.74%***	15.73%***
	(1.77)	(−2.43)	(3.03)	(0.86)	(−1.90)	(2.59)	(2.61)	(−2.82)	(3.71)
FF3 alpha	3.35%**	−8.86%**	12.22%***	2.63%	−4.53%*	7.16%**	4.21%***	−10.31%***	14.52%***
	(2.03)	(−2.40)	(2.89)	(1.38)	(−1.66)	(2.30)	(2.86)	(−2.96)	(3.78)
FF5 alpha	2.93%	−8.10%**	11.02%***	2.39%	−4.32%	6.70%*	3.80%**	−9.64%***	13.44%***
	(1.64)	(−2.29)	(2.63)	(1.14)	(−1.55)	(1.95)	(2.47)	(−2.89)	(3.54)

The table reports compounded and simple annualized excess return, standard deviation, Sharpe ratio, CAPM alpha, FF3 alpha and FF5 alpha for 36-month volatility (VOL), beta (BETA) and idiosyncratic volatility (IVOL) sorted quintile portfolios and for the zero-cost long-short portfolio (P1-P5). P1 (P5) stands for the low (high) risk portfolio and. Panel A, Panel B, Panel C, and Panel D show the results for portfolios with 1-month, 3-month, 6-month, and 12-month holding periods, respectively. All metrics are annualized, and Sharpe ratios are calculated from compounded excess returns. Newey-West (1987) *t*-statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and *** respectively.

Table 12. Results for different market states.

Statistic	Total volatility	Beta	Idiosyncratic Volatility	Market
$\mu_{i,1}$	0.9115***	0.9576***	0.9201***	0.9566***
$\mu_{i,2}$	0.1835**	0.0898	0.6614*	0.1650*
$t_{\mu_{i,1}}$	17.1183	37.0856	12.7147	31.7636
$t_{\mu_{i,2}}$	2.2198	1.1069	1.7618	1.8501
$\sigma_{i,1}^2$	0.0009***	0.0008***	0.0011***	0.0012***
$\sigma_{i,2}^2$	0.0039***	0.0040***	0.0026	0.0065***
$t_{\sigma_{i,1}^2}$	3.9543	7.0837	6.7110	5.9697
$t_{\sigma_{i,2}^2}$	4.2254	3.6244	1.4913	3.8170

The table reports the average excess return of various low-volatility strategies for different market states. Here μ_{ij} denotes the average payoff of zero-cost strategy *i* in state *j*, and σ_{ij}^2 denotes the corresponding variance. Using a two-state Markov-Switching model, we examine state-dependent average payoffs and state-depending variances for $i = \{1, 2, 3, 4\}$, where $i = 1$ represents the zero-cost low-volatility portfolio derived from total volatility, $i = 2$ represents the zero-cost low-volatility portfolio derived from beta factor exposure, $i = 3$ represents the zero-cost low-volatility portfolio derived from idiosyncratic volatility, and $i = 4$ represents the excess market factor. Furthermore, $t(\cdot)$ denotes the metric-specific *t*-statistic. ***, **, * indicates statistical significance on a 10%, 5%, or 1% level.

Summary

The results provide strong evidence for the existence of a low-risk anomaly in Nordic equity markets. The main findings indicate that low-risk portfolios, particularly those sorted by idiosyncratic volatility, outperform high-risk portfolios in both raw and risk-adjusted terms. The anomaly is

more pronounced in small-cap stocks and persists across multiple formation periods, holding periods, and weighting schemes. Robustness tests confirm that the results are not driven by data-snooping, lookback window selection, or alternative risk factors, reinforcing the validity of the findings. These findings align with prior research by Blitz and van Vliet (2007), Frazzini and Pedersen (2014), and Blitz, Hanauer, and van Vliet (2021), which document the persistence of the low-risk anomaly across different markets and time periods.

While the primary focus of this study has been to document the presence and robustness of the low-risk anomaly in Nordic equity markets using various risk measures, formation windows, and firm size groups, we acknowledge that deeper insights into the underlying mechanisms would further enrich the analysis. One potential avenue involves examining the role of investor composition – such as the relative participation of retail versus institutional investors – in shaping risk-return profiles. Prior research (e.g. Barberis and Huang 2008; Stambaugh, Yu, and Yuan 2015) suggests that retail investors may exhibit preference for lottery-like stocks, potentially

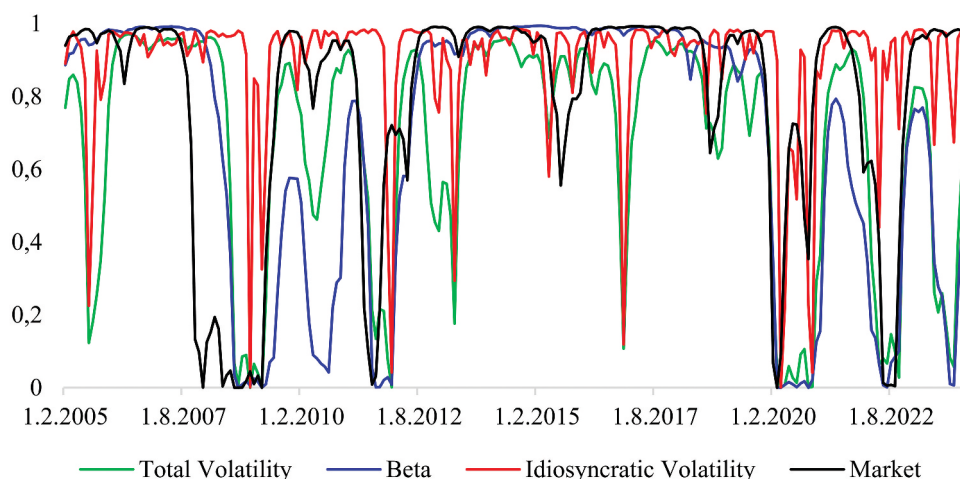


Figure 4. Smoothed state-probabilities. This figure shows the smoothed state-probabilities derived from estimated Marko-Switching models for the Nordic market index (Market) and zero-cost long-short portfolios based on 36-month rolling sorts of Total Volatility, Beta, and Idiosyncratic Volatility.

contributing to the underperformance of high-volatility portfolios. Similarly, institutional constraints or regulatory features unique to the Nordic context, such as capital requirements or portfolio benchmarking practices, could inhibit arbitrage and help sustain the anomaly. Although such factors fall outside the empirical scope of the current dataset, we recognize their relevance and encourage future research to explore how investor behaviour and regulatory structures interact with asset pricing anomalies in regional markets.

VI. Conclusion

Summary of the key findings

This study examines the low-risk anomaly in Nordic equity markets from February 2005 to March 2024, analysing the relationship between risk and return through various measures (volatility, beta, idiosyncratic volatility), rolling windows, holding periods, and market capitalization segments. The study confirms that low-risk equities outperform high-risk equities in both raw excess returns and risk-adjusted returns, supporting the presence of the low-risk anomaly. Long-short zero-cost portfolios sorted by idiosyncratic volatility and using 36-month rolling windows demonstrated the most robust results, consistently yielding significant CAPM, FF3, and

FF5 alphas. In practice, the low-risk anomaly is often exploited through long-only portfolios, such as smart beta ETFs, which demonstrated high Sharpe ratios and superior risk-adjusted performance. However, long-only portfolios yielded fewer statistically significant alphas compared to long-short strategies. Notably, short leg contributions dominated in long-short portfolios, highlighting limitations of long-only approaches in capturing alpha. Large-cap stocks showed inconsistent evidence of the anomaly, with significant alphas found primarily in idiosyncratic volatility-sorted portfolios. In contrast, small-cap stocks exhibited a stronger inverse risk-return relationship, driven largely by underperformance of high-risk portfolios. Despite these findings, only a minority of low-risk portfolios across both large- and small-cap segments achieved significant alphas. Longer holding periods (3, 6, and 12 months) validated the viability of low-risk strategies with lower turnover rates. Although alphas slightly declined over time for certain measures, their statistical significance persisted. Subperiod analysis indicates that the anomaly has strengthened over the study period.

Managerial and policy implications

The findings of this study have important implications for fund managers, institutional investors, and policymakers, particularly in Nordic markets and

beyond. The robust performance of low-risk portfolios, especially those sorted by idiosyncratic volatility, suggests that low-volatility investment strategies can enhance risk-adjusted returns. Fund managers should consider allocating capital towards low-risk stocks or integrating low-volatility factors into quantitative investment models to improve portfolio efficiency. Given that longer risk measurement periods (e.g. 36 months) yield stronger return spreads, investors should adopt a long-term perspective when implementing low-risk strategies. For portfolio construction, investors can apply the findings by adjusting factor exposures to overweight low-volatility stocks, optimizing portfolios for downside protection while maintaining competitive returns. Smart beta strategies incorporating these insights can enhance diversification and mitigate market downturn risks. For policymakers, the results provide insights into market dynamics and efficiency. The persistence of low-risk return anomalies suggests that risk-based asset pricing models may not fully capture investors' behaviour. Policymakers can use these insights to assess market stability, identify potential mispricing, and ensure transparent risk disclosures, fostering a more efficient and resilient financial market.

Finally, we acknowledge that environmental, social, and governance (ESG) considerations may interact with risk-return dynamics in the Nordic context, given the region's strong emphasis on sustainability in both policy and investing. While ESG factors fall outside the scope of the current study, integrating ESG dimensions into the analysis of the low-risk anomaly represents a valuable direction for future research. Such extensions could explore whether ESG characteristics help explain cross-sectional return patterns or affect the persistence and viability of low-risk strategies in markets with high sustainability standards.

Limitations and future research

Overall, our study provides robust evidence for the low-risk anomaly in Nordic equity markets, with IVOL-sorted portfolios exhibiting the strongest performance. While small-cap stocks demonstrate a more pronounced anomaly, the findings remain consistent across risk measures, holding periods, and subsample analyses. These results offer valuable insights into the persistence and applicability of low-

risk strategies. Future research should address the drivers of the low-risk anomaly, as no consensus exists on its underlying causes. Expanding studies to other asset classes and exploring fundamental-based risk measures in addition to price-based measures could provide deeper insights.

Another valuable direction for future research would be to compare the persistence and strength of the low-risk anomaly in the Nordic region with other European markets, such as the DACH or Baltic countries. Such cross-regional analyses could help disentangle region-specific effects from broader pan-European drivers and shed light on how local market structures, regulatory environments, or investor behaviours contribute to the observed risk-return patterns. While this study is intentionally focused on Nordic markets, expanding the scope in future work could offer deeper insights into the generalizability of the anomaly across different institutional settings.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

References

- Alquist, R., A. Frazzini, A. Ilmanen, and L. Pedersen. 2020. "Fact and Fiction About Low-Risk Investing." *The Journal of Portfolio Management* 46 (6): 72–92. <https://doi.org/10.3905/jpm.2020.1.146>.
- Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *The Journal of Finance* 61 (1): 259–299. <https://doi.org/10.1111/j.1540-6261.2006.00836.x>.
- Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2009. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics* 91 (1): 1–23. <https://doi.org/10.1016/j.jfineco.2007.12.005>.
- Baker, M., B. Bradley, and Taliaferro. 2014. "The Low-Risk Anomaly: A Decomposition into Micro and Macro Effects." *Financial Analysts Journal* 70 (2): 43–58. <https://doi.org/10.2469/faj.v70.n2.2>.
- Baker, M., B. Bradley, and J. Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility

- Anomaly.” *Financial Analyst Journal* 67 (1): 40–54. <https://doi.org/10.2469/faj.v67.n1.4>.
- Baker, N. L., and R. A. Haugen. 2012. “Low Risk Stocks Outperform within All Observable Markets of the World.” *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2055431>.
- Bali, T. G., and N. Cakici. 2008. “Idiosyncratic Volatility and the Cross Section of Expected Returns.” *Journal of Financial and Quantitative Analysis* 43 (1): 29–58. <https://doi.org/10.1017/S002210900000274X>.
- Barberis, N., and M. Huang. 2008. “Stocks as Lotteries: The Implications of Probability Weighting for Security Prices.” *American Economic Review* 98 (5): 2066–2100. <https://doi.org/10.1257/aer.98.5.2066>.
- Black, F., M. C. Jensen, and M. Scholes. 1972. “The Capital Asset Pricing Model: Some Empirical Tests.” *Studies in the Theory of Capital Markets*: 79–121. <https://ssrn.com/abstract=908569>.
- Blitz, D., M. X. Hanauer, and P. van Vliet. 2021. “The Volatility Effect in China.” *Journal of Asset Management* 22 (5): 338–349. <https://doi.org/10.1057/s41260-021-00218-0>.
- Blitz, D., J. Pang, and P. van Vliet. 2013. “The Volatility Effect in Emerging Markets.” *Emerging Markets Review* 16:31–45. <https://doi.org/10.1016/j.ememar.2013.02.004>.
- Blitz, D., and P. van Vliet. 2007. “The Volatility Effect.” *The Journal of Portfolio Management* 34 (1): 102–113. <https://doi.org/10.3905/jpm.2007.698039>.
- Blitz, D., P. van Vliet, and G. Baltussen. 2020. “The Volatility Effect Revisited.” *The Journal of Portfolio Management* 46 (2): 45–63. <https://doi.org/10.3905/jpm.2019.1.114>.
- Bradrania, R., and J. F. Veron. 2023. “The Beta Anomaly in the Australian Stock Market and the Lottery Demand.” *Pacific-Basin Finance Journal* 77:101903. <https://doi.org/10.1016/j.pacfin.2022.101903>.
- Bradrania, R., J. Veron, and W. Wu. 2023. “The Beta Anomaly and the Quality Effect in International Stock Markets.” *Journal of Behavioral and Experimental Finance* 38:100808. <https://doi.org/10.1016/j.jbef.2023.100808>.
- Chen, L. H., G. J. Jiang, D. D. Xu, and T. Yao. 2020. “Dissecting the Idiosyncratic Volatility Anomaly.” *Journal of Empirical Finance* 59:193–209. <https://doi.org/10.1016/j.jempfin.2020.10.004>.
- Fama, E. F. 1970. “Efficient Capital Markets: A Review of Theory and Empirical Work.” *Journal of Finance* 25 (2): 383–417. <https://doi.org/10.2307/2325486>.
- Fama, E. F., and K. R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33 (1): 3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5).
- Fama, E. F., and K. R. French. 2008. “Dissecting Anomalies.” *The Journal of Finance* 63 (4): 1653–1678. <https://doi.org/10.1111/j.1540-6261.2008.01371.x>.
- Fama, E. F., and K. R. French. 2015. “A Five-Factor Asset Pricing Model.” *Journal of Financial Economics* 116 (1): 1–22. <https://doi.org/10.1016/j.jfineco.2014.10.010>.
- Fama, E. F., and K. R. French. 2018. “Choosing Factors.” *Journal of Financial Economics* 128 (2): 234–252. <https://doi.org/10.1016/j.jfineco.2018.02.012>.
- Fong, K. Y. L., C. W. Holden, and C. A. Trzcinka. 2017. “What are the Best Liquidity Proxies for Global Research?” *Review of Finance* 21 (4): 1355–1401. <https://doi.org/10.1093/rof/rfx003>.
- Frazzini, A., and L. Pedersen. 2014. “Betting Against Beta.” *Journal of Financial Economics* 111 (1): 1–25. <https://doi.org/10.1016/j.jfineco.2013.10.005>.
- Fu, F. 2009. “Idiosyncratic Risk and the Cross-Section of Expected Stock Returns.” *Journal of Financial Economics* 91 (1): 24–37.
- Glück, M., B. Hübel, and H. Scholz. 2021. “Currency Conversion of Fama-French Factors: How and Why.” *The Journal of Portfolio Management* 47 (2): 157–175. <https://doi.org/10.3905/jpm.2020.1.192>.
- Grobys, K., V. Fatmy, and T. Rajalin. 2024. “Combining Low-Volatility and Momentum: Recent Evidence from the Nordic Equities.” *Applied Economics* forthcoming. <https://doi.org/10.1080/00036846.2024.2337806>.
- Grobys, K., and T. Huhta-Halkola. 2019. “Combining Value and Momentum: Evidence from the Nordic Equity Market.” *Applied Economics* 51 (26): 2872–2884. <https://doi.org/10.1080/00036846.2018.1558364>.
- Hamilton, J. 1994. *Time Series Analysis*. Princeton, NJ: Princeton University Press.
- Ince, O. S., and R. B. Porter. 2006. “Individual Equity Return Data from Thomson Datastream: Handle with Care.” *Journal of Financial Research* 29 (4): 463–479. <https://doi.org/10.1111/j.1475-6803.2006.00189.x>.
- Jokipii, A., and S. Vähämaa. 2006. “The Free Cash Flow Anomaly Revisited: Finnish Evidence.” *Journal of Business Finance & Accounting* 33 (7–8): 961–978. <https://doi.org/10.1111/j.1468-5957.2006.00620.x>.
- Joshi, N., and M. Joshi. 2019. “The Volatility Effect: Recent Evidence from Indian Markets.” *Theoretical Economics Letters* 9 (6): 2152–2164. <https://doi.org/10.4236/tel.2019.96136>.
- Kohls, T., and F. Mager. 2023. “Profitability and Low-Risk Anomalies Reexamined.” *Global Finance Journal* 56:100776. <https://doi.org/10.1016/j.gfj.2022.100776>.
- Landis, C., and S. Skouras. 2021. “Guidelines for Asset Pricing Research Using International Equity Data from Thomson Reuters Datastream.” *Journal of Banking & Finance* 130:106128. <https://doi.org/10.1016/j.jbankfin.2021.106128>.
- Leivo, T. 2012. “Combining Value and Momentum Indicators in Varying Stock Market Conditions: The Finnish Evidence.” *Review of Accounting and Finance* 11 (4): 400–447. <https://doi.org/10.1108/14757701211279187>.
- Leivo, T., and E. Pätäri. 2009. “Performance of the Value Strategies in the Finnish Stock Markets.” *Journal of Money, Investment and Banking* 2 (8): 5–24.
- Li, X., R. Sullivan, and L. Garcia-Feijóo. 2014. “The Limits to Arbitrage and the Low-Volatility Anomaly.” *Financial Analysts Journal* 70 (1): 52–63. <https://doi.org/10.2469/faj.v70.n1.3>.

- Lintner, J. 1965. "Security Prices, Risk, and Maximal Gains from Diversification." *The Journal of Finance* 20 (4): 587–615. <https://doi.org/10.1111/j.1540-6261.1965.tb02930.x>.
- Moreira, A., and T. Muir. 2017. "Volatility-Managed Portfolios." *The Journal of Finance* 72 (4): 1611–1644. <https://doi.org/10.1111/jofi.12513>.
- Newey, W. K., and K. D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703–708. <https://doi.org/10.2307/1913610>.
- Nikkinen, J., P. Sahlström, K. Takko, and J. Äijö. 2009. "Turn-of-the-Month and Intramonth Anomalies and U.S. Macroeconomic News Announcements on the Thinly Traded Finnish Stock Market." *International Journal of Economics and Finance* 1 (2): 3–12. <https://doi.org/10.5539/ijef.v1n2p3>.
- Perras, P., A. Reberger, and N. Wagner. 2020. "The Low-Volatility Anomaly Revisited." *Credit and Capital Markets – Kredit Und Kapital* 53 (2): 221–244. <https://doi.org/10.3790/ccm.53.2.221>.
- Rinne, E., and S. Vähämaa. 2011. "The 'Dogs of the Dow' Strategy Revisited: Finnish Evidence." *European Journal of Finance* 17 (5–6): 451–469. <https://doi.org/10.1080/1351847X.2010.544951>.
- Schmidt, P. S., U. Von Arx, A. Schimpf, A. F. Wagner, and A. Ziegler. 2011. "On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications." *Economics Working Paper Series, No. 11/141*. <https://hdl.handle.net/10419/171584>.
- Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *The Journal of Finance* 19 (3): 425–442. <https://doi.org/10.1111/j.1540-6261.1964.tb02865.x>.
- Silvasti, V., K. Grobys, and J. Äijö. 2021. "Is Smart Beta Investing Profitable? Evidence from the Nordic Stock Market." *Applied Economics* 53 (16): 1826–1839. <https://doi.org/10.1080/00036846.2020.1853669>.
- Stambaugh, R. F., J. Yu, and Y. Yuan. 2015. "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle." *Journal of Finance* 70 (5): 1903–1948. <https://doi.org/10.1111/jofi.12286>.
- Van Vliet, P. 2018. "Low Volatility Needs Little Trading." *The Journal of Portfolio Management* 44 (3): 33–42. <https://doi.org/10.3905/jpm.2018.44.3.033>.