Norwegian School of Economics
Bergen, Fall 2022

Does climate transition investments pay off?

An empirical analysis of active Nordic funds and performance effects of exposure to carbon transition risk

Sivert Eikrem and Mathias Lorentsen

Supervisor: Associate Professor: Jørgen Haug

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis was written as part of our Master's degree in Economics and Business Administration at Norwegian School of Economics (NHH).

Our main objective was to contribute to the existing literature on a relevant topic. With the increasing focus on sustainable finance, we wanted to bring empirical evidence to the discussion on how investment strategies involving sustainability affect performance. Completing the thesis has challenged us to educate ourselves on highly interesting topics, and we believe that our work is of value and interest to investors and academics.

Throughout this semester, we have acquired valuable knowledge in the field of sustainable finance by applying financial theory and econometric analyses, which may prove valuable in our future professional careers.

We would like to thank our supervisor, Associate Professor Jørgen Haug, for valuable guidance and for encouraging us to pursue our independent motivation and interest. We would also like to thank our fellow students for constructive discussions and friends and family for their support along the way.

Norwegian School of Economics

Bergen, December 2022

Sivert Eikrem

Mathias Lorentsen

Abstract

Sustainable finance and investment strategies have received increasing attention the previous years. In this thesis, we investigate the performance effects of carbon transition risk exposure in Nordic mutual funds. The analysis is restricted to 655 funds between the period from March 2017 to September 2022. We provide evidence that carbon transition risk does not independently impact the risk-adjusted performance in Nordic mutual funds. This result is inconsistent with existing literature on the topic where expanding carbon transition risk has a negative impact on performance.

Furthermore, we conduct a portfolio analysis where we investigate the impact of active management on performance within high and low carbon risk environments. Including this perspective does not change the result, and we conclude that the carbon risk does not impact risk-adjusted performance in our sample. As we find that carbon risk is closely related to volatility and systematic risk, we hypothesize that carbon risk are increasingly accounted for by financial risk. This could explain why our findings deviate from the literature, as indirectly changing financial risk would not change the risk-adjusted performance. The decreasing performance of growth stocks due to rising interest rates could also eliminate the excess risk-adjusted return of low carbon risk funds.

Keywords – Carbon Transition Risk, Active Funds, ESG

Contents

List of figures

List of tables

1 Introduction

Climate change and global warming is potentially the most pressing challenge we face. Simultaneously, the challenge is growing as a risk factor to financial markets due to its impact on assets and the transition it demands from the global economy.

Scientific evidence has proved that emissions of greenhouse gasses are the leading cause of global warming (Alexiadis, 2007). Among the gasses, carbon dioxide, CO_2, is referred to as the most threatening (IPCC, 2021). Therefore, an essential part of the risk caused by climate change is the CO_2 intensity in organizations, countries, and the global economy (Praisley, 2022). This risk is referred to as carbon transition risk, or simply carbon risk, and reflects the risks associated with restricting carbon emissions within a short period. From an investor perspective, this yields a carbon risk exposure in all portfolios (Hale, 2018). Asset managers can implement socially responsible investment strategies to contribute to the transition and reduce carbon risk. These strategies involve maximizing financial performance combined with social and environmental value. Due to the increasingly environmentally cautious world, the strategy has grown popular. There is, however, deviating opinions regarding the performance effects of these strategies (Schoenmaker and Schramade, 2019).

This thesis aims to investigate active Nordic funds and the performance effects of carbon risk exposure. We do this through two empirical approaches. First, we analyze the independent effects of exposure to carbon risk on performance and volatility. We also include insight into how capital flow is affected by the carbon risk to understand the willingness to finance the climate transition. Second, we estimate the combined effects of carbon risk exposure and the degree of active management. Through this approach, we can evaluate the performance effects within isolated carbon risk environments.

We study a sample of 655 Nordic mutual funds between March 2017 and September 2022. In the first empirical approach, we analyze the full sample. In the second, we divide the data into four portfolios of 41 funds based on boundaries of high/low carbon risk and high/low degree of active management.

In the first empirical approach, we estimate regressions to evaluate the effect of carbon risk exposure on risk-adjusted performance calculated as the alpha (α) of multi-factor models. These estimations yield an extensive understanding of how α moves when carbon risk expands. Furthermore, we add insight into how the carbon risk impacts the total risk of Nordic fund portfolios through a regression on return volatility. As mentioned, we also regress carbon risk on capital flow. The results indicate that our model does not find any significant relation between carbon risk exposure and α, despite capital flowing towards low-carbon risk funds. We also find that carbon risk and volatility are significantly related. Hence, the total financial risk increases by increasing the carbon risk.

Regarding the combined effects of carbon risk exposure and the degree of active management, we introduce this part by testing differences in means of returns within each portfolio. Here, we find no statistical evidence of any combination of high/low carbon risk exposure and degree of active management outperforming the other. Secondly, we estimate multi-factor models across the portfolios to investigate potential α. These models fail to prove any significant risk-adjusted performance within either constructed portfolio. Hence, an active or passive investment strategy within high or low carbon risk environments does not yield excess risk-adjusted returns.

As our results deviate from existing literature, we discuss potential causes of the insignificant relation between carbon risk and risk-adjusted performance. We hypothesize that it might be due to carbon risk increasingly reflecting financial risk. As higher carbon risk increases both volatility and systematic risk, it seems likely that carbon risk is indirectly accounted for by the established risk factors by Fama-French and Carhart. This being true, indirectly changing the financial risk through carbon risk will not improve risk-adjusted performance. Furthermore, the decreasing performance of growth stocks due to rising interest rates could also have eliminated the α found in previous literature in low carbon risk funds.

Our thesis contains six sections. Section 2 introduces relevant theories on climate change, climate finance, and active management. Further, it presents relevant literature and our research question. In section 3, we describe our data sampling, screening, and variable construction. Section 4 contains a preview of our methodology. In section 5, we present descriptive statistics of our sample and our empirical results. Lastly, we summarize and conclude the thesis in section 6.

2 Background and literature review

This section discusses how climate change affects the environment and financial market. We address fund management strategies and climate risk sources before reviewing the literature on how carbon risk impacts financial performance. Finally, we present our research question.

2.1 Climate change

Climate change refers to long-term changes in global temperature and weather patterns. The changes have the potential to dramatically influence life on Earth through intense droughts, water scarcity, severe fires, rising sea levels, flooding, melting polar ice, storms, and declining biodiversity (United Nations, 2022). The cause of the change is broadly discussed, but research has shown that human activity has significantly impacted the temperature increase. The consumption of fossil fuels accompanied by the emission of greenhouse gasses (GHG) is considered the principal source of human impact on climate change. The most critical GHG is carbon dioxide, CO_2 (IPCC, 2021).

Due to its implications on sustaining life on Earth as we know it, climate change is potentially the most defining sustainability issue we are facing (Attenborough, 2021). Consequently, it is vital to stop climate disruption and reverse its impact by reducing CO_2 emissions. The urgency has been attracting an increasing amount of attention. In 2015, the United Nations (UN) Framework Convention on Climate Change arranged the Conference of Parties 21 in Paris, leading to the Paris Agreement. The agreement is a legally binding treaty to limit global warming in all 196 UN member countries. The treaty is a landmark as it was the first binding agreement where all nations committed to combating climate change (UNFCCC, 2015). The Glasgow Climate Pact is an example of a more recent international commitment to the climate change cause, pledging UN states to phase down coal power and inefficient subsidies for fossil fuels (UNFCCC, 2022).

The increasing attention to climate change puts pressure on institutional and technological action to reduce carbon footprint and transit to a climate-resilient economy. This focus also contributes to the accountability held to businesses for their environmental impact through legislation, taxation, and stakeholder pressure. Hence, climate change represents a growing risk for all companies (Pinner and Sneader, 2019).

2.2 Climate finance

The UN defines climate finance as "local, national, or transnational financing, which may be drawn from public, private and alternative sources" that contributes to the climate cause (UNEP, 2022). J.P.Morgan (2022) points out that the corporate sector has an important role in stopping climate change by allocating capital to sustainable projects.

While adapting to the climate transition, companies increasingly adopt long-term value creation (LTVC) in their decision-making. LTVC includes financial, societal, and environmental value (Schoenmaker and Schramade, 2019). In this regard, the interest in socially responsible investing (SRI) has increased as an investment strategy. SRI are investments that consider LTVC by maximizing risk-adjusted financial return combined with social and environmental value (Schoenmaker and Schramade, 2019). However, this strategy conflicts with the traditional financial theory of efficient markets and portfolio management. As all relevant and available information incorporates into market prices, investors cannot systematically beat the market (Markowitz, 1952; Sharpe, 1964; Fama, 1970). This being true, SRI is inefficient as it constraints portfolio diversification.

2.3 The financial risk of climate change

Within financial risk, systematic risk is caused by factors beyond individual or organizational control (CFI, 2022b). With its impact on assets, organizations, and the financial system beyond individual control, climate change can therefore be considered a systematic risk (Gelzinis and Steele, 2019). The risks caused by climate change to financial stability are frequently divided into physical- and transition risks (Board, 2020) as illustrated in figure 2.1.

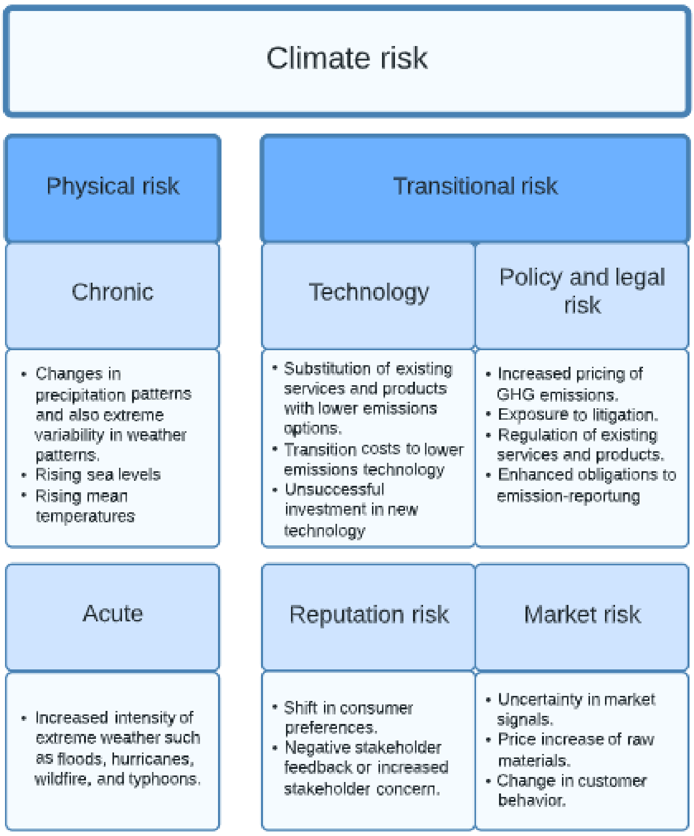
2.3.1 Physical risk

Physical risk results from the increase in extreme variations in weather patterns. Also, it deals with changes in long-term precipitation patterns and increased incidence and severity of extreme weather (Hale, 2018). These risk factors contribute to an increase in the risk of financial instability. Dafermosa et al. (2018) found that climate change can gradually degenerate firms' liquidity, leading to a higher rate of default due to the destruction of assets. They also argue that the damages can lead to portfolio reallocation, which might gradually reduce corporate bond prices.

2.3.2 Transition risk

Transition risk addresses how vulnerable a company is to the transition towards a oslow-carbon economy (Hale, 2018). The four main drivers of transition risk are policy and legal regulations, technology risk, market risk, and reputation risk. According to the Paris Agreement, the goal is to deliver net-zero emissions by 2050 (UNFCCC, 2015), increasing the pressure on companies to change their operations towards carbon-free methods. Going forward, we focus on transition risk in the scope of carbon emission dependency.

Figure 2.1: Climate risk



Note: Figure 2.1 gives a short but more in-depth explanation of climate risk, divided into physical and transition risks

2.4 Mutual fund portfolio management

2.4.1 Active management

Mutual funds can be managed based on several strategies, but the two general directions are active and passive management. Active management focuses on outperforming a fund index such as the S&P500 or the Norwegian OSEFX by actively buying and selling stocks. Active management relies on the belief that the *Efficient Market Hypothesis* is incorrect (CFI, 2022a). That being true, investment managers can modify risk and the volatility of returns compared to the benchmark. The main objective is to create risk-adjusted excess returns. A study from Grossman and Stiglitz (1980) addresses a paradox explaining that if the market is efficient, no investor has incentives to use resources to extract and trade on the information. This means tha markets must be inefficient enough to compensate active investors for their costs and efficient enough to discourage additional active management.

2.4.2 Tracking error

Tracking error measures the degree of risk in a portfolio by measuring the volatility of the differences in return between the benchmark and the portfolio (Grinold and Kahn, 1999). Moreover, this shows a standard deviation percentage difference between the investor and benchmark returns. Grinold and Kahn (1999) defines tracking error as:

$$TE = \sigma(R_P - R_B) = \sigma(R_A) \tag{2.1}$$

where R_P is the return of the portfolio and R_B is the return of the benchmark. Since tracking error indicates how close the fund follows the benchmark, it is often used to measure active risk. Although funds aim to have low tracking error, tracking error is a necessary evil to gain excess return (Gupta et al., 1999).

2.5 Literature review

Our contribution to existing literature concerning carbon transition risk and fund performance is twofold. While previous research has focused on global and US data, this thesis presents insight from the Nordic countries. Moreover, we offer a new perspective on how active management affects the performance of funds within different carbon risk environments.

Reboredo and González (2021) studied the low carbon transition risk in mutual fund portfolios, focusing on managerial involvement and performance effects on US funds. They found that a socially responsible focus and managerial ownership reduce the fund's carbon risk exposure, while more active management increases fund exposure to carbon risk. Further, Kuang and Liang (2022) constructed a novel carbon risk measure to assess mutual funds' carbon risk exposure based on holding data from the mutual funds. Moreover, they looked at how this exposure affects mutual funds' risk, performance, and flow on a global dataset. Both studies find that higher carbon risk in fund portfolios decreases risk-adjusted performance.

In a study published in 2022, Ceccarelli et al. examined the impact of the release of new information on fund flows and position changes for a sample of US and European mutual funds from Morningstar's carbon risk metrics. They found that the availability of this information caused a surge in demand for low carbon funds, suggesting that climate information can influence the direction of capital flows toward more sustainable investments. These findings align with those of Spiegel and Zhang (2013), who explored the role of risk on fund flows and found similar results.

In addition to the aforementioned studies, Carbone et al. (2021) investigated the relationship between low carbon transition risk and firm credit risk. They discovered that well-prepared firms for the transition to a low-carbon economy also had lower credit risk. On the topic of the cost of carbon risk, Chava (2014) found that firms with higher carbon emissions tend to have a higher cost of capital, while Jung et al. (2018) found a similar association with a higher cost of debt. These findings suggest that addressing carbon risk can benefit firms in various ways.

Recently, Hsu et al. (2022) examined the impact of industrial pollution on asset pricing. They found that firms with high pollution levels are more vulnerable to environmental regulation risk, leading to a higher required average return. Similarly, Bolton and Kacperczyk (2021a) investigated whether carbon emissions affect the cross-section of stock returns in the US and found that both direct and indirect carbon emissions significantly positively affect US firms' stock returns. In contrast, Rakowski (2010) explored the relationship between daily mutual fund flow volatility and fund performance, finding a significant negative correlation between the two for US open-end mutual funds.

2.6 Research question

As earlier mentioned, this thesis aims to explore whether exposure to carbon transition risk and the degree of active management can explain the risk-adjusted performance of mutual stock funds in Nordic countries. Furthermore, we believe that the perspective of active management within the scope of carbon risk can provide new insight into the impact on fund performance. Therefore, our master's thesis primarily focuses on the following research question:

"How does carbon risk exposure relate to risk-adjusted performance in Nordic mutual funds, and how does this relationship vary across different levels of active management?"

We intend to answer the research question through an analysis of two parts. First, we analyze our full data sample to investigate how carbon risk impacts Nordic mutual fund performance independently. After that, we present a portfolio study based on the division of funds in four portfolios regarding their carbon risk and active management represented by tracking error. In this way, we can interpret the combined effects of carbon risk and the degree of active management on mutual fund performance.

The following chapter describes the data extraction and modification process implemented to execute statistical tests.

3 Data

This section explains the procedure for extracting and preparing data for empirical analysis. We also describe the process of sampling and screening the data before we explain how we construct our variables and portfolios.

3.1 Data sources

Our primary data source, Morningstar Direct, is a research platform to develop, select, and monitor investments for different funds, stocks, and other financial instruments. Additionally, Kenneth R. French's data library gives access to various risk factors used in the multi-factor regression analysis.

3.1.1 Carbon Risk Score (CRS)

Sustainalytics' Carbon Risk Ratings evaluate firms' risk exposure of the transition to a low-carbon economy to assess a company's carbon risk. Furthermore, the rating derives from the basis of the company's management and overall carbon exposure. The management reflects the company's ability to manage, e.g., energy efficiency, greener products and services, and carbon emissions. Moreover, the overall carbon exposure is determined by the company's products and services, kind of business, and operations (Hale, 2018). Hence, the evolution of a company's management of carbon issues and material exposure determines the ratings, which vary from 0 to 100. The scores indicate risk that is negligible (0), low (0-10), medium (10-30), high (30-50), and severe (<50).

Furthermore, Morningstar Direct provides a CRS for mutual stock funds, stating a weighted average of the exposures to firm-level Sustainalyics CRS (Hale, 2018). The database consists of risk ratings for approximately 30 000 funds worldwide, where portfolios with lower CRS are better positioned to transit toward a low-carbon economy. In general, portfolios with an overweight towards utilities, energy, materials, and industrial sectors have higher levels of carbon risk. On the other hand, portfolios with overweight towards healthcare and technology have lower levels of carbon risk. Simultaneously, risk level often depends on the specific companies held in the different portfolios (Hale, 2018).

3.1.2 Other financial variables

Regarding financial data, Morningstar Direct provides identifier data, fund returns, total fund value, and benchmark information. Furthermore, an important part of our analysis builds on risk-adjusted fund performance, measured by excess returns. The necessary factors to calculate this are retrieved from Kenneth R. French's data library, which calculates their variables based on data from the Bloomberg database (French, 2022a).

3.2 Sample selection

In this thesis, we analyze mutual funds based on CRS and the degree of active fund management. Due to the calculation of fund CRS based on exposure to firm-level CRS, we require all funds to be open-end stock funds. Funds exposed to money markets or bonds are thus excluded from the sample. As our analysis applies to funds with headquarters in the Nordic countries, we also restrict the sampling to Norway, Sweden, Denmark, Finland, and Iceland. These criteria yield 2324 relevant funds, which include both operating and decommissioned funds. Carbon risk rating availability restricts our sample period from Q1 2017 until Q3 2022.

Regarding the Fama-French factors, Kenneth R. French's data library provides categories specifying geography and market development degree. As the funds we analyze are exposed to stocks from all parts of the world, the natural category choice was international and intercontinental factors. Furthermore, we chose the factors explaining the developed markets as most of the sampled funds have this exposure.

3.3 Screening

3.3.1 Carbon risk considerations

The most central variable in this thesis is the CRS which represents the carbon risk in the fund portfolios. Thus, the screening is customized to get the most out of this variable. To circumvent a small sample size of 23 observed quarters, we use monthly data for variables where this is available. This yields 67 observed months. We date CRS observations to end-of-quarter months to make the quarterly stated CRS compatible with monthly data.

Carbon risk scores from, e.g., Q2 2018, are thus dated as June 2018. A moving average further calculates the missing monthly data between the observations. To minimize survivorship bias, we do not require continuous observations of CRS. Funds operating within the CRS era but are now decommissioned are therefore included. Removing funds with no observed CRS leaves us with 1337 funds. Of these funds, 531 have complete cases of CRS, meaning that they have been rated at all quarters since 2017. Thus, some funds have fewer observations than others.

Moreover, to avoid incubation bias, we remove observations when a fund's A share class is shorter than two years within the analyzed period. The screening process so far leads to the exclusion of Icelandic funds. Going forward, referring to the Nordics only applies to Norway, Sweden, Denmark, and Finland.

3.3.2 Active management considerations

The degree of active management is also an important factor to consider while we structure our data. To calculate the chosen variable for active management (tracking error), we need a designated benchmark. Therefore, we require sampled funds to have a benchmark recognized by Morningstar Direct. Extracting these benchmarks yields 310 individual financial instruments. By matching the funds with their benchmark and associated variables, the sample size is reduced to 655 funds with a total of 32 613 monthly observations.

3.4 Portfolio construction

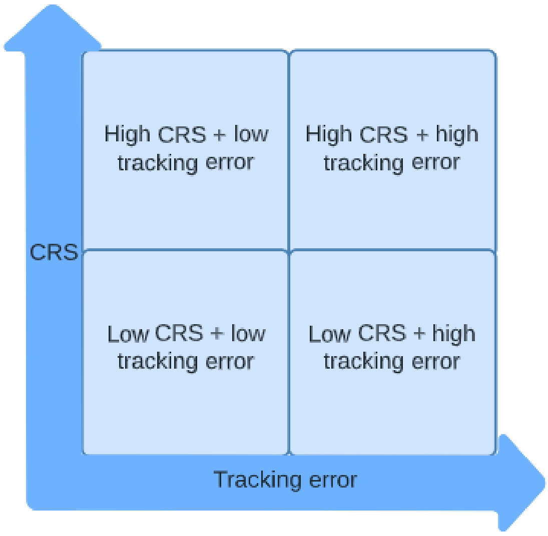
Before going into detail on portfolio construction, we reintroduce tracking error. As stated in section 2.4.2, we calculate tracking error as follows:

$$TE = \sigma(R_P - R_B) = \sigma(R_A) \tag{3.1}$$

We pair the sampled funds with their benchmark ID and the associated monthly return to execute this operation. After that, we calculate the standard deviation of the difference between each monthly fund return, R_P, and benchmark return, R_B.

We calculate means of tracking error and CRS to categorize funds and allocate them to portfolios. The allocation is illustrated in figure 3.1 and is based on thresholds to ensure portfolio differences. We assign funds to two percentile groups with 25% top and bottom average CRS. The same approach applies to defining high and low tracking error within each grouping of CRS, which allocates four portfolios of 41 funds.

Figure 3.1: Portfolio construction



Note: Figure 3.1 illustrates our various portfolios according to CRS and tracking error.

Moreover, we constructed value-weighted and equally-weighted portfolios. In the value-weighted portfolio, we weigh funds according to their total value. Equally-weighted portfolios, however, consist of equally-weighted funds. We include both equally-weighted and value-weighted portfolios to compare our results based on two perspectives and potentially ensure robustness. These two weighting methods reflect two views on the portfolios. Concerning equally-weighted funds, we observe the transversal trend across the individual fund managers. By introducing value-weights, however, we emphasize each fund's size to interpret the portfolios' trend as a whole.

When a fund is closed down, the weight will be 0% after this point in time. The shares invested in the delisted funds are distributed among the remaining funds according to whether the portfolio is equally-weighted or value-weighted.

3.5 Variable definitions

3.5.1 Risk measures

Volatility for mutual funds is measured using historical volatility within the analyzed period. This is measured as the standard deviation of return within each fund. We also compute this variable for the constructed portfolios.

3.5.2 Risk-adjusted performance

To investigate the effects of carbon risk on risk-adjusted performance, we construct variables that consider risk when measuring returns. This includes the Sharpe ratio and the Treynor Ratio. The Sharpe ratio is an expression that states the return adjusted for the risk-free rate relative to the return volatility (Sharpe, 1966). The ratio is also referred to as the excess return reward.

$$SharpeRatio = \frac{R_P - R_F}{\sigma_P} \tag{3.2}$$

The Treynor ratio is known as a reward-to-volatility measure. The model determines the excess return over the risk-free rate generated for each unit of portfolio risk (Treynor, 2015).

$$TreynorRatio = \frac{R_P - R_F}{\beta_P} \tag{3.3}$$

In the context of funds, units of portfolio risk are determined by the β_P, which refers to the systematic risk of a fund compared to its benchmark. When computing the Treynor ratio of the constructed portfolio, the denominator reflects the exposure to the systematic risk of the global developed markets. In both instances, the β is calculated as the first risk factor of the Fama-French five-factor with momentum model explained in section 4.1.

Moreover, we use the intercept from the multi-factor models of Fama-French and Carhart to calculate risk-adjusted performance. The estimations are applied to all individual funds and to the constructed portfolios. In that way, we are able to approach the effect on risk-adjusted performance regarding both the market as a whole and within the mentioned allocation criteria (section 3.4).

3.5.3 Other variables

We also consider other variables that could affect the risk-adjusted fund performance. This includes the natural logarithm of the total fund value, flow, age, and domicile variables. Monthly fund flow refers to a fund's growth due to the supply of new capital. To calculate this, we subtract the total net assets of two subsequent months, controlling for the returns gained in the first month. Mathematically, this is expressed as follows:

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})}{TNA_{i,t-1}} \tag{3.4}$$

where $TNA_{i,t}$ represents the total net assets of fund i in the end of month t. Moreover, $r_{i,t}$ is the return of fund i at month t.

Furthermore, we subtract the given time from the fund's inception date to compute a specific fund's age. Finally, we created a corresponding dummy variable for each Nordic country to interpret the domiciles' information. The binary variable holds the value of 1 when the fund has the relevant domicile and 0 if not.

The following section details the methodology we apply to analyze the data.

4 Methodology

4.1 Multi-factor models

This section explains the Fama-French five-factor model + momentum (FF5+MOM). We apply the model to assess the performance effects of carbon risk across the Nordic fund market and within specific portfolio environments. The model is estimated as follows:

$$\begin{aligned} R_i - R_F = \alpha_i + \beta_{i,M} \cdot MKT + \beta_{i,SMB} \cdot SMB + \beta_{i,HML} \cdot HML + \\ \beta_{i,RMW} \cdot RMW + \beta_{i,CMA} \cdot CMA + \beta_{i,MOM} \cdot MOM + \epsilon_i \end{aligned} \tag{4.1}$$

The FF5+MOM is an expansion of CAPM, the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart), and the Fama-French five-factor model (FF5). The rationale behind CAPM is to compensate investors with higher returns for taking on non-diversifiable systematic risks. To expand this understanding and isolate abnormal returns, FF3, Carhart, and FF5 include additional factors to the market risk factor (MKT) from CAPM (Carhart, 1997; Fama and French, 1993; French, 2022b).

FF3 includes a size factor (SMB) and a value factor (HML). SMB is short for "small minus big" and equals the difference between diversified portfolio returns for small and large assets. HML is short for "high minus low" and reflects the difference between high and low book-to-market returns. Compared to CAPM, FF3 adjusts for outperforming tendencies, which improves the model (Fama and French, 1993).

Moreover, Carhart includes the momentum factor to implement the tendency of well-performing portfolios to continue to perform well. Correspondingly, bad-performing portfolios often continue to perform poorly (Carhart, 1997). Furthermore, Jegadeesh and Titman (1993) states that buying winners and selling losers is positive for performance, while Wiest (2022) finds a broad academic agreement of momentum affecting profits.

Further, FF5 is an extended model of the FF3 model with additional factors for profitability (RMW) and investments (CMA). RMW is short for "robust minus weak" and is the difference between the portfolio returns of a diversified portfolio of robust and weak profitability assets. CMA is short for "conservative minus aggressive" and is known as the difference between portfolio returns of low and high investment firms (Fama and French, 2014). These factors are implemented to explain more of the expected portfolio returns. Fama and French (2015) concludes that the list of anomalies shrinks when using the FF5 model compared to FF3. Further, Fama and French (2014) also argues that FF5 has a more comprehensive explanation of the average stock returns than FF3.

We chose the FF5+MOM model as our primary model because it provides a more comprehensive perspective than the other factor models. By incorporating additional variables, we aim to improve our ability to explain the variation in stock returns, as previously demonstrated by Fama and French (2015). Furthermore, by including more risk factors in the model, we can better isolate the underlying factors associated with specific results in our analysis. This improves our understanding of the relationship between carbon transition risk and risk-adjusted performance. However, we acknowledge that including additional factors does not ambiguously improve the model, as the factor betas can be disturbed by each other (Blitz et al., 2022). Therefore, we compare our FF5+MOM estimations with other multi-factor models to improve our understanding of this potential source of misinterpretation.

There are also sample-specific arguments for including some of the risk factors in our primary model. Regarding momentum, Baltussen et al. (2021) states that this has been one of the most well-performing factors in parts of the period we analyze. We also include the profitability and investment factors to account for the adaptation of mutual funds towards quality and high-growth firms in response to a potential reduction of 30% in CRS (Hale, 2018).

4.2 Model testing

The five Gauss-Markov assumptions need to be fulfilled regarding the robustness of our OLS regression models. This includes 1) linear parameters, 2) no perfect collinearity, 3) zero conditional mean, 4) homoskedasticity, and 5) no auto/serial correlation (Woolridge, 2020). We test linear parameters by inspecting residual versus fitted plots and checking for no clear patterns. Moreover, we check for collinearity using Variance Inflation Factor (VIF) tests and zero conditional means by observing normality through QQ plots and histograms. Further, we test for homoskedasticity by conducting a Breush-Pagan test. Finally, we test for autocorrelation by running a Breush-Godfrey test. In the following, we explain potential threats to the OLS assumptions as we present our results.

5 Results

In this section, we analyze how exposure to carbon risk and the degree of active management influence performance in Nordic mutual funds. We split the section into three parts. First, we provide an overview of the sample through descriptive statistics and a preliminary display of portfolio performance.

Second, we present the empirical analysis on the full sample, giving a Nordic perspective on how CRS affects fund performance compared to similar studies on US and global mutual funds (Reboredo and González, 2021; Kuang and Liang, 2022).

In the third part, we evaluate the constructed portfolios' performance by presenting multi-factor models. We address our models' robustness to discuss the validity of our results throughout both analyses.

5.1 Descriptive statistics and preliminary results

5.1.1 Full sample descriptive statistics

Our sample comprises 655 funds, which yields 32 613 monthly observations. Table 5.1 presents the funds' summary statistics for March 2017 to September 2022.

Regarding the CRS, the mean observation is 9.31, with a standard deviation of 4.18 risk points. The maximum CRS is 54.28, and the minimum CRS is 0. Moreover, the statistics show tendencies of right-skewed asymmetries tilted against low CRS, as illustrated in figure 5.1. This tells us that most funds have a CRS between low (0-10) and medium (10-30). Furthermore, the 25th and 75th percentile have CRS of 6.83 and 11.14. This implies indicative thresholds for low and high CRS in the extent of the portfolio construction (statistics available in section 5.1.3). The construction is, however, based on fund CRS means, which makes the true boundaries deviate from the percentiles introduced in table 5.1. The second criterion for the portfolio construction, tracking error, has a mean value of -0.08%, indicating that the sampled funds give slightly lower returns than their benchmark on average. The 25th and 75th percentiles are -0.74% and 0.56%, which imply indicative boundaries within the two CRS percentiles in the portfolio construction.

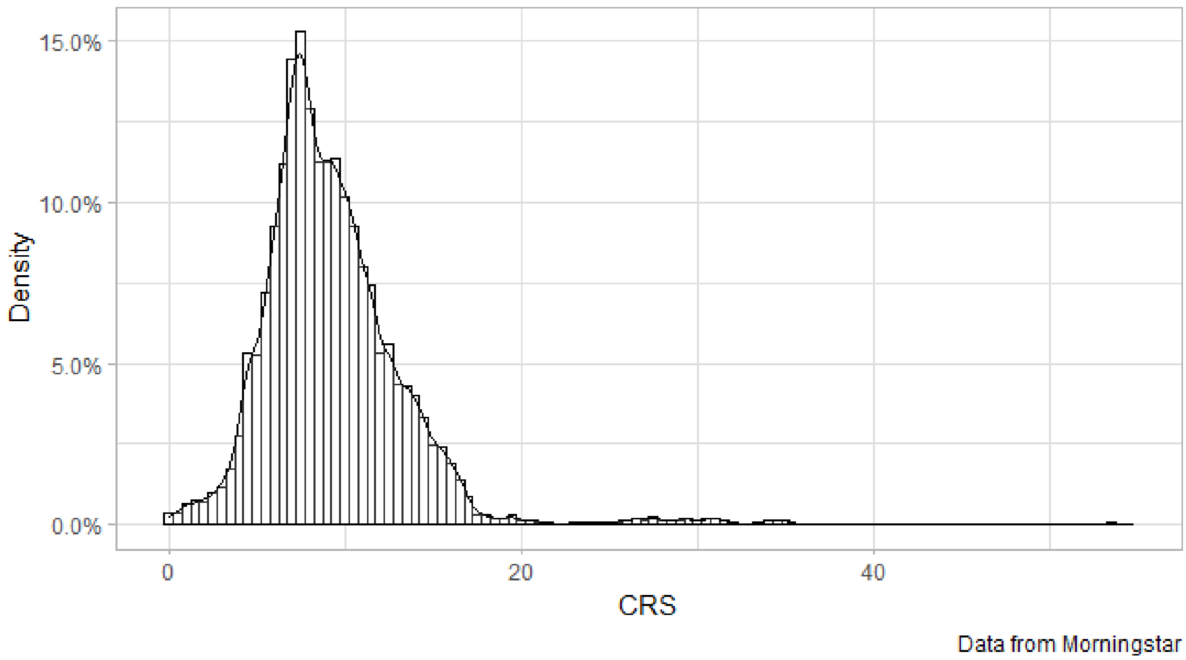
Table 5.1: Descriptive statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
CRS	9.31	4.18	0.00	6.83	8.68	11.14	54.28
Returns	0.43	5.58	-41.71	-2.69	1.00	3.70	44.01
RF	0.08	0.07	0	0.01	0.1	0.1	0
Benchmark return	0.51	5.34	-45.84	-2.43	1.15	3.55	25.77
α_{FF3}	-0.15	0.18	-0.70	-0.25	-0.13	-0.05	0.57
$\alpha_{FF5+MOM}$	-0.16	0.20	-0.85	-0.28	-0.14	-0.07	0.60
$\beta_{Benchmark-RF}$	1.01	0.09	0.20	0.97	1.00	1.04	1.81
β_{SMB}	0.09	0.18	-0.37	-0.02	0.05	0.18	0.93
β_{HML}	0.02	0.21	-0.67	-0.10	0.02	0.14	0.69
β_{RMW}	0.04	0.23	-1.05	-0.05	0.04	0.14	0.66
β_{CMA}	-0.02	0.26	-0.89	-0.16	-0.01	0.10	0.88
β_{MOM}	0.02	0.12	-0.42	-0.04	0.01	0.07	0.51
Sharpe	0.07	0.89	-1.77	-0.51	0.18	0.69	1.58
Treynor	0.36	4.76	-9.29	-2.76	0.91	3.63	8.61
Volatility	5.43	1.12	0.81	4.79	5.18	5.91	11.27
Tracking error	-0.08	1.41	-5.36	-0.74	-0.05	0.56	5.08
Size	18.86	1.50	9.86	17.96	18.94	19.84	24.49
Flow	0.0001	0.005	-0.03	-0.002	0.0004	0.002	0.03
Age	15.63	8.85	2.00	7.83	15.58	21.42	47.00
Norway	0.18	0.39	0	0	0	0	1
Sweden	0.18	0.39	0	0	0	0	1
Finland	0.23	0.42	0	0	0	0	1
Denmark	0.40	0.49	0	0	0	1	1

Notes: Table 5.1 reports descriptive statistics for the variables we used in this thesis. The sample includes 655 mutual funds with 32 613 monthly observations between March 2017 and September 2022. The descriptive statistics include means, standard deviation, minimum, maximum, and percentiles (25%, 50%, and 75%) for all variables. The data are winsorized where large outliers occur due to calculations to omit potential misinterpretation of our results. The table describes the statistics for carbon risk score (CRS), returns (monthly %), risk-free rate (RF), benchmark return, risk-adjusted return (α) using FF3 and FF5+MOM, β values for the FF5+MOM, where SMB equals small-minus-big, HML equals high-minus-low, RMW equals robust-minus-weak, CMA equals conservative-minus-aggressive, and MOM equals momentum. Moreover, the model includes volatility, tracking error, Sharpe ratio and Treynor ratio, fund size (natural logarithm of total assets), flow, age, and country variables for the Nordic countries.

The mean monthly return is 0.43%, while the standard deviation of returns is 5.58%, indicating a large spread of returns. This is substantiated by the variable range between -41.71% and 44.01%. Further, the average monthly α is slightly negative, with a value of -0.15% in the FF3 and -0.16% in the FF5+MOM model. The $\beta_{Benchmark-RF}$ is 1.01 with a standard deviation of 0.09, indicating that most funds take on quite similar proportions

Figure 5.1: CRS distribution



Note: Figure 5.1 shows the distribution of monthly CRS for Nordic mutual funds from March 2017 to September 2022. We observe a right-skewed graph tilted against low CRS where most funds have a score between low (0-10) and medium (10-30).

of systematic risk as their benchmarks. Regarding the other risk factors, SMB, HML, RMW, and MOM are positive, while CMA is negative.

We also include other variables we expect to affect risk-adjusted performance. The funds' flow has a monthly mean close to zero (0.0001%) but is somewhat tilted to the right side with modest flow dispersion among funds. The mean observed fund age is 15.63 years, while only 25% of the observations are younger than 7.83 years. Lastly, we note that Danish funds are dominating with 40% of the observations.

5.1.2 Correlation matrix

In table 5.2, we present a pairwise correlation matrix of the variables used in our empirical analysis. The matrix will give some context to the portfolio characteristics presented in section 3.4. By observing the correlation, we can consider whether there are variables that can cause multicollinearity. In that regard, we particularly note that the Sharpe ratio, Treynor ratio, and returns are highly correlated. Furthermore, the significant correlation of 91% of α_{FF3} and $\alpha_{FF5+MOM}$ could potentially imply a threat.

Table 5.2: Correlation matrix

	CRS	Returns	α_{FF3}	$\alpha_{FF5+MOM}$	$\beta_{Benchmark-RF}$	Volatility	Tracking error	Sharpe	Treynor	Size	Flow	Age	Norway	Sweden	Denmark
Returns	-0.0051														
α_{FF3}	-0.0012	0.02***													
$\alpha_{FF5+MOM}$	-0.011*	0.024***	0.91***												
$\beta_{Benchmark-RF}$	0.054***	-0.00043	-0.17***	-0.17***											
Volatility	0.36***	-0.0079	0.18***	0.19***	0.32***										
Tracking error	-0.0065	0.28***	0.11***	0.11***	-0.0018	0.026***									
Sharpe	-0.008	0.95***	0.018***	0.022***	-0.011*	-0.028***	0.24***								
Treynor	-0.0028	0.96***	0.023***	0.026***	-0.012**	-0.0061	0.25***	0.99***							
Size	-0.19***	0.022***	0.14***	0.12***	0.046***	0.03***	0.02***	0.018***	0.021***						
Flow	-0.02***	0.64***	0.055***	0.049***	-0.0012	0.022***	0.18***	0.61***	0.62***	0.078***					
Age	0.038***	-0.011*	0.035***	0.0059	0.011*	0.092***	0.006	-0.013**	-0.01*	0.15***	-0.034***				
Norway	0.18***	0.0017	0.078***	0.057***	0.18***	0.38***	0.012**	-0.0029	0.0022	0.091***	0.023***	0.11***			
Sweden	-0.13***	-0.0024	0.019***	-0.027***	-0.16***	-0.11***	0.00076	0.0025	0.0014	0.23***	0.011**	0.07***	-0.22***		
Denmark	-0.068***	0.00059	-0.073***	-0.012**	-0.023***	-0.19***	-0.0076	0.0027	-0.00085	-0.21***	-0.019***	-0.097***	-0.39***	-0.39***	
Finland	0.027***	-3.4e-05	-0.0042	-0.014**	0.0079	-0.027***	-0.0027	-0.0028	-0.0022	-0.047***	-0.0093*	-0.049***	-0.26***	-0.26***	-0.45***

*Note: Table 5.2 presents a pairwise correlation matrix of the variables used in our analysis. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***. The data are winsorized where large outliers occur due to calculations to omit potential misinterpretation of our results. We note large and significant correlations between 1) α of FF3 and FF5+MOM and 2) Returns, Sharpe, and Treynor ratio. High correlations between variables might lead to multicollinearity in the regressions, as presented in figure A4.1. We thus seek to circumvent the combined use of the mentioned variables in our regression estimations.*

5.1.3 Portfolio descriptive statistics

In the following paragraphs, we compare our constructed portfolios concerning performance and other characteristics. Table 5.3 presents the descriptive statistics of the constructed portfolios and a portfolio consisting of all 655 funds. We divide the equally-weighted and value-weighted portfolios into two panels for comparison purposes. We refer to the portfolios as, e.g., High/Low or Low/High, where the designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error.

Table 5.3: Descriptive statistics of portfolio performance

	Sharpe Ratio	Treynor Ratio	Mean Return	Std.Dev	Min	Max
Panel A: Equally Weighted						
Full sample portfolio	0.07	0.32	0.42	4.97	-14.87	13.79
High/High portfolio	0.05	0.25	0.40	6.37	-23.39	20.80
High/Low portfolio	0.04	0.21	0.32	5.46	-18.82	15.35
Low/High portfolio	0.10	0.47	0.54	4.83	-11.52	11.39
Low/Low portfolio	0.11	0.53	0.62	4.81	-11.82	12.49
Panel B: Value Weighted						
Full sample portfolio	0.07	0.32	0.42	4.97	-14.81	13.77
High/High portfolio	0.05	0.26	0.41	6.39	-23.45	20.87
High/Low portfolio	0.04	0.21	0.33	5.46	-18.74	15.29
Low/High portfolio	0.10	0.47	0.55	4.85	-11.57	11.36
Low/Low portfolio	0.11	0.54	0.62	4.81	-11.84	12.47

Note: Table 5.3 shows the monthly means of the performance variables for the equally-weighted and value-weighted portfolios. The designation before "/" refers to Carbon Risk Score, while the one after refers to tracking error.

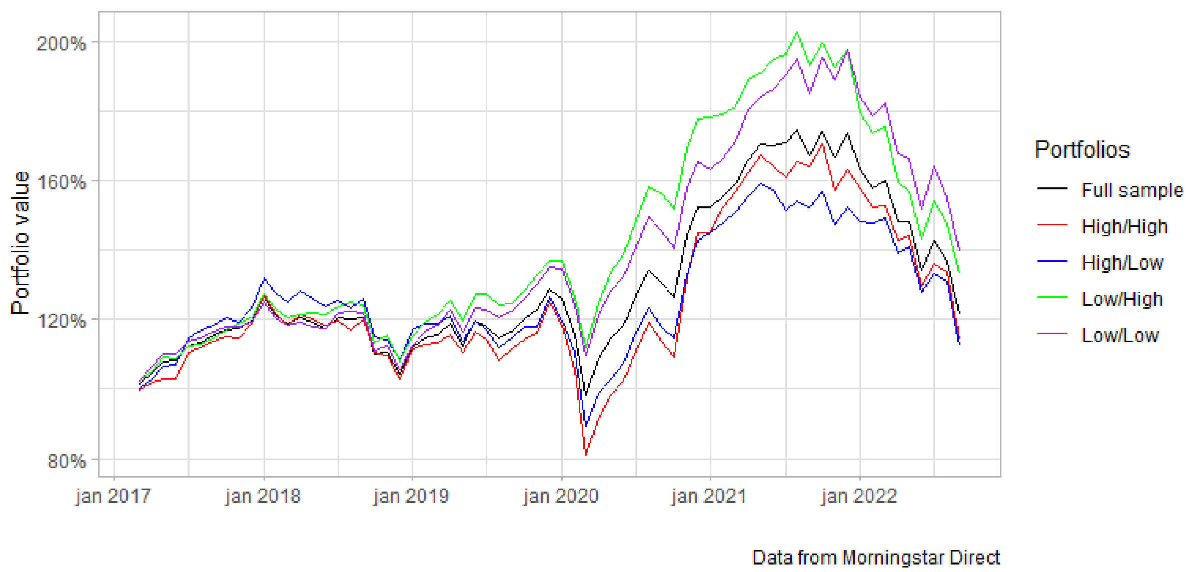
The statistics indicate that portfolios with low carbon risk generate higher returns, Sharpe ratio, and Treynor ratio than portfolios with high carbon risk and the full sample portfolio. The returns are also less volatile in the low carbon risk portfolios, indicating that the CRS proxies for some of the dispersion of returns. The significant correlation of 36% between volatility and CRS presented in table 5.2 also supports this relation.

Regarding tracking error, the volatility of returns from high tracking error portfolios is higher than low tracking error portfolios. However, there is less consensus to be drawn about the Sharpe and Treynor ratios. Within the high-carbon risk portfolios, the Sharpe ratio decreases from high tracking error to low, while we observe the opposite in the case of the low carbon risk portfolios. This regularity also applies to the Treynor ratio and the mean returns. The pattern could be related to managing risk when a high benchmark risk might outperform a passive position. On the other hand, active management within a low-risk environment will likely decrease performance (Morgan Stanley, 2022).

In sum, the statistics give some preliminary indications that low carbon risk funds yield higher risk-adjusted returns and lower volatility than the full sample and the high-carbon risk funds. Exposure to carbon transition risk might thus be associated with declining performance in an increasingly environmentally cautious world. Therefore, in low carbon risk portfolios, choosing a passive position is generally preferable over an active one.

Figure 5.2 presents an overview of the cumulative returns of all portfolios to visualize the performance. The returns are, however, not risk-adjusted and do not give an exhaustive insight to the performance. A corresponding visualization for the value-weighted portfolios is found in appendix A1.2.

Figure 5.2: Cumulative growth in equally-weighted portfolios

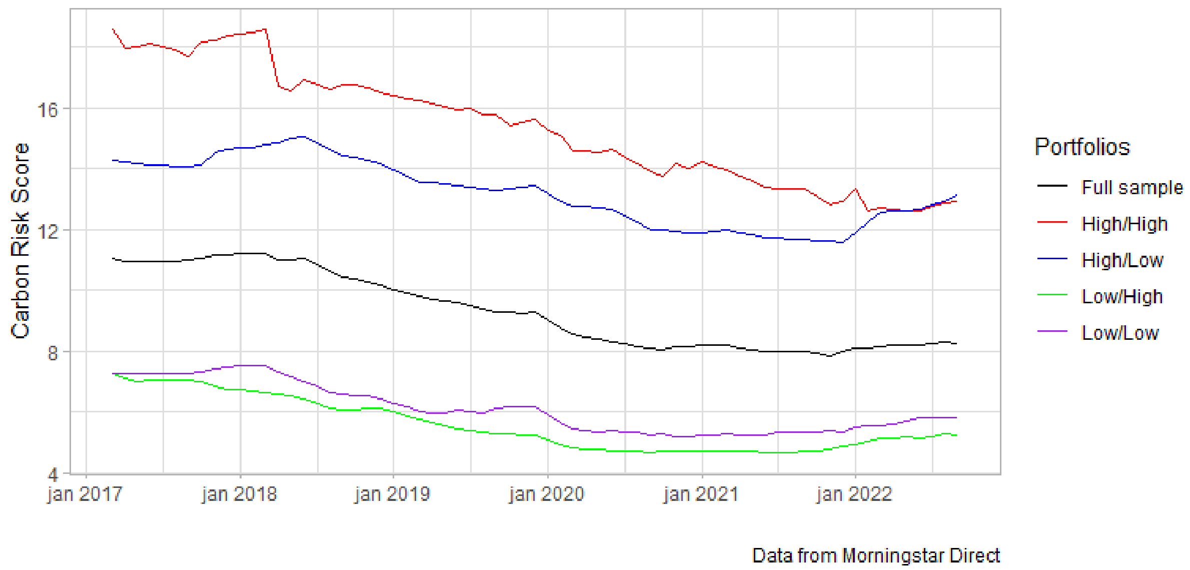


Note: Figure 5.2 visualizes the cumulative growth in the equally-weighted portfolio during the period from March 2017 to September 2022.

An interesting feature of the statistics is that there seem to be few performance differences in the equally-weighted and value-weighted portfolios. Literature concerning value weights in funds suggests that large funds often lack the flexibility to adjust to market fluctuations which may decrease performance (Kelly, 2022). An example is that managers may have problems purchasing large shares of stocks without increasing the share price, given the stock is not frequently traded. This being true, our value-weighted portfolios should have lower Sharpe and Treynor ratios than the equally-weighted portfolios. However, (Tortima, 2020) states that the general fund size in the US is significantly larger than in the European countries. The proportionally large funds in our sample might thus be smaller than characterized as large funds in the literature. This would make them less affected by flexibility restrictions when growing proportionally large, which could explain why we see little difference in performance.

Another finding regarding the characteristics of the portfolios is linked to the development of exposure to carbon risk. As presented in Figure 5.3, there seems to be a downward-sloping trend across all portfolios regarding exposure to carbon risk. This might indicate two parallel phenomena. The first is that the fund managers are increasingly concerned about the carbon risk and want to decrease this fund exposure. An argument supporting this is that there seems to be a link between CRS and the volatility of returns, documented in table 5.2.

Figure 5.3: CRS development across equally-weighted portfolios



Note: Figure 5.3 visualizes the average Carbon Risk Score development across the equally-weighted portfolios from March 2017 to September 2022.

The second phenomenon could be that the carbon risk is increasingly concerning the firm executives, influencing them to adapt management and operations to a low-carbon economy. This would, in turn, imply a downward-sloping carbon risk across securities. Without empirical evidence of the phenomena, we do not conclude that any of these effects impact our data. It does, however, seem likely that they both have some parallel influence. Additionally, the development of technology could play a role in these trends. Developing new technologies and innovations linked to reducing carbon emissions and mitigating carbon risk could be important for firms to protect their long-term viability and profitability (Stern and Valero, 2021). Therefore, technology adoption could lead to a decrease in carbon risk across the Nordic fund market.

We summarize the average fund age and exposure to funds from each country in table 5.4. The average age ranges from 16.06 to 13.67 years in the equally-weighted portfolios. The portfolio with the highest average CRS and tracking error holds the oldest funds, and there is a significant positive correlation between age and CRS (3.8%). However, the High/Low portfolio has a relatively low mean age of 13.67 years compared to the full sample portfolio with 15.63 years, indicating no systematic pattern regarding age and portfolio allocation.

Table 5.4: Portfolio characteristics

	Mean Age	**Norway**	**Sweden**	**Denmark**	**Finland**
Panel A: Equally Weighted					
Full sample portfolio	15.63	0.18	0.18	0.40	0.23
High/High portfolio	16.06	0.51	0.03	0.24	0.21
High/Low portfolio	13.67	0.45	0.12	0.36	0.07
Low/High portfolio	13.87	0.12	0.36	0.30	0.22
Low/Low portfolio	13.67	0.07	0.18	0.66	0.09
Panel B: Value Weighted					
Full sample portfolio	15.73	0.19	0.19	0.40	0.23
High/High portfolio	16.17	0.53	0.03	0.23	0.21
High/Low portfolio	13.49	0.45	0.13	0.35	0.07
Low/High portfolio	14.42	0.14	0.36	0.28	0.22
Low/Low portfolio	13.67	0.08	0.18	0.65	0.09

Note: Table 5.4 shows the monthly means of age and country proportion variables for the equally-weighted and value-weighted portfolios. The designation before "/" refers to Carbon Risk Score, while the one after refers to tracking error. As the statistics are "means", the sum of shares invested in each country is not necessarily equal to 100%

Considering the exposure to funds from the Nordic countries, we observe some interesting deviations from the full sample portfolio to the constructed ones. The exposure to Norwegian funds is disproportionately large within both portfolios with high average carbon risk. Considering the equally-weighted portfolios, the High/High and High/Low portfolios have an average proportion of Norwegian funds of respectively 51% and 46% compared to 19% in the full sample portfolio. On the other hand, the Low/High and Low/Low portfolios have an exposure to Norwegian funds below the full sample portfolio mean. This pattern might be due to a higher carbon risk of Norwegian funds, which is supported by a significant correlation of 18% between the CRS and the Norway variable as presented in table 5.2. Sweden and Denmark, however, have a significant negative correlation to CRS of respectively 13% and 6.8%. This might explain the low exposure to these countries in the high CRS portfolios and the high exposure to respectively Sweden and Denmark in the Low/High and Low/Low portfolios.

5.2 Full sample analysis

In this subsection, we present an empirical analysis of the full sample to introduce a Nordic perspective on how carbon risk independently affects fund performance. CRS is thus our main independent variable in the regression models. The analysis consists of regressions on variables we expect to be relevant. First, we analyze the risk-adjusted performance, represented by the constant, α, of the FF3 and the FF5+MOM models. Secondly, we present a regression on the volatility of returns, adding an empirical perspective to our discussion on the connection between carbon risk and financial risk. We also analyze the flow of capital to understand investors' views on carbon risk further.

Regarding the robustness of the analysis, the regression models are calculated with clustered standard errors. The usual OLS standard errors will generally be incorrect because they assume that u_{it} is serially uncorrelated. As we have sampled observations in clusters from individual funds, we allow for autocorrelation within entities. Furthermore, the standard errors keep the model robust for heteroskedasticity within and across entities. Moreover, we run VIF tests for all regressions to avoid multicollinearity. We also control for time-fixed effects to omit misinterpretation due to effects such as the macro shocks that characterize parts of the analyzed period. We account for threats to the remaining OLS assumptions when this is relevant.

5.2.1 Risk-adjusted performance and carbon risk

To investigate whether risk-adjusted performance, i.e., the multi-factor α, is sensitive to the CRS, we estimate the following equation 5.1:

$$\alpha_{i,t} = \omega + \beta CRS_{i,t} + \theta Controls_{i,t} + \epsilon_{i,t} \tag{5.1}$$

where α_i is the dependent variable and is obtained by estimating FF3 and FF5+MOM. Moreover, the independent variable is the CRS for fund i. Finally, we included control variables that we expect to affect risk-adjusted performance, including volatility, tracking error, size, flow, age, and country-specific variables.

Table 5.5: Fama-French five-factor with momentum α and CRS

	Dependent variable:			
	$\alpha_{FF5+MOM}$			
	(1)	(2)	(3)	(4)
CRS	0.0002	−0.004**	−0.003	−0.003
	t = 0.107	t = −2.013	t = −1.422	t = −1.399
Volatility		0.040***	0.038***	0.040***
		t = 4.451	t = 4.147	t = 4.278
Tracking error		0.015***	0.014***	0.014***
		t = 12.828	t = 12.904	t = 13.059
Size			0.013**	0.016**
			t = 2.092	t = 2.423
Flow			1.337**	1.292**
			t = 2.562	t = 2.508
Age				−0.0005
				t = −0.580
Norway				−0.023
				t = −0.925
Sweden				−0.028
				t = −1.180
Finland				−0.013
				t = −0.639
Observations	32,613	32,613	32,613	32,613
R^2	0.00002	0.052	0.062	0.065
Adjusted R^2	−0.002	0.050	0.060	0.063

*Note: Table 5.5 presents the OLS estimation of the parameters of our regression model between the risk-adjusted performance (α) and Carbon Risk Score (CRS). The regression is estimated from equation 5.1, and includes the following control variables: volatility, tracking error, size, flow, age, and country-specific variables. Moreover, the t-statistics are estimated using clustered standard errors. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

Our regression results implies that there is no empirical evidence of CRS influencing the risk-adjusted performance in either the FF3 (appendix A2.1) or the FF5+MOM model (table 5.5). Regarding the FF5+MOM model, an exception is presented in column (2). We find a significant negative impact at a 5% level, indicating that low CRS ratings are associated with better risk-adjusted performances. Adding additional control variables, however, the result loses its significance, indicating that column (2) might be disturbed by omitted variable bias. Therefore, we conclude that our model does not find any empirical association between the CRS and risk-adjusted performance.

This finding is consistent with traditional financial theory (Markowitz, 1952; Sharpe, 1964; Fama, 1970), stating that investors cannot systematically beat the market. This would make SRI concerning carbon risk inefficient as it reduces investment possibilities and constrains portfolio diversification. Alternatively, the FF3 and FF5+MOM models might include risk factors that indirectly measure carbon risk. That being true, regressing the intercept of these models on a factor that contributed to estimating it naturally does not give any significant outcome. We discuss this hypothesis closer in section 5.3.

The insignificant results, however, are inconsistent with the study of Reboredo and González (2021) and Kuang and Liang (2022) on US and global mutual funds. Several factors might cause the difference in conclusion. An example of this is differences in our sample criteria in terms of geography and time period. Reboredo and González (2021) analyses US mutual funds with observations between 2017 and 2018, while Kuang and Liang (2022) investigates international funds from 2012 to 2020. Our analysis deviates from the existing literature as we include data until the last available quarter while restricting the sample to the Nordic countries. The difference in samples essentially gives different premises to evaluate the relation between risk-adjusted performance and carbon risk. Including observations from 2021 and 2022 can particularly be decisive for the conclusion. Due to increasing interest rates, the value of expected future cash flows is decreasing, which implies falling returns for growth stocks (Monroe and Handzy, 2021). Assuming that funds with low carbon risk have an overweight of assets invested in this kind of stock, recent macro changes might have eliminated the excess risk-adjusted returns found in previous literature. Observing the cumulative portfolio growth in figure 5.2, the performance gap between high and low carbon risk funds also seems to become smaller the recent quarters. We further discuss the exposure towards growth stocks in section 5.3.

Concerning our control variables, volatility is positive and significant on a 1% level in all three models that include the measure. This holds for both the α_{FF3} and $\alpha_{FF5+MOM}$. This relation is consistent with Reboredo and González (2021), who found that an expanding carbon risk increases volatility. Moreover, tracking error is significantly positive on a 1% level. This indicates that higher tracking error could increase the risk-adjusted performance, in line with the theory described in section 2.4.2. Moreover, this is consistent with α being the excess return of an investment after adjusting for random fluctuations and volatility (Chen, 2022). The results are reasonable, as one must deviate from the benchmark to outperform it.

Moreover, size and fund flow are positive and statistically significant. This means that an increase in size and fund flow increases the α in both models. Further, this contradicts the results of Reboredo and González (2021) on US data. As discussed in section 5.1.3, however, Tortima (2020) states that the general fund size in the US is significantly larger than in the Nordic countries. The sampled funds that are proportionally large might thus be less affected by the constraints on flexibility concerning large funds in a global context (Kelly, 2022). This being true, our sampled funds' performance is likely to be less affected due to fewer restrictions on flexibility.

To conclude, our models do not prove any statistically significant relation between carbon risk and risk-adjusted performance. This is supported by the low R^2 in the FF3 and FF5+MOM models. The measure of fit indicates that carbon risk does not explain much of the variation in α. Alternatively, the carbon risk is potentially accounted for by the risk factors included in the multi-factor models that estimate risk-adjusted performance. Decreasing the performance of growth stocks due to rising interest rates could also have eliminated the excess risk-adjusted returns found in previous literature on low carbon risk funds.

5.2.2 Fund volatility and carbon risk

Further, we examine how carbon risk affects the volatility of returns to interpret the relation between carbon risk and total risk. Consequently, we estimated the regression model from equation 5.2 in table 5.6.

$$Volatility_{i,t} = \omega + \beta CRS_{i,t} + \theta Controls_{i,t} + \epsilon_{i,t} \tag{5.2}$$

Table 5.6: Fund volatility and CRS

	Dependent variable:					
	Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
CRS	0.114***	0.114***	0.114***	0.108***	0.111***	0.094***
	t = 9.156	t = 9.167	t = 9.084	t = 8.620	t = 9.249	t = 73.325
Tracking error		0.021***	0.005**	−0.001	−0.004**	−0.005
		t = 4.226	t = 2.305	t = −0.351	t = −1.992	t = −1.459
$\alpha_{FF5+MOM}$			1.010***	1.212***	1.143***	1.002***
			t = 4.576	t = 5.449	t = 5.650	t = 36.407
$\beta_{Benchmark-RF}$				4.131***	4.011***	3.653***
				t = 8.460	t = 8.727	t = 57.521
β_{SMB}				0.968***	0.996***	0.835***
				t = 5.096	t = 5.440	t = 30.738
β_{HML}				−0.708***	−0.679***	−0.710***
				t = −3.155	t = −3.084	t = −21.464
β_{RMW}				0.619***	0.562***	0.627***
				t = 3.379	t = 3.020	t = 23.220
β_{CMA}				−0.864***	−0.881***	−1.050***
				t = −5.494	t = −5.631	t = −48.037
β_{MOM}				−0.174	−0.206	−0.557***
				t = −0.513	t = −0.604	t = −12.080
Size					0.038	0.001
					t = 1.591	t = 0.152
Flow					7.405***	5.899***
					t = 4.307	t = 4.981
Age						0.003***
						t = 4.976
Norway						0.832***
						t = 59.074
Sweden						0.242***
						t = 16.986
Finland						0.114***
						t = 9.117
Observations	32,613	32,613	32,613	32,613	32,613	32,613
R^2	0.167	0.168	0.201	0.366	0.369	0.435
Adjusted R^2	0.165	0.166	0.199	0.365	0.368	0.434

Note: Table 5.6 provides the results concerning fund volatility and CRS. The regression is estimated from equation 5.2 and includes the following control variables: $\alpha_{FF5+MOM}$*,* β *values for the FF5+MOM risk factors, size, flow, age, and country-specific variables. Moreover, the t-statistics are estimated using clustered standard errors. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

We find a positive relationship between total risk and carbon risk where the coefficient estimates in columns 1-6 are significant on a 1% level. This is consistent with Reboredo and González (2021) and Kuang and Liang (2022), which indicates that funds reduce volatility by managing carbon risk. According to Morningstar, however, it is estimated that carbon risk can be reduced by 10%, holding everything else constant (Hale, 2018). Therefore, carbon risk only seems to proxy for a fraction of the total risk, reflected by the R^2 of 16,7% for in column (1).

Concerning our control variables, the results indicate that $\beta_{Benchmark-RF}$ is positively related to volatility on a 1% level. This suggests that funds with β values above the benchmark tend to have higher volatility. Secondly, tracking error is statistically significant in columns (2), (3), and (5) but insignificant when we add additional control variables. This indicates uncertainty in our models where omitted variable bias could disturb the consensus as we include more variables. A non-significant relation could be reasonable, as tracking error depends on a benchmark that can be volatile or stable depending on its risk exposure. Therefore, having a high tracking error relative to a stable benchmark might not yield high volatility and vice versa.

Furthermore, $\alpha_{FF5+MOM}$ is positive and statistically significant, which indicates that an increase in α also causes an increase in volatility. Moreover, this is consistent with α being the excess return of an investment after adjusting for random fluctuations and volatility (Standard Chartered, 2022). The risk factors that significantly increase volatility are the $\beta_{Benchmark-RF}$, β_{SMB}, and β_{RMW}. Hence, having exposure to small-cap and high-profitability stocks is related to a higher standard deviation of returns. However, the β_{HML}, β_{CMA}, and β_{MOM} factors significantly decrease volatility. This implies that exposure to stocks categorized by high book-to-market, aggressive investment, or previously high returns reduces volatility.

Flow and age also have positively significant coefficients on a 1% level, indicating that an increase in capital flow and age increases volatility. Another interesting observation is that compared to Denmark, both Norway, Sweden, and Finland have a positive statistically significant relation on a 1% level to volatility. This indicates that funds in these countries yield higher volatility compared to Denmark.

When testing this model for multicollinearity using the VIF test, we find a correlation between the α_{FF3} and $\alpha_{FF5+MOM}$ that would cause multicollinearity. To circumvent unreliable inferences, we choose to keep the $\alpha_{FF5+MOM}$ as it is more complementary regarding risk factors (Fama and French, 2015), which potentially can increase the explanatory power. The VIF results are illustrated in the appendix in figure A4.1.

To conclude, we find that carbon risk and total risks are significantly related. Hence, the total financial risk increases by increasing the carbon risk. In that regard, we hypothesize that the close relationship could be a potential cause of the insignificant impact of carbon risk on risk-adjusted performance. That being true, the risk-adjusted performance naturally does not change by indirectly changing the risk through CRS.

5.2.3 Fund flows and carbon risk

Furthermore, we want to examine the transition effect of carbon risk on net fund flow. Section 3.5.3 explains that flow refers to a fund's growth or decline in value due to the supply of new capital. An example of why this is interesting in the context of our research question is that high net inflow often reflects growing optimism among investors. In turn, this typically increases the price of the underlying assets, thereby increasing the fund's return (Giles, 2020). Growing concern about SRI could also affect fund flow as the investment strategy has recently grown popular (Schoenmaker and Schramade, 2019).

We estimate the following regression to measure the effect of carbon risk on fund flow:

$$Flow_{i,t} = \omega + \beta CRS_{i,t} + \theta Controls_{i,t} + \epsilon_{i,t} \tag{5.3}$$

where "$Flow$" is the net fund flow calculated as in equation 3.4. Moreover, CRS is our independent variable while tracking error, $\alpha_{FF5+MOM}$, $\beta_{Benchmark-RF}$, Sharpe ratio, volatility, size, age, and country variables are applied as control variables.

CRS has significant negative coefficients across the estimated models, indicating that an increase in carbon risk has detrimental effects on fund flow. This is consistent with the findings of Ceccarelli et al. (2022) concluding that information on funds' low carbon risk exposure increases the demand. Spiegel and Zhang (2013) presents similar findings on the role of risk on fund flows. Moreover, consistent with existing literature, SRI is likely to affect investment decisions, which should be reflected in the funds' flow (Reboredo

Table 5.7: Flow and CRS

	Dependent variable:					
	Flow					
	(1)	(2)	(3)	(4)	(5)	(6)
CRS	−0.00003***	−0.00003***	−0.00003***	−0.00001*	−0.00004***	−0.00002***
	t = −4.028	t = −4.261	t = −3.862	t = −1.723	t = −4.509	t = −3.435
$\alpha_{FF5+MOM}$		0.001***	0.002***	0.001***	0.001***	0.001***
		t = 6.205	t = 7.539	t = 5.683	t = 4.018	t = 4.763
$\beta_{Benchmark-RF}$			0.001**	0.001***	0.0004	−0.0002
			t = 2.232	t = 2.583	t = 0.703	t = −0.601
β_{SMB}			−0.0003	−0.0002	−0.0004**	−0.0002*
			t = −1.385	t = −1.230	t = −1.996	t = −1.880
β_{HML}			−0.0004	−0.0004*	−0.0002	−0.0002
			t = −1.584	t = −1.859	t = −1.014	t = −1.534
β_{RMW}			0.001***	0.001***	0.001**	0.0004***
			t = 3.545	t = 3.459	t = 2.534	t = 3.144
β_{CMA}			−0.0001	−0.0001	0.0001	−0.0001
			t = −0.425	t = −0.812	t = 0.393	t = −0.937
β_{MOM}			0.001**	0.001*	0.001	0.0005**
			t = 2.178	t = 1.811	t = 1.639	t = 2.314
Sharpe				0.003***	0.003***	0.003***
				t = 37.843	t = 35.271	t = 47.737
Volatility					0.0002***	0.0002***
					t = 5.229	t = 6.767
Tracking error					0.0001***	0.0001***
					t = 6.779	t = 8.765
Size						0.0002***
						t = 13.191
Age						−0.00002***
						t = −9.270
Norway						0.0002**
						t = 2.550
Sweden						−0.00002
						t = −0.304
Finland						−0.00002
						t = −0.314
Observations	32,613	32,613	32,613	32,613	32,613	32,613
R^2	0.001	0.005	0.006	0.096	0.100	0.107
Adjusted R^2	−0.001	0.003	0.004	0.094	0.098	0.104

*Notes: Table 5.7 provides the results concerning the Nordic fund flows and the CRS. The regression is estimated from equation 5.3. It includes the following control variables: $\alpha_{FF5+MOM}$, β values for the FF5+MOM risk factors, Sharpe ration, volatility, tracking error, size, age, and country-specific variables. Moreover, the t-statistics are estimated using clustered standard errors. The statistical significance at the 10%, 5% and 1% levels are indicated by *, **, and ***.*

and González, 2021). Investors from Western Europe and, to some extent, the USA, Japan, and other OECD countries specifically stand out where the general investor is more concerned about making sustainable choices (Bolton and Kacperczyk, 2021b). Thus, the finding is reasonable, as increasing carbon risk should affect environmentally concerned investors. Moreover, we have previously concluded that the carbon risk reflects some financial risk. This would imply that risk-averse investors also are less likely to invest in high-carbon risk funds.

Considering control variables, $\alpha_{FF5+MOM}$ is positively significant on a 1% level, suggesting that expanding excess return increases flow. Our model also implies that flow increases when the Sharpe ratio and the momentum factor expand. Furthermore, RMW coefficients are positive and significant, suggesting that funds tilting toward high-profitability stocks increase investor demand. Combined, these findings indicate that capital flow moves towards high performance. This assumption seems reasonable as investors tend to flow towards high-performing funds (Giles, 2020). Moreover, tracking error has a positive and significant effect on flow. Hence, we expect capital to flow towards low CRS and high-tracking error funds that perform well.

As we have concluded, our models do not prove any significant relation between carbon risk and risk-adjusted performance. However, we now know that capital flow moves towards high-performance funds. As this is also true for low CRS and high tracking error, we might find that considering the combination of variables can yield a positive risk-adjusted performance. We further investigate this relation in the last part of our analysis.

5.3 Portfolio performance

In this part, we introduce an empirical perspective to whether combinations of tracking error and carbon risk can explain the risk-adjusted performance of Nordic mutual funds. First, we present t-tests on the mean of differences in returns across combinations of carbon risk and degree of active management. After that, we estimate multi-factor regression models to evaluate whether some investment strategies outperform others.

In both analyses, we divide the equally-weighted and value-weighted portfolios into panels for comparison purposes. We primarily focus on the equally-weighted portfolio but comment on the value-weighted if we consider the results particularly interesting. We refer to the portfolios as, e.g., High/Low or Low/High, where the designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error.

5.3.1 Mean of difference in returns

In table 5.8, we present means of difference in returns with the associated t-test statistics. The statistics are included to evaluate whether the returns are significantly different in the portfolios. The tests are paired and two-sided, meaning we pair portfolios and measure whether the mean difference in returns is significantly different from zero. The null hypothesis is thus that the mean difference in returns is zero, while the alternative hypothesis is that there are differences in means.

Table 5.8: T-tests on portfolio returns

	Mean of difference	T-statistic	P-value
Panel A: Equally-weighted			
High/High vs. High/Low	0.08	0.44	0.66
Low/High vs. Low/Low	-0.07	-0.66	0.51
High/High vs. Low/High	-0.14	-0.38	0.71
High/Low vs. Low/Low	-0.29	-1.03	0.31
High/High vs. Low/Low	-0.22	-0.60	0.55
Panel B: Value-weighted			
High/High vs. High/Low	0.09	0.49	0.62
Low/High vs. Low/Low	-0.08	-0.69	0.50
High/High vs. Low/High	-0.13	-0.36	0.72
High/Low vs. Low/Low	-0.30	-1.04	0.30
High/High vs. Low/Low	-0.21	-0.59	0.56

Note: Table 5.8 shows the t-test results from the mean of difference in monthly returns. We divide the equally-weighted and value-weighted portfolios into two panels for comparison. The designation before "/" refers to Carbon Risk Score, while the one after "/" refers to tracking error.

As presented in the table, the largest difference in mean monthly returns is found in the High/Low vs. Low/Low with a value of 0.3% in the value-weighted portfolios. However, the t-statistic of this deviation is -1.04, which is within the boundaries of significance. This is also indicated by the high p-value of 0.3. Therefore, we cannot reject the hypothesis that the mean difference in returns is zero. Further, this implies that the preliminary indications of some portfolios outperforming others have no statistical support from this test.

5.3.2 Fama-French multi-factor models

In the following, we present the estimates of multi-factor models, which enable us to discuss whether some investment strategies outperform others in terms of intensity of CRS and tracking error. As earlier concluded, there is no empirical evidence of an association between the CRS and risk-adjusted performance in our sampled data on Nordic mutual funds. Hence, dividing the sample into portfolios based on CRS should not independently yield any premium. However, taking active management into account, we might see differences in portfolio performance. The multi-factor model included in this section is the FF5+MOM, while the regression tables for the FF3, Carhart, and FF5 models are found in section A3.

Regarding the robustness of our multi-factor models, resilience against some of the OLS assumptions is formerly established. Specifically, the risk factors have been proven to affect stock returns significantly and indicate that assumptions 1) and 2) hold (Woolridge, 2020). Considering the assumption of homoskedasticity and autocorrelation, we test all portfolios for these sources of misinterpretation. In the Breuch-Pagan test (appendix A4.1), we document potential heteroskedasticity in the High/Low and the Low/High portfolio. Regarding autocorrelation, we find concerning indications in the Breusch-Godfrey test of the High/High and Low/High portfolios (appendix A4.2). As a result, we run the regressions with Newey-West estimators, controlling for heteroskedasticity and autocorrelation (Newey and West, 1987).

In table 5.9, we present the results from the FF5+MOM model, as stated in equation 4.1. Regarding our research question, we do not find any significant $\alpha_{FF5+MOM}$ in either constructed portfolio. These results are consistent with what we find in the other multi-factor models (A3.1, A3.2, A3.3). There is, however, an exception where $\alpha_{Carhart}$ is significantly negative in the equally-weighted Low/High portfolio at a 10% level. This indicates that holding a low carbon risk portfolio with a high tracking error might negatively impact performance. Our arguments in the preliminary results also support this finding, suggesting that an active strategy in a low-risk environment is unfavorable. Nevertheless, this finding seems unreliable as we have no evidence of it in the other multi-factor models. Hence, conducting an active or passive SRI strategy concerning carbon risk does not yield any positive risk-adjusted performance.

Table 5.9: Fama-French five-factor with momentum

	Portfolios tested:									
	Equally weighted					Value weighted				
	Full sample	High/High	High/Low	Low/High	Low/Low	Full sample	High/High	High/Low	Low/High	Low/Low
Constant (α)	-0.235^{**}	-0.122	-0.192	-0.118	-0.111	-0.232^{**}	-0.115	-0.191	-0.118	-0.104
	t = -2.234	t = -0.561	t = -0.980	t = -1.540	t = -1.107	t = -2.220	t = -0.531	t = -0.977	t = -1.595	t = -1.056
β_{MKT}	1.051^{***}	1.278^{***}	1.131^{***}	0.981^{***}	1.001^{***}	1.052^{***}	1.284^{***}	1.131^{***}	0.984^{***}	1.000^{***}
	t = 30.616	t = 16.498	t = 16.223	t = 35.094	t = 38.390	t = 30.735	t = 16.550	t = 16.225	t = 36.013	t = 39.709
β_{SMB}	0.119^{*}	0.566^{***}	0.387^{***}	0.108	-0.098	0.116^{*}	0.570^{***}	0.385^{***}	0.107	-0.100
	t = 1.730	t = 3.424	t = 2.932	t = 1.545	t = -1.549	t = 1.699	t = 3.460	t = 2.910	t = 1.576	t = -1.635
β_{HML}	0.005	0.270	0.173	-0.261^{***}	-0.119^{*}	0.002	0.268	0.168	-0.257^{***}	-0.115^{*}
	t = 0.078	t = 1.591	t = 1.209	t = -4.858	t = -1.802	t = 0.027	t = 1.566	t = 1.179	t = -4.955	t = -1.800
β_{RMW}	-0.045	-0.310^{*}	-0.398^{***}	-0.109^{**}	0.080	-0.041	-0.309^{*}	-0.402^{***}	-0.101^{*}	0.078
	t = -0.622	t = -1.664	t = -2.938	t = -1.973	t = 1.001	t = -0.576	t = -1.653	t = -2.962	t = -1.897	t = 1.023
β_{CMA}	0.126	0.163	0.202	0.026	0.094	0.127	0.174	0.208	0.019	0.091
	t = 1.359	t = 0.713	t = 0.974	t = 0.346	t = 1.271	t = 1.394	t = 0.757	t = 1.005	t = 0.276	t = 1.257
β_{MOM}	0.095^{*}	0.185	0.244^{**}	0.075	0.020	0.095^{*}	0.188	0.246^{**}	0.075	0.021
	t = 1.649	t = 1.363	t = 2.296	t = 1.384	t = 0.474	t = 1.662	t = 1.389	t = 2.307	t = 1.406	t = 0.500
Observations	67	67	67	67	67	67	67	67	67	67
R^2	0.973	0.923	0.912	0.981	0.977	0.974	0.923	0.911	0.983	0.978
Adjusted R^2	0.971	0.916	0.903	0.980	0.975	0.971	0.916	0.902	0.981	0.976

*Notes: Table 5.9 provides the FF5+MOM regression results concerning the constructed portfolios. We divide the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score, while the one after "/" refers to tracking error. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

The finding on risk-adjusted performance gives further insight into the discussion regarding whether the multi-factor models indirectly account for carbon risk through the other risk factors. As our regressions on the constructed portfolios indicate, shifting carbon risk exposure up or down does not impact the risk-adjusted performance. This is also the case regardless of the degree of active management. Hence, carbon risk is potentially irrelevant for α or accounted for by the risk factors included in the models.

In all multi-factor models, however, we find a significant negative monthly α in the equally-weighted and value-weighted full sample portfolios. This indicates that the sampled Nordic funds jointly produced negative excess returns compared to the developed international stock market. The broad underperformance of the Nordic mutual fund market supports the traditional financial theory of efficient markets (Markowitz, 1952; Sharpe, 1964; Fama, 1970), stating that one cannot beat the market.

Furthermore, we observe that variations in portfolio returns are significantly associated with the exposure to the β_{MKT} across portfolios. There are, however, differences between the coefficients, where the portfolios with high carbon risk are more sensitive to changes in market prices than the ones with lower carbon risk. High/High holds the highest β_{MKT} (1.278), while Low/High holds the lowest (0.981). As the β_{MKT} reflects the systematic risk, this finding extends our understanding of how carbon risk impacts financial risk. We have previously proved that carbon risk expands along the volatility of returns which measures the total risk. The β coefficients further indicate a positive relation regarding systematic risk where the funds with the 25% highest carbon risk have a higher market exposure than the rest of the market.

Moreover, exposure to systematic risk increases when the tracking error within the high-carbon risk portfolios expands. On the other hand, low carbon risk portfolios decrease systematic risk when reducing tracking error. This finding is consistent with the association of carbon risk and volatility in table 5.3, implying that systematic risk and total risk move correspondingly within each carbon transition risk environment. The co-movement suggests that managers of low carbon risk funds are more sensitive to total and systematic risk than managers of high-carbon risk funds. Increasing the intensity of our active management variable should thus lead to larger deviations from market returns in high-carbon risk funds. In contrast, we would expect the opposite in low carbon risk funds. However, we do not have evidence of differences across portfolio coefficients, which undermines the clarity of these findings. Additionally, the analysis of the relationship between carbon risk and volatility (table 5.6) reveals that Norwegian funds have a higher total risk than those in neighboring countries. As high-carbon risk portfolios have disproportionately large exposure towards Norwegian funds (table 5.4), high volatility is also to be expected.

Taking the coefficients of the size factor, β_{SMB}, both portfolios with high carbon risk have an overweight of large market cap stocks at the 1% significance level. This holds for both equally-weighted and value-weighted portfolios. One possible explanation for this phenomenon could be the overweight of Norwegian funds in high CRS portfolios. These funds may have significant exposure to the energy-dominated domestic OSEFX index, represented by a few large companies. Companies in this sector are generally more exposed to carbon risk (Hale, 2018), which implies that the β_{SMB} of high CRS funds might be impacted by having this market as a benchmark. The dominance of energy companies is exemplified by *Equinor* that accounted for 26% of the total OSEBX market cap in September 2022 (Øgrim, 2022). Furthermore, the sixth largest company listed on the index is the oil and gas operator *Aker BP* (Gram, 2022). However, the Norwegian mutual fund index, OSEFX, has a max cap of 9% per company (Euronext, 2021) which reduces this effect to some extent. Nevertheless, one must expect large cap firms to influence the Norwegian mutual funds. We also note that the β_{SMB} of the full sample portfolio is positive at a 10% level, implying that the Nordic mutual fund market could be tilted towards large market cap firms.

Regarding the value factor, β_{HML}, high carbon risk portfolios tend to invest in high book-to-market firms while low carbon risk portfolios tilt towards the opposite. These trends are significant at the 1% level in the High/High, High/Low, and Low/High portfolios and at the 5% level in the Low/Low portfolio. This pattern holds for both equally-weighted and value-weighted portfolios. This is consistent with Hales's 2018, findings that value funds typically have higher CRS than growth funds. Value firms generally rely on business models that are appropriate for the pre-carbon transition era and typically tilt toward utilities, materials, and energy.

In contrast, growth firms generally build on business models of generating profits in the future, where the low-carbon economy is an expected condition (Hale, 2018). To grow, they depend on implementing, e.g., new technologies and adapting to the transition toward a low carbon society. Low carbon risk firms might generally have future cash flows that are proportionally larger than they are now. This would lead to a higher market price than the firm's book value. By contrast, high-carbon risk firms may have lower growth prospects in future cash flows, resulting in a stock price that reflects the book value. This could lead to low carbon risk funds being tilted towards low book-to-market firms, while high-carbon risk funds would be expected to have the opposite tendency.

The finding that low carbon risk funds have an overweight of growth stocks also gives further perspective to why our results on carbon risk performance effects deviate from established litterateur. With decreasing performance of growth stocks due to recently rising interest rates (Kinserdal, 2022), it seems likely that the excess risk-adjusted return is eliminated. We also observe that the performance gap between high and low carbon risk funds recently has decreased 5.2.

Furthermore, both high carbon risk portfolios load negatively on the profitability factor, β_{RMW}, implying an overweight of funds investing in weak profitability companies. As the high carbon risk portfolios were significantly tilted towards high book-to-market firms, this result was somewhat unexpected due to factors such as streamlining and economies of scale typically observed in large companies. As stated in the literature review, however, researchers have found that firms with high carbon emissions have a higher cost of capital (Chava, 2014) and cost of debt (Jung et al., 2018), which could both explain our results.

Another factor that could undermine the advantages of established carbon-intensive streamlining is the Pigouvian carbon tax. Currently, Norway, Sweden, and Finland are among the countries with the highest taxation per metric ton of CO_2 equivalent (Sethi, 2022), which amplifies the importance of this cost for our sample. Moreover, the profitability factor-coefficients might deviate from expectation as the assets in high-carbon risk portfolios face a higher risk. Carbone et al. (2021) studied the impact of the transition to a low-carbon economy and found that higher emissions often lead to higher credit risk. Additionally, Hsu et al. (2022) found that high-pollution firms are more exposed to environmental regulation risk, which requires higher average returns. To mitigate this risk, firm managers may be forced to restructure the business, which could temporarily reduce profitability.

Regarding the investment factor, β_{CMA}, both high carbon risk portfolios have a significantly positive coefficient, which indicates conservative investments. This is consistent with the idea that firms in these funds have made conservative investments to adjust to carbon transition risk. Lastly, we find that both high carbon risk portfolios load positively on the momentum factor, β_{MOM}. This indicates that these portfolios are built upon funds that have traded stocks based on historical performance, picking the stocks that have performed well in the last 3-12 months (Carhart, 1997). These results are consistent across equally-weighted and value-weighted portfolios at a 1% significance level. We also find indications of this strategy across the Nordic mutual fund market, reflected by the full sample portfolio, which has a significantly positive β_{MOM} at a 10% level.

To conclude, we do not find any significant premium associated with investing in low carbon risk fund portfolios, regardless of the degree of active management. Hence, we find no empirical evidence that these investment strategies align with positive risk-adjusted performance. Our results thus indicate that implementing an SRI strategy regarding carbon risk will not improve risk-adjusted performance. We argue that this might partly be due to carbon risk being accounted for by the other risk factors implemented in the multi-factor models. In addition, the decreasing performance of growth stocks due to rising interest rates could also have eliminated the excess risk-adjusted returns found in previous literature on low carbon risk funds.

Regarding the validity of the results, they could potentially be affected by sample selection bias. As we only include funds with designated benchmarks as described in section 3.3, the analysis is vulnerable to systematic differences in benchmarked and non-benchmarked funds. We are especially concerned as this criterion restricts the CRS rating criteria by about 50% in terms of the number of funds included. Nevertheless, a benchmark is a necessary evil to analyze the effects of active management. Regarding external validity, we do not have evidence that our findings are generalizable. Research with the same time extension on another sample of mutual funds could thus still indicate a significant relationship between carbon risk and risk-adjusted performance.

6 Conclusion

In this thesis, we aim to investigate the relationship between carbon transition risk and the performance of active Nordic mutual funds. We explicitly intenend to answer the following research question:

"How does carbon risk exposure relate to risk-adjusted performance in Nordic mutual funds, and how does this relationship vary across different levels of active management?".

We approach the question with two empirical analyses. First, we investigate the independent effects of carbon risk. Our findings suggest that no significant relationship exists between risk-adjusted performance and carbon risk exposure. Second, we estimated the combined impact of carbon risk and the degree of active management. We find that the degree of active management does not produce excess risk-adjusted performance in either high or low carbon risk environments.

As our results deviate from existing literature, we discuss potential causes of the insignificant relation between carbon risk and risk-adjusted performance. We hypothesize that it might be because carbon risk increasingly reflects financial risk. As higher carbon risk increases volatility and systematic risk, it seems likely that carbon risk is indirectly accounted for by the established risk factors by Fama-French and Carhart, contributing to estimating the risk-adjusted performance. This being true, indirectly changing financial risk through carbon risk will not improve risk-adjusted performance. Furthermore, the decreasing performance of growth stocks due to rising interest rates could also eliminate the previously documented excess risk-adjusted returns in low carbon risk funds.

In future research, it would be interesting to further examine the interplay between carbon risk and financial risk. Involving unsystematic risk as an explanatory variable would increase this understanding as we primarily focus on systematic and total risk. Additionally, incorporating a carbon risk factor into the multi-factor models could provide further insight into the relationship between financial performance and carbon risk. It would also be worthwhile to investigate country and industry effects and how this impacts the transition to a low-carbon economy. Finally, our thesis relies on the carbon risk estimates of a single institution. Studying the financial performance based on alternative evaluations could potentially give a more comprehensive understanding.

References

Alexiadis, A. (2007). Global warming and human activity: A model for studying the potential instability of the carbon dioxide/temperature feedback mechanism. *Ecological Modelling*, 203(3):243–256.

Attenborough, D. (2021). Cop26 opening speech. https://www.youtube.com/watch?v=MTkm19hvHio.

Baltussen, G., Lansdorp, S., and Vidojevic, M. (2021). What's up with Momentum? *Robeco*.

Blitz, van Vliet, and Hanauer (2022). Fama-French 5-factor model: why more is not always better. https://www.robeco.com/me/insights/2022/03/fama-french-5-factor-model-why-more-is-not-always-better.html,

Board, F. S. (2020). The Implications of Climate Change for Financial Stability. https://www.fsb.org/wp-content/uploads/P231120.pdf.

Bolton, P. and Kacperczyk, M. T. (2021a). Do investors care about carbon risk? *Journal of Financial Economics*, 122:517–549.

Bolton, P. and Kacperczyk, M. T. (2021b). Global pricing of carbon-transition risk. *Working Paper*.

Carbone, S., Giuzio, M., Kapadia, S., Krämer, J. S., Nyholm, K., and Vozian, K. (2021). The low-carbon transition, climate commitments and firm credit risk. *Working Paper Series*.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Ceccarelli, M., Ramelli, S., and Wagner, A. F. (2022). Low-carbon mutual funds. *Swiss Finance Institute Research Paper*.

CFI (2022a). Active Management: The use of human capital to manage a portfolio of funds. https://corporatefinanceinstitute.com/resources/wealth-management/active-management/.

CFI (2022b). Systematic Risk. https://corporatefinanceinstitute.com/resources/risk-management/systematic-risk/.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, 60:2223–2247.

Chen, J. (2022). Alpha: What It Means in Investing, With Examples. https://www.investopedia.com/terms/a/alpha.asp.

Dafermosa, Y., Nikolaidib, M., and Galanisc, G. (2018). Climate Change, Financial Stability and Monetary Policy. *Ecological economic*, 152:219–234.

Euronext (2021). INDEX RULE BOOK. https://live.euronext.com/en/product/indices/NO0007035335-XOSL/market-information.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *The Journal of Economics*, 33:3–56.

Fama, E. F. and French, K. R. (2014). A five-factor asset pricing model. *The Journal of Financial Economics*, 116:1–22.

Fama, E. F. and French, K. R. (2015). Dissecting Anormalies with a Five-Factor Model. *Working paper.*

French, K. R. (2022a). Current Research Returns. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Benchmarks.

French, K. R. (2022b). Description of Fama/French 5 Factors (2x3). https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/f-f_5_factors_2x3.html,

Gelzinis, G. and Steele, G. (2019). Climate Change Threatens the Stability of the Financial System. https://www.americanprogress.org/article/climate-change-threatens-stability-financial-system/.

Giles, M. (2020). What Are Fund Flows and Why Do They Matter? https://www.morningstar.com/articles/1014854/what-are-fund-flows-and-why-do-they-matter.

Gram, T. (2022). Oslo Børs. https://snl.no/Oslo_B%C3%B8rs.

Grinold, R. and Kahn, R. (1999). *A Quantitative Approach for Producing Superior Returns and Selecting Superior Returns and Controlling Risk.* McGraw Hill.

Grossman, S. J. and Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, 70.

Gupta, F., Prajogi, R., and Stubbs, E. (1999). The Information Ratio and Performance. *The Journal of Portfolio Management*, 26:33–39.

Hale, J. (2018). Measuring Transition Risk in Fund Portfolios. https://www.morningstar.com/content/dam/marketing/shared/Company/LandingPages/CarbonRisk/Carbon_Risk_Paper.pdf?cid=EMQ_.

Hsu, Li, K., and Tsou, C.-Y. (2022). The pollution premium. *Journal of Finance, Forthcoming.*

IPCC (2021). Climate change widespread, rapid, and intensifying. https://www.ipcc.ch/site/assets/uploads/2021/08/IPCC_WGI-AR6-Press-Release_en.pdf.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48.

J.P.Morgan (2022). JPMorgan Climate Change Solutions Fund. https://am.jpmorgan.com/no/en/asset-management/adv/investment-themes/sustainable-investing/capabilities/climate-change-solutions-fund/?gclid=CjwKCAiAp7GcBhA0EiwA9U0mticlyNATUBJqXUnWseuQaInLh1-rgRm5tEVx0E9JfBLAaNLZMWHt1BoC6BwE&gclsrc=aw.ds.

Jung, J., Herbohn, K., and Clarkson, P. (2018). Carbon Risk, Carbon Risk Awareness and the Cost of Debt Financing. *Journal of Business Ethics*, 150:1151–1171.

Kelly, R. C. (2022). Mutual Funds: Does Size Really Matter? https://www.investopedia.com/articles/mutualfund/03/071603.asp.

Kinserdal, F. (2022). Påvirker inflasjonen aksjemarkedet? https://www.nhh.no/nhh-bulletin/artikkelarkiv/2022/februar/pavirker-inflasjonen-aksjemarkedet/.

Kuang, H. and Liang, B. (2022). Carbon Risk Exposure in the Mutual Fund Industry. *SSRN*.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7:77–91.

Monroe, J. and Handzy, D. (2021). Ahead of the curve: Will rising rates see value stocks win? https://www.ipe.com/current-edition/ahead-of-the-curve-will-rising-rates-see-value-stocks-win/10054715.article.

Morgan Stanley (2022). A New Take on the Active vs. Passive Investing Debate. https://www.morganstanley.com/articles/active-vs-passive-investing,

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55:703–708.

Pinner and Sneader (2019). Earth to CEO: Your company is already at risk from climate change. https://www.mckinsey.com/capabilities/sustainability/our-insights/earth-to-ceo-your-company-is-already-at-risk-from-climate-change.

Praisley, J. (2022). The 4 Main Drivers of Transition Risk, and Why the Risks Are Increasing. https://www.garp.org/risk-intelligence/sustainability-climate/4-main-drivers-of-transition-risk-220412.

Rakowski, D. (2010). Fund Flow Volatility and Performance. *The Journal of Financial and Quantitative Analysis*, 45.

Reboredo, J. C. and González, L. A. O. (2021). Low carbon transition risk in mutual fund portfolios: Managerial involvement and performance effects. *Business Strategy and The Environment*.

Schoenmaker, D. and Schramade, W. (2019). *Principles of Sustainable Finance*. Oxford University Press.

Sethi, M. (2022). What Countries Have A Carbon Tax? https://www.gccfintax.com/articles/what-countries-have-a-carbon-tax--4100.asp.

Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19:425–442.

Sharpe, W. F. (1966). The Sharpe Ratio. *The Journal of Business*, 39(1):119–138.

Spiegel, M. and Zhang, H. (2013). Mutual fund risk and market share-adjusted fund flows. *Journal of Financial Economics*, 108.

Standard Chartered (2022). Alpha and beta: How to use these terms for a better investment portfolio. https://www.sc.com/sg/stories/alpha-and-beta/.

Stern, N. and Valero, A. (2021). Innovation, growth and the transition to net-zero emissions. *Research Policy*, 50(9).

Tortima, R. (2020). An investment comparison: US x Europe. https://britech.global/en/blog-en/an-investment-comparison-us-x-europe/.

Treynor, J. L. (2015). Market Value, Time, and Risk. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2600356.

UNEP (2022). Climate Finance. https://www.unep.org/explore-topics/climate-action/what-we-do/climate-finance.

UNFCCC (2015). The Paris Agreement. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.

UNFCCC (2022). The Glasgow Climate Pact – Key Outcomes from COP26. https://unfccc.int/process-and-meetings/the-paris-agreement/the-glasgow-climate-pact-key-outcomes-from-cop26.

United Nations (2022). What is climate change? https://www.un.org/en/climatechange/what-is-climate-change.

Wiest, T. (2022). Momentum: what do we know 30 years after Jegadeesh and Titman's seminal paper? *Financial Markets and Portfolio Management*.

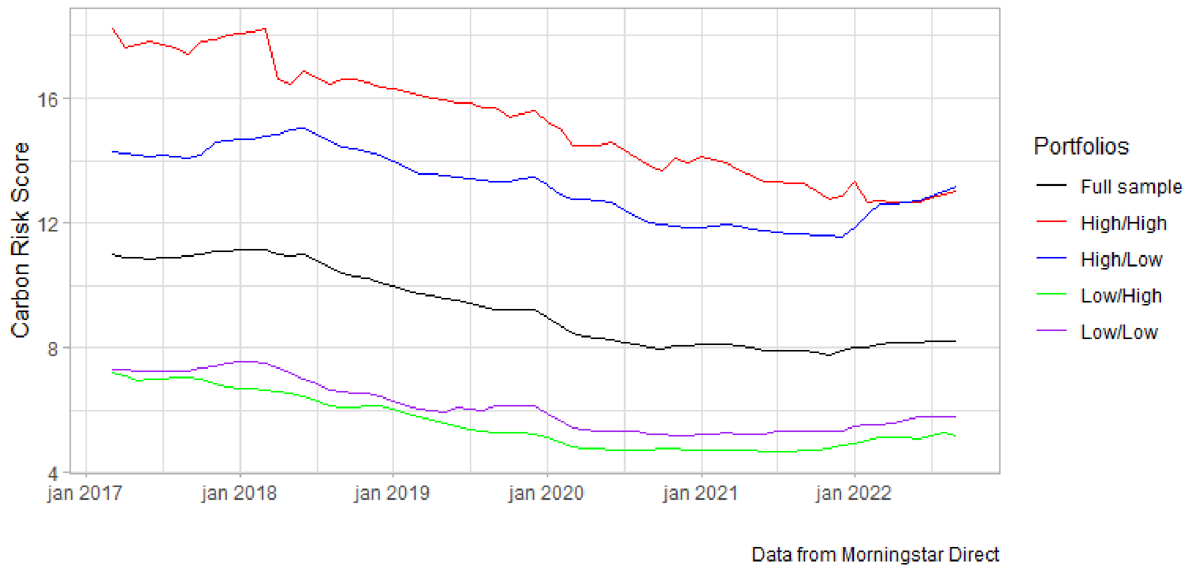
Woolridge, J. (2020). *Introductory econometrics - a modern approach.*, volume 5. Cengage Learning.

Øgrim, T. D. (2022). Uten olje er Oslo Børs som alle andre. https://www.dnb.no/dnbnyheter/no/bors-og-marked/uten-olje-er-oslo-bors-som-alle-andre-wmio.

Appendix

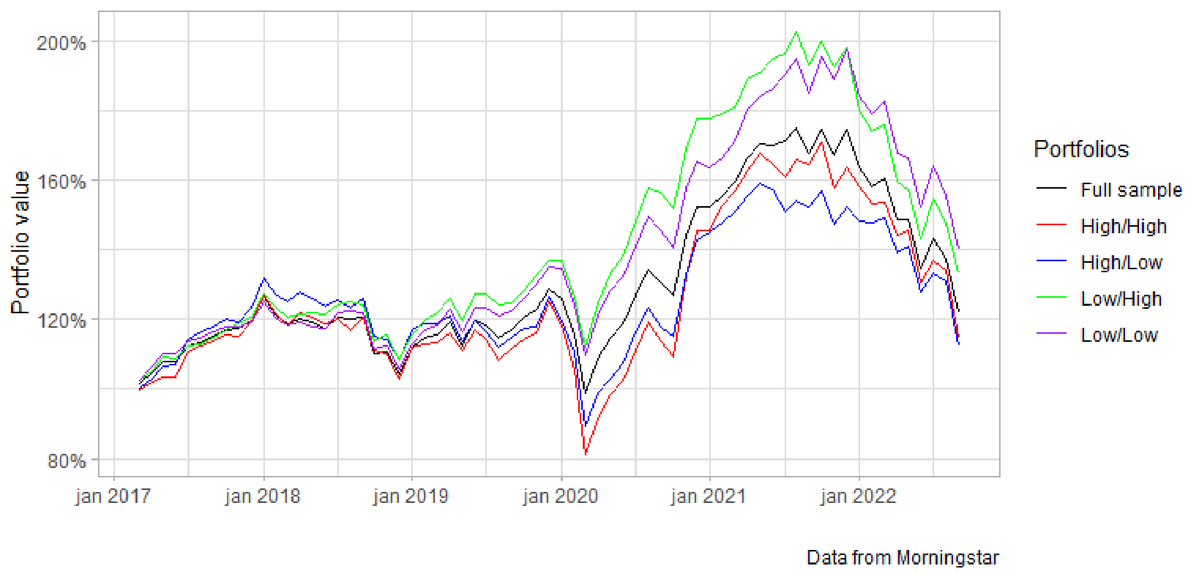
A1 Value-weighted portfolio characteristics

Figure A1.1: CRS development across value-weighted portfolios



Note: Figure A1.1 visualizes the average Carbon Risk Score development across the value-weighted portfolios from March 2017 to September 2022.

Figure A1.2: Cumulative growth in value-weighted portfolios



Note: Figure A1.2 visualizes the cumulative growth in the value-weighted portfolios from March 2017 to September 2022.

A2 Full sample regression models

Table A2.1: Fama-French three-factor α and CRS

	Dependent variable:			
	α_{FF3}			
	(1)	(2)	(3)	(4)
CRS	0.001	−0.003	−0.001	−0.001
	t = 0.472	t = −1.289	t = −0.690	t = −0.697
Volatility		0.032***	0.030***	0.030***
		t = 4.029	t = 3.706	t = 3.581
Tr.error		0.014***	0.013***	0.013***
		t = 12.852	t = 12.650	t = 12.715
Size			0.015***	0.014***
			t = 2.849	t = 2.755
Flow			1.596***	1.596***
			t = 3.773	t = 3.820
Age				−0.00001
				t = −0.014
Norway				0.003
				t = 0.141
Sweden				0.005
				t = 0.255
Finland				0.005
				t = 0.282
Observations	32,613	32,613	32,613	32,613
R^2	0.0004	0.046	0.062	0.062
Adjusted R^2	−0.002	0.044	0.060	0.060

*Note: Table A2.1 presents the OLS estimation of the parameters of our regression model between the risk-adjusted performance (α) and Carbon Risk Score (CRS). The regression is estimated from equation 5.1, and includes the following control variables: volatility, tracking error, size, flow, age, and country-specific variables. Moreover, the t-statistics are estimated using clustered standard errors. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

A3 Portfolio regression models

Table A3.1: Fama-French three-factor model

	Portfolios tested:									
	Equally weighted					Value weighted				
	Full sample	High/High	High/Low	Low/High	Low/Low	Full sample	High/High	High/Low	Low/High	Low/Low
Constant	−0.175	−0.044	−0.101	−0.091	−0.079	−0.171	−0.034	−0.100	−0.090	−0.073
	t = −1.635	t = −0.222	t = −0.501	t = −1.178	t = −0.760	t = −1.601	t = −0.172	t = −0.495	t = −1.211	t = −0.710
Mkt.RF	1.011***	1.199***	1.026***	0.953***	0.990***	1.012***	1.203***	1.025***	0.957***	0.990***
	t = 45.734	t = 19.660	t = 22.872	t = 58.639	t = 49.747	t = 46.198	t = 19.620	t = 22.827	t = 60.261	t = 51.688
SMB	0.114*	0.621***	0.469***	0.138**	−0.134***	0.110*	0.623***	0.468***	0.136**	−0.136***
	t = 1.908	t = 4.278	t = 3.615	t = 2.258	t = −2.633	t = 1.838	t = 4.289	t = 3.585	t = 2.296	t = −2.723
HML	0.050*	0.416***	0.312***	−0.241***	−0.113***	0.046	0.419***	0.310***	−0.243***	−0.112***
	t = 1.699	t = 6.818	t = 4.666	t = −11.150	t = −6.021	t = 1.590	t = 6.804	t = 4.618	t = −11.495	t = −6.066
Observations	67	67	67	67	67	67	67	67	67	67
R^2	0.970	0.916	0.893	0.980	0.976	0.971	0.916	0.892	0.981	0.977
Adjusted R^2	0.969	0.912	0.888	0.979	0.975	0.969	0.912	0.887	0.980	0.976

*Notes: Table A3.1 provides the regression results from the Fama-French three-factor model concerning the constructed portfolios. We have divided the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

Table A3.2: Carhart four-factor model

	Portfolios tested:									
	Equally weighted					Value weighted				
	Full sample	High/High	High/Low	Low/High	Low/Low	Full sample	High/High	High/Low	Low/High	Low/Low
Constant	−0.234**	−0.157	−0.250	−0.134*	−0.095	−0.230**	−0.149	−0.250	−0.132*	−0.088
	t = −2.282	t = −0.702	t = −1.166	t = −1.718	t = −0.930	t = −2.271	t = −0.671	t = −1.168	t = −1.761	t = −0.883
Mkt.RF	1.042***	1.258***	1.104***	0.975***	0.998***	1.043***	1.263***	1.104***	0.979***	0.998***
	t = 33.252	t = 18.455	t = 17.393	t = 36.571	t = 40.863	t = 33.399	t = 18.452	t = 17.375	t = 37.575	t = 42.217
SMB	0.115*	0.624***	0.472***	0.139**	−0.134***	0.111*	0.626***	0.471***	0.137**	−0.135***
	t = 1.951	t = 4.262	t = 3.917	t = 2.187	t = −2.618	t = 1.898	t = 4.301	t = 3.882	t = 2.221	t = −2.708
HML	0.103***	0.519***	0.447***	−0.202***	−0.099***	0.099***	0.523***	0.446***	−0.204***	−0.098***
	t = 3.156	t = 10.026	t = 7.148	t = −7.840	t = −3.855	t = 3.054	t = 10.259	t = 7.116	t = −8.249	t = −3.882
MOM	0.114*	0.218*	0.288**	0.083	0.030	0.113**	0.223*	0.290***	0.082	0.030
	t = 1.956	t = 1.667	t = 2.570	t = 1.574	t = 0.814	t = 1.970	t = 1.705	t = 2.585	t = 1.582	t = 0.837
Observations	67	67	67	67	67	67	67	67	67	67
R^2	0.973	0.921	0.906	0.981	0.977	0.973	0.921	0.905	0.982	0.978
Adjusted R^2	0.971	0.916	0.900	0.980	0.975	0.972	0.916	0.899	0.981	0.976

*Notes: Table A3.2 provides the regression results from the Carhart four-factor model concerning the constructed portfolios. We have divided the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

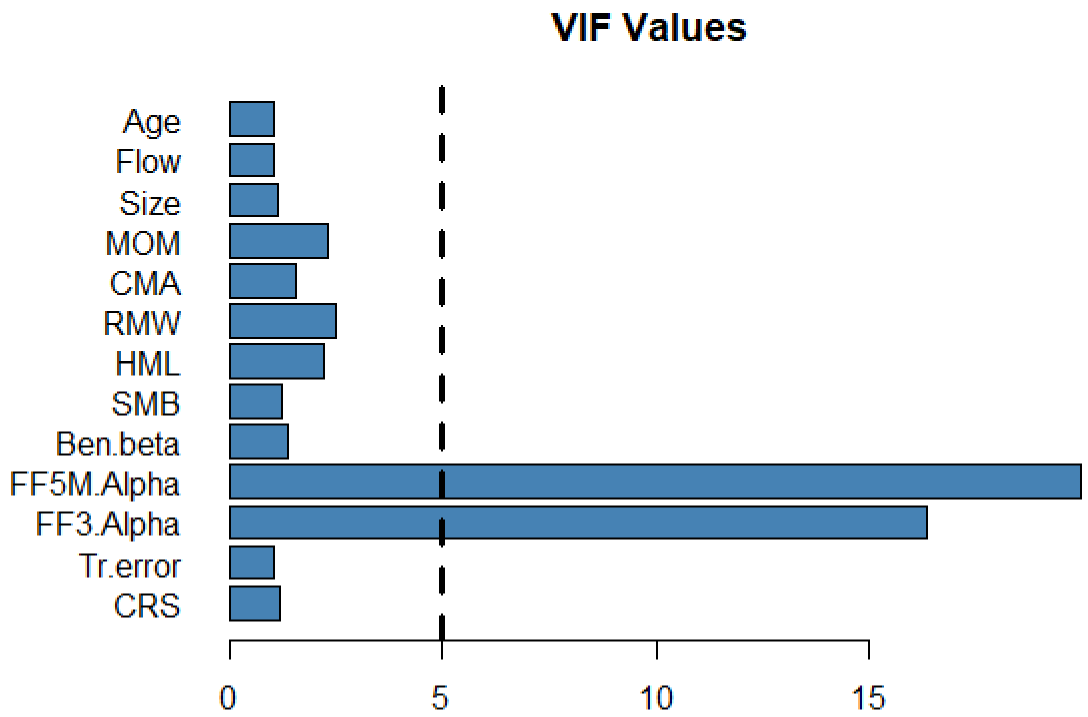
Table A3.3: Fama-French five-factor model

	Portfolios tested:									
	Equally weighted					Value weighted				
	Full sample	High/High	High/Low	Low/High	Low/Low	Full sample	High/High	High/Low	Low/High	Low/Low
Constant	−0.188*	−0.031	−0.072	−0.081	−0.101	−0.185*	−0.022	−0.070	−0.081	−0.094
	t = −1.815	t = −0.156	t = −0.369	t = −1.026	t = −0.977	t = −1.802	t = −0.112	t = −0.361	t = −1.060	t = −0.924
Mkt.RF	1.033***	1.243***	1.084***	0.967***	0.997***	1.034***	1.248***	1.084***	0.970***	0.996***
	t = 36.382	t = 17.374	t = 18.331	t = 42.547	t = 41.808	t = 36.623	t = 17.378	t = 18.269	t = 43.844	t = 43.388
SMB	0.119*	0.565***	0.386***	0.107	−0.098	0.116*	0.570***	0.384***	0.107	−0.101*
	t = 1.796	t = 3.303	t = 2.955	t = 1.607	t = −1.560	t = 1.755	t = 3.330	t = 2.928	t = 1.644	t = −1.645
HML	−0.081	0.104	−0.046	−0.329***	−0.137***	−0.084	0.099	−0.053	−0.325***	−0.133***
	t = −1.189	t = 0.648	t = −0.279	t = −6.243	t = −2.813	t = −1.252	t = 0.615	t = −0.318	t = −6.365	t = −2.833
RMW	−0.072	−0.363**	−0.469***	−0.131**	0.074	−0.068	−0.364**	−0.474***	−0.123**	0.072
	t = −0.966	t = −2.116	t = −3.191	t = −2.063	t = 0.965	t = −0.922	t = −2.118	t = −3.204	t = −1.996	t = 0.982
CMA	0.193*	0.292	0.373	0.078	0.109*	0.193**	0.306	0.380*	0.072	0.105*
	t = 1.943	t = 1.294	t = 1.631	t = 0.993	t = 1.657	t = 1.978	t = 1.352	t = 1.666	t = 0.958	t = 1.651
Observations	67	67	67	67	67	67	67	67	67	67
R^2	0.972	0.920	0.903	0.980	0.977	0.972	0.920	0.902	0.982	0.978
Adjusted R^2	0.969	0.913	0.895	0.979	0.975	0.970	0.913	0.894	0.980	0.976

*Notes: Table A3.3 provides the Fama-French five-factor results concerning the constructed portfolios. We have divided the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error. The statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***.*

A4 Robustness tests

Figure A4.1: VIF values of volatility regression



Note: Figure A4.1 visualizes the Variance Inflation Factor (VIF) values when regressing Carbon Risk Score on volatility of returns. As illustrated, the correlation of $\alpha_{FF5+MOM}$ *and* α_{FF3} *implies a VIF value that surpasses the barrier which cause multicollinearity. To circumvent this issue, we exclude the* α *from the FF3 model from the regression.*

Table A4.1: Breusch-Pagan test for heteroskedasticity

	FF3		**Carhart**		**FF5**		**FF5+MOM**	
	(BP)	P-Value	(BP)	P-Value	(BP)	P-Value	(BP)	P-Value
Panel A: Equally weighted								
Full sample	0.9053	0.8241	5.2656	0.2611	1.5068	0.9123	6.4433	0.3754
High/High	0.5476	0.9083	3.4828	0.4805	4.8661	0.4324	7.8688	0.2479
High/Low	0.6213	0.8915	3.9026	0.4193	4.026	0.5457	11.226	0.0816
Low/High	5.6991	0.1272	14.165	0.0068	6.0259	0.3037	15.036	0.020
Low/Low	0.7109	0.8706	2.3343	0.6745	2.5805	0.7643	3.9464	0.6839
Panel B: Value weighted								
Full sample	0.8661	0.8336	5.2709	0.2606	1.4637	0.9172	6.318	0.3885
High/High	0.517	0.9151	3.5051	0.4771	4.7906	0.442	7.8595	0.2486
High/Low	0.6167	0.8926	3.8745	0.4233	3.9033	0.5634	11.029	0.0875
Low/High	5.2572	0.1539	13.877	0.0077	5.4705	0.3612	14.589	0.0237
Low/Low	0.7294	0.8663	2.2259	0.6943	2.4287	0.7872	3.7189	0.7147

Note: Table A4.1 shows the results of the Breusch-Pagan test for homoscedasticity."BP" represents the test statistics, which follows a chi-squared distribution. We have divided the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error. The null hypothesis for this test is that the error variances are all equal, i.e., homoscedasticity. We document potential heteroskedasticity in the High/Low portfolios at a 10 % level and in the Low/High at a 5% level and thus reject the null hypothesis in these instances.

Table A4.2: Breusch-Godfrey test for autocorrelation

	FF3		Carhart		FF5		FF5+MOM	
	(LM)	P-Value	(LM)	P-Value	(LM)	P-Value	(LM)	P-Value
Panel A: Equally weighted								
Full sample	0.5312	0.4661	0.0662	0.7969	1.0276	0.3107	0.2650	0.6067
High/High	1.2959	0.255	0.8596	0.3538	2.7426	0.0977	2.0483	0.1524
High/Low	0.8938	0.3445	0.7689	0.3806	3.1557	0.0757	2.9277	0.0871
Low/High	0.0320	0.858	0.069	0.7928	0.0432	0.8354	0.0168	0.8969
Low/Low	0.3689	0.5436	0.5252	0.4686	0.4732	0.4915	0.6545	0.4185
Panel B: Value weighted								
Full sample	0.5867	0.4437	0.090	0.7642	1.1056	0.2930	0.3060	0.5802
High/High	1.4071	0.2355	0.9736	0.3238	3.002	0.0832	2.2815	0.1309
High/Low	0.8683	0.3514	0.7352	0.3912	3.0894	0.0788	2.8485	0.0915
Low/High	0.1348	0.7135	0.0014	0.9703	0.1552	0.6936	0.0089	0.925
Low/Low	0.5185	0.4715	0.7083	0.40	0.6307	0.4271	0.8506	0.3564

Note: Table A4.2 shows the results of the Breusch-Godfrey test for autocorrelation. "LM" represents the test statistics. We have divided the equally-weighted and value-weighted portfolios into two panels for comparison purposes. The designation before "/" refers to Carbon Risk Score while the one after "/" refers to tracking error. The null hypothesis is that there is no autocorrelation in our portfolios. We document potential autocorrelation in the High/High and Low/High portfolios on a 10% significance level.