Vaasan yliopisto
UNIVERSITY OF VAASA

Eetu Hartikainen

Low-Risk Anomaly

Evidence from the Nordic equity markets

School of Accounting and Finance
Master's thesis in Finance
Master's Degree programme in Finance

Vaasa 2024

UNIVERSITY OF VAASA			
School of Accounting and Finance			
Author:	Eetu Hartikainen		
Title of the Thesis:	Low-Risk Anomaly: Evidence from the Nordic equity markets		
Degree:	Master of Science in Economics and Business Administration		
Programme:	Master's Degree Programme in Finance		
Supervisor:	Janne Äijö		
Year:	2024	**Pages:**	77

ABSTRACT:

This study seeks to examine the low-risk anomaly in Nordic equity markets from February 2005 to March 2024. While the low-risk anomaly has been a subject of extensive research, particularly in US markets, it remains under-researched in the Nordic context. To address this gap, this study aims to provide a comprehensive analysis of the anomaly within the Nordic region. Given the absence of standardized methodologies for analyzing the low-risk anomaly, this study investigates the efficacy of various approaches to exploit this phenomenon. Specifically, portfolios sorted by volatility, beta, and idiosyncratic volatility are analyzed, utilizing rolling risk measurement periods of 36, 24, and 12 months. Furthermore, this study assesses the robustness of the low-risk anomaly across different market capitalizations, namely large-cap and small-cap stocks. It also evaluates the persistence of the anomaly over holding periods exceeding the standard one-month duration.

The findings confirm the presence of a low-risk anomaly in Nordic equity markets. Low-risk portfolios consistently outperform high-risk portfolios, generating superior raw excess returns and risk-adjusted returns. All long-short portfolios tested across various methodologies produced statistically significant FF5 alphas, with the majority also yielding significant FF6 alphas. Strongest results were driven by idiosyncratic volatility sorted portfolios whereas beta sorted portfolios generated weakest results. Additionally, 36-month sorted portfolios generated the most pronounced differences between lowest and highest risk portfolios, whereas 12-month sorted portfolios generated the least pronounced differences. Furthermore, the low-risk anomaly is more driven by the short leg than the long leg. Results for large cap stocks were mixed, as the return spreads between low-risk and high-risk portfolio were more muted and only idiosyncratic volatility sorted portfolios generated statistically significant FF5 alpha. Furthermore, low-risk anomaly is robust to longer holding periods (up to 12 months).

KEYWORDS: Low-risk, Low-volatility, Low-beta, Anomaly

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen yksikkö

Tekijä:	Eetu Hartikainen
Tutkielman nimi:	Low-Risk Anomaly: Evidence from the Nordic equity markets
Tutkinto:	Kauppatieteiden maisteri
Oppiaine:	Rahoituksen maisteriohjelma
Työn ohjaaja:	Janne Äijö
Vuosi:	2024 **Sivumäärä:** 77

TIIVISTELMÄ:

Tämä tutkimus tarkastelee alhaisen riskin anomaliaa Pohjoismaisilla osakemarkkinoilla helmikuusta 2005 maaliskuuhun 2024. Vaikka ilmiötä on tutkittu laajasti erityisesti Yhdysvalloissa, Pohjoismaissa aiheeseen liittyvä tutkimus on ollut rajallista. Koska alhaisen riskin anomalian mittaamiseen ei ole yhtä yleisesti hyväksyttyä menetelmää, tässä tutkimuksessa vertaillaan erilaisia mittausmenetelmiä niiden eroavaisuuksien selvittämiseksi. Anomalian esiintyvyyttä arvioidaan mittaamalla riskiä volatiliteetin, betan ja idiosynkraattisen volatiliteetin avulla, käyttäen eripituisia riskin mittausjaksoja. Lisäksi tutkimuksessa tarkastellaan anomalian esiintyvyyttä suurissa ja pienissä osakkeissa sekä pitoajoilla, jotka ovat pidempiä kuin tavanomainen yhden kuukauden jakso.

Tämä tutkielma osoittaa alhaisen riskin anomalian esiintyvyyden Pohjoismaisilla osakemarkkinoilla. Tutkimuksen tulokset osoittavat, että matalariskiset osakkeet tuottavat paremmin kuin korkeariskiset osakkeet. Kaikki eri menetelmillä muodostetut "long-short"-portfoliot saavuttivat positiivisen ja tilastollisesti merkitsevän FF5 alphan, ja lähes kaikki saavuttivat myös tilastollisesti merkitsevän FF6 alphan. Suurimmat tuottoerot matalariskisten ja korkeariskisten osakkeiden välillä havaitaan, kun riski määritellään idiosynkraattisen volatiliteetin perusteella, kun taas pienimmät erot ilmenevät betan perusteella määritellyssä riskissä. Lisäksi tuottoerot korostuvat eniten, kun osakkeet jaotellaan 36 kuukauden riskin perusteella, ja pienimmät erot syntyvät, kun jaottelu tehdään 12 kuukauden riskin perusteella. Tulokset osoittavat, että alhaisen riskin anomalia johtuu enemmän korkeariskisten osakkeiden alituotosta kuin matalariskisten osakkeiden ylituotosta. Suurten osakkeiden osalta tulokset olivat ristiriitaisia, sillä tuottoero matalariskisten ja korkeariskisten osakkeiden välillä kaventui merkittävästi, ja ainoastaan idiosynkraattisen volatiliteetin perusteella jaoteltu portfolio tuotti tilastollisesti merkitsevän FF5 alphan. Lisäksi tutkimus osoittaa, että alhaisen riskin anomalia esiintyy myös pidemmillä, jopa 12 kuukauden, pitoajoilla.

AVAINSANAT: Alhainen riski, Alhainen volatiliteetti, Alhainen beta, Anomalia

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1 Introduction

Modern finance is based on the premise of efficient markets, where asset prices reflect all available information and thus are correctly valued. In efficient markets, asset price changes are random and unpredictable, making it impossible for investors to consistently outperform or underperform the market. According to the efficient market hypothesis (EMH), the only method to alter the return is by adjusting the riskiness of the portfolio. This concept is clearly expressed by another fundamental principle of modern finance, the capital asset pricing model (CAPM). The CAPM predicts a positive and linear relationship between risk and return, where risk is measured as the beta of a stock, representing its systematic risk relative to the market portfolio.

Since the 1970s, when Fama popularized efficient market hypothesis, academics have discovered many elements that violate the hypothesis. In their early empirical studies of CAPM, Black et al. (1972) discovered that the security market line was flatter than what the model predicted, indicating that low-risk stocks yielded higher returns than they should have, according to the model, while high-risk stocks underperformed the model's estimates. Later, many other risk factors and anomalies were discovered, leading to the realization that the single-factor model was not sufficient in explaining the cross section of stock returns. The size factor, value factor, and momentum factor are other widely known risk factors that independently capture the abnormal returns of various stock types, which the CAPM fails to explain.

The low-risk anomaly describes the phenomenon where lower-risk assets outperform their riskier counterparts within the same asset class. While often associated with stock markets, this anomaly has also been observed in other asset classes such as bonds, commodities, and futures (see e.g., Alquist et al., 2020; Blitz et al., 2020; Frazzini & Pedersen, 2014). The measurement of this phenomenon can be approached in a multitude of ways. Risk assessment can be conducted utilizing metrics such as beta, volatility, or idiosyncratic volatility, over varying trailing periods ranging from 1 to 60 months, and employing different measurement intervals, such as monthly, weekly, or daily returns. Therefore, no single definitive method exists to measure the low-risk anomaly, but rather a variety of suitable approaches.

Low-risk anomaly has been described as one of the greatest anomalies in finance due to its success over long term period (Baker et al., 2011). The low-risk factor has demonstrated a notable degree of stability over the decades, and its magnitude has been substantial when compared to other factors. Blitz et al. (2020) documented that the volatility factor achieved a positive risk premium in every decade from 1929 to 2018, averaging 5.8 percent per annum. In contrast, size, value, profitability, and investment factors were unable to achieve such stability or magnitude. The robust characteristics of the low-risk anomaly are not a coincidence, but rather a result of behavioral biases, constraints, and agency issues that lead to market inefficiencies (see Chapter 3.2).

1.1 Purpose of the study

The purpose of this study is to investigate the low-risk anomaly in Nordic equity markets from February 2005 to March 2024. Given the absence of standardized methodologies for analyzing the low-risk anomaly, this study aims to assess the effectiveness of different approaches in exploiting it. Specifically, the research analyzes portfolios sorted by volatility, beta, and idiosyncratic volatility, utilizing rolling risk measurement periods of 36, 24, and 12 months. Furthermore, the robustness of the low-risk anomaly will be evaluated across different market capitalizations, specifically large-cap and small-cap stocks, and holding periods extending beyond the standard one-month period.

1.2 Intended contribution

Existing research on low-risk anomalies predominantly focuses on the US equity market or broader regions such as Europe. While some studies include Nordic countries as part of a broader sample (e.g., Baker & Haugen, 2012; Bradrania et al., 2023; Frazzini &

Pedersen, 2014), their analysis of the low-risk anomaly within individual countries is often limited, typically focusing only on long-short portfolios using a single risk measurement. Silvasti et al. (2021) and Grobys et al. (2024) investigated multi-factor strategies in Nordic equity markets, with the low-risk anomaly being one aspect of their broader studies. However, because their primary focus was on combined factor models, the specific analysis of the low-risk anomaly was comparatively narrow. This leaves room for more focused research on the low-risk anomaly, including studying and comparing various methodologies. Hence, this study aims to contribute to existing literature by providing a comprehensive study on low-risk anomaly in Nordic equity markets.

1.3 Development of hypotheses

This study aims to investigate the existence of the low-risk anomaly in Nordic equity markets. While no research has exclusively focused on this phenomenon in the Nordic context, evidence from broader studies suggests its presence. Baker and Haugen (2012) found that low-volatility stocks outperformed high-volatility stocks in Finland, Sweden, Denmark, and Norway. Bradrania et al. (2023) further supported this by reporting the presence of the low-beta anomaly in Sweden, Denmark, and Norway, although not in Finland. Additionally, Grobys et al. (2024), in a broader study examining the combined performance of low-volatility and momentum strategies, also observed that low-volatility stocks outperformed high-volatility stocks in Nordic equity markets. Moreover, the presence of the low-risk anomaly has been documented in broader European markets as well (Blitz & van Vliet, 2007). Therefore, the first hypothesis of this study is formulated as follows:

H1: Low-risk anomaly exists in Nordic equity markets.

Empirical evidence suggests that numerous anomalies exhibit stronger performance in small-cap stocks (Alquist et al., 2018). Li et al. (2014) further highlight that the alpha associated with low-risk anomaly disappears when excluding illiquid penny stocks.

Similarly, Bali and Cakici (2008) observed no significant relationship between idiosyncratic risk and cross-sectional expected returns after excluding smallest and least liquid stocks. However, Auer and Schuhmacher (2015) provide evidence for the beta anomaly's persistence even within the largest and most liquid U.S. stocks. Moreover, multiple studies confirm the presence of the low-risk anomaly in larger stocks, albeit with diminished strength compared to smaller stocks (see e.g., Baker et al., 2011; Alquist et al., 2020). Given this nuanced landscape, the second hypothesis of this study is to investigate the existence of the low-risk anomaly specifically within large-cap equities.

H2: Low-risk anomaly exists in large cap equities.

While most studies on the low-risk anomaly utilize one-month holding periods, a common practice in factor research, this may not be the most optimal approach in practice. If a stock's risk characteristics remain stable over longer durations, less frequent rebalancing could yield similarly promising results while reducing transaction costs and operational complexity. Empirical evidence supports this notion. Van Vliet (2018) and Alquist et al. (2020) demonstrate that low-risk investment strategies can be effectively implemented with a relatively low portfolio turnover. This suggests that the risk characteristic of stocks tends to persist over time, making less frequent rebalancing a viable option. Furthermore, Blitz et al. (2013) and Blitz et al. (2021) report substantial and statistically significant low-volatility alphas even with holding periods extending up to five years, suggesting the robustness of the low-risk anomaly over longer timeframes. In contrast, Li et al. (2014) find that the alpha of a zero-cost portfolio diminishes rapidly after the second month following portfolio formation. Thus, the third hypothesis is as follows:

H3: Low-risk anomaly exists with longer holding periods.

1.4 Structure of the study

The structure of this study is organized as follows. After the introduction chapter, the second chapter examines financial theories relevant to the low-risk anomaly, including the efficient market hypothesis and asset pricing models. The third chapter reviews existing academic literature on the low-risk anomaly and offers a comprehensive explanation of the phenomenon. The fourth chapter details the data and methodology employed in the study. The fifth chapter presents and discusses the findings, including an analysis of the study's limitations. The final, sixth chapter, provides a summary and conclusion, along with suggestions for future research.

2 Theory

This chapter reviews the relevant theoretical background of the low-risk anomaly. First, it introduces the efficient market hypothesis (EMH). The second relevant theory is asset pricing models, including the original capital asset pricing model (CAPM) introduced independently by Sharpe (1964), Lintner (1965), and Mossin (1966), along with later extensions of the model. Additionally, the Sharpe ratio, a key metric for portfolio performance assessment, is introduced.

2.1 Efficient market hypothesis

The efficient market hypothesis states that security prices fully reflect all available information and are consequently always valued correctly. Therefore, any mispricing in the markets is eliminated, making it impossible for investors to generate above-market risk-adjusted returns in the long-term by utilizing public, private or historical information since the market has already incorporated it into the prices. The only way to modify investment returns is by adjusting the risk level associated with the investments. (Fama, 1970.) Fama (1970) divided market efficiency into three forms based on the degree of information incorporated into market prices: weak form, semi-strong form and strong form.

The weak form conditions are met when stock prices reflect all the past market information, such as historical price action, returns and volumes. Should this be the case, forecasting future returns by exploiting historical market patterns or trends is not possible and thus technical analysis is ineffective. The semi-strong form of the hypothesis asserts that current market prices fully reflect all publicly available information, which encompasses historical market data. This suggests that any information that is known and available, be it related to the past, present, or expected future, has already been factored into the market prices. Therefore, it is not possible to generate abnormal returns by analyzing financial statements or reading news, as analysts’ forecasts about future earnings and macroeconomic predictions are already incorporated into today's price. The strong form of hypothesis refers to scenario where all information is reflected in current market prices. In addition to publicly available information, prices also consider all insider information that is available to only a few. Assuming this hods true, there is nothing that investors can do to generate abnormal returns, as all insider information will be factored into the price long before it becomes public. (Fama, 1970.)

Fama (1970) argues that market conditions can impact the market's efficiency to reflect information. The ideal conditions for market efficiency would exist when there are no transaction costs, all information is freely accessible to everyone, and there is a universal consensus on how current information influences the present and future price of each stock. Even though these would be ideal conditions, they are not necessary. Market efficiency can still be achieved if enough investors account for all available information, even in the face of potential transaction costs and differing opinions. (Fama, 1970.)

2.2 Asset pricing models

This section introduces asset pricing models, which are tools used to measure the expected return of a risky asset based on various risk factors. While there are multiple models used for asset pricing, this section will focus only on some of the most widely known models.

2.2.1 Capital asset pricing model

The capital asset pricing model, or CAPM, introduced by Sharpe (1964), Lintner (1965), and Mossin (1966), is a widely used asset pricing model that describes the relationship between the expected return of a risky asset and its risk, measured as beta, also known as systematic risk. CAPM is built on top of Markowitz's (1952) portfolio theory, which assumes that market participants aim to maximize expected returns while minimizing portfolio variance. CAPM assumes that the relationship between risk and return is positive and linear. The formula is commonly known as follows.

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{1}$$

Where: $E(R_i)$ = the expected return of stock i
R_f = the risk-free rate
β_i = the beta of the stock i
$E(R_m)$ = the expected return of market m

The CAPM is a simple model, trying to explain the full complexity of real-life markets by relying only on three variables, beta, risk-free rate and expected market return. It recognizes only one sort of risk, systematic risk, which is measured as the covariance of the return of an asset i and the return of the market, divided by the variance of the market return (Bodie et al., 2014). The model is constructed based on the premise of a simplified world, relying on several assumptions about participant behavior and market structure that are not feasible in the real world. The assumptions underlying the CAPM as presented in Bodie et al. (2014) are as follows.

1. Individual behavior
    a. Investors are rational, mean-variance optimizers.
    b. Investors planning horizon is a single period.
    c. Investors have homogenous expectations.
2. Market structure
    a. All assets are publicly held and trade on public exchanges, shorting is allowed, and investors can borrow or lend at a risk-free rate.
    b. All information is publicly available.
    c. No taxes.
    d. No transaction costs.

Despite the popularity of the CAPM, its empirical performance has been disappointing, as the returns on the low-beta stocks are too high and the returns for high-beta stocks are too low. This could be attributed to either the model's unrealistic assumptions or the challenges in implementing robust tests of the model. For example, the composition of the "market portfolio" used in CAPM calculations is not strictly defined. While it's common to use only stocks, the portfolio could also include a variety of assets such as real estate, human capital, and other assets. There is not an absolute correct approach to defining this portfolio. (Fama and French, 2004.)

2.2.2 Three factor model

Following the introduction of the CAPM, researchers discovered that factors other than systematic risk also influence stock returns. Banz (1981) found that a stock's market capitalization, determined by multiplying the stock's price with the number of outstanding shares, can help explain the variation in average returns. He demonstrated that stocks of smaller companies tend to yield higher average returns compared to those of larger companies. Furthermore, Stattman (1980) and Rosenberg et al. (1985) found that the ratio of a firm's book value of common equity to its market value (B/M) can influence stock returns. Specifically, they observed that stocks with a high B/M ratio tend to perform better than stocks with a low B/M ratio.

Fama and French (1993) introduced an extended version of the CAPM by adding two new factors to the traditional model. They argue that the CAPM beta itself does not fully account for the cross-section of expected returns on US stocks. They further contend that there exist other variables, not included in traditional asset pricing theory, that demonstrate a reliable ability to explain these average returns. Therefore, the new model, also known as the Fama-French three-factor model (FF3), adds the size factor and the value factor, small minus big (SMB), also known as the size factor, quantifies the difference in returns between small and large capitalization stocks, capturing the relative outperformance of smaller stocks. On the other hand, high minus low (HML), also referred to as the value factor, measures the difference in returns between stocks with high and low B/M ratios. This factor captures the superior performance of stocks with lower B/M ratios. (Fama and French, 1993.)

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_i SMB + h_i HML + e_i \tag{2}$$

Where:	R_i	= the return on security or portfolio i
	R_f	= the risk-free rate
	a_i	= the intercept
	R_m	= the return on the market portfolio
	SMB	= the return on small stocks minus large stocks
	HML	= the return on high B/M stocks minus low B/M stocks
	b_i, s_i, h_i	= the factor loadings on market, size and value factors
	e_i	= the zero-mean residual

2.2.3 Four factor model

Carhart (1997) was the first to introduce the four-factor model, which adds a momentum factor to the FF3 model. Carhart (1997) finds that mutual funds that have performed well in the past year are likely to yield returns above the average in the next year. However, this trend does not continue into the years that follow. The momentum risk factor, also known as winner minus loser (WML), captures the difference in returns between the winning and losing stocks. The formula for the 4-factor model is as follows:

$$R_i - R_f = a_i + b_i\left(R_m - R_f\right) + s_i SMB + h_i HML + w_i WML + e_i \tag{3}$$

Where WML is the return on winner stocks minus loser stocks and w_i is the factor loading on momentum factor and all other variables are the same as in three-factor model.

2.2.4 Five factor model

Fama and French (2015) introduce five-factor model (FF5), which adds two risk factors on top of three-factor model. They argued that the three-factor model was unable to account for a significant portion of the variation in average returns associated with profitability and investments. By incorporating these two factors into the model, they believed it would enhance the model's performance and explanatory power. The profitability factor, robust minus weak (RMW), represents the difference in returns on stocks with robust and weak profitability. The investment factor, or conservative minus aggressive (CMA), gauges the difference in returns of low and high investment firms. The FF5 model is structured as follows.

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_i \quad (4)$$

Where RMW is the profitability factor and CMA is the investment factor. r_i is the factor loading on profitability factor and c_i is the factor loading on investment factor. All other variables remain consistent with those in the three-factor model.

2.2.5 Six factor model

Fama and French (2018) extended five-factor model with one new factor. Up minus down (UMD), or momentum factor captures the phenomenon that stocks which have performed well in the past tend to continue performing well, and vice versa. The six-factor model is as follows:

$$R_i - R_f = a_i + b_i(R_m - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + m_i UMD + e_i \quad (5)$$

Where UMD is the momentum factor and m_i is the factor loading on momentum factor. All other variables remain consistent with those in the five-factor model.

2.3 Portfolio performance

William Sharpe (1966) introduced the reward-to-variability ratio to measure mutual fund performance relative to risk. The metric was later renamed the Sharpe ratio due to poor adoption of its original name. Specifically, Sharpe ratio calculates the portfolios risk adjusted return and it is calculated as follows (Sharpe, 1994):

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

Where, R_p is the return of portfolio, R_f is the risk-free rate and σ_p is the standard deviation of the portfolios excess return over the risk-free rate. While numerous metrics are available for assessing portfolio performance, this study focuses exclusively on the Sharpe ratio.

3 Literature review

This chapter presents the current academic literature on the low-risk anomaly. The first subchapter examines empirical studies, while the second subchapter explores potential explanations for the anomaly.

3.1 Empirical studies

Since the introduction of the Capital Asset Pricing Model (CAPM), numerous studies have emerged, presenting empirical data that does not align with the model's predictions. Specifically, the CAPM's estimation of the correlation between risk and returns appears to be inconsistent with observed market behavior. Black et al. (1972) examined U.S. stock returns from 1931 to 1965. They found that the returns of high-beta stocks were higher than those of low-beta stocks. However, the difference was smaller than what the CAPM predicted. The intercept was negative for high-risk stocks and positive for low-risk stocks. Moreover, the authors noted that both the slope and the intercept were unstable over time, which violated the assumptions of the traditional CAPM theory. Haugen and Heins (1975) also examined U.S. stock returns from 1926 to 1971 and found no evidence of risk premiums in the stock market. On the contrary, their results indicated a negative relationship between risk and returns. Furthermore, Fama and French (1992) challenged the validity of the CAPM theory, as they demonstrated that stock returns are more related to size and book-to-market equity, rather than beta, which exhibits no significant relation with returns.

Ang et al. (2006) investigate the impact of idiosyncratic volatility on stock returns using a sample of NYSE, AMEX, and NASDAQ listed stocks from January 1963 to December 2000. The authors sort stocks into value-weighted quintiles based on the one-month idiosyncratic volatility relative to Fama and French three-factor model and report a negative and significant relation between idiosyncratic volatility and stock returns, as the average monthly simple return of the highest idiosyncratic volatility quintile is 1.06% lower than that of the lowest idiosyncratic volatility quintile. Furthermore, they replace idiosyncratic volatility with total volatility and conduct a similar analysis. The results are consistent with the previous one, as the lowest risk quintile outperforms the highest risk quintile by 0.97% in average monthly return. Moreover, the authors report that the FF3 model fails to account for the results, as the alpha spread between bottom and top quintile is large and statistically significant, implying that the low-risk portfolios generate higher risk-adjusted returns than the high-risk portfolios, after controlling for the market, size, and value factors. To confirm the robustness of their results, the study conducts a subsample analysis where it investigates the FF3 alphas of each quintile in different sample periods. The findings confirm previous results, as the low-risk quintile consistently outperforms the high-risk quintile in terms of FF3 alpha across all decades of the sample period. Furthermore, this superior performance holds true across various economic conditions, including recessions, expansions, volatile periods, stable periods, and even when holding periods are extended up to one year.

Ang et al. (2009) extend the study of Ang et al. (2006), which examined the negative relation between idiosyncratic volatility and stock returns in the US market. To test the robustness and generality of their findings, and to rule out the possibility of data snooping, they conduct a similar analysis on 23 developed countries, both individually and in various geographic groupings, over the period from 1980 to 2003. Consistent with Ang et al. (2006), Ang et al. (2009) report negative correlation between idiosyncratic risk and alphas, after adjusting for market, size and value factors. They documented a monthly alpha spread of -1.31% between the quintiles with the highest and lowest idiosyncratic risk across the entire set of countries. When excluding the U.S. from the sample, the alpha spread narrowed to -0.67% per month.

Bali and Cakici (2008), building on the work of Ang et al. (2006), investigated the relationship between risk, measured by idiosyncratic volatility, and return using longer risk measurement periods (24-60 months) and monthly data. A significant negative correlation was found only when using value-weighted quantile portfolios and daily data from the prior month. This relationship was not observed in equal-weighted portfolios or those sorted with longer monthly observations. Moreover, Bali and Cakici (2008) found no relationship between risk and return in large-cap stocks, suggesting that the results of Ang et al. (2006) were driven by illiquid small-cap stocks. They also observed that low-risk quintile stocks tend to be large, while high-risk stocks tend to be small.

Blitz and van Vliet (2007) discovered that high-risk stocks perform considerably worse than low-risk stocks. In their study, they analyzed around 2,000 global large-cap stocks from 1985 to 2006. These stocks were divided into equally weighted deciles based on their three-year historical volatility of weekly returns. According to Blitz and van Vliet (2007), the low-risk decile portfolio generated an average excess return of 7.3% above the risk-free rate. This result was significantly better compared to the highest risk decile, which only achieved an excess return of 1.4%. However, when considering all the stocks studied, the average excess return amounted to 6%, making the 7.3% figure less remarkable in comparison. Additionally, when considering risk-adjusted returns, the difference becomes more pronounced. The single-factor alpha spread between the portfolios with the lowest and highest risk is 12%, out of which 3.9% can be explained by value and size factors. This leaves an 8.1% FF3 alpha spread between the deciles with the highest and lowest risk. Blitz and van Vliet (2007) also studied the phenomenon regionally, in US, Europe and Japan. They found similar results, showing that, regionally, low-volatility stocks have higher excess returns and Sharpe ratios than high volatility stocks.

Afterwards, the study carried out by Blitz et al. (2013) demonstrates that the volatility effect is not confined to developed countries but is also observable in emerging markets. The authors analyze the S&P/IFC Investable Emerging Markets Index, which includes an average of 1000 stocks from 30 emerging markets throughout their sample period ranging from 1988 to 2010. The results are consistent with findings from developed equity markets, showing a flat or negative relation between risk and return. Furthermore, the authors observe a strengthening of the volatility effect over time within emerging equity markets. Later research by Blitz et al. (2021) confirms the existence of the low-risk anomaly in China, showing it to be robust when considering the Fama-French six-factor model. Furthermore, both studies demonstrate that the low-risk anomaly holds true over extended holding periods, ranging from 6 to 60 months. Specifically, Blitz et al. (2013) observed only a gradual decrease in alpha for top and bottom volatility quintile portfolios over longer holding periods. Meanwhile, Blitz et al. (2021) found that alpha remained consistent between 12-month and 1-month holding periods, with only a gradual decline thereafter. Both studies also identified the low-volatility anomaly in larger stocks, specifically those within the top 50% by market capitalization.

Baker et al. (2011) also find evidence that supports the low-risk anomaly. Their research focus on the total returns of companies listed in the US from 1968 to 2008. They conduct a comprehensive analysis of all companies, as well as a separate examination of the top 1000 stocks based on market capitalization. Authors divide samples into five equal quintiles based on the risk, which is measured by trailing five-year volatility or beta. Furthermore, quintiles are rebalanced each month to match the current level of risk, assuming no transaction costs are incurred. The results demonstrate that the low-risk quintile outperformed the high-risk quantile, as shown by higher annualized excess returns and a superior one-factor alpha across all tested methods. Moreover, the largest gap between the low and high-risk quantiles was observed in the full sample of stocks using volatility as a measure of risk, where $1 invested in the low-risk quantile grew to $59.55 in nominal terms, while the same dollar invested in the high-risk quantile shrank to $0.58. Baker et al. (2011) additionally highlight that high-beta stocks were able to generate higher returns in rising markets, but suffered larger losses in down markets, resulting in an underperformance relative to low-beta stocks over the entirety of the 41-year time span.

Li et al. (2014) challenge the findings of earlier studies (Ang et al., 2006; 2009; Blitz and van Vliet, 2007; Baker et al., 2011) that suggest low-risk strategies are profitable. Using the sample period of 1963 to 2010, Li et al. (2014) analyze the low-risk anomaly in the US, sorting stocks into quintiles using beta and different variations of idiosyncratic volatility as a measure of risk. Authors find that FF3 alpha for idiosyncratic volatility sorted long-short zero-cost portfolios is positive and significant across all risk variations, but weaker in equal-weighted quintiles compared to value-weighted quantiles. In contrast to Blitz et al. (2013, 2021) and Ang et al. (2006), the results show a monotonic decline in alpha after the first month of portfolio formation and complete vanishing after two months in all variations. Therefore, exploiting the low-risk anomaly requires frequent rebalancing, which reduces the actual returns due to transaction costs. Moreover, the authors argue that penny stocks have a significant role in the low-risk anomaly, as their exclusion from the sample has a meaningful negative impact on the alpha spreads across the board. Out of the different variations, the authors find that by measuring risk with one-month idiosyncratic volatility, calculated from daily observations, and applying value-weighted quintiles is the most efficient way to arbitrage the spread between the low-risk and high-risk quintiles, producing a monthly FF3 alpha of 1.19%. However, the alpha spread decreases to 0.38% after excluding penny stocks from the sample.

Baker and Haugen (2012) investigate the relationship between volatility and total stock returns in 21 developed and 12 emerging markets from 1990 to 2011. Their sample stocks represent 99.5% of the market capitalization in each country and include non-survivors. They rank the stocks within each country into deciles based on their 24-month trailing total return volatility. In all markets analyzed, the lowest risk decile consistently outperformed the highest risk decile in terms of total returns. This disparity was further amplified when returns were adjusted for risk. Furthermore, an analysis of rolling 3-year returns reveals that high-risk stocks outperformed their low-risk counterparts only infrequently, indicating that global equity markets impose a negative reward on risk taking.

Frazzini and Pedersen (2014) study betting against beta (BAB) factor, which is the strategy of going long low-beta assets and short on high-beta assets, while adjusting the leverage of each position to have beta one. Authors find that BAB factor provides significant positive risk adjusted returns in US throughout the full sample period of 1926 to 2012 and in four subperiods. The BAB factor, within the U.S. market, exhibits robust monthly FF3 alpha of 0.73%, alongside a Sharpe ratio of 0.78. The results also demonstrate the robustness of the BAB factor across other developed countries, based on the sample period from 1984 to 2012. Out of 19 other developed countries analyzed, the BAB factor has positive Sharpe ratios in 18 and positive four-factor alphas in 13, indicating that the BAB factor works well across developed markets. Furthermore, Frazzini and Pedersen (2014) sort stocks into deciles based on their beta, giving equal weights to the stocks in each portfolio using the same sample periods. The average returns across deciles are nearly identical, suggesting a flat security market line in the US. Furthermore, both the alphas and Sharpe ratios of these deciles exhibit a near-monotonic decrease from low to high-beta portfolios. Additionally, the study demonstrates that BAB factors earn positive returns in Treasury markets, corporate bonds markets and in futures markets, indicating that low-risk anomaly exists in different asset classes.

Novy-Marx and Velikov (2021) criticized the findings of Frazzini and Pedersen (2014), stating that the impressive performance of the BAB factor is primarily due to unconventional methodologies rather than a true market anomaly. Specifically, they argued that the rank-weighted portfolio construction heavily overweights micro- and nano-cap stocks, leading to inflated returns. When transaction costs associated with trading these illiquid securities are factored in, Novy-Marx and Velikov (2021) estimated that the profitability of the BAB factor would be reduced by nearly 60%, significantly diminishing its attractiveness as an investment strategy. In contrast, Chen et al. (2020) show that idiosyncratic volatility anomaly is robust while excluding microcaps and penny stocks.

Baker et al. (2014) propose that the low-risk anomaly can be attributed to two components. The micro component involves the selection of low-risk stocks, while the macro component refers to the choice of low-risk countries and industries. They find that both components contribute to the low-risk anomaly in 29 US industries and in 31 developed countries. The study shows that micro selection of low-beta stocks leads to significant reduction in risk without meaningful impact on returns, whereas the selection of low-beta industries or countries leads to modest difference in risk, with increasing returns.

Therefore, micro selection allows for reducing risk without sacrificing returns, while macro selection offers increasing returns without rising risk.

Novy-Marx (2014) takes more skeptical view on low-risk strategies. The author finds that low-risk strategies generate statistically significant FF3 alpha, but shows that the outperformance is driven by shorting small unprofitable growth stocks. Therefore, the anomaly can be explained by controlling for size, value and profitability. Similarly, Fama and French (2016) argue that low-risk anomaly can be explained by profitability and investment factor.

According to Blitz et al. (2020), the low-risk anomaly is a robust phenomenon across global equity markets, driven primarily by volatility and cannot be explained by factors such as value, profitability, or exposure to interest rate changes. Authors find the relation between risk and return to be negative in the US and globally, using compounded returns, multiple variations of risk and sample periods. Blitz et al. (2020) further confirms the earlier findings of Blitz et al. (2007) that the main driver of low-risk anomaly appears to be volatility rather than beta.

Alquist et al. (2020) study long-short low-risk investing strategies. They employ six statistical risk metrics and four fundamental risk measures. The data, collected monthly, spans from 1931 to 2019 for the statistical risk metrics, and from 1957 to 2019 for the fundamental risk measures. Notably, their findings diverged from those of Fama and French (2016), as they identified positive alphas for all strategies relative to a six-factor model. The authors also challenged the conclusions of Fama and French (2016), arguing that their assertion of the CAPM's obsolescence while simultaneously claiming that low-risk investing does not generate alpha represents a fundamental contradiction. Additionally, Alquist et al. (2020) show that low-risk factors performed better out-of-sample than in-sample, suggesting the premium has not been arbitraged away and is not due to data mining.

Alquist et al. (2020) additionally address concerns about low-risk strategies, specifically their sensitivity to transaction costs and reliance on small-cap stocks (see e.g., Li et al., 2014). They show that low-risk strategies can be implemented with moderate turnover, mitigating transaction costs. In their study, nine out of ten strategies had monthly turnovers of around 40% or less. In comparison, the Fama-French value factor and momentum demonstrated turnovers of 26% and 100%, respectively. Moreover, Alquist et al. (2020) demonstrate that low-risk investing is effective even with liquid large-cap stocks, albeit with slightly weaker performance than small caps. This finding aligns with Alquist et al. (2018), who observed that various risk factors, including value, momentum, and profitability, tend to perform better in small-cap equities compared to large-cap equities.

Silvasti et al. (2021) investigate smart beta strategies in Nordic equity markets between 1991 and 2019. They construct monthly rebalanced, equally weighted quintile portfolios using the main listed stocks from Finland, Sweden, Denmark, and Norway. The study reveals that while the low beta quintile outperforms the high beta quintile in terms of excess returns and CAPM alpha, the second-lowest beta quintile generates the highest excess returns and alpha. Moreover, large low beta stocks surpass small low beta stocks in performance. However, due to a more significant underperformance of small low beta equities compared to their large counterparts, the spread in excess returns and CAPM alpha between low and high beta portfolios is more pronounced in the small-cap segment. Similarly, Grobys et al. (2024) identify the presence of a low volatility anomaly in Nordic main listed equities, though the alpha is subsumed when controlling for the FF5 factors. Additionally, their research explores the impact of different risk formation periods (60 to 12 months) and finds that a 36-month period yields the highest payoffs.

3.2 Explanations

This section examines the explanations for the low-risk anomaly, which are broadly classified into three distinct categories: constraints, behavioral biases, and agency issues.

3.2.1 Constraints

Black (1972) demonstrated that borrowing restrictions can lead to low-beta stocks performing relatively well in risk adjusted terms. The author employs a theoretical model to illustrate that the risk-return relation remains linear under borrowing restrictions as predicted by the CAPM, but with a smaller slope. According to Black (1973), margin rules, bankruptcy laws, and tax rules are some of the borrowing restrictions that contribute to the anomaly. He also states that investors tend to avoid borrowing even when they have the opportunity, and instead they bid up the prices of high-beta stocks, leaving low-beta stocks relatively attractive. Using TED spread as a proxy for funding conditions, Frazzini and Pedersen (2014) examine the effect of funding constraints on the BAB factor. They show that the BAB returns decrease as the TED spread increases, implying that investors have to de-leverage and sell low-beta stocks over time to adapt to the current situation where banks are limiting credit availability. Moreover, the authors present evidence that investors who face borrowing constraints, such as retail investors and mutual funds, hold assets with an average beta above one, while investors who have no borrowing constraints, such as leveraged buyout (LBO) funds or Berkshire Hathaway, purchase assets with an average beta below one using leverage, and therefore exploit the low-risk anomaly. The authors also argue that the popularity of leveraged exchange-traded funds (ETFs) indicates that many investors are subject to borrowing constraints, as they cannot access leverage directly.

Another constraint that can explain the low-risk anomaly is the short selling constraint, as it helps to understand why high-risk stocks can be overvalued. Miller (1977) provided a theoretical basis for this argument, by showing that in market where short selling is scarce or absent, the stock price will be determined by the most optimistic minority, as the pessimists are constrained to short the stock. Therefore, when there is a high divergence of opinions about the fair value of a company, the stock is likely to be overpriced. Moreover, since risk and uncertainty tend to increase the divergence of opinions, the expected returns will be lower for risky stocks.

According to Blitz et al. (2014) regulatory constraints are one of the possible explanations for the low-risk anomaly. The authors argue that regulatory constraints can influence the behavior of institutional investors, such as pension funds, who may face limits on their equity allocation. For example, pension funds may be restricted to invest only a certain percentage of their portfolio in stocks, regardless of how risky they are. The authors note that regulators do not differentiate between high-risk and low-risk stocks as distinct asset classes and therefore institutional investors prefer to invest in high-risk stocks to maximize their expected returns within the given limit.

3.2.2 Behavioral biases

Secondly, low-risk anomaly can be explained by investors irrational behavior. Baker et al. (2011) argue that low-risk anomaly can be explained by investors preference for lotteries, representativeness bias and overconfidence. Additionally, Blitz et al. (2020) includes attention-grabbing bias in their explanation.

Kahneman and Tversky (1979) introduced the prospect theory, which describes how people make decisions when there is risk involved. The theory shows that people tend to overweight low probability events. This behavioral bias leads people to buy lottery tickets, even though they have a negative expected return. A similar preference for lotteries can be observed in financial markets, where people seek positive skewness in their investments. As a result, they buy financial insurance and speculative assets, which limit the left tail and enhance the right tail respectively, which results in their overvaluation. (Ilmanen, 2012). Kumar (2009) discovered that certain socioeconomic groups have a disproportionate preference for lottery-type stocks. These stocks are characterized by positively skewed payoffs, high-volatility, and low prices, and those investing more in these stocks tend to experience greater underperformance. Furthermore, Lin and Yang (2023) find that also analysts prefer lottery stocks as they tend to be too optimistic about future earnings of these firms.

The concept of representativeness bias argues that people tend to overlook the significance of empirical data and statistics, choosing instead to focus on handpicked anecdotes and occurrences. For instance, an investor seeking investment opportunities might examine the returns of Microsoft since its Initial Public Offering, concluding that substantial wealth can be accumulated by investing in emerging technology companies that are newly listed. However, this perspective ignores the fact that IPOs have historically underperformed in the market, making this a statistically irrational decision. (Baker et al., 2011.)

Svenson (1981) find that 93 percent and 88 percent of American drivers considered themselves to be more skillful and safer than the median driver, respectively. Similarly, overconfidence is present in financial markets, for example, each active manager is under the impression that they can outperform the market (Blitz et al., 2014). Moreover, Cornell (2009) argues that investors, confident in their superior stock-picking skills, tend to focus on segments characterized by high volatility and high skewness, given the potential for higher returns in these areas. This behavior amplifies the low-risk anomaly by increasing the prices of high-risk stocks.

Barber and Odean (2008) suggest that individual investors, constrained by limited resources to study and select stocks, tend to prefer those that capture their attention. It is more effortless to choose familiar companies and those featured in the news, rather than investing limited time in screening random companies for portfolio construction. The authors study attention grabbing bias by observing news, unusual trading volume, and extreme returns. They discovered that individual investors tend to buy significantly more of the stocks that capture their attention than those that do not. The authors highlight that when purchases are driven by attention, it can cause a temporary surge in a stock’s price, which subsequently results in subpar returns. These stocks are primarily located within the high-volatility area of the market, whereas boring low-volatility stocks represent the other side of the spectrum (Blitz et al., 2014).

3.2.3 Agency issues

Thirdly, the low-risk anomaly can be attributed to agency issues. Baker and Haugen (2012) propose that agency conflicts can arise among professional investment managers within their organizations, and between these professionals and the clients they serve.

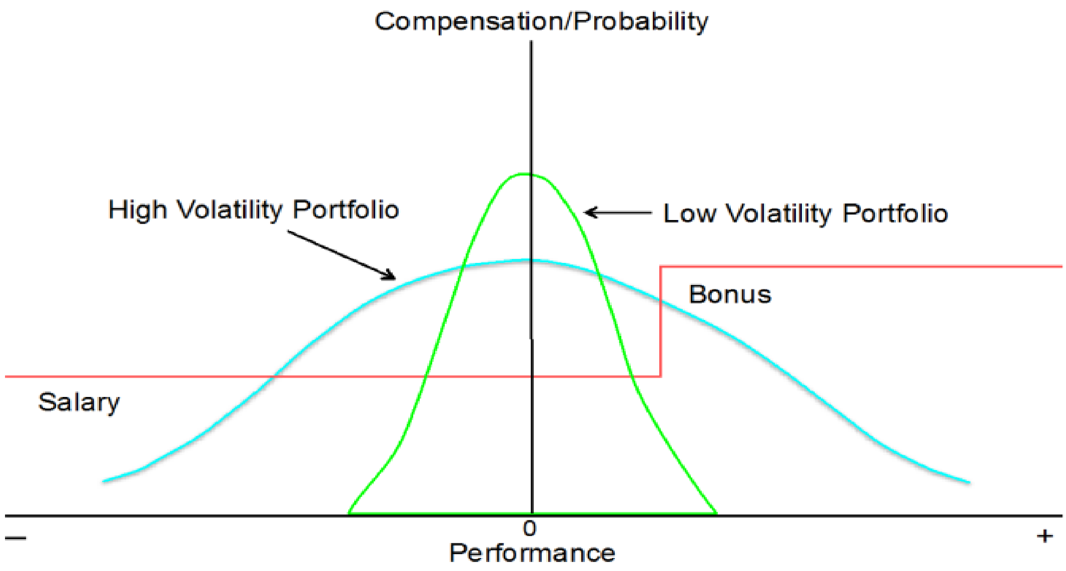

Figure 1. Illustration of investment manager compensation structure and probability distribution of returns for high-volatility and low-volatility portfolios (Baker & Haugen, 2012).

Figure 1 illustrates how the manager's option-like reward system can amplify the low-risk anomaly by encouraging the selection of riskier stocks. A manager is paid a base salary and has an opportunity to earn a bonus if the performance exceeds the threshold. By investing in high-volatility stocks, the manager can increase the expected value of their compensation without risking their base salary. (Baker & Haugen, 2012.) In addition, a lab-in-the-field experiment was carried out by Kirchler et al. (2018), involving a substantial number of financial professionals who frequently make investment decisions. The authors find that ranking and tournament incentives drive risk-taking behavior.

Secondly, Baker and Haugen (2012) argue that the structure of investment decisions creates incentives to prefer riskier stocks. Analysts pitch their investment cases to the Chief Investment Officer (CIO) in regular investment committee meetings. To advance in their careers and to impress the CIO and fellow colleagues, analysts tend to propose stocks characterized by above-average media attention and volatility. These stocks are used to build a model portfolio, which serves as a guide for the construction of individual portfolios for clients. Moreover, the interesting nature of these investments makes it easier for professional money managers to explain their allocation decisions to their clients.

Baker and Haugen (2012) conducted an empirical study to determine whether institutional investors hold riskier stocks, by examining the largest 1000 stocks in the US during 2000 and 2009. Stocks were categorized into deciles based on size, and each decile was then further divided into three groups based on the percentage of stock held by institutions. The findings reveal that, except for the smallest decile where the volatility of the most and least owned stocks was found to be equal, institutions tend to hold more volatile stocks in each decile. Additionally, they find that volatile stocks attract more analyst coverage and receive greater media attention.

Additional evidence has also indicated that agency issues contribute to the low-risk anomaly. Chevalier and Ellison (1997) argue that the interests of mutual fund companies and their investors are not completely aligned. Investors aim to maximize risk-adjusted expected returns, while mutual fund companies strive to increase the inflow of investments to maximize their profits. The authors find that these companies have an incentive to modify the risk level of their funds to attract more investments. This modification can take the form of "gambling" or indexing to secure overperformance in the fourth quarter, depending on the fund's year-to-date performance relative to its benchmark. Sirri and Tufano (1998) find that consumers invest disproportionately more in funds that have recently performed exceptionally well. The market beta for the aggregate portfolio of equity mutual funds, as found by Karecski (2002), is around 1.05. He argues that mutual fund managers have incentive to allocate capital toward high-beta stocks is due to the investors chase of past relative performance. Overweighting high-beta stocks flattens the security market line. The author also notes that fund outperformance is primarily rewarded during bull markets. Therefore, outperforming during these up markets is the most critical goal. Conversely, during bear markets, cash inflows tend to dry up.

4 Data and methodology

This section provides a comprehensive overview of the data and methodologies employed in this study. Additionally, the selection of this specific data and the chosen methodological approach is thoroughly discussed in this section, ensuring transparency and methodological soundness.

4.1 Data

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

4.1.1 Equities

Data is collected from stocks listed in Helsinki, Stockholm, Copenhagen, and Oslo stock exchanges. Following Grobys and Huhta-Halkola (2019), Iceland is excluded from the sample. While geographically part of the Nordic region, Iceland's stock market is characterized by a limited number of stocks and a relatively small total market capitalization. The sample is restricted to main-listed stocks on the Helsinki (OMXH), Stockholm (OMXS), Copenhagen (OMXC), and Oslo stock exchanges (OSEAX), excluding less liquid and smaller stocks commonly found on non-main lists such as First North. Following Silvasti et al. (2021), the smallest 10% of stocks by market capitalization are also removed each month to further address liquidity concerns.

Monthly index constituents were collected from Datastream for the full sample period to identify all stocks included in the main indices each month. Any gaps in this data were filled by manually verifying index composition changes in LSEG Workspace. Furthermore, the dataset was screened in Datastream using multiple filters. The sample was restricted to equity securities only (Ince & Porter, 2006). Following Fong et al. (2017), only primary quotations and major securities traded in local currency were included in the sample. Furthermore, other residual cross-listings were identified and excluded based on the local listing identifiers specific to each country (Landis & Skouras, 2021). The resulting sample includes only one primary security per company, listed on one of the main exchanges in the sample countries. This excludes secondary share classes and stocks primarily listed elsewhere. This filtering process is essential to ensure the creation of truly equal-weighted portfolios, as the Nordic markets are characterized by numerous companies with multiple share classes and cross-listings (e.g., Nordea, listed on OMXH, OMXC, and OMXS).

In addition to static screens, dynamic screens are employed to mitigate the influence of outliers and data errors. Specifically, following Schmidt et al. (2017), monthly observations exceeding 890% are deleted. Furthermore, following Ince and Porter (2006), returns are omitted if the return in one month or the previous month is above 300% and the cumulative return of those two months is below 50%. Furthermore, to be included in the portfolios, a stock must have 36 months of consecutive monthly return data while being continuously listed on one of the main lists. This includes maintaining the main listing at the beginning of each month when portfolios are formed.

For each company in the sample, monthly total return indexes and market values were collected. As each market operates in its own currency, all data was converted to euros to ensure comparability of returns and market capitalizations. To address potential rounding errors in return calculations due to Datastream's default two-decimal precision, especially for small total return index values (Landis & Skouras, 2021), all collected total return indices were recorded with a minimum of five decimal places.

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

Table 1 reveals a total of 1113 unique stocks were included in portfolios throughout the sample period. On average, portfolios held 532 stocks monthly, ranging from 494 to 585. While Finland, Denmark, and Norway contributed similar numbers of stocks, Sweden's contribution is approximately double that of each of these countries. The average market capitalization across all stocks is 2,042 million euros, with a median of 274 million euros. This distribution highlights the characteristic structure of Nordic equity markets, featuring numerous small-cap stocks alongside a limited number of large-cap firms.

4.1.2 Market index and risk-free rate

The market index employed in this study is constructed following the methodology of Silvasti et al. (2021). Specifically, the index is calculated as the equal-weighted average of the excess returns of all-share indices in each sample market. To maintain consistency with individual stock returns, euro denominated total return data is utilized for index computation. Additionally, due to the limited availability of total return index data for OMXS before 2003, price index data of OMXS is used for that period.

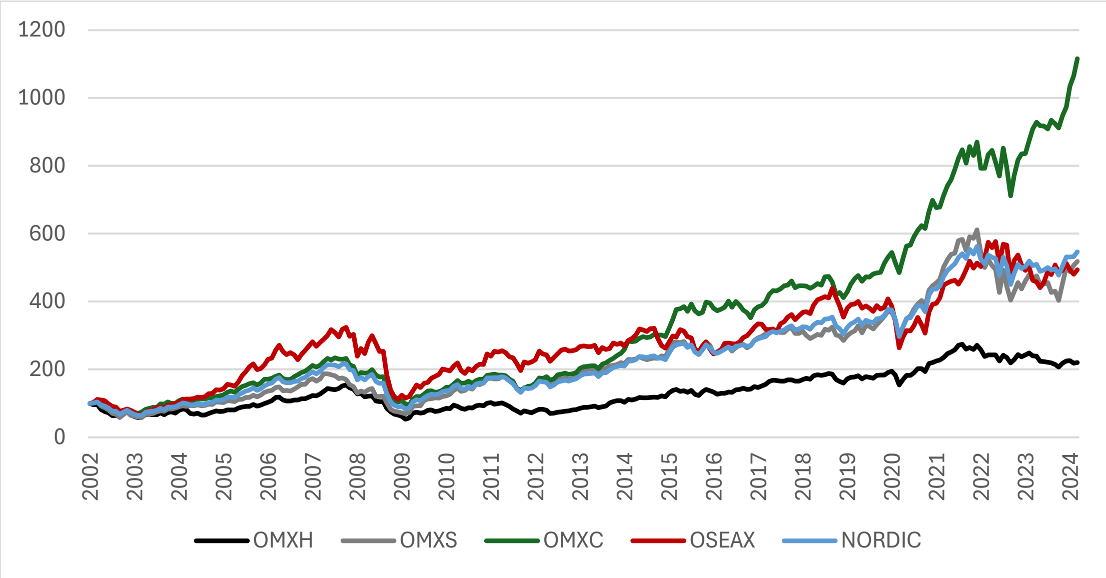

Figure 2. Cumulative excess return of OMXH, OMXS, OMXC, OSEAX and Nordic market index

While the US Treasury bill rate is frequently employed as a risk-free rate in prior research, its application in this study is inappropriate given that all data is denominated in euros rather than US dollars. Therefore, the three-month Euribor offered rate is utilized as the risk-free rate to convert all return data into excess return form.

4.1.3 Fama and French factors

All factor data is collected from Kenneth French's data library, except for the market factor (MKT), which is defined as the excess monthly return of the Nordic market index. Given the unavailability of specific Nordic risk factors, European monthly risk factors were selected as a suitable proxy. Factor returns, originally reported in US dollars, were converted to euros to mitigate the effects of currency fluctuations and maintain consistency throughout this study. The conversion of the long-short factors, namely SMB, HML, RMW, CMA, and MOM, was conducted following the methodology outlined by Glück et al. (2021), detailed as follows:

$$LS_t^{EUR} = \frac{1}{(1+r_{FX,t}^{USD/EUR})} LS_t^{USD} \tag{7}$$

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.

4.2 Methodology

This section outlines the methodological framework employed in the study. It begins by detailing the risk measurement techniques implemented, followed by a comprehensive description of the portfolio construction methodology. Finally, alternative methodologies used for robustness checks are presented and discussed.

4.2.1 Risk measures

This study investigates the low-risk anomaly by employing three widely used 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 three-year measurement window aligns with the methodology of Blitz and van Vliet (2007), although their study utilized weekly returns, whereas this research employs monthly observations. Furthermore, Blitz et al. (2013) calculated past stock volatility using three-year monthly observations.

The second risk measure employed to sort stocks into quintile portfolios is beta, representing a company's systematic risk or sensitivity to broader market fluctuations. Beta is calculated by regressing a stock's excess total returns against the excess total returns of Nordic market index. Consistent with the volatility measure, a rolling 36-month period is utilized for the beta calculation.

The final risk measure examined is idiosyncratic volatility (IVOL), representing the unsystematic or company-specific risk that is independent of broader market movements. Following the methodology of Ang et al. (2006), idiosyncratic risk is derived from the residuals of the Fama-French three-factor model. Specifically, IVOL is defined as the standard deviation of the residuals obtained from a rolling 36-month regression of a stock's excess returns on the market (MKT), size (SMB), and value (HML) factors. This methodology diverges slightly from that of Ang et al. (2006), who calculated idiosyncratic volatility based on one-month daily returns. Expanding upon this approach, Bali and Cakici (2008) also calculated idiosyncratic volatility, utilizing both within-month daily returns and longer-term (24-60 month) monthly observations. Notably, their research revealed a negative and significant relationship between risk and return exclusively for the within-month daily calculations. This finding suggests that the longer monthly observations employed in this study may offer a more conservative approach.

4.2.2 Portfolio construction

At the start of each month, stocks are sorted into quintile portfolios based on their rolling 36-month risk. In addition to the five long-only portfolios, a long-short, zero-cost portfolio is created by taking a long position in the lowest-risk quintile (P1) and a short position in the highest-risk quintile (P5). This process is repeated throughout the full sample period. Furthermore, if a stock is delisted from the main market indices for any reason, it will be liquidated from the portfolio at the end of the respective month. The sale price will be the closing price on the last trading day of the month, or the last recorded price if trading has ceased.

Following the methodologies employed by Silvasti et al. (2021) and Grobys and Huhta-Halkola (2019), equal-weighted portfolios are utilized in this study. This decision is primarily driven by the composition of the sample, which includes a large number of small-cap companies and a limited number of very large companies. A value-weighted approach would unduly emphasize these few large-cap firms, potentially distorting the results. Notably, Novo Nordisk's market value represented approximately 20% of the total sample at the end of the observation period, while Nokia would have dominated a value-weighted portfolio in the early 2000s.

4.2.3 Alternative methodologies

For robustness, different methodologies are utilized. Firstly, additionally to 36-month rolling risk measurement period, 24-month and 12-month periods are tested to assess the potential impact of varying risk measurement windows on the results. To ensure comparability across different risk measure periods, a consistent 36-month sample of consecutive return data is required to be included in portfolios. While this may exclude some recently listed companies, it guarantees a uniform sample across all analyses, regardless of the risk measure or lookback period.

Low-risk anomaly will also be tested in large and small companies. Following Blitz et al. (2013, 2021), two distinct set of quintile portfolios are created where the large one contains only stocks that have market capitalization above the 50th percentile at the beginning of the month, whereas small portfolios will be created by constructing portfolios only using stocks that market capitalization is at or below the 50th percentile at the beginning of the month. Similarly to other methods, stocks need to have at least 36 consecutive months of viable return data to be included in portfolios.

Lastly, the study will test different holding periods by creating five quintile risk portfolios that purchase stocks based on rolling 36-month risk and hold them for 3, 6, and 12 months before reallocating capital based on the latest risk rankings. For example, a low-risk portfolio (P1) using a 12-month holding period will buy the lowest 20% risk stocks at the start of month 1, based on the prior 36 months of risk, and hold those stocks for 12 months. At the start of month 13, it will reallocate capital into the stocks then ranked in the lowest 20% based on the updated 36-month risk measurement. While the composition of each portfolio remains fixed during its holding period, the portfolios are rebalanced to equal weighting at the start of each month. Thus, due to monthly equal weighting, this method does not fully replicate longer holding periods, but it still allows us to assess the persistence of stocks' risk characteristics and the feasibility of a low-risk strategy with relatively low turnover. If a stock is removed from the sample, it is sold at the end of the month of removal, using the last recorded price of that month. Remaining portfolio constituents are held until the next rebalancing. Consistent with Blitz et al. (2013, 2021), to increase the statistical power of tests with longer holding periods, overlapping portfolios are used as in Jegadeesh and Titman (1993). Specifically, assuming a holding period of N months, the return for a particular month, denoted as month t, is calculated by computing the average return of the portfolios established during the N months preceding and including month t.

5 Results

This chapter presents the findings of the empirical study and provides a comparative analysis with existing literature. Initially, results for all measurement periods are presented, encompassing descriptive statistics and alphas. The chapter then delves into results for small and large stocks, followed by an examination of longer holding periods and subperiods. Finally, the chapter concludes by discussing limitations of the study.

5.1 Results for all risk measurement periods

The results for portfolios sorted by 36-month, 24-month, and 12-month risk measurement periods are presented in this section. The analysis begins with descriptive statistics, followed by the presentation of alphas derived from the Capital Asset Pricing Model (CAPM), as well as the Fama-French Three-Factor (FF3), Five-Factor (FF5), and Six-Factor (FF6) models.

5.1.1 Descriptive results

Table 2 presents descriptive statistics for volatility sorted quintile portfolios and long-short zero-cost portfolios using 36-month, 24-month and 12-month rolling risk measurement periods. Presented results consist of annualized compounded and simple excess returns, annualized standard deviations, Sharpe ratios and maximum drawdowns.

Across all measurement periods, high-risk portfolios consistently demonstrate the lowest excess returns, while the remaining portfolios (P1 to P4) exhibit comparable performance. Although the low-risk portfolios do not achieve the highest raw excess returns, they consistently achieve the highest Sharpe ratio across all tested methods due to their superior excess returns relative to volatility. Furthermore, within each lookback period, Sharpe ratios exhibit a near-monotonic decline from low-risk to high-risk portfolios.

The analysis reveals consistent results across different rolling periods used to measure volatility, with subtle variations. Notably, the highest Sharpe ratio, compounded and simple returns for the low-risk portfolio (P1) are achieved using a 24-month rolling volatility sort, while the lowest returns and Sharpe ratio for the high-risk portfolio (P5) are associated with the longest risk measurement period (36-month). The largest spread in both compounded and simple returns between P1 and P5 is observed in portfolios sorted based on 36-month volatility, reaching 8.14%, followed by 7.88% and 7.44% for 24-month and 12-month sorts, respectively. The standard deviation spreads between the first and fifth quintile portfolios remain consistent across all methods, ranging from -11.22% to -11.66%, and the Sharpe ratio spreads are nearly identical.

Table 2. Descriptive statistics for volatility sorted portfolios

The table reports compounded and simple 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.

	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%**	11.65%**	10.43%*	10.46%*	3.12%	5.64%
	(2.19)	(2.40)	(1.92)	(1.81)	(0.48)	(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%**	10.53%**	10.38%*	9.05%	4.80%	4.85%
	(2.51)	(2.15)	(1.93)	(1.50)	(0.75)	(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%**	9.10%*	10.92%**	10.10%*	4.71%	4.88%
	(2.33)	(1.89)	(2.10)	(1.73)	(0.73)	(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%

Table 3 presents the same metrics as Table 2, but with stocks sorted into quintile portfolios based on rolling beta rather than volatility. Results are broadly similar to the volatility sorted portfolios, however the return differences between the low-risk and high-risk portfolios are less pronounced. The largest return spread is seen in the 36-month sorted portfolios, with a 3.84% difference in compounded returns and a 1.31% difference in simple returns. This spread nearly vanishes in the 12-month beta-sorted portfolios, where the compounded return spread is 1.36% and the simple return spread is -0.57%.

Consistent with the findings from volatility-sorted portfolios, the highest excess returns and Sharpe ratio for the lowest-risk portfolio are achieved with 24-month sorting periods, while the lowest excess returns and Sharpe ratio for the highest-risk portfolio are associated with 36-month sorting periods. However, in contrast to volatility-sorted portfolios, a narrowing of standard deviation spread between low- and high-risk portfolios is evident as the risk formation window shortens. Furthermore, Sharpe ratios exhibit a non-monotonic decline from P1 to P5.

Table 3. Descriptive statistics for beta sorted portfolios

The table reports compounded and simple 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.

	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%*	9.28%**	11.40%**	9.57%*	6.42%	1.31%
	(1.89)	(1.97)	(2.14)	(1.68)	(0.97)	(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%**	8.01%*	10.33%**	10.02%*	7.59%	0.86%
	(1.99)	(1.66)	(2.03)	(1.74)	(1.16)	(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%	8.59%*	10.55%**	10.57%*	7.63%	-0.57%
	(1.55)	(1.85)	(2.07)	(1.92)	(1.16)	(-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%

Lastly, table 4 shows the descriptive statistics for idiosyncratic volatility sorted portfolios. Whereas the spread between low-risk portfolios is more muted in beta sorted portfolios compared to volatility sorted portfolios, it is more pronounced in IVOL sorted portfolios. In contrast to volatility and beta sorted low-risk portfolios, implied volatility (IVOL) sorted low-risk portfolios achieve the highest compounded excess returns compared to other risk quintile portfolios, representing the simultaneous attainment of the highest returns and lowest risk.

Consistent with other methods, the highest P1 returns are achieved by 24-month sorts, and the lowest P5 returns are achieved by 36-month sorts. Similarly, the highest return spread is observed in 36-month sorted portfolios where the difference in compounded and simple excess returns between P1 and P5 is 10.96% and 8.66%, respectively.

Table 4. Descriptive statistics for idiosyncratic volatility sorted portfolios

The table reports compounded and simple 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.

	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%**	10.50%**	11.05%**	10.17%*	2.01%	8.66%***
	(2.55)	(2.06)	(2.07)	(1.81)	(0.32)	(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%***	9.98%**	10.16%*	9.51%*	3.79%	7.17%**
	(2.62)	(2.03)	(1.85)	(1.66)	(0.62)	(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%**	9.99%**	10.18%*	9.56%*	4.90%	4.86%
	(2.25)	(2.02)	(1.93)	(1.71)	(0.79)	(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%

Overall, results are consistent with several previous studies (see e.g., Blitz & van Vliet, 2007; Blitz et al., 2013; Ang et al., 2006) indicating that the lowest-risk quintile portfolios consistently outperform the highest-risk quintiles in terms of compounded returns across all nine methodologies examined. The mean excess return spread is also positive in eight out of nine tested methods. Moreover, historical riskiness appears to be a predictor of one-month forward riskiness, as evidenced by the monotonic increase in standard deviation from low-risk to high-risk quintiles across all studied methods. The average volatility of the low-risk quintile is 14.23%, while the high-risk quintile averages 24.67%.

Furthermore, maximum drawdowns exhibit a near-monotonic decline from low-risk to high-risk quintile portfolios.

While results using different risk measures provide promising evidence of a low-risk anomaly in Nordic equity markets, methodological variations yield distinct outcomes. Specifically, 36-month sorts produce the largest excess return spread between P1 and P5, contrasting with the smallest spreads observed in 12-month periods. Furthermore, the Sharpe spread between low-risk and high-risk portfolios tends to decrease as the lookback period shortens. Among the risk measures examined, portfolios sorted by idiosyncratic volatility exhibit the widest simple and compounded return spread between the low-risk and high-risk portfolios, followed by volatility-sorted portfolios, with beta-sorted portfolios displaying the lowest spread. This pattern is also mirrored in the Sharpe ratio spreads.

Consistent with findings from Blitz & van Vliet (2007) and Chen et al. (2020), analysis reveals that portfolio returns generally increase when moving from low-risk to medium-risk portfolios, when sorted by volatility or beta. However, beyond the middle quintile, returns begin to decline, culminating in a sharp drop for the highest-risk portfolio. This pattern is also observed in idiosyncratic volatility (IVOL) sorted portfolios, with the key difference being that returns start to decline after the low-risk quintile rather than the medium-risk quintile. While Blitz and van Vliet (2007) and Chen et al. (2020) used decile portfolios rather than quintiles, a comparable pattern emerges. Additionally, the dramatic decrease in returns for the highest-risk portfolio aligns with the findings of Baker et al. (2011).

5.1.2 Alphas

Table 5 displays the results for annualized CAPM, FF3, FF5 and FF6 regression alphas for 36-month, 24-month and 12-month volatility sorted portfolios and long-short zero-cost portfolios. A clear negative trend in alphas is observed as portfolio risk increases. This pattern aligns with the behavior of excess returns. Furthermore, the highest P1 alphas are associated with 24-month volatility-sorted portfolios, while the lowest P5 alphas are found in 36-month sorted portfolios. Long-short portfolios achieve their highest alphas when sorted on 36-month volatility.

All long-short portfolios and high-risk portfolios yield statistically significant alphas. However, only volatility portfolios sorted on 24-month and 12-month periods generate statistically significant alphas within the low-risk portfolios. Furthermore, the highest P1 alphas are observed when controlling for the Fama-French three-factor (FF3) model, while the lowest alphas are generated when regressing with the Fama-French six-factor (FF6) model. This suggests that the FF6 factors provide the most comprehensive explanation of low-risk portfolio returns among the tested models. Nonetheless, a substantial portion of the returns remains unexplained, as evidenced by the FF6 alphas of the long-short zero-cost portfolios, which range from 8.31% to 7.15%.

Table 5. Alphas for volatility sorted portfolios

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.

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

Table 6 presents the alphas for portfolios sorted on beta. While a general trend of declining alphas from low-risk to high-risk portfolios is observed, this decline is not strictly monotonic. The highest alphas in the 36-month and 12-month sorted portfolios occur in the middle quintile (P3), and only the 24-month sort shows the highest alphas in the low-risk quintile. Conversely, high-risk portfolios consistently yield the most negative alphas across all beta-sorted portfolios. Furthermore, the 24-month sorted portfolios produce the highest alphas among low-risk portfolios, while the 36-month beta-sorted portfolios yield the lowest high-risk portfolio alphas. The 36-month beta-sorted portfolios also generate the widest alpha spreads between P1 and P5.

While beta-sorted portfolios exhibit patterns similar to volatility-sorted portfolios, the results are less pronounced. Alpha magnitudes are smaller, resulting in lower alphas for long-short portfolios. Statistical significance is also less frequent among beta-sorted portfolios, with only high-risk portfolios and long-short zero-cost portfolios demonstrating significance. Furthermore, the highest P1 alphas (though not statistically significant) are observed when controlling for the Fama-French 3-factor (FF3) model, while controlling for the FF6 model yields the smallest magnitudes.

Table 6. Alphas for beta sorted portfolios

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.

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

Table 7 presents the regression alphas for quintile portfolios and zero-cost long-short portfolios sorted on 36-month, 24-month, and 12-month idiosyncratic volatility (IVOL). These results are the most pronounced and statistically significant compared to other tested methods. Notably, all P1 alphas are statistically significant in both the 24-month and 36-month IVOL sorts, a contrast to other methodologies. IVOL sorted portfolios also exhibit the closest approximation to a monotonic decline in alphas from low-risk to high-risk portfolios. Consistent with other methods, the highest P1 alphas are derived from the 24-month sorted portfolios, while the lowest P5 alphas and highest long-short zero-cost portfolio alphas are generated by sorting on 36-month IVOL. Furthermore, as observed with other methodologies, controlling for FF3 factors yields the highest P1 alphas, while controlling for FF6 factors results in the weakest alphas.

Table 7. Alphas for idiosyncratic volatility sorted portfolios

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.

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

In conclusion, the empirical analysis provides robust evidence supporting the existence of the low-risk anomaly. While many quintile portfolios did not exhibit statistically significant alphas, all long-short zero-cost portfolios consistently generated positive and significant CAPM alphas, ranging from 4.5% to 12.63%, with the majority reaching significance at the 1% level. Similarly, each long-short portfolio demonstrated statistically significant positive FF3 alphas, spanning from 4.13% to 12.03%. These findings were mirrored in the FF5 alpha results, where all long-short zero-cost portfolios yielded positive and statistically significant alphas between 4.26% and 11.12%. The FF6 regressions further corroborated these results, with seven out of nine cases exhibiting statistically significant positive alphas. The two exceptions, characterized by non-significant alphas, originated from shorter risk measurement periods within the beta sorted portfolios.

The analysis reveals that the long leg of the long-short portfolio achieves the highest and most statistically significant alphas when portfolios are sorted on 24-month rolling risk, while the short leg delivers the most negative and statistically significant results using 36-month sorts. Notably, the highest and most statistically significant zero-cost long-short portfolio alphas are obtained by sorting portfolios based on 36-month rolling risk, with the short leg generally contributing more significantly than the long leg. This finding is consistent with previous research (e.g., Blitz & van Vliet, 2007; Ang et al., 2006) demonstrating that the negative alphas of high-risk portfolios tend to be larger in absolute value than the positive alphas of low-risk portfolios.

Portfolios sorted by idiosyncratic volatility exhibit the highest alpha spreads and statistical significance, whereas those sorted by beta yield the weakest and least statistically significant results. This finding aligns with Blitz and van Vliet (2007), who found lower CAPM alpha spreads in beta-sorted portfolios compared to volatility-sorted portfolios across all studied regions. Their reported 2.7% difference for Europe aligns closely with the 3.1% alpha spread difference observed in this study between portfolios sorted by 36-month volatility and beta. Furthermore, Baker et al. (2011) find larger alpha spreads in volatility-sorted portfolios compared to beta-sorted portfolios in developed markets, while Blitz et al. (2013) find the same pattern in emerging markets.

Table 8 displays FF6 alphas and factor loadings for long-short (P1-P5), low-risk (P1), and high-risk (P5) portfolios formed using 36-month rolling sorts on volatility, beta, and idiosyncratic volatility. As previously noted, all long-short and high-risk portfolio FF6 alphas are statistically significant, whereas only the IVOL-sorted low-risk portfolio exhibits statistical significance. From six-factor loadings, MKT and SMB loadings provide statistically significant results in all portfolios. As expected, MKT loading is significantly lower in low-risk portfolios than in high-risk portfolios, and the highest spread in MKT loading can naturally be found in beta sorted portfolios. Additionally, the SMB factor suggests that high-risk portfolios could have a greater allocation to smaller companies, as the SMB loading for high risk-portfolios on average is 0.94 and for low-risk portfolios 0.33, respectively. This is consistent with previous studies, which find that high-risk stocks tend to be small in size (see, e.g., Bali & Cakici, 2008; Novy-Marx, 2016). Furthermore, the MOM factor loading is statistically significant at the 1% level for beta sorted high-risk portfolio and long-short portfolio. In contrast to Fama and French (2016), profitability (RMW) and investment (CMA) factors appear to have limited explanatory power, with RMW loading only statistically significant at the 10% level in IVOL-sorted long-short portfolios, and CMA factor loadings not reaching statistical significance.

Table 8. Six-factor regressions

The table reports the FF6 regression results for 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) stands for 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.

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

5.2 Results for large and small stocks

Table 9 presents the results for volatility, beta, and idiosyncratic volatility, sorted low-risk, high-risk, and long-short zero-cost portfolios using 36-month measuring periods. Panel A displays the results for large-cap stocks, while Panel B focuses on small-cap stocks.

In line with previous research (see e.g., Baker et al., 2011; Alquist et al., 2020; Bali & Cakici, 2008; Silvasti et al., 2021), the difference between low-risk and high-risk portfolios is less pronounced in large-cap stocks compared to small-cap stocks. This difference in simple excess returns is minimal for large caps, ranging from -0.92% to 1.26% between low-risk and high-risk portfolios, with the largest spread observed in IVOL sorted portfolios and the smallest in beta sorted portfolios. Even when considering excess compounded returns, the maximum spread for large caps remains a modest 3.24%. Conversely, the low-risk anomaly is significantly more pronounced in small-cap stocks, exhibiting a clear distinction in excess returns between low-risk and high-risk portfolios. The spread in excess compounded returns for small caps ranges from 9.54% to 12.53%, while for excess simple returns, it spans from 4.86% to 8.61%. Consistent with the large-cap findings, IVOL-sorted portfolios also yield the largest difference in returns between low-risk and high-risk portfolios for small caps.

Despite the negligible difference in excess returns between low-risk and high-risk portfolios for large-cap stocks, the risk profile of these portfolios is significantly different. The spread in standard deviation, ranging from 8.52 to 10.96 points, leads to a Sharpe ratio for low-risk portfolios that is more than double that of high-risk portfolios. This disparity in risk and Sharpe ratio is even more pronounced in small-cap stocks.

Both large-cap and small-cap long-short zero-cost portfolios generate statistically significant CAPM alpha, albeit with varying magnitudes and levels of statistical significance. Small-cap long-short portfolios exhibit CAPM alpha ranging from 12.59% to 14.61%, all of which are statistically significant at the 1% level. Conversely, large-cap portfolios yield alpha between 5.21% and 5.81%, demonstrating statistical significance at the 5% or 10% level. Consistent with the observed CAPM alphas, both FF3 and FF5 alphas are generally more than twice as large in small-cap portfolios compared to large-cap portfolios, with the small-cap portfolios maintaining statistical significance at the 1% level. Notably, only IVOL sorted large-cap long-short portfolios generated statistically significant FF5 alpha, while all generated statistically significant FF3 alpha.

Table 9. Results for large and small stocks

The table reports compounded and simple 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.

	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%**	9.96%	0.02%	9.99%**	10.91%*	-0.92%	11.20%***	9.94%	1.26%
	(2.56)	(1.57)	(0.01)	(2.41)	(1.67)	(-0.26)	(2.70)	(1.64)	(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%*	-3.37%*	5.81%**	2.31%	-2.90%	5.21%*	2.78%**	-2.78%	5.56%**
	(1.77)	(-1.66)	(2.24)	(1.52)	(-1.30)	(1.85)	(2.20)	(-1.48)	(2.50)
FF3 alpha	2.44%*	-2.75%	5.19%**	2.37%*	-2.35%	4.72%*	2.86%**	-2.31%	5.17%**
	(1.80)	(-1.51)	(2.12)	(1.76)	(-1.10)	(1.71)	(2.33)	(-1.34)	(2.43)
FF5 alpha	1.97%	-2.13%	4.10%	1.99%	-2.52%	4.50%	2.13%	-2.03%	4.16%*
	(1.18)	(-1.12)	(1.45)	(1.23)	(-1.10)	(1.42)	(1.59)	(-1.12)	(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%*	0.93%	6.55%	6.85%	0.12%	6.73%	9.28%**	-0.52%	9.81%**
	(1.80)	(0.13)	(1.48)	(1.53)	(0.02)	(1.65)	(2.12)	(-0.08)	(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%	-11.54%***	12.59%***	0.36%	-13.11%***	13.47%***	2.26%	-12.35%***	14.61%***
	(0.52)	(-3.04)	(3.27)	(0.15)	(-4.08)	(3.79)	(1.18)	(-3.42)	(4.06)
FF3 alpha	1.58%	-10.40%***	11.98%***	0.93%	-11.96%***	12.89%***	2.80%*	-11.41%***	14.21%***
	(0.92)	(-3.13)	(3.14)	(0.45)	(-3.98)	(3.50)	(1.74)	(-3.63)	(3.98)
FF5 alpha	1.67%	-10.05%***	11.71%***	0.66%	-11.16%***	11.83%***	2.89%*	-10.68%***	13.57%***
	(0.91)	(-2.79)	(2.82)	(0.31)	(-3.44)	(3.17)	(1.73)	(-3.08)	(3.45)

Figure 3 illustrates the compounded annual excess returns for each quintile portfolio sorted by volatility, beta, and idiosyncratic volatility (IVOL) for both large-cap and small-cap stocks, along with their corresponding CAPM betas. A subtle return differential is observed between large and small stocks in lower-risk portfolios, but this difference becomes increasingly pronounced in higher-risk portfolios, primarily explaining the observed return spread difference. The underperformance of high-risk small-cap stocks similarly influences the long-short portfolio alphas reported in Table 9. Notably, the long-leg alphas of small-cap portfolios are smaller in magnitude and demonstrate less statistical significance than those of large-cap portfolios. However, the substantial negative alphas associated with the short leg of small-cap portfolios are the primary driver of the overall alpha spread differential between large and small-stock portfolios.

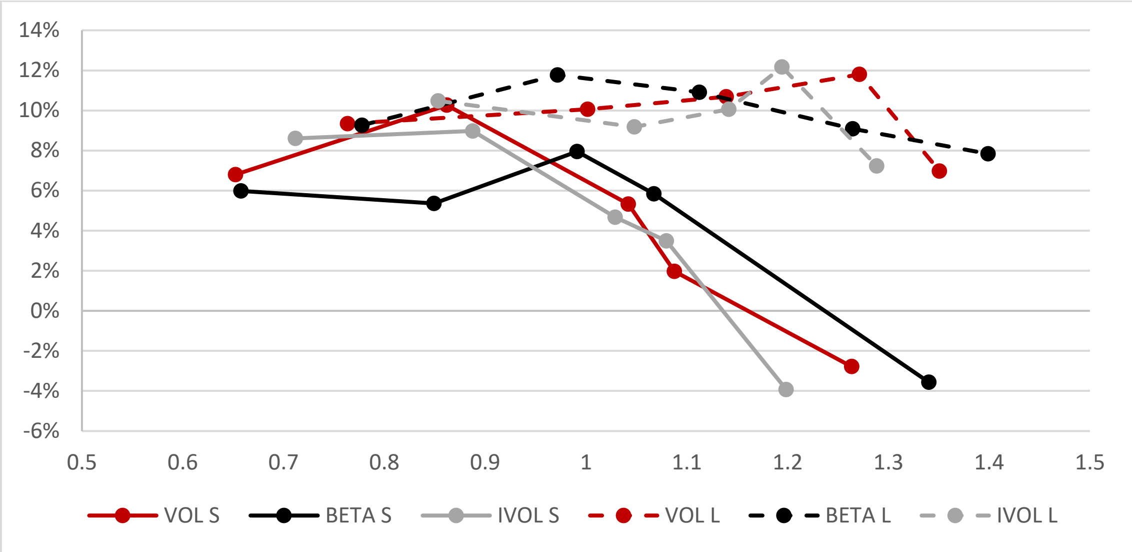

Figure 3. Annualized compounded return and beta relationship of each quintile portfolios sorted by 36- month volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL) for large-cap (L) and small-cap (S) stocks.

In conclusion, while Nordic large-cap long-short zero-cost portfolios do generate statistically significant CAPM and FF3 alphas, the magnitude of these alphas is approximately halved compared to the results observed in the total sample. Furthermore, the inclusion of profitability (RMW) and investment (CMA) factors in the FF5 model appears to subsume the large-cap long-short portfolio alphas in volatility and beta sorted portfolios, rendering them statistically insignificant. Conversely, the distinction between low-risk and high-risk portfolios is more pronounced among small-cap equities, suggesting a potentially stronger low-risk anomaly effect within this size segment.

5.3 Results for longer holding periods

Table 10 presents the results for longer holding periods in low-risk, high-risk and long-short zero cost portfolios sorted by 36-month rolling volatility, beta and idiosyncratic volatility. Specifically, the studied holding periods are 3-months, 6-months and 12-months. Consistent with earlier studies (see e.g. Blitz et al., 2013, 2021; Baker et al., 2014), the findings indicate that low-risk stocks generally maintain their low-risk status, while high-risk stocks tend to remain high risk, providing evidence that the low-risk anomaly persists even with extended holding periods.

The compounded return spreads of portfolios sorted by volatility and idiosyncratic volatility (IVOL) exhibit a monotonic decline as the holding period increases from 1 to 12 months. Conversely, beta-sorted portfolios show a slight monotonic increase in compounded return spreads. However, these differences are modest, with the return spreads for volatility and IVOL sorted portfolios decreasing by 1.21% and 1.86% respectively, while those for beta-sorted portfolios increase by 1.27% over the same period. Furthermore, a comparable trend is evident in simple return spreads.

Consistent with excess returns, the standard deviation of low-risk and high-risk portfolios remains relatively stable across different holding periods, from one month to twelve months. This suggests that the aggregate risk profile of the underlying stocks does not change significantly in the 12-month period following the initial risk measurement. Consequently, the Sharpe ratios of low-risk and high-risk portfolios remain relatively consistent across different holding periods.

All long-short zero-cost portfolios exhibit statistically significant positive alphas under the CAPM, Fama-French three-factor (FF3), and Fama-French five-factor (FF5) models. Consistent with the trend observed in excess returns, alphas generally decrease as the holding period lengthens for portfolios sorted by volatility and idiosyncratic volatility (IVOL), while alphas generally increase as the holding period lengthens for beta-sorted portfolios. Furthermore, the decrease (increase) in alphas observed in long-short portfolios with longer holding periods, sorted by volatility and idiosyncratic volatility (beta), can be attributed to the simultaneous reduction (elevation) of long leg alphas, coupled with an opposing increase (decrease) in short leg alphas.

Table 10. Results for longer holding periods

The table reports compounded and simple 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.

	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%**	3.12%	5.64%	7.73%*	6.42%	1.31%	10.68%**	2.01%	8.66%***
	(2.19)	(0.48)	(1.51)	(1.89)	(0.97)	(0.37)	(2.55)	(0.32)	(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%	-9.26%***	10.94%***	0.82%	-7.07%***	7.88%***	2.71%**	-9.92%***	12.63%***
	(1.21)	(-3.22)	(3.51)	(0.47)	(-2.97)	(2.94)	(2.31)	(-3.58)	(4.43)
FF3 alpha	1.90%	-8.34%***	10.24%***	1.18%	-6.20%***	7.38%***	2.93%***	-9.10%***	12.03%***
	(1.50)	(-3.35)	(3.40)	(0.82)	(-2.87)	(2.72)	(2.71)	(-3.83)	(4.47)
FF5 alpha	1.68%	-7.72%***	9.40%***	0.97%	-5.99%**	6.96%**	2.61%**	-8.51%***	11.12%***
	(1.14)	(-2.85)	(2.76)	(0.61)	(-2.54)	(2.38)	(2.13)	(-3.33)	(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%**	3.86%	4.74%	7.94%*	6.40%	1.54%	10.45%**	2.77%	7.68%**
	(2.18)	(0.60)	(1.31)	(1.94)	(0.97)	(0.43)	(2.48)	(0.44)	(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%	-8.41%***	9.94%***	0.95%	-6.99%***	7.94%***	2.47%**	-9.17%***	11.63%***
	(1.12)	(-3.01)	(3.28)	(0.59)	(-2.91)	(2.90)	(2.09)	(-3.43)	(4.15)
FF3 alpha	1.74%	-7.51%***	9.25%***	1.30%	-6.13%***	7.43%***	2.69%**	-8.36%***	11.05%***
	(1.40)	(-3.08)	(3.16)	(0.95)	(-2.81)	(2.70)	(2.49)	(-3.63)	(4.15)
FF5 alpha	1.50%	-6.54%**	8.04%**	1.06%	-5.84%**	6.89%**	2.36%*	-7.35%***	9.71%***
	(1.04)	(-2.45)	(2.44)	(0.69)	(-2.51)	(2.34)	(1.93)	(-2.89)	(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%**	3.97%	4.51%	8.59%**	6.37%	2.22%	10.37%**	3.06%	7.31%**
	(2.14)	(0.62)	(1.28)	(2.10)	(0.97)	(0.62)	(2.45)	(0.49)	(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%	-8.34%***	9.70%***	1.61%	-6.99%***	8.61%***	2.33%**	-8.98%***	11.31%***
	(1.01)	(-3.03)	(3.27)	(0.98)	(-2.91)	(3.13)	(1.99)	(-3.33)	(4.01)
FF3 alpha	1.59%	-7.45%***	9.04%***	1.97%	-6.12%***	8.09%***	2.57%**	-8.18%***	10.75%***
	(1.30)	(-3.07)	(3.14)	(1.42)	(-2.78)	(2.91)	(2.41)	(-3.51)	(4.00)
FF5 alpha	1.27%	-6.23%**	7.50%***	1.83%	-5.77%**	7.60%**	2.22%*	-6.85%**	9.07%***
	(0.90)	(-2.25)	(2.94)	(1.18)	(-2.43)	(2.57)	(1.86)	(-2.56)	(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%**	3.98%	4.48%	8.76%**	6.12%	2.64%	10.25%**	3.46%	6.79%**
	(2.13)	(0.63)	(1.29)	(2.12)	(0.94)	(0.76)	(2.41)	(0.55)	(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%	-8.34%***	9.54%***	1.73%	-7.13%***	8.86%***	2.13%*	-8.56%***	10.69%***
	(0.92)	(-3.08)	(3.27)	(1.01)	(-3.10)	(3.29)	(1.80)	(-3.19)	(3.77)
FF3 alpha	1.45%	-7.46%***	8.91%***	2.09%	-6.29%***	8.39%***	2.37%**	-7.77%***	10.14%***
	(1.21)	(-3.14)	(3.15)	(1.49)	(-2.97)	(3.09)	(2.17)	(-3.33)	(3.75)
FF5 alpha	1.05%	-6.17%**	7.22%**	1.80%	-5.68%**	7.49%**	2.00%*	-6.39%**	8.39%***
	(0.78)	(-2.19)	(2.16)	(1.15)	(-2.36)	(2.47)	(1.66)	(-2.31)	(2.63)

Figure 4 displays the average monthly excess returns for low-risk and high-risk portfolios, calculated using an overlapping portfolio formation methodology. Each data point represents the mean portfolio return in the specific month following its formation. Although the low-risk portfolio returns trend slightly lower each month, the return gap between low-risk and high-risk portfolios persists throughout the entire 12-month period after portfolio formation.

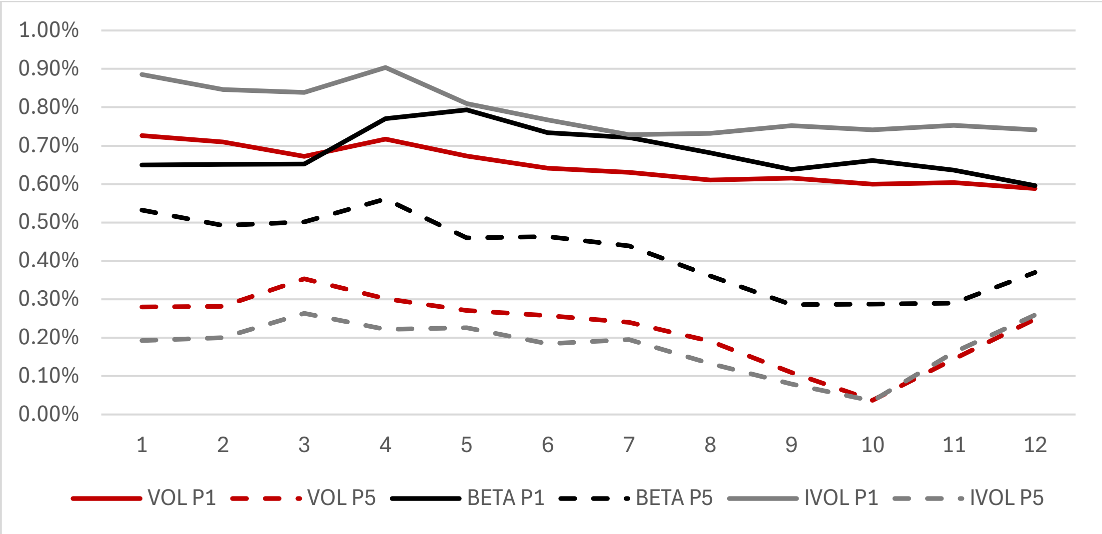

Figure 4. Average monthly excess return of 36-month volatility (VOL), beta (BETA), idiosyncratic volatility (IVOL) sorted low-risk (P1) and high-risk (P5) portfolios each month after portfolio formation.

In conclusion, the findings of this study align with those of Blitz et al. (2013, 2021). Both studies reported relatively stable and statistically significant 1-factor alphas over extended holding periods (1 to 60 months) in emerging markets and China, respectively. Furthermore, this study's results on longer holding periods is supported by Baker et al. (2014), who demonstrated that stocks sorted into quintile portfolios based on 60-month rolling beta exhibit a high degree of stickiness in their risk characteristics. Specifically, they found a greater than 95% probability for a stock to remain in its initial top or bottom quintile after one month.

5.4 Subsample results

Finally, two distinct subperiods, each spanning nearly a decade, were created to further examine the low-risk anomaly. In table 11, panel A encompasses the initial subperiod from February 2005 to August 2014, while Panel B covers the subsequent subperiod from September 2014 to March 2024.

Consistent with Blitz and van Vliet (2007), low-risk stocks outperformance against high-risk stocks is rather strengthening than diminishing. Compounded and excess return spreads are higher in latter subperiod for volatility and idiosyncratic volatility sorted portfolios, whereas the spread weakens for beta sorted portfolios. Additionally, all long-short portfolios CAPM alphas are positive and statistically significant for both subperiods, while strengthening in latter period. Furthermore, FF3 and FF5 alphas for long-short portfolios are larger in the latter subperiod compared to the first, with the exception of beta-sorted portfolios. Additionally, while only FF3 alphas are statistically significant in the first subperiod, both FF3 and FF5 long-short portfolio alphas exhibit statistical significance in the latter period.

Table 11. Results for subperiods

The table reports compounded and simple 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.

	VOL			BETA			IVOL		
	Q1	Q5	Q1-Q5	Q1	Q5	Q1-Q5	Q1	Q5	Q1-Q5
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)

In addition to the two distinct subperiods, Figure 5 illustrates the one-year rolling excess return in volatility, beta, and idiosyncratic volatility for long-short zero-cost portfolios, in comparison to the Nordic market index. While the returns of long-short zero-cost portfolios generally remain stable throughout the period, they occasionally experience negative year-over-year returns. The figure visually confirms a negative correlation between these portfolios and the market index, especially pronounced during periods of extreme market fluctuations, such as the financial crisis and the 2020-2021 stock market rally. Furthermore, while the three long-short zero-cost portfolios tend to move in tandem, some dispersion is evident, particularly in recent years where the beta-sorted portfolio appears to lag behind.

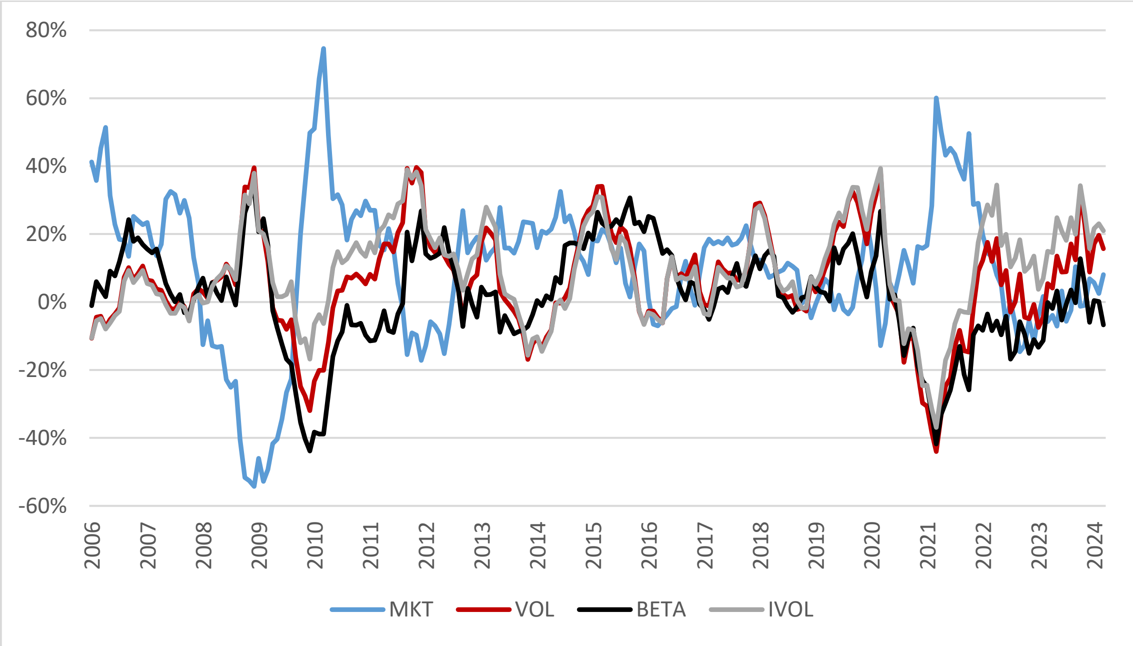

Figure 5. Rolling 12-month excess returns for the Nordic market index (MKT) and zero-cost long-short portfolios (P1-P5) formed based on 36-month rolling sorts of volatility (VOL), beta (BETA), and idiosyncratic volatility (IVOL).

5.5 Limitations

The study presents certain methodological limitations that warrant consideration. Firstly, the reliance on monthly observations, while a common practice, may not adequately capture the nuanced fluctuations in stock prices that occur within a month or on an intraday basis. The inclusion of higher frequency data could potentially alter the risk profile of the stocks in the sample and, consequently, influence the study's findings. While the chosen approach might be more conservative, as studies have found stronger evidence of the low-risk anomaly utilizing daily observations rather than monthly observations (see e.g., Li et al., 2014; Bali & Cakici, 2008). Furthermore, the choice of portfolio weighting, although justified in the context of Nordic equity markets, could also affect the results if alternative weighting schemes were employed.

Secondly, this study does not account for transaction costs, which may impact the profitability of low-risk strategies. Given that low-risk portfolios typically comprise larger, more liquid equities, their associated transaction costs tend to be lower (van Vliet, 2018). However, this observation pertains solely to the long (low-risk) side of the portfolio. The short (high-risk) side often consists of smaller, more volatile equities that are more expensive to trade. Moreover, shorting costs tend to rise with increasing volatility, and highly volatile stocks are more likely to be recalled (Drechsler & Drechsler, 2016; D'Avolio, 2002). Therefore, incorporating transaction costs into the analysis would likely diminish the observed profitability of low-risk strategies.

The study employs multiple regression analysis utilizing Fama-French factors adapted to the European market. While the factors were converted into euros following Glück et al. (2021) to address currency fluctuations, it is important to acknowledge that European-specific factors may not fully capture the unique dynamics of the Nordic equity markets. Employing factors specifically tailored to the Nordic region could potentially enhance the explanatory power of the models and yield different results. Furthermore, to ensure consistency across sample markets with varying currencies, all returns were converted into euros, and stock risk measurements were derived from euro-denominated total returns. While Nordic currencies have generally remained stable throughout the sample period, it is worth noting that calculating stock risk from local currencies could introduce minor variations in the results.

6 Conclusions and summary

This thesis investigates the low-risk anomaly in Nordic equity markets from February 2005 to March 2024. The study analyzes the relationship between risk and return using various risk measures (volatility, beta, idiosyncratic volatility), rolling windows (36, 24, 12 months), holding periods (1, 3, 6, 12 months), and market capitalization segments (large-cap, small-cap).

The findings confirm the presence of a low-risk anomaly in Nordic equity markets, where low-risk equities outperform high-risk equities in terms of both raw excess returns and risk-adjusted returns. Specifically, all tested rolling risk measurement windows, including 36-month, 24-month and 12-month sorted volatility, beta and idiosyncratic volatility sorted long-short zero cost portfolios generated large and statistically significant CAPM, FF3 and FF5 alphas and almost all generated statistically significant FF6 alphas. Thus, the first hypothesis is accepted. Furthermore, strongest results were provided by sorting stocks by Idiosyncratic volatility and 36-months when comparing the risk measurement and measurement period, respectively.

While theoretical studies often focus on long-short portfolios, the low-risk anomaly is typically exploited through long-only portfolios, such as smart beta ETFs (Blitz et al., 2020). Consequently, from a practical perspective, the most relevant portfolio performance metric is that of the low-risk portfolio. Although the low-risk quintile portfolio did not yield the highest raw excess returns across in the majority of tested methods, it consistently delivered the highest Sharpe ratios, demonstrating superior risk-adjusted performance. Unlike long-short portfolios, low-risk portfolios yielded inconsistent results, with statistically significant alphas achieved by a limited number of tested methods. Notably, the highest and most statistically significant alphas within the low-risk quintile were obtained using 24-month sorts. Moreover, long leg alphas are considerably smaller than short leg alphas, indicating that short positions contribute more significantly to long-short portfolio alphas. This suggests that a long-only strategy would not capture the majority of potential alpha.

Large-cap stocks yielded inconsistent results, with a substantial narrowing of the return spread between low and high-risk portfolios. All long-short portfolios generated statistically significant CAPM and FF3 alphas. However, the inclusion of profitability (RMW) and investment (CMA) factors appeared to explain the returns of volatility and beta-sorted long-short portfolios, leaving only idiosyncratic volatility-sorted portfolios to generate statistically significant FF5 alpha. Thus, the hypothesis that the low-risk anomaly exists in large-cap stocks is supported only for idiosyncratic volatility-sorted portfolios, but not for volatility or beta-sorted portfolios. Additionally, small-cap stocks provided stronger evidence of the inverse relationship between risk and return, with all long-short portfolios demonstrating statistically significant alphas. The wider alpha spreads in small caps were primarily driven by high-risk portfolios, as large-cap low-risk portfolios generally exhibited higher raw excess returns and alphas compared to their small-cap counterparts. However, only a limited number of low-risk portfolios in both large and small caps achieved statistically significant alphas.

Results for longer holding periods (3, 6, and 12 months) confirmed the viability of a low-risk strategy with relatively low turnover, as all long-short zero-cost portfolios consistently generated statistically significant positive CAPM, FF3, FF5, alphas. Although alphas gradually declined over extended holding periods for volatility and IVOL sorted portfolios, their statistical significance persisted, thus supporting the final hypothesis. Furthermore, subperiod analysis reveals that the low-risk anomaly in Nordic equity markets is not weakening, but rather strengthening over time.

While some studies have explored low-risk anomalies in other asset classes, the majority of research has concentrated on equities, leaving room for future research to expand into other asset classes. Additionally, future research should prioritize identifying the drivers of the low-risk anomaly. Despite numerous explanations and suggestions, no clear consensus has emerged regarding the underlying causes, underscoring the need for further investigation to fully understand this phenomenon. Moreover, rather than relying solely on price-based risk measures to study the low-risk anomaly, future research could explore the application of fundamental-based risk measures within Nordic equity markets (Alquist et al., 2020).

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