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The Financial Cost of Sustainable Investing in the Nordic Region

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The Financial Cost of Sustainable Investing in the Nordic Region - Master Thesis

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Abstract

This master thesis investigates whether there are financial costs associated with sustainable investing with a focus on the Nordic stock market. We apply two different models to test our hypotheses. Firstly, inspired by Hong & Kacperczyk (2009), we estimate whether "sin" stocks generate abnormal returns. Overall, we find mixed evidence on investors paying a financial cost from negatively screening "sin" stocks. For both Sweden and Finland, we find excess returns associated with "sin" stocks. Further, we investigate the relationship between sustainability ratings, specifically ESG Ratings, and risk-adjusted returns. We do not detect a significant relationship between superior ESG Ratings and superior risk-adjusted returns. Consistent with existing literature, we present mixed evidence on whether sustainable investing implies financial costs.

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1 Introduction and Research Motivation

The purpose of this thesis is to empirically investigate the financial costs of imposing sustainable investment criteria on an investment universe with a focus on Nordic stocks. Further, we investigate the impact of various socially responsible criteria on the performance of such screened stock portfolios.

We apply two different methods to answer our research question. We have gathered our data from two different data providers. Firstly, we have gathered data for Method 1 from Thompson Reuters Datastream. For this method, we are interested in replicating parts of the well-known article *"The price of sin: The effects of social norms on markets"* by Hong & Kacperczyk (2009) using Nordic data. In particular, we are interested in whether stocks considered as "sinful" can generate excess returns, and whether the exclusion of such companies from an investment universe can result in the loss of financial returns. Secondly, the data needed for Method 2 is accessed through proprietary data from MSCI databases. In addition to investigating overall ESG scores for different companies, the MSCI ESG Rating provides granular data which allows us to analyze subsets of the ESG-scores and construct multiple portfolios based on different criteria.

The investor landscape has changed dramatically over the past years. The idea that investors as shareholders only want to maximize profits is no longer the rule. The millennium generation is making its way into the financial industry, with a greater need for purpose and fulfillment (Moore, 2014). The Environmental-Social-Governance ("ESG") investment framework is growing in significance amongst both institutional and retail investors. The practice of ESG-investing began in the 1960s as socially responsible investing, with investors excluding stocks or entire industries from their portfolios based on business activities such as tobacco production or involvement in the South African apartheid regime (Fulton et al., 2012). Both for "ethical funds" but also integrated in "conventional funds", ESG information is used for red flagging and to manage risk (van Duuren et al., 2016). The growing interest in Responsible Investing (RI)[1] raises the natural question whether pursuing an investment mandate towards ESG-criteria requires sacrificing financial

[1]RI sometimes is used interchangeably with ESG-investing, socially responsible investing (SRI), or sustainable investing (SI). In this thesis, we refer to the definition of Fulton et al.2012, which states that sustainable investing is the broader category, encompassing both socially responsible

performance (Zhang, 2017). Recently, a growing number of institutional investors seek to integrate ESG-criteria into their portfolios (Giese et al., 2018). Following this trend, financial institutions are offering a wider variety of ESG-services. For example, in Norway, Storebrand launched the fund Storebrand Global ESG A in 2017 and Nordea has launched Stars funds that proactively selects highly rated ESG companies.

In this thesis, we pay particular attention to the potential financial costs of applying sectoral exclusionary screening criteria on portfolios' financial performance. "Sin" industries (tobacco, gambling, and alcohol) have traditionally been perceived to violate social norms, due to their addictive nature and adverse impact on physical and mental health (Novak & Bilinski, 2014). Further, exclusionary screening is one of the oldest "values-based" investment criteria that fall into the sub-category of "socially responsible investing" and into a broader class of "sustainable investing" (Fulton et al., 2012).

Even though exclusionary screening is generally regarded as an outdated approach by academic literature on sustainable investing, Hoepner and Schopohl (2016) argue that this method is growing in popularity among large institutional investors. Current literature generally shows that sustainable investing has evolved to more sophisticated strategies, such as active ownership, shareholder engagement, positive screening, and best-in-class investing approach (Sparkes & Cowton, 2004; Fulton et al., 2012).

The Norwegian government has played a leading role in sustainable investments. Norway manages one of the world's largest sovereign wealth funds (asset under management valued at NOK8.9 trillion at 09/04/2019). To respond to the heightened level of public scrutiny, its government has been placing strong emphasis on ethical guidelines of the fund's investments, in particular by banning investments in companies that contribute to serious human rights violation, severe environmental damages, corruption, and other particularly serious violation of fundamental ethical norms (Hoepner & Schopohl, 2016). Besides these "conduct-based" screening criteria, the fund also exercises products-based negative screening, such as exclusions

investing (SRI), a relatively "older" concept, and responsible investing (RI), i.e., the integration of ESG criteria into the investment universe.

of coal-based energy, nuclear weapons, and tobacco. Many Nordic asset managers are following in the footstep of this fund.

We are interested in measuring the financial costs of imposing sustainable investing criteria on a portfolio, using Norwegian and Nordic evidence. In particular, we want to analyze the risk-adjusted returns for Nordic portfolios with a sustainable investment mandate and sector-based exclusionary screening approach, and whether the excluded stocks actually would have generated excess returns. With a focus on the Nordics, we are also interested in the relationship between public ratings of sustainable investments (e.g., the MSCI ESG Ratings) and market-based returns. Given the mixed evidence on sustainable investments presented in the Literature review, we hypothesize that on average, stocks with superior ratings generate the same risk-adjusted returns as the ones with inferior ratings. We construct "long-short" theoretical portfolios, as presented in the Methodology section below, to empirically test the presence of abnormal returns associated with sustainable investing.

Furthermore, we are also looking to explore the relationship between stock returns and a "sin" stock factor, inspired by the classical Hong & Kacperczyk (2009) study. At the time of our study, there has been no literature investigating the "sin" stocks effect for the Nordic region, in particular. Consequently, we are aiming to fill in this gap. The finding will also aid our understanding of whether omitting certain sinful stocks will lead to a loss of returns for SRI-oriented funds.

2 Literature review

In this section, we review existent empirical results on the impact of sustainable investing, which includes the use of social-responsibility screens, on investment performance. Even though we expect a positive "sin" stocks factor (associated with returns), based on the classical Hong & Kacperczyk (2009) study, the results on sustainable investment returns have been mixed and, therefore, inconclusive. Specifically, Fulton et al. (2012), show in their literature review on sustainable investment, that due to the mixed results on potential SRI fund outperformance (or underperformance), there is a perception that "the market does not price social responsibility characteristics". They further argue that there could be two reasons for these conflicting results. One is that most SRI funds tend to incorporate a mixture of negative and positive social responsibility screening, which could result in loss of "sin" stocks' outperformance or additional gains of sustainable firms. Since the results on these outperformances are divided, the overall impact on portfolio returns is uncertain. In addition, it is difficult to disentangle fund managers' stock selection skills and "timing activities" from the risk-adjusted returns of SRI and conventional funds (Fulton et al., 2012).

2.1 Evidence against sustainable investing

Mueller (1991) examined the risk-adjusted returns of 10 socially responsible mutual funds over the period 1984 through 1988 and found that socially responsible mutual funds earned an average of 1.03% less per year (t-value of -3.83) than comparable funds. A study by Hamilton et al. (1993) used Jensen's alpha to examine the risk-adjusted performance of all socially responsible mutual funds listed in the Lipper Analytical data bank as of December 1990. When they examined the performance of all socially responsible mutual funds that had been in existence for 5 or more years, they found that 9 of the mutual funds exhibited negative alphas while the other 8 exhibited positive alphas. They found that the difference in mean monthly excess returns for the 17 socially responsible mutual funds in existence for at least five years (-0.063%) and a corresponding set of conventional mutual funds (-0.140%) was not statistically significant (t-value of -0.92). Similarly, the difference in mean excess returns for the 15 socially responsible mutual funds established after 1985 (-0.277%) and a corresponding set of conventional mutual funds (-0.042%) was not statistically significant (t-value of 0.85).

Hong & Kacperczyk (2009) show empirical evidence for the effects of social norms on markets by studying "sin" stock, i.e., publicly traded companies involved in producing alcohol, tobacco, and gaming. They show that "sin" stocks are less held by norm-constrained institutions such as pension plans as compared to mutual or hedge funds, and find a significant price effect in the order of 15–20% from large institutional investors shunning "sin" stocks. They find that "sin" stocks have higher expected returns than otherwise comparable stocks, consistent with them being neglected by norm-constrained investors and facing greater litigation risk heightened by social norms. Moreover, they find that "sin" stocks outperform their comparables by 29 basis points per month.

Furthermore, Chong et al. (2006) find that the risk-adjusted performance of stocks in the "Vice Fund" (the antithesis of SRI) is superior to both the Domini Social and the Standard & Poor's 500. Similarly, Fabozzi et al. (2008) show that "sin" stocks (alcohol, tobacco, gaming) outperform the market. Also, Trinks & Scholtens (2017) concludes that investing in "controversial" stocks in many cases results in additional risk-adjusted returns, whereas excluding them may reduce financial performance.

In a recent empirical study from Hoepner & Schopohl (2016), the authors conduct a time-series analysis of the performance implications of the exclusion decisions of two leading Nordic investors, Norway's Government Pension Fund-Global (GPFG) and Sweden's AP-funds. They find that the portfolios of excluded companies do not generate an abnormal return relative to the funds' benchmark index. The only exception is the equal-weighted exclusionary screen of tobacco, which tends to outperform the fund's benchmark. While this finding provides initial evidence that the performance effect differs between "norm-based" and "sector-based" exclusionary screens, they are cautious when interpreting this finding, since the respective value-weighted portfolio does not outperform. Hence this finding is more likely to result from small stocks effects than any tobacco characteristics (Adamsson & Hoepner, 2015).

When evaluating the performance of general funds relative to SR funds, Leite et al. (2018) observe that SR and general funds investing in Sweden and Europe perform similarly, whereas SR funds investing globally underperform their conventional peers. Furthermore, Sauer (1997) finds that avoiding "sin" companies leads to less diversification, lower expected return, additional screening- and monitoring costs.

Auer & Schuhmacher (2016) analyze the performance of socially (ir)responsible investments in the Asia-Pacific region, the United States, and Europe. They find that regardless of geographical region, industry or ESG-criterion, active selection of high- or low-rated stocks do not provide superior risk-adjusted performance in comparison to passive stock market investments. Moreover, they find that in certain industries in Europe, and depending on the ESG-criterion, investors pay the price for being socially responsible in their stock selection. Investors, therefore, obtain a significantly lower risk-adjusted performance than the passive benchmarks.

Furthermore, in a recent study exploring whether socially responsible investors outperform an excess market return on the Italian Stock Exchange, Landi & Sciarelli (2019) found no statistically significant evidence of ESG assessment on Italian Blue Chips'abnormal returns.

2.2 Evidence showing superior returns of sustainable investing

On the other hand, Fulton et al. (2012) claim to find overwhelming evidence that firms with high ratings for CSR- and ESG-factors have a lower (ex-ante) cost of capital in terms of debt and equity (lower risk fundamentally). Also, Fulton et al. (2012) claim to find compelling evidence that strong CSR-and ESG-factors are correlated with superior corporate financial performance, both market- and accounting-based.

In a study on the relationship between employee satisfaction and long-term stock returns, Edmans (2011) shows that a value-weighted portfolio of the "100 Best Companies to Work For in America" earned an annual four-factor alpha of 3.5% from 1984 to 2009, and 2.1% above industry benchmarks. Edmans further argues that the stock market does not fully value intangibles, even when independently verified by a highly public survey on large firms. Besides, Edmans claim that certain SRI screens based on employee welfare might improve investment returns.

Also, Weber et al. (2010) find outperformance of SRI funds in their analysis of 151 SR funds relative to the MSCI World Index from 2001 to mid-2009, concluding that SRI Funds yield returns above average.

Kempf & Osthoff (2007) implement a simple trading strategy based on socially responsible ratings from the KLD Research & Analytics: buy stocks with high socially responsible ratings and sell stocks with low socially responsible ratings. They find that this strategy leads to abnormal returns of up to 8.7% per year. The maximum abnormal returns are reached when investors employ the best-in-class screening approach, using a combination of several socially responsible screens at the same time, and restrict themselves to stocks with extreme socially responsible ratings.

The MSCI Research Insight report shows that high ESG-rated companies tended to show higher profitability, higher dividend yield, lower idiosyncratic tail risks, and higher valuations (Giese et al., 2017). Further, Verheyden et al. (2016) find that ESG-screening not only does not hurt performance but improves risk-adjusted returns. On the return side, they find that ESG-screening adds about 0.16% in annual performance, on average. From a risk perspective, they find volatility, drawdowns, and CVaR (conditional value at risk) to be lower than for the un-screened universe. Echoing this finding, a recent study by Eccles et al. (2014) reported finding that "High" sustainability companies outperform "Low" sustainability companies in terms of stock market- and accounting performance.

2.3 Mixed evidence

Gil-Bazo & Ruiz-Verdu (2008) find that SRI funds run by specialized management companies outperform comparable conventional funds by more than 2.6% annually. However, SRI funds run by generalist management underperform the market, but not to a highly significant degree.

A report by Chaudhry et al. (2016) highlights that the key attributes of ESG Investing lie within portfolio construction. While the return profile may not be the selling point, not having ESG-factors in a portfolio significantly increases volatility, lowers potential Sharpe ratios and leads to a higher probability of suffering larger drawdowns during times of market stress.

3 Hypotheses

In this section, we present opposing theories that support or nullify sustainable/ESG investing, based on the opportunity costs or additional financial benefits of the investment portfolio. We then summarize our two main null hypotheses.

3.1 Theories against sustainable investing

"Sin" companies have higher expected return Hong & Kacperczyk (2009) due to lack of risk sharing and neglect from institutional investors with high reputational risk, resulting in share prices being compressed and lower than fundamental values. The authors also find lower betas for "sin" companies and link these to the neglect from traditional large investors, since "sin" stocks lack risk sharing with the markets. They argue that "sin" stocks generate higher idiosyncratic risk not captured by the CAPM (e.g., litigation risk) and higher expected returns than their comparables.

Furthermore, modern portfolio theory suggests that including socially responsible criteria implies a financial penalty. Markowitz (1952) shows that social screens constrain the portfolio's mean-variance optimization framework and the limitations imposed by screening reduce the potential diversification of SRI portfolios. This loss of diversification can, therefore, heighten portfolio risks, in addition to sacrificing returns. A study that echoes this theory is by Barnett & Salomon (2006), who find that financial performance varies with the types of social screens used. Moreover, they find that that as the number of social screens used by SRI-funds increases, financial returns decline at first, but then rebound as the number of screens reaches a maximum. Also, if we assume markets are efficient, securities' prices would already incorporate all relevant factors, including financial consequences from sustainable investing, whereby no selection criteria can provide consistently superior performance (Moskowitz, 1972).

Finally, existing literature shows that implementation of social screens increases costs of obtaining and monitoring information (Barnett & Salomon, 2006; Areal et al., 2013).

3.2 Theories supporting sustainable investing

One viewpoint argues that the information associated with corporate social responsibilities may not be fully incorporated in the prices of securities, allowing portfolios constructed on this information to provide superior returns, as in Moskowitz (1972). An underlying assumption to this hypothesis is that stock markets misplace information on CSR in the short run such that ESG/SRI-funds may outperform conventional funds in the long run (Renneboog et al., 2008). Advocates of SRI argue that screening practices allow fund managers to generate value-relevant non-public information on issues such as managerial competencies and superior corporate governance, see for example Renneboog et al. (2008).

We suggest that the ability to generate such non-public information could generate "first-mover's advantage" to these portfolios. As a consequence, the potential loss of efficiency as a result of the use of a "restricted universe" of securities can be more than offset by the inclusion of companies representing better investment opportunities (Barnett & Salomon, 2006). This viewpoint is further supported by stakeholder theory (Freeman, 1984), which argues that social investors have a multi-attribute utility function that does not just include risk-reward optimization, but also incorporates personal and societal values (Bollen, 2007). In addition, SRI-screens can be viewed as filters to identify managerial competencies and superior corporate governance or to eliminate or reduce the potential costs of corporate social crisis and environmental disasters (Renneboog et al., 2008).

3.3 Null hypotheses

Due to the mixed empirical evidence on potential financial costs associated with sustainable investments, our null hypotheses are as follows:

H1: There are excess returns associated with "sinful" stocks in the Nordics.

H2: Nordic stocks with low ESG ratings generate the same risk-adjusted returns as stocks with higher ESG rating.

4 Methodology and data

To empirically measure the effect of incorporating sustainable investment criteria into the investment universe, we employ two different methods. Firstly, we replicate parts of the classical "sin" stocks paper written by Hong & Kacperczyk (2009), using Nordic stocks as defined in the following paragraph, and data provided by Thomson Reuters Eikon. The main purpose is to estimate the statistical significance of a "sin" stocks dummy, after controlling for variables well-known for explaining stocks' excess returns.

In the second model, we construct a "sustainable investing" strategy by "longing" the top-rated stocks, and "shorting" the bottom-rated stocks in a pool of Nordic stocks rated by MSCI in their ESG-datasets. The MSCI Nordic Countries Investable Market Index (IMI) captures large-, mid- and small cap representation across Denmark, Finland, Norway, and Sweden. These four countries are in terms of market capitalization the largest constituents in the Nordics. Due to our data selection pool, we have excluded Iceland from our definition of the Nordics in this master thesis. Moreover, the main purpose of this method is to empirically test if such a trading strategy yields any significant abnormal returns, after controlling for the Carhart four factors. We refer to a study by Kempf & Osthoff (2007) for the portfolio construction and alpha testing method. More details of the two methods are presented in the following sections.

4.1 Method 1

We estimate cross-sectionally the impact of being associated with a "sin" industry on a stock's excess return. Hong & Kacperczyk (2009) argues that there is a societal norm against financing firms that promote "human vice". Consequently, institutional investors would refrain from investing in these stocks. Commitment to such socially responsible investing mandates, therefore, lead managers of pension funds, insurance funds, and endowments to filter out "sinful" stocks such as the ones belonging to the tobacco-, alcohol- or gaming industry. Avoiding to incorporate these companies into the investment universe could lead to a financial cost from the lack of diversification (Hong & Kacperczyk, 2009).

Further, Hong & Kacperczyk (2009) argue that individual (retail) investors are more willing to hold "sin" stocks, as they are more able to keep away from the constraints of societal norms. Mutual funds and hedge funds are also arguably less influenced by societal opinions and attracted to the compressed prices of "sin" stocks, as they are arbitrageurs in the first place. Hong & Kacperczyk (2009) find that empirically, "sin" stocks indeed have less institutional ownership compared to their industry comparables (stocks of otherwise comparable characteristics). Specifically, sin stock comparables (defined as those with similar Fama & French (1997) industry groupings as the "sin" stocks), have on average about 28% of their shares held by institutions. On the other hand, "sin" stocks have about 23% of their shares held by institutions[2]. Also, the authors show that "sin" stocks are less covered by analysts. In their observation period, "sin" stock comparables on average receive coverage

[2]The authors do not find significant differences between the proportion of "sin" stocks held by mutual funds and hedge funds (the "natural arbitrageurs") and other classes of institutional investors. This shows that mutual funds or hedge funds are not necessarily "smarter" investors than individuals.

from about 1.7 analysts compared to merely 1.3 for "sin" stocks.

The authors further show that "sin" stocks yield lower valuation ratios (e.g., price-to-book and price-to-earnings) relative to other firms. Specifically, valuation ratios of "sin" stocks are on average about 15 – 20% lower than those of other companies (after controlling for differences in other stock characteristics) from 1965 to 2006. Due to the neglect of institutional investors, prices of "sin" stocks will be lower than their fundamental values, caused by limited risk sharing, which means higher expected returns than comparable stocks (Hong & Kacperczyk, 2009). Merton (1987) finds that the CAPM does not hold due to neglect or limited risk sharing, and idiosyncratic risk (not only beta) matters for asset pricing. Hong & Kacperczyk (2009) also argue that "sin" companies face higher litigation risks due to the nature of their products. Additionally, "sin" stocks could offer higher dividends with lower valuation, partially caused by more conservative accounting (thanks to stringent regulatory scrutiny) (Berman, 2002). Another study suggesting higher expected returns for "sin" stocks is done by Geczy et al. (2005), showing that for an investor looking to optimize his or her portfolio from mutual funds, limiting themselves to the ones with an SRI-mandate could be costly[3].

Using time-series regressions, Hong & Kacperczyk (2009) find that a portfolio built by longing "sin" stocks and shorting their comparables yields a return of 26 basis points per month, after adjusting for a four-factor model. Secondly, the authors find that "sin" stocks outperform comparable firms by 0.29% per month cross-sectionally, after accounting for well-known determinants of expected returns. The purpose of this section is to replicate parts of the Hong & Kacperczyk (2009) paper using Nordic stock returns data to see whether the results hold under a different geographical context. The Hong & Kacperczyk (2009) study features an out-of-sample test on sin stocks in seven large markets in Europe and Canada. They find that sin stocks in these markets also outperform other stocks by about 2.5% a year, at the 10% significance level. However, the study did not introduce any results on the Nordic region alone, hence motivating us to conduct the below analysis.

[3]The paper finds that whilst an investor who believes that a multi-factor pricing model generates returns can incur a cost of 30 bps/month, another who believes in managerial skill (in this case, a socially responsible fund) can incur a cost of more than 100 bps/month.

4.1.1 Regression model

We follow the research by Hong & Kacperczyk (2009) to estimate the following return forecasting regression. Our coefficient of interest is c_1, measuring whether "sin" stocks (e.g., tobacco, gaming, alcohols) generate abnormal returns, after controlling for other firm characteristics. Hong & Kacperczyk (2009) hypothesize that c_1 is significantly positive, meaning "sin stocks" is a significant price factor. The study finds a significantly positive coefficient for the "SINDUM" variable under the main regression specification. Our research, however, hypothesizes that the "sin stocks" effect should be zero, given reasons mentioned in the Literature review.

$$\mathit{ExcRet}_{it} = c_0 + c_1 \mathit{SINDUM}_{it-1} + \mathbf{c}_2 \mathbf{X}_{it-1} + \epsilon_{it} \qquad i = 1, ..., N$$

ExcRet is the return of stock *i*, net of the risk-free rate. SINDUM equals one if the stock is a sin stock and zero otherwise. $\mathbf{X}_{it-1}$ is a vector of firm characteristics (e.g., firm's size, industry beta, firm's market to book ratio) that are well-known predictors of stock returns. Various permutations of the variables are presented in our results. ϵ_{it} is a measurement error. $\mathbf{c}_2$ is the vector of loadings on the control variables. Parameters are estimated using Fama & MacBeth (1973) regression method, with standard errors estimated using the Newey & West (1986) approach. Control variables are the ones that are proven predictors of stock returns (Hong & Kacperczyk, 2009). In the first step of the Fama & MacBeth (1973) approach, for every single period, a cross-sectional regression is performed. We then obtain coefficient estimates corresponding to T periods. Then, in the second step, the final coefficient estimates are obtained as the average of the T first step coefficient estimates. We refer to Newey & West (1986) to adjust the standard errors to be heteroskedasticity- and -autocorrelation-robust. Petersen (2009) states that that a "time effect" (residuals of a given year may be correlated across different firms (cross-sectional dependence)) may be commonly found in equity returns and earnings surprises, and since the Fama-MacBeth procedure is designed to address a time effect, the Fama-MacBeth standard errors are unbiased.

The explanatory variables include *SINDUM*, *logSize*, *mtb*, *ret12m*, *beta*, *turnover*, *BLEV* and *age*. It is noted that the dependent variable (*ExcRet*) is regressed against lagged values of *LogSize*, *mtb*, *ret12m*, *beta*, *turnover*, and *BLEV*. First of all, *ExcRet* is the monthly return of a stock net of the risk-free rate (excess return). For calculation of stock returns, total return indices (datatype "RI" on Datastream) on the stocks in the sample is utilized. Simple, discrete returns over a month, R_t, is calculated from a listing's return index at the start of the month, RI_t, and the end of the month, RI_{t+1}. The computation formula is $R_t = \frac{RI_{t+1}}{RI_t} - 1$. For the risk-free returns, the Swedish 30-day (or 1 month) T-bill rate (data type 'SDTB30D' on Datastream) is chosen. The raw Datastream rate (in percent and on annual basis (RF_t^Y) is adjusted to its monthly equivalent (RF_t^M) by the formula $RF_t^M = (1 + \frac{RF_t^Y}{100})^{\frac{1}{12}} - 1$. *LogSize* is simply the natural logarithm of the firm's market value at the end of month *t* (datatype 'MV'). *mtb* is defined as the natural logarithm of the market-to-book ratio of stock *i* at the end of month *t* (datatype 'MV' for market values and 'WC03501' for book values on Datastream). *ret12m* (in %) is defined as the arithmetic average of the most recent 12 months of returns on stock *i* leading up to and including month *t*. *beta* represents the time-varying industry beta estimated using the past three years (36 months) of monthly returns. Specifically, it is estimated at the end of each month using the past 36 months of returns data regressed against returns of the firm's respective market indices (i.e., Norway, Denmark, Sweden, and Finland). *turnover* is defined as the average of daily share turnover in stock *i* — computed by dividing the total volume of shares traded (datatype 'VO') by the number of shares outstanding at the end of month *t* (datatype 'IBNOSH'). *BLEV* is total debt (Datastream data type 'WC03255') divided by the sum of total debt and book equity (Datastream data type 'WC03501'). Finally, *age* is the natural logarithm of the firm's age, measured by the number of years since the stock was first listed, based on stock data on Datastream.

Our key variable of interest, *SINDUM*, is set to 1 if a listing falls into our definition of a "sin" stock (i.e., belonging to the alcohol/tobacco/gaming/defense industry) in our observation period. Industry classifications are extracted from Datastream with primarily datatypes 'WC07040' (ICB, ICB code from Worldscope), 'WC07021' (SIC1, SIC primary code from Worldscope), and ICBIC' & 'ICBIN' (ICB industry code and name). We additionally refer to classifications from datatypes 'MSC-SIC' & 'MSCISC' (MSCI Sector and Sub-Industry GICS codes), 'and 'TR1' & 'TR1N' (TRBC (Thomson Reuters Business Classification) economic sector code and name) to supplement missing data when necessary. We follow the approach of Hong & Kacperczyk (2009) for "sin" stocks definition and classification. Accordingly, stocks with SIC codes 2100–2199 belong to the beer group, and those with SIC codes of 2080–2085 are in the smoke (tobacco products) group. Unfortunately, the Fama-French classification scheme does not separate gaming stocks from hotel stocks or other entertainment stocks. To identify gambling stocks, we refer to the ICB codes of the stocks, which encode gambling firms as 5752 (FTSE International Limited, 2012). Finally, we expanded the definition of "sin" stocks to include companies belonging to the defense industry, as we believe that these companies play a role in the proliferation of violence in the world[4]. We follow the Fama & French (1997) industry classification for defense stocks definition (SIC codes 3480-3489, 3760-3769, 3795 - all under the "Guns" group as per Fama & French (1997)).

We additionally create the dummy variable *GDUM*, following the approach of Hong & Kacperczyk (2009). Accordingly, *GDUM* equals one if a stock is classified as "sin", or is a firm belonging to the following categories in the Fama & French (1997) industry classifications - 2 (food), 3 (soda), 4 (beer), 5 (smoke), 7 (fun), 43 (meals). Furthermore, as the original Hong & Kacperczyk (2009) study does not report clearly how *GDUM* is defined for defense companies under the scope of "sin" stocks, to account for the wider industry effect for stocks belonging to the defense industries, we set *GDUM* equal to 1 for listings with Industry Classification Benchmark (ICB) Level 1 as 2000 (Industrials) (FTSE International Limited, 2012). Under the industry classification structure of FTSE International Limited (2012), the defense subsector (code 2717) is placed under sector Aerospace & Defense (code 2710), super-sector Industrial Goods & Services (code 2700), and the Industrials (code 2000) industry. Except for stocks falling under these larger sectors, the remaining are assigned zero values.

The purpose of adding this dummy variable is to isolate the effect of institutional investors' and analysts' preference of holding and analyzing stocks in other industries over industries included in the definition of *GDUM*, leading to the suppressed prices of "*GDUM* stocks" (Hong & Kacperczyk, 2009). In this way, sin stocks are properly matched with their industry comparables, and we, therefore, can address the issue of related industry effects. In other words, we have now adequately controlled for key characteristics that are correlated with a stock's "sin" status, enabling

[4]Hong & Kacperczyk (2009) do not include defense stocks into the scope of "sin" stocks as they argue that it is not clear these are considered sinful by many Americans.

us to distinguish a “sin” effect from general industry effect (Hong & Kacperczyk, 2009).

4.1.2 Data

To select all relevant listings in Nordics, we have carried out an extensive data collection procedure. The constituent lists refer to the sample to be extracted from Thomas Reuters Datastream. From the raw constituent list, we collect 858 observations from Norway, 603 from Finland, 804 from Denmark, and 2862 observations from the Swedish market. To secure robust and reliable results, we gathered monthly market data from 1989 until 2018. Ince & Porter (2006) discovered many important issues on classification and how screening data through the use of Thomas Reuters Datastream can impact the time series of country portfolio returns. With some small modifications, we follow the procedure utilized by Lilloe-Olsen (2016) to screen our data, which is inspired by the two-step procedure of Ince & Porter (2006).

We apply a cross-sectional static screen, which is carried out through several steps to eliminate duplicate listings, items other than common equity and other non-relevant listings. The first step sorts the data sample on security type (Datastream datatype “TYPE”). Following this procedure, we delete entries other than Thomas Reuters Datastream definition of common equity (“EQ”). The second step sorts the data depending on the instrument of the entry (Datastream datatype “TRAD”). We then remove listings other than “Ordinary shares”. Thirdly, the default “NAME” static is utilized. The Nordic entries that do not have observations in the later chosen time window will read as #ERROR and are removed from the sample. The fourth step tackles the issue of dual- or multiple stock listings of a firm. We use the Datastream datatype “MAJOR” and keep the primary security type “Y” and remove the non-major security listing with datatype MAJOR = “N”. The fifth step involves the Datastream datatype “ENAME”. This variable provides extended names that might contain information on what type a particular entry is, and to identify entries that are only ordinary- or common shares. A non-common equity phrase in this variable is cause for manual deletion and is inspired by Lilloe-Olsen (2016) as “Redemp Shares”, “SDRs”, and “Rights”. We end up with an observation window from 05-1989 until 12-2018.

As our data covers stocks listed in 4 different Nordic exchanges with different currencies, all currency-denominated data (such as market capitalization, or book value) is translated to a common currency. More importantly, the use of a common currency allows us to use a single risk-free rate in order to calculate stocks' excess returns, our dependent variable. We follow the approach of Olsen (2016) to select Swedish Krona (SEK) as the common currency, as the Stockholm stock exchange is arguably the largest in the Nordics, with more than 2000 listings, compared to more than 800 for Denmark and Norway, and more than 500 for Finland. This explains why our selected risk-free rate is the 30-day Swedish T-bill rate.

4.1.3 Summary Statistics

We here present different summary statistics from our findings. Table 1 refers to the time-series averages of cross-sectional means and standard deviation for the variables used for the regression. Table 2 presents summary statistics of key variables for all the years in our observation window (1989 - 2018) (we calculated the averages of means and standard deviations across all months in our observation window). Table 3 shows the distribution of "sin" and "non-sin" stocks by country and year in our sample. Table 4 provides an overview of the "sin" stocks in the sample period (we only report stocks with non-missing data on all of our variables[5]). We additionally report a Pearson Correlation Matrix in Table 5. From Table 4, we see that Sweden is the country with the highest number of "sin" stocks in our sample (9), followed by Denmark (5), Finland (1) and Norway (1). This could be explained by the fact that Sweden has the largest stock exchange in the Nordics by the number of active listings, at the time of our study. Another contributing factor is that according to Casino News Daily (2018), Stockholm has recently become a favorite stock exchange among Europe's online gambling companies, with 19 companies being listed on it, as of June 2018.

[5]The initial list of "sin" stocks consists of 38 listings. We then removed listings that are not classified as "ordinary shares", including depository receipts, redemption shares, and rights. Afterward, we retained only stocks with complete data on all of our variables. We finally ended up with 16 listings, as presented in Table 4

[6]As extracted from Datastream

Table 1: Summary Statistics - Means and Standard Deviations

This table reports summary statistics (time-series averages of cross-sectional means and standard deviation) for the variables used for the regressions. *ExcRet* (in %) is the monthly return of a stock net of the risk-free rate (excess return). For calculation of stock returns, total return indices (data type 'RI' on Datastream) on the stocks in the sample will be utilized. Simple, discrete returns over a month, R_t, will be calculated from a listing's return index at the start of the month, RI_t, and the end of the month, RI_{t+1}. The computation formula is $R_t = \frac{RI_{t+1}}{RI_t} - 1$. For the risk free returns, the 30-day (or 1 month) rate (data type 'SDTB30D' on Datastream) is chosen. The raw Datastream rate (in percent and on annual basis (RF_t^Y) is adjusted to its monthly equivalent (RF_t^M) by the formula $RF_t^M = (1 + \frac{RF_t^Y}{100})^{\frac{1}{12}} - 1$. *ret12m* (in %) is defined as the arithmetic average of the most recent 12 months of returns on stock i leading up to and including month *t*. *BLEV* is total debt (Datastream data type 'WC03255') divided by the sum of total debt and book equity (Datastream data type 'WC03501'). *age* is the natural logarithm of the firm's age, measured by the number of years since the stock was first listed, based on stock data on Datastream. *beta* is the firm's market beta, which is calculated at the end of each month using the past 36-months of data, against the returns of the firm's respective market indices. *mtb* is defined as the natural logarithm of the market-to-book ratio of stock *i* at the end of month *t* (datatype 'MV' for market values and 'WC03501' for book values on Datastream). *LogSize* is simply the natural logarithm of the firm's market value at the end of month *t* (datatype 'MV'). Finally, *turnover* is defined as the average of daily share turnover in stock *i* — computed by dividing the total volume of shares traded (datatype 'VO') by number of shares outstanding at the end of month *t* (datatype 'IBNOSH').

Variable	**Time-series average of means**	**Time-series average of standard deviation**
ExcRet (%)	0.679	5.510
ret12m (%)	1.171	2.210
BLEV	0.397	0.081
age	2.064	0.318
beta	0.878	0.094
mtb	0.383	0.356
LogSize	7.554	0.538
turnover	0.003	0.003

Table 2: Summary Statistics - Means by Year

This table reports summary statistics of the variables used for the regressions of all years in our sample period. Definitions of the variables could be found in table 1.

Year	*ExcRet* (%)	*LogSize*	*ret12m* (%)	*BLEV*	*beta*	*age*	*mtb*	*turnover*
1989	0.094	7.569	3.039	0.608	1.002	1.628	0.381	0.002
1990	-3.932	6.998	-0.207	0.605	.92	1.518	-0.063	0.001
1991	-1.633	6.783	-0.785	0.593	0.919	1.589	-0.346	0.001
1992	-1.200	6.481	-1.680	0.536	0.913	1.653	-0.707	0.002
1993	6.614	6.999	4.680	.51	0.949	1.730	-0.041	0.004
1994	0.621	7.295	3.896	0.451	1.063	1.796	.18	0.004
1995	-0.125	7.174	0.706	0.409	0.979	1.733	.12	0.003
1996	2.877	6.838	1.575	0.391	0.795	1.776	0.221	0.003
1997	1.539	7.181	3.269	0.391	0.725	1.856	0.477	0.003
1998	-1.213	7.311	0.536	0.393	0.706	1.835	0.494	0.003
1999	2.137	7.143	0.006	0.401	0.724	1.808	0.367	0.004
2000	-0.151	7.322	2.730	0.385	0.716	1.819	0.553	0.003
2001	-0.564	7.195	-0.928	0.371	0.775	1.853	0.451	0.003
2002	-2.297	7.325	-0.861	.34	0.856	1.917	.36	0.003
2003	3.236	7.341	0.333	0.338	0.863	2.043	0.298	0.004
2004	2.270	7.713	3.588	0.334	0.862	2.179	0.605	0.004
2005	3.513	7.993	3.236	0.336	0.848	2.242	0.707	0.004
2006	1.575	8.191	2.630	0.347	0.852	2.242	0.864	0.013
2007	-0.323	8.223	1.695	0.366	0.934	2.171	0.911	0.007
2008	-5.796	7.769	-2.793	0.387	0.944	2.157	0.481	0.006
2009	4.948	7.586	-0.228	0.358	0.940	2.241	0.208	0.005
2010	1.384	7.694	2.557	0.334	0.923	2.348	0.442	0.003
2011	-2.191	7.615	0.103	0.345	0.946	2.399	0.404	0.002
2012	1.010	7.577	-0.108	0.346	0.965	2.421	0.344	0.002
2013	2.315	7.695	1.593	0.342	0.956	2.488	0.473	0.002
2014	0.864	8.059	2.010	0.344	0.909	2.552	0.591	0.003
2015	1.471	8.145	1.135	0.354	0.807	2.514	0.612	0.003
2016	1.702	8.178	.99	0.352	0.827	2.422	0.606	0.002
2017	0.974	8.238	1.899	0.335	.87	2.365	0.781	0.002
2018	-0.306	8.896	0.786	0.371	0.873	2.494	0.693	0.002

Table 3: Distribution of "sin" stocks

This table presents distribution of "sin" and "non-sin" stocks by country and year. The definition of "sin" stocks could be found in table 4 and in the text.

	Non-Sin Stocks				**Sin Stocks**			
	Denmark	Finland	Norway	Sweden	Denmark	Finland	Norway	Sweden
1989	.	4	17	44	.	.	.	.
1990	.	7	18	49	.	.	.	.
1991	.	14	24	55	.	.	.	.
1992	.	14	24	72	.	.	.	1
1993	.	16	28	78	.	.	.	1
1994	.	17	33	91	.	1	.	2
1995	.	34	51	115	.	1	.	2
1996	117	42	70	136	3	1	.	2
1997	117	44	83	142	3	1	.	2
1998	111	46	93	173	4	1	.	2
1999	93	83	105	185	4	1	.	2
2000	79	92	86	193	4	1	.	2
2001	78	94	92	198	4	1	.	1
2002	69	91	88	160	3	1	.	1
2003	65	88	83	152	3	.	.	1
2004	73	84	93	140	3	.	.	1
2005	69	87	107	144	3	.	.	1
2006	70	92	121	160	3	.	.	1
2007	73	97	149	178	3	.	.	2
2008	71	97	154	177	3	.	.	2
2009	67	88	149	209	3	.	.	3
2010	62	91	147	218	3	.	.	4
2011	66	95	156	214	3	.	.	5
2012	60	92	139	244	3	.	.	4
2013	58	81	133	239	3	.	.	3
2014	55	83	126	234	3	.	.	3
2015	52	89	133	217	3	.	.	3
2016	49	96	138	245	3	.	.	4
2017	48	102	134	291	4	.	1	5
2018	26	71	74	170	1	.	1	4

Table 4: List of "Sin" Stocks

This table lists all stock listings falling into our definition of a "sin" stock (i.e. belonging to the alcohol/tobacco/gaming/defense industry) in our observation period. We only include listings with non-missing data for our variables in the regression analyses. "Dead" denotes that the listing has been delisted at the time of this study. Industry classifications are extracted from Datatream with primarily datatypes 'WC07040' (ICB, ICB code from Worldscope), 'WC07021' (SIC1, SIC primary code from Worldscope), and ICBIC' & 'ICBIN' (ICB industry code and name). We additionally refer to classifications from datatypes 'MSCSIC' & 'MSCISC' (MSCI Sector and Sub-Industry GICS codes), 'and 'TR1' & 'TR1N' (TRBC (Thomson Reuters Business Classification) economic sector code and name) to supplement missing data when necessary. We follow the approach of Hong & Kacperczyk (2009) for "sin" stocks definition and classification. Accordingly, stocks with SIC codes 2100–2199 belong to the beer group, and those with SIC codes of 2080–2085 are in the smoke group. Unfortunately, the Fama-French classification scheme does not separate gaming stocks from hotel stocks or other entertainment stocks. To identify gambling stocks, we refer to the ICB codes of the stocks, which encode gambling firms as 5752 (FTSE International Limited, 2012). Finally, we expanded the definition of "sin" stocks to include companies belonging to the defense industry, as we believe that these companies play a role in the proliferation of violence in the world. We follow the Fama & French (1997) industry classification for defense stocks definition (SIC codes 3480-3489, 3760-3769, 3795 - all under the "Guns" group as per Fama & French (1997)). We only list stocks with non-missing data on our variables (described in Table 1).

Name[6]	**Country**
ALBANI BRYGG. B DEAD - DELIST 30/05/02	DENMARK
ARCUS	NORWAY
BETSSON B	SWEDEN
BOSS MEDIA DEAD - 21/04/08	SWEDEN
CARLSBERG B	DENMARK
CELSIUS B DEAD - DELIST 20/03/00	SWEDEN
CHERRY B	SWEDEN
ENLABS	SWEDEN
EVOLUTION GAMING GROUP	SWEDEN
HARBOES BRYGGERI B	DENMARK
HARTWALL A DEAD - DELIST 19/12/02	FINLAND
KEYNOTE MEDIA GROUP DEAD - 06/08/12	SWEDEN
NETENT	SWEDEN
ROYAL UNIBREW	DENMARK
SCANDINAVIAN TOBACCO	DENMARK
SPENDRUPS B DEAD - DELIST 21/08/01	SWEDEN

Table 5: Correlation Matrix

This table presents pairwise correlation between key variables in our “sin” stocks regression analysis. Significance levels are also included.

Corr.	ExcRet	LogSize	mtb	ret12m	beta	turnover	BLEV	age
ExcRet	1.0000							
LogSize	0.0553***	1.0000						
mtb	0.0832***	0.2397***	1.0000					
ret12m	0.3055***	0.1848***	0.2926***	1.0000				
beta	-0.0090**	0.1220***	0.0319***	-0.0161***	1.0000			
turnover	0.0059*	0.0057*	0.0166***	0.0167***	0.0169***	1.0000		
BLEV	-0.0223***	0.0659***	-0.3019***	-0.0809***	-0.0868***	-0.0164***	1.0000	
age	0.0140***	0.3633***	-0.0750***	0.0128***	0.0091**	-0.0203***	0.0658***	1.0000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.1.4 Regression Results

Table 6 shows no statistically significant effect of *SINDUM* on excess returns, regardless of variable permutation used. On the other hand, we detect a negative and significant impact of *lagmtb* and *lagBLEV* on stock’s excess returns when looking at the most elaborate specification in column (8). Conversely, *lagret12m* is positive and economically and statistically significant. The remaining variables (*lagLogSize*, *lagbeta*, *lagturnover* and *age*) do not show significant coefficient estimates. The insignificant coefficient of lagged time-varying beta is consistent with the finding by Hong & Kacperczyk (2009) and also with earlier papers, as stated by the authors. Hong & Kacperczyk (2009), in their study on the “sin” effect of U.S. stocks, also find that lagged market-to-book is significantly and negatively associated with excess returns, whereas lagged past 12-month average returns show a positive relationship with the dependent variable (i.e., a short-term momentum effect). They also detect a statistically significant positive effect of size on returns (approximately -.13% in their main regression model), whereas our results exhibit no significance on the estimated parameter of *lagLogSize* (which is very close to 0 in all eight columns in Table 6). On the other hand, Hong & Kacperczyk (2009) shows a significantly negative coefficient of lagged market-to-book (approximately -1.14%), consistent with our results (estimated coefficient -7.7% and p-value less than .001). This indicates that stocks with higher market-to-book ratios (growth stocks) perform poorer than stocks carrying lower relative market cap to book equity (value stocks). According to Griffin & Lemmon (2002), a popular explanation for the book-to-market premium in equity returns is that firms with higher book-to-market values (lower market-to-book) are assigned a higher risk premium due to their greater risk of distress. Chen & Zhang (1998) find that value stocks (stocks with lower market-to-book, or higher book-to-market ratios) are riskier because they are usually firms under distress, have financial leverages, and face substantial uncertainty in future earnings. They additionally find that value stocks offer significantly higher returns in international markets such as Japan, Hong Kong, and Malaysia, besides the United States. Echoing this finding, Fama & French (1995) show that low book-to-market ratio is commonly seen among firms with high average returns on capital (growth stocks), whereas a high book-to-market ratio is typical of relatively distressed firms.

Another interesting finding is the significantly negative coefficient of *lagBLEV* (approximately -1.53%), indicating that stocks with higher debts yield relatively lower excess returns. These results are inconsistent with the majority of accepted theories such as the Miller & Modigliani (1958) theorem, the trade-off theory, and the pecking order hypothesis. First of all, the Modigliani & Miller theorem suggests that highly leveraged firms should have high return due to the risk associated with financial distress costs. On the other hand, the trade-off theory (or optimal capital choice), developed by Myers (1984), suggests that companies with a large number of safe assets, such as tangible assets, in combination with a high income will finance their activities with more debt. The reason is that managers regard the capital structure decision of their firms as a trade-off selection between tax shields (from interest expenses) and costs of financial distress (from high leverage). Therefore, there should be an optimal debt ratio for each firm, and managers will adjust to a debt-to-equity ratio at which the marginal benefits of the tax shield equals the marginal cost of financial distress, explaining why more profitable firms (lower cost of distress) has higher gearing. On the other hand, a firm with a lower debt ratio should, based on this logic, generate a lower return (Brealey et al., 2011).

On the other hand, we find the negative coefficient of *lagBLEV* to be consistent with the market-timing theory. Accordingly, stock returns should be negatively correlated with leverage because managers typically become irrational and decrease their firms' leverage levels when their stock prices are high (Brealey et al., 2011).

Additionally, Masulis & Korwar (1986), Asquith & Mullins Jr (1986), and Hovakimian et al. (2004) show that equity is issued more often when firms' stock prices are high, indicating that the debt ratio will be lower when stock prices are higher. There are also empirical findings suggesting other reasons for this negative relationship. Adami et al. (2013) suggest that the higher-leverage-lower-return relationship is explained by the possibility that investors prefer to invest in firms that are more financially flexible, hence reaping higher returns when doing so.

As *GDUM* picks up the effect due to industry comparables, we are now able to isolate the wider sector effect from the "clean" sin-stock effect. We, however, do not detect any statistically significant relationship between either *SINDUM* and *GDUM* and monthly excess returns of Nordic stocks. These results differ with findings in the Hong & Kacperczyk (2009) classical study, in which "sin" stocks generate about 29bps excess returns compared to non-sin counterparts, after controlling for the same explanatory variables. Column (8) in Table 6 also exhibits a positive but insignificant coefficient estimate on *SINDUM* (approximately 2.4%). One possible reason leading to this difference could be the fact that we are including stocks belonging to four different markets in the cross-sectional regressions, without accounting for potential country fixed effects, caused by time-invariant unobserved heterogeneity in the context of our panel data. The uncontrolled country factor may be correlated with our regressors, leading to an omitted variable bias. Taking this into account, we run a Hausman test to investigate the necessity of incorporating country fixed effect into our model. The null hypothesis is that the preferred model is random effects versus the alternative, the fixed effects (Greene, 2008), and tests whether the unique errors (u_i) are correlated with the regressors, whereas the null hypothesis is they are not. Our results (suppressed for brevity) from the Hausman test shows a non-significant p-value (less than .05), showing no need for a fixed effects model. Regardless, we proceed to test if the previous results still hold under the Fama & MacBeth (1973) regression model, taking into account country fixed effects. Table 8 shows that even when controlling for country fixed effects (by including country dummies - suppressed in the table for brevity), the results are similar to Table 6. This leads us to conclude that our results are unlikely to be biased by a country fixed effect.

For robustness purpose, Table 9 reports Fama & MacBeth (1973) regression results in 3 different equal periods, i.e. 1989/05 - 1999/03, 1999/04 - 2009/02, and 2009/03 - 2018/12. Similarly, we do not detect any "sin" stock effect explaining excess returns. On the other hand, we find *GDUM* to be significantly negative (approximately -0.54%) in the 1989 - 1999 period. This indicates a negative impact of stocks belonging to selected industries (food, soda, industrials and so forth) on excess returns in this period. Additionally, we find *lagmtb* and *lagBLEV* to be negative and significant, and *lagret12m* to be significantly positive - similar results to Table 6. Interestingly, we find stocks turnover to positively predict returns in the first period (coefficient = 9.6%). This is in contrast with the finding by Hong & Kacperczyk (2009), as well as a number of studies showing that stock returns decrease in stock turnover (a "illiquidity premium") (e.g. research by Datar et al. (1998) and Hu (1997)).

Table 7 presents separate Fama & MacBeth (1973) regressions in each country (Norway, Denmark, Sweden, and Finland) to test if the results still hold. Interestingly, we observe economically and statistically significant (at the 5% significance level) and positive *SINDUM* in the Sweden and Finland regressions (estimated coefficients are .0118 and .0080, respectively). In other words, sin stocks outperform comparable stocks by about 118- and 80 basis points per month, or about 14% and 10% per year in Sweden and Finland, respectively. As for Norway and Denmark, *SINDUM* are also positive, although statistically insignificant. Possible reasons leading to the superior excess returns of "sin" stocks have been pointed out above. Fundamentally, "sin" stocks are possibly priced lower than the values they are worth due to societal norms constraining large institutional investors to hold the stocks, also leading sell-side analysts to provide less coverage. Consequently, this leads to limited risk sharing of these stocks, and coupled with heightened litigation risks inherent in "sin" products, their stock prices are compressed and expected returns are therefore higher.

4.1.5 Preliminary Conclusion to Method 1

For the overall Nordic market, we are not able to detect a significant *SINDUM* throughout our sample period, even with various permutations utilized. Initially, we do not find evidence that suggests that there are financial costs for portfolios subjecting to sector-based exclusionary screening of "sin" stocks in the Nordics. However, if we separate the Nordic market by countries, we find evidence that suggests that there may, in fact, be financial costs for portfolios subjecting to sector-based exclusionary screening criteria on “sin” stocks. Interestingly, we find a statistically and economically significant SINDUM for the largest equity market in the Nordic, namely Sweden. Sweden is also the country where we have the most observations N = 53064 compared to Denmark, where we have the fewest observations and N = 18506.

Moreover, the result also holds for Finland. However, the *SINDUM* coefficient is smaller in Finland compared to Sweden (0.8% compared to 1.18%). Therefore, the financial costs for excluding “sin” stocks is largest in Sweden. For Norway & Denmark, we do not detect a significant *SINDUM*, implying that there are no financial costs for portfolios subjecting to sector-based exclusionary screening of “sin” stocks in these countries.

Table 6: Sin Stocks Fama Macbeth Regressions

This table reports the results of Fama & MacBeth (1973) cross-sectional regressions for the period of 1989 – 2018, with Newey & West (1986) standard errors. The dependent variable is *ExcRet*, defined as the monthly return of a stock net of the risk-free rate (the 30-day Swedish T-bill rate). *ExcRet* is regressed on a selected set of explanatory variables (lagged (previous month-end) values of a set of well-known predictors of stock returns (Hong & Kacperczyk, 2009), including *lagLogSize*, *lagmtb*, *lagret12m*, *lagbeta*, *lagturnover*, and *lagBLEV*. *Age* is the current month-end (*t*) value. *SINDUM* is set as 1 if a stock belongs to one of the "sin" industries, and 0 otherwise. *GDUM* equals one if a stock is a "sin" stock or comes from the Fama & French (1997) industry groupings, i.e. 2 (food), 3 (soda), 7 (fun), and 43 (meals), or belongs in the Industrials (code 2000) industry (FTSE International Limited, 2012), and 0 otherwise. Detailed definitions could be found in table 1 and in the text.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SINDUM	0.0015	0.0026	0.0028	0.0037	0.0029	0.0031	0.0023	0.0024
	(0.0032)	(0.0030)	(0.0028)	(0.0028)	(0.0027)	(0.0027)	(0.0028)	(0.0028)
lagLogSize	0.0000	0.0006	0.0000	-0.0000	-0.0001	-0.0001	0.0002	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
lagmtb		-0.0055***	-0.0066***	-0.0065***	-0.0063***	-0.0062***	-0.0075***	-0.0077***
		(0.0012)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0009)	(0.0009)
lagret12m			0.1637***	0.1642***	0.1674***	0.1667***	0.1565***	0.1568***
			(0.0351)	(0.0351)	(0.0328)	(0.0331)	(0.0331)	(0.0327)
GDUM				-0.0015	-0.0016	-0.0017	-0.0018	-0.0017
				(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
lagbeta					-0.0001	-0.0002	-0.0008	-0.0008
					(0.0019)	(0.0019)	(0.0018)	(0.0018)
lagturnover						0.2709	0.2581	0.2631
						(0.1603)	(0.1621)	(0.1629)
lagBLEV							-0.0154***	-0.0153***
							(0.0027)	(0.0027)
age								-0.0006
								(0.0008)
N	124099	124099	124099	124099	124099	124099	124099	124099

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Sin Stocks Fama Macbeth Regressions

This table reports Fama & MacBeth (1973) regression results by country (Norway, Denmark, Sweden, and Denmark). Standard errors are estimated using the Newey & West (1986) method.

	Norway	Denmark	Sweden	Finland
SINDUM	0.0002	0.0017	0.0118*	0.0080*
	(0.0007)	(0.0030)	(0.0055)	(0.0037)
lagLogSize	-0.0002	0.0012	0.0013	0.0035
	(0.0008)	(0.0007)	(0.0007)	(0.0022)
lagmtb	-0.0107***	-0.0055***	-0.0084***	-0.0043
	(0.0022)	(0.0014)	(0.0013)	(0.0024)
lagret12m	0.2241***	0.2152***	0.1132*	0.1488**
	(0.0404)	(0.0414)	(0.0456)	(0.0554)
GDUM	-0.0010	-0.0037	-0.0007	-0.0033
	(0.0019)	(0.0020)	(0.0013)	(0.0047)
lagbeta	-0.0064*	-0.0004	-0.0022	-0.0210
	(0.0032)	(0.0023)	(0.0026)	(0.0150)
lagturnover	-0.1256	0.6131	-0.5211	0.6027
	(0.3209)	(0.4775)	(0.4650)	(1.7526)
lagBLEV	-0.0164**	-0.0103*	-0.0189***	-0.0252***
	(0.0051)	(0.0040)	(0.0033)	(0.0063)
age	-0.0010	0.0008	-0.0012	-0.0009
	(0.0014)	(0.0012)	(0.0010)	(0.0038)
N	30056	18506	53064	22473

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Sin Stocks Fama Macbeth Country Fixed-Effects Regressions

This table presents results of the Fama & MacBeth (1973) cross-sectional regressions for the period of 1989 - 2018 of *ExcRet*, the monthly return of a stock net of the Swedish 30-day T-bill rate on the lagged (previous month) values of a set of well-known predictors of stock returns. Formal definitions of explanatory variables could be found in table 1 and the text. All regressions include country dummy variables (for Norway, Sweden, Denmark, and Finland) to control for country fixed effects. Standard errors are adjusted for serial correlation (referring to Newey & West. 1986).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SINDUM	0.0015	0.0026	0.0028	0.0037	0.0029	0.0031	0.0023	0.0033
	(0.0032)	(0.0030)	(0.0028)	(0.0028)	(0.0027)	(0.0027)	(0.0028)	(0.0029)
lagLogSize	0.0000	0.0006	0.0000	-0.0000	-0.0001	-0.0001	0.0002	0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
lagmtb		-0.0055***	-0.0066***	-0.0065***	-0.0063***	-0.0062***	-0.0075***	-0.0079***
		(0.0012)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0009)	(0.0009)
lagret12m1			0.1637***	0.1642***	0.1674***	0.1667***	0.1565***	0.1543***
			(0.0351)	(0.0351)	(0.0328)	(0.0331)	(0.0331)	(0.0325)
GDUM				-0.0015	-0.0016	-0.0017	-0.0018	-0.0016
				(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
lagbeta					-0.0001	-0.0002	-0.0008	-0.0009
					(0.0019)	(0.0019)	(0.0018)	(0.0018)
lagturnover						0.2709	0.2581	0.2101
						(0.1603)	(0.1621)	(0.1579)
lagBLEV							-0.0154***	-0.0165***
							(0.0027)	(0.0025)
age								-0.0008
								(0.0007)
N	124099	124099	124099	124099	124099	124099	124099	124099
Country fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Sub-Period Regressions

This table reports sub-period regressions, using Fama & MacBeth (1973) method, with Newey & West (1986) standard errors. Definitions of variables can be found in table 1 and table 6.

	1989/05 to 1999/03	1999/04 to 2009/02	2009/03 to 2018/12
SINDUM	-0.0070	0.0068	0.0075
	(0.0056)	(0.0042)	(0.0041)
lagLogSize	-0.0003	0.0001	0.0010
	(0.0012)	(0.0008)	(0.0006)
lagmtb	-0.0063***	-0.0101***	-0.0068***
	(0.0015)	(0.0016)	(0.0014)
lagret12m	0.1478*	0.1560***	0.1667**
	(0.0720)	(0.0404)	(0.0520)
GDUM	-0.0054*	0.0002	0.0001
	(0.0021)	(0.0015)	(0.0013)
lagbeta	0.0012	-0.0034	-0.0002
	(0.0027)	(0.0031)	(0.0033)
lagturnover	0.9601*	0.1317	-0.3074
	(0.3924)	(0.1481)	(0.2068)
lagBLEV	-0.0125*	-0.0128*	-0.0207***
	(0.0054)	(0.0051)	(0.0029)
age	-0.0008	0.0000	-0.0011
	(0.0016)	(0.0014)	(0.0009)
N	21651	47838	54610

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Method 2

We long top-rated stocks and short low-rated stocks, based on MSCI ESG Ratings coverage on the Nordic IMI+, then test for the risk-adjusted alphas of this theoretical portfolio (Kempf & Osthoff, 2007; Hitchens et al., 2015).

4.2.1 Methodology

To analyze if there is a relationship between ESG ratings of stocks and risk-adjusted returns, we construct and test alphas of a "long top-short bottom" portfolio over a selected holding period, i.e., one month. The idea is that at the end of each month, we rank the stocks in the index under coverage by MSCI from the best performer ("top") to the worst performer ("bottom") according to their industry-adjusted ESG scores. Based on these monthly ratings, we then split the stocks into four quartile portfolios. The top quartile would then contain the best-ranked stocks, while the bottom quartile holds the worst-ranked stocks. We explore both average ratings across different ESG areas and area-specific scores (E, S, and G).

4.2.2 Portfolio formation techniques

As the purpose of this study is to investigate whether sustainable investments will lead to any abnormal returns (above the expected returns explained by the Carhart four factors), the idea is to construct a zero-investment strategy that goes long in stocks with superior ESG ratings and short in the ones with inferior ESG ratings. We mainly follow the approaches of Kempf & Osthoff (2007) and use both overall industry-adjusted ESG ratings and individual pillar scores in E, S, and G. The use of industry-adjusted ESG ratings is to ensure comparability across industries and to avoid any bias towards certain sectors in our portfolio construction[7].

At the end of each month $t-1$, we rank all stocks in the Nordic IMI based on the monthly MSCI ESG ratings and in "E", "S", and "G" separately, and also on the industry-adjusted overall ESG rating. As mentioned above, the use of industry-adjusted ESG rating is to remove a possible bias towards some industries in the

[7] Kempf & Osthoff (2007) use 10% as the main cut-off points to place stocks into the "long" and "short" portfolios. However, we choose 25% as our cut-off point, due to a smaller pool of stocks covered by the MSCI ESG datasets.

portfolio construction (without adjusting for industry relativity, companies in certain sectors might score higher than others). We elaborate on the details of how MSCI determines the weights in the Data section. We then "long" the high-rated portfolio, consisting of the top 25% of all stocks, and "short" the low-rated portfolio, consisting of the bottom 25% of all stocks. The "long-short" portfolio is then held for one month, before being reconstructed in the following month. For robustness purpose, we also test alphas exclusively for Norwegian stocks (since we have access to the Norwegian factor data). We additionally build portfolios based on "lagged" ESG ratings (i.e., the last ESG ratings available) to account for possible information delays in real life. We believe that by reshuffling the portfolio each month, we will be able to timely capture changes in the ESG ratings of stocks in the pool and build the most up-to-date "sustainable investment portfolios".

4.2.3 Regression model

As we conjecture that there is no significant financial impact of ESG or sustainable investment, the risk-adjusted return (alpha) of this portfolio should be approximately zero. If the alpha is significantly positive (negative), then ESG/sustainable investment ("long" the top-rated stocks and "short" the bottom-rated stocks) could potentially lead to superior (inferior) risk-adjusted returns. We calculate the portfolio's abnormal return (alpha), based on the Carhart's four-factor model. We are mainly interested in the annual cross-sectional alpha (α_i) in the following model:

$$R_{it} - R_{rf} = \alpha_i + \beta_{1i}(R_{mt} - R_{rf}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \epsilon_{it}$$

α_i denotes the abnormal return of the portfolio i. The dependent variable $R_{it} - R_{rf}$ is the monthly return of portfolio i in month t, minus the risk-free rate. We select two different risk-free rates - the U.S T-bill rates (provided by Fama & French, and the Norwegian risk-free rates (provided by Bernt Arne Ødegaard). The four independent variables (factors) are defined as the returns of four zero-investment factor portfolios (Kempf & Osthoff, 2007). First of all, $R_{mt} - R_{ft}$ denotes the excess return of the market portfolio over the risk-free rate. Two market portfolios are selected - the Norwegian OBX benchmark index returns (provided by Bernt Arne Ødegaard) and returns on Europe's value-weight market portfolio, built and provided by Fama & French. The next factor, SMB_t, denotes the return difference between a small- and a large-cap portfolio in month t. HML_t denotes the return difference between a high and a low book-to-market portfolio in month t. Finally, MOM_t is defined as the return difference between portfolios of stocks with high and low returns over the past twelve months. We provide more details on how the factors are calibrated by the authors in the sections to follow.

4.2.4 Data

Through a collaborative project with Gjensidigestiftelsen, MSCI has kindly provided the MSCI ESG rating which covers the MSCI Nordic IMI. The index contains 279 stocks in the Nordics, covering approximately 99% of the free float-adjusted market capitalization in each country (MSCI, 2018).

Following the acquisition of RiskMetrics in 2009, MSCI ESG Research gained access to a provider of non-pure financial portfolio analysis services to investors, namely KLD. As a consequence of the acquisition, the MSCI ESG Rating team shifted the model weights on certain Key Issues. In order to score issues which were previously considered of lesser importance or previously left blank, MSCI could now apply KLD's Global Socrates to score all companies on Key Issues. Previously, the Key Issues would account for roughly 80% of the total model weight, where the remaining 20% arrived from the less relevant issues. However, the model weights were changed in May 2011. Following the change in methodology, the Key Issues would account for 100% of the model weight. Throughout the full history of the ESG-framework, the sum of Environment-, Governance-, and Social scores had always equaled 100%. Before the change in methodology, the model industry weights were the same for all companies. In order to adjust for industry weights and impact, the ratings were adjusted in 2011 by GICS (Global Industry Classification Standard) Sub-industry. This modification allowed companies to have different weights and a more granular ESG analysis by Key Issues and industry adjustments.

The MSCI ESG Rating Methodology is carefully described in MSCI ESG Research (2018a), and we will highlight the key points which are particularly relevant for this thesis. Firstly, MSCI Ratings measures and analyzes companies' risk and opportunities arising from three pillars, namely environmental, social, and governance issues. Across these pillars, MSCI covers ten different themes. For each theme, MSCI measures different key issues, as illustrated in Figure 1. The MSCI ESG

Figure 1: MSCI ESG Key Issue Hierarchy (MSCI ESG Research, 2018)

3 Pillars	10 Themes	37 ESG Key Issues	
Environment	Climate Change	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Resources	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opp's in Renewable Energy
Social	Human Capital	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opp's in Nutrition & Health
Governance	Corporate Governance*	Board* Pay*	Ownership* Accounting*
	Corporate Behavior	Business Ethics Anti-Competitive Practices Tax Transparency	Corruption & Instability Financial System Instability

Ratings universe varies over the sample period. As of 2018, MSCI ESG Ratings covers over 13,000 equity and fixed income issuers linked to over 590,000 equity and fixed income securities (MSCI ESG Research, 2018a). MSCI maintain and support MSCI ESG Rating History beginning with active ratings as of January 1st, 2007. From 2007 – 2012, the universe consists of the top 1,500 companies of the MSCI World Index by market capitalization, the top 25 to 200 companies of the MSCI Emerging Markets Index, the top 275 companies of MSCI UK Investible Market Index (IMI), and the MSCI Australia 200 Index.

In 2014, the MSCI Nordic IMI[8] were added to the Ratings coverage (MSCI ESG

[8]The MSCI Nordic Countries Investable Market Index (IMI) was launched on June 5th, 2007. The index captures large, mid and small cap firms across Denmark, Finland, Norway, and Sweden. The index consists of roughly 280 equities, which cover approximately 99% of the float-adjusted market

Research, 2017). Consequently, the ESG coverage on Nordic stocks in the period before 2014 is limited to stocks which was a part of the 1,500 companies of the MSCI World Index by market capitalization.

As the Nordic IMI covers the largest companies in the Nordics by market capitalization, there is a possibility that our analysis results might be subject to a data selection issue. Specifically, the abnormal returns ("alphas") generated from our suggested trading strategies presented in the following sections might not be a result from sustainable investing (i.e., going long on stocks with highest ratings) or unsustainable investing (going long on stocks with lowest ratings), but a "size" effect from large stocks investing. However, as we are going to compare the magnitude of alphas generated from sustainable investing versus unsustainable investing, rather than analyzing the alphas on their own, we hope to be able to isolate such possible "size" effect from the results.

The MSCI ESG Rating Time Series is available as a monthly time series. The Ratings are typically updated on an annual basis. However, the update frequency is not firmly fixed to a certain month in a year. Some underlying data may be updated more frequently. If any of these changes trigger a change in the overall rating, MSCI will re-rate the company throughout the year (MSCI ESG Research, 2018b).

The ESG Rating framework is industry relative and applies a weighted average approach. Key Issue weights are formed at GICS ("Global Industry Classification Standard")[9] industry-level dependent on each industry's relative significance and the time horizon associated with identified issues. Each Key Issue normally contributes to 5% - 30% of the composite ESG scores. Weights setting takes into account (1) the contribution of the industry (compared to all other industries) to the impact on the environment or society; and (2) the expected timeline the risks or opportunity for companies in the industries to materialize.

capitalization in each country. As of March 2019, the top five sectors in the index are Industrials (24.27%), Financials (16.59%), Health Care (14.9%), Materials (8.16%) and Information Technology (7.83%) which accounts for roughly 71.75% of the total weight. Interestingly, the country weights vary quite substantially. Sweden has the largest weight (44.53%) followed by Denmark (26.15%) and Finland (16.52%), and lastly Norway has the smallest weight (13.7%).

[9]The Global Industry Classification Standard (GICS) was developed by and is the exclusive property of MSCI and Standard & Poor's.

Similar to the ESG Rating, Key Issues and the associated weights are reviewed and updated at the end of each calendar year. For example, Corporate Governance is a theme within the Governance pillar and is by MSCI always considered material. Therefore, issues within this theme are always weighted and analyzed for all firms. In addition to this, the framework allows for firm-specific exceptions where weights can depart from the industry standard weights. For every firm, a weighted Average Key Issue score is computed based on the underlying Key Issue scores and weights. Ultimately, theme weights are formed followed by pillar weights. For example, let's assume a firm achieves a score of 6 in the Environmental pillar, a score of 5 in the Social pillar and a score of 8 in the Governance pillar. Let us further assume that the weights in the E/S/G-pillars for this company are 30/30/40. The weighted average Key Issue score would then be 6.5.

Key Issue scores are computed by combining the exposures and management ratings in relevant material risks and opportunities (under the issue). According to the ESG Ratings Methodology by MSCI ESG Research (2018a), a risk is "material" to an industry when it is likely that companies in a given industry will incur substantial costs in connection to it. An example is a regulatory ban on a key chemical input requiring reformulation. On the other hand, an opportunity is material to an industry when it is likely that companies in an industry could capitalize on it for profit. An example given by MSCI is opportunities in clean technology for the LED lighting industry. Material risks and opportunities for each industry are identified by a quantitative model, with room for company-specific exceptions (e.g., firms with unusual or diversified business models or firms facing controversies).

As Key Issue scores are the combined results of risk and opportunities exposure and management, a company with high exposure must also have solid management, whereas a company with limited exposure can have a more modest approach. MSCI measures risk exposure on a 0 - 10 scale, with 0 representing "no exposure" and 10 representing "very high exposure". Afterward, MSCI analysts consider the firm's developed strategies and its track record of managing these specific levels of risks or opportunities. In addition to this, the framework allows for a deduction from the overall management score (on each issue), if there are controversies occurring within the last three years. Similar to Exposure, Management is scored on a 0 - 10 scale, where 0 represents no evidence of management efforts and 10 represents indications of very strong management.

Assessment of opportunities, as part of computing Key Issue scores, is done similarly to risks. However, there is a minor difference in combining exposure and management. Based on a firm's current business and geographic segments, exposure indicates the relevance of the opportunity. On the other hand, the management score measures the company's capacity to capitalize on such opportunities. For most firms with relatively limited exposure, the Key Issue score would be constrained towards the middle range (i.e., around 5), while high exposure allows for both higher and lower scores.

In addition to the steps above, controversies, defined as "an instance or ongoing situation in which company operations and or products allegedly have a negative environmental, social, and/or governance impact" (MSCI ESG Research, 2018a), are also considered on a case-by-case basis. If a case is deemed by an analyst to indicate structural problems that could pose future material risks, the firm in question will suffer a large deduction from the Key Issue score. Ultimately, the weighted average Key Issue score is transformed into a final letter rating. The transformation of the score is carried out through normalizing by industry. Industries are given a range of scores annually by establishing a rolling three year average of the top, and bottom scores among the MSCI ACWI Index constituents and the values are set at the 97.5^{th} and 2.5^{th} percentile. Employing these ranges, the Weighted Average Key Issue Score is transformed into an Industry Adjusted Score from 0 - 10, where 10 is best, and 0 is worst. Consequently, the Industry Adjusted Score corresponds to a rating ranging between best (AAA) and worst (CCC), as illustrated in Figure 2. The evaluations of firm performance are not absolute. They are rather intended to be relative to the standards and performance of a company's industry peers. As the final-industry adjusted company score is a fairer measurement of the relative performance of a firm to its peers, it is employed as the main index to rank stocks to build our trading strategies in our analysis section.

Figure 2: The Final Industry Adjusted Company Score (MSCI ESG Research, 2018)

Letter Rating	Final Industry-Adjusted Company Score
AAA	8.6* - 10.0
AA	7.1 – 8.6
A	5.7 – 7.1
BBB	4.3 – 5.7
BB	2.9 – 4.3
B	1.4 – 2.9
CCC	0.0 – 1.4

4.2.5 Factors Data

We regress excess returns from our trading strategies on 4 factors based on the Carhart (1997) model - SMB (small-minus-big), HML (high-minus-low), MOM (momentum strategy), and excess market returns. As our portfolios are built from a pool of Nordic public firms, ideally, our pricing factors are constructed using pan-Nordic data. However, at the time of this study, we are unable to find such data sources. We, therefore, referred to the publicly available factors data for the Norwegian and European stocks, provided by Bernt Arne Ødegaard and Fama & French, respectively.[10]

We extract pricing factors for the European region from the data set "Fama/French 3 Factors for Developed Markets" on the authors' website. The data set covers monthly returns from July 1990 to March 2019. To construct the SMB and HML factors, Fama & French sort stocks in the European region into two market cap and three book-to-market equity (B/M) groups at the end of each June. Specifically,

[10]The Norwegian factors data in details in the two papers "Empirics of the Oslo Stock Exchange: Basic Results" and "Empirics of the Oslo Stock Exchange: Asset Pricing Results", both by Bernt Arne Ødegaard.

"big" stocks are those in the top 90% of June market cap for the region, and "small" stocks are those in the bottom 10%. The B/M breakpoints for a region are the 30^{th} and 70^{th} percentiles of B/M for the big stocks of the region. The independent 2x3 sorts on size and B/M then result in six value-weight portfolios, *SG*, *SN*, *SV*, *BG*, *BN*, and *BV*, where *S* and *B* indicate small or big and *G*, *N*, and *V* indicate growth stocks (low B/M), neutral stocks, and value stocks (high B/M). Given the 2x3 partioning, SMB is calculated as the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios. On the other hand, HML is calculated by Fama & French as the equal-weight average of the returns for the two high B/M portfolios (for the region) minus the average of the returns for the two low B/M portfolios:

$$SMB = \frac{Small\,Value + Small\,Neutral + Small\,Growth}{3} + \frac{Big\,Value + Big\,Neutral + Big\,Growth}{3}$$

$$HML = \frac{Small\,Value + Big\,Value}{2} - \frac{Small\,Growth + Big\,Growth}{2}$$

The market factor is defined by Fama & French as the return on a region's value-weight market portfolio (R_m) minus the U.S. one month T-bill rate (R_f). $R_m - R_f$ for July of year t to June of $t + 1$ include all stocks for which the authors have market equity data for June of t.

The European momentum factors (MOM) are extracted from the "Momentum Factors for Developed Markets" dataset provided by Fama & French, which include monthly returns from November 1990 until March 2019. On a monthly basis, the authors conduct 2x3 sorts on size and lagged momentum to construct the momentum portfolios. Specifically, for portfolios formed at the end of month t–1, the lagged momentum return is a stock's cumulative return for month t–12 to month t–2. In addition to this, another partitioning is done using the 30^{th} and 70^{th} percentile breakpoints of the lagged momentum returns of the big stocks of the European region. Based on this sorting design, Fama & French generate six value-weight portfolios - *SL*, *SN*, *SW*, *BL*, *BN*, and *BW*, where *S* and *B* indicate small and big and *L*, *N*, and *W* indicate losers, neutral, and winners (bottom 30%, middle 40%, and top 30%, respectively). Finally, the momentum factors (denoted as "WML" by Fama & French) is calculated as the equal-weight average of the returns for the two winner portfolios for a region minus the average of the returns for the two loser portfolios:

$$WML = \frac{Small\ High + Big\ High}{2} - \frac{Small\ Low + Big\ Low}{2}$$

As for the Norwegian factor portfolios, the author apply similar calculation methodology to Fama & French (1998) to calculate the HML and SMB returns, using Norwegian data. Carhart Momentum factor (denoted as *PR1YR* by the author) is calculated similarly to the method developed by Carhart (1997), using Norwegian data. As for the market factor, we extract data (provided by the same author) from the monthly series of returns on the OBX, consisting of the 25 most traded securities on the Oslo Stock Exchange (Oslo Børs). Finally, we download Norwegian risk-free rates (monthly) from the same website[11].

To be consistent with the excess market returns calculated by the authors, we compute portfolios' excess returns in two different ways for the two regression models (using European factors and Norwegian factors). Specifically, we use U.S T-bill rates (provided by Fama & French) to compute excess returns when running regressions on European factors. As for Norwegian factors model, we apply Norwegian risk-free rates to compute portfolio returns.

4.2.6 Descriptive Statistics

Table 10 shows industry-adjusted average ESG scores from 2007 to 2018 as per our proprietary data provided by MSCI[12]. We observe a fairly stable trend of the mean scores throughout the years. The average score across all years is 6.3, while the all-time low score and the all-time high score is 0 and 10, respectively. In addition, we have illustrated the scores by country in Figure 3, where we observe the decreasing trend, especially in Sweden for the last three years. Similarly, we observe the industry-adjusted mean scores decreases from 2016 from 6.4 until 2018 at 6.1.

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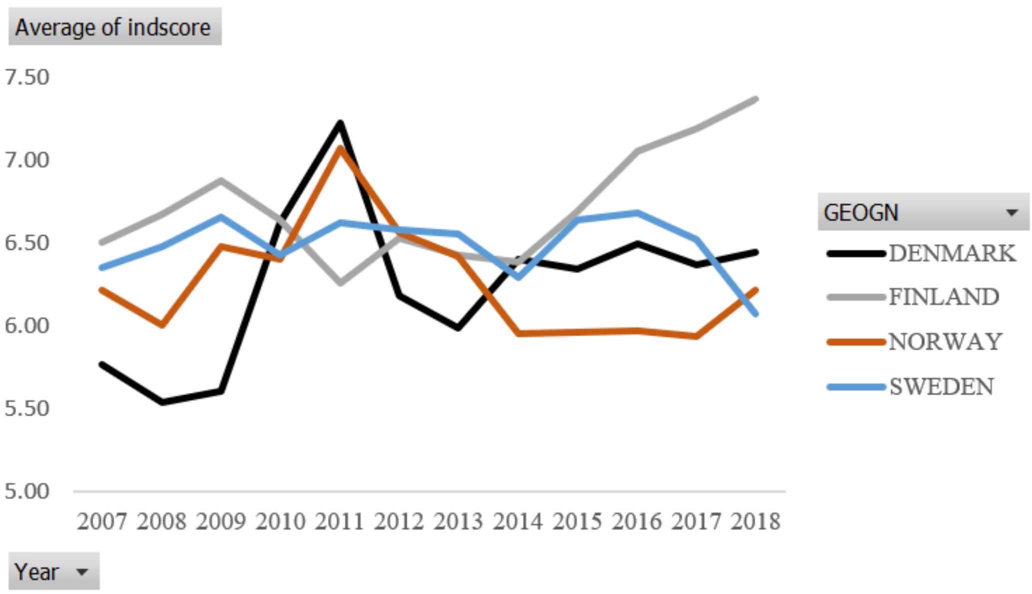
[11]The data found at http://finance.bi.no/ bernt/financial_data/ose_asset_pricing_data/index.html

[12]Reproduced by permission of MSCI ESG Research LLC

Table 10: Industry-Adjusted ESG Scores

Year	**Mean**	**Median**	**Min**	**Max**
2007	6.2	6.2	1.4	10.0
2008	6.2	6.3	1.0	10.0
2009	6.4	6.5	1.0	10.0
2010	6.5	6.5	1.0	10.0
2011	6.6	6.5	1.4	10.0
2012	6.4	6.4	1.4	10.0
2013	6.2	6.2	0.0	10.0
2014	6.1	6.4	0.0	10.0
2015	6.3	6.5	0.0	10.0
2016	6.4	6.8	0.0	10.0
2017	6.3	6.5	0.0	10.0
2018	6.1	6.3	0.0	10.0
Total	6.3	6.4	0.0	10.0

Figure 3: Average Industry Score By Country



4.2.7 Industry overview

Furthermore, we present statistics of weighted average ESG scores per industry in Table 19 attached in Appendix 6 [13]. Accordingly, we detect some deviation in ESG ratings of different industries. Industries such as *Apparel Retail* (7.4 in mean score), *Specialty Retail* (7.7), and *Construction Materials* (7.5) have relatively high ratings, whilst the bottom-rated industries include *Commodity Chemicals* (3.1), *Surface Transport* (3.8), and *Bank - Emerging Markets* (3.8). For a detailed overview of

[13]The industry classification is provided by MSCI in their ESG datasets

the number of stocks from different industries and the respective industry weights throughout our sample period, we refer to Table 20 in Appendix 6.

4.2.8 Results

Table 11: Regression Results for Portfolio Created Using Industry-Relative Ratings

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI ESG industry-adjusted ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - “long” the stocks placed in the top quartile & “short” the stocks placed in the bottom quartile. *Reverse* refers to our “reverse” trading strategy, which is to “long” bottom-rated stocks and “short” top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	-0.0115	-0.0338	-0.0195	-0.238***					0.0000617	0.137
	(0.0898)	(0.0728)	(0.0683)	(0.0708)					(0.00261)	
Reverse1	0.0244	0.0340	0.0234	0.257***					-0.00398	0.150
	(0.0914)	(0.0737)	(0.0685)	(0.0721)					(0.00261)	
Good1	0.0839	0.0666	-0.0268	0.621***					0.00194	0.650
	(0.0725)	(0.0711)	(0.0817)	(0.0559)					(0.00241)	
Bad1	0.102	0.100	-0.00534	0.868***					-0.0000848	0.720
	(0.0823)	(0.0805)	(0.101)	(0.0600)					(0.00291)	
Main2					-0.0288	0.634	-0.748*	-0.223	-0.0634***	0.00526
					(0.172)	(0.527)	(0.329)	(0.206)	(0.00893)	
Reverse2					0.494**	1.215*	-0.571	-0.252	-0.0661***	0.0564
					(0.175)	(0.565)	(0.401)	(0.203)	(0.00980)	
Good2					0.834***	1.008	-1.014**	-0.298	-0.0598***	0.133
					(0.186)	(0.536)	(0.384)	(0.227)	(0.00924)	
Bad2					1.095***	1.298*	-0.925*	-0.312	-0.0611***	0.204
					(0.188)	(0.555)	(0.420)	(0.225)	(0.00972)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11 presents the results of our trading strategies using industry-adjusted ESG ratings. First of all, we do not detect any significant alphas for all models using Norwegian factors. On the other hand, we find significant and negative alphas for all four portfolios under the European factors model. The alphas of both “main” and “reverse” portfolios are negative, and almost the same (approximately -6%), even though the "main" strategy seems to yield a slightly lower abnormal loss. When turning to the "good" and "bad" trading strategies separately, we also find almost similar alphas (also approximately -6%), even though the bottom-rated stocks yield more losses than the top-rated ones. Our preliminary finding, therefore, suggests that there are no statistically significant positive abnormal returns generated by a sustainable investment strategy based on ESG ratings in the Nordics.

Contrary to the study by Kempf & Osthoff (2007), we are not yet able to find significantly positive abnormal returns by using firms' overall ESG ratings[14]. The difference in results could be attributed to several reasons. First of all, the two studies differ in time periods - the Kempf & Osthoff (2007) study used KLD ratings data from 1991 until 2003, whereas we use MSCI ESG Ratings data from 2007 to 2018. Secondly, (Kempf & Osthoff (2007) used the KLD datasets, which cover all stocks in the S&P 500 and the DS 400, whereas we use the MSCI ESG datasets, covering the Nordic IMI. In addition to this, there are fundamental differences in the way ESG/social responsibility scores are constructed in the two studies. Specifically, the Kempf & Osthoff (2007) involves a manual transformation of presences of strengths/concerns (in each sub-criterion), as per KLD data, into overall numerical scores for each of the six criteria, whereas we employ directly final scores from MSCI[15]. Another attributing factor is the lack of access to pan-Nordic asset pricing factors at the time of our study. The use of Nordic factors could arguably lead to a better explanatory power of the model and generate more accurate alpha estimates. Finally, we are, to a certain extent, limited by the coverage span of the MSCI ESG

[14]The authors in the study found that investors can earn high abnormal returns by following the simple long-short strategy by implementing the "positive screening approach" or the "best-in-class screening approach", but not the "negative screening approach". Accordingly, the best-in-class approach typically leads to the highest alphas (up to about 8.7% per year). Furthermore, the alphas stay significant even after taking into account reasonable transaction costs.

[15]KLD evaluates the companies according to multiple criteria. KLD discerns between two broad categories: qualitative and exclusionary criteria. The authors use six qualitative criteria in the study, including *community*, *diversity*, *employee relations*, *environment*, *human rights*, and *product*. For each criterion, KLD evaluates multiple sub-criteria. The sub-criteria can be divided into strengths and concerns. Each sub-criterion then has a zero/one score, with one indicating the presence of strength or concern, zero indicating absence of both. To get such an overall score, the authors first transform the concerns into strengths by taking the binary complements, then summing up the scores of the sub-criteria and normalizing this sum to a range from zero to one.

datasets, which only feature ratings from 2007 to 2018.

The negative alphas here suggest that these trading strategies offer a return that is significantly lower than the expected returns suggested by the Carhart four-factor models. As previously mentioned, the stocks covered by the MSCI ESG database are the largest in the Nordics in terms of market capitalization. Therefore, the negative alphas found in these regressions might be results from a “large-cap” investment strategy, rather than a sustainable (or unsustainable) investment strategy. If we are to assume the negative alphas (or zero alphas - according to the Norwegian factors model) are the results of large-cap stocks, there are a few contributing factors. First of all, large companies have limited growth potential, compared to smaller firms. Most large firms are already utilizing their installed capacity almost fully. Therefore, the scope for improving operating margins is slight, and the earnings of these companies do not provide much leeway to generate an excess return (Chadha, 2011).

In addition to this, the classical efficient markets hypothesis might account for the lackluster generation of alpha in our trading strategies. The hypothesis states that if everyone is entitled to the same access to information and possesses the ability to trade with the same efficiency, it is extremely difficult for anyone to beat the market returns. In other words, all information publicly available to investors have already been reflected in current stock prices (semi-strong market efficiency). Therefore, one cannot expect to generate any abnormal returns above the market benchmark.

In a study by Boström & Petersson (2012), some of the large-cap funds in the Nordics, including SEB Sverigefond Småbolag, and Ålandsbanken Swedish Small Cap offer a negative alpha generated from CAPM regressions. Based on Jensen’s alpha measure in this study, three of the five funds, including Handelsbanken Svenska Småbolag, Lannebo Småbolag, and Skandia Småbolag Sverige, have positive alpha values and thereby yield abnormal returns. On the contrary, SEB Sverigefond Småbolag and Ålandsbanken Swedish Small Cap achieve a lower return than that suggested by CAPM. The authors find that small-cap funds outperform and are a safer investment than large-cap funds in every single time period, including pre-crisis and crisis periods.

We also notice a lower explanatory power (adjusted R^2) provided by the European factors model, compared to when we use Norwegian factors. The poorer fit of the European factors model leads us to interpret the significant and negative alphas with caution[16]. . Therefore, this suggests a further improvement to the model, by regressing portfolio returns on Nordic factors data (instead of Norwegian or European factors) for better explanatory power of the factors.

An interesting finding is that the market beta[17] of the "main" (i.e., "long" top-rated stocks and "short" bottom-rated stocks) portfolio is negative (significant in the Norwegian factors model and non-significant in the European factors model). However, the market beta of the "reverse" strategy is positive and significant. This holds for both Norwegian and European market factors. We could interpret the negative beta of the trading strategy as an investment that moves in the opposite direction from the stock market (in this case, the Oslo Benchmark Index OBX, given the significance of the beta). Specifically, when the market rises, the "long-short" portfolio would fall, and vice versa. These counter-cyclical movements with the market show some signal that the portfolio could be utilized as hedging strategies against market-wide volatility, or overall fluctuations in the state of the economy.

Under the European factors model, positive coefficient for the "reverse" strategy and the bottom-rated portfolio. SMB beta for the "main" and "reverse" portfolios are positive but non-significant. It is possible that "smaller" stocks in the universe are ranked lower in terms of ESG, which explains why a reverse trading strategy, as well as investments into "bad" stocks might create significantly positive SMB loadings. Another possible reason is that Nordic companies are relatively smaller in size compared to their other European counterparts, leading to the positive loading on

[16]The well-known goodness of fit statistic R-squared is given by the ratio of the explained sum of squares to the total sum of squares (Brooks, 2019). A modification of R-squared is often made, which takes into account the loss of degrees of freedom associated with adding extra variables. This is known as the adjusted R-squared.

$$\bar{R}^2 = 1 - \left[\frac{T-1}{T-k}(1-R^2)\right]$$

[17]A market beta coefficient is a measure of the volatility, or systematic risk, of an individual stock in comparison to the unsystematic risk of the entire market. In statistical terms, beta represents the slope of the line through a regression of data points from an individual stock's returns against those of the market (Investopedia, n.d.).

SMB.

In addition, we observe that high-rated portfolios and low-rated portfolios differ systematically with respect to the book-to-market factor, HML. The high-rated portfolio has a lower loading on this factor, i.e., it possibly includes more growth stocks than the low-rated portfolio does. In the European factors model, we find significantly negative HML beta coefficients, indicating a possibility that the stocks covered in the MSCI ESG ratings universe are dominated by growth firms (by European standards).

Trading Strategies Built on Environmental Ratings

MSCI Environmental Rating: There are in total four underlying themes covered in the Environmental pillar, namely *Climate Change*, *Natural Resources*, *Pollution & Waste*, and *Environmental Opportunities*. Within these themes, MSCI ESG analysts rank firms based on 13 key issues (e.g., Carbon Emissions, Product Carbon Footprint, and Toxic Emissions & Waste) (MSCI ESG Research, 2018a). The Environmental pillar scores are constructed from firms' *Risk/Opportunities Exposure* and *Risk/Opportunities Management* scores.

We find a significantly positive alpha of 0.62% for the bottom-rated portfolios, under the European factors model, as shown in Table 11. We can attribute this to a possibility that the bottom-rated portfolios contain many oil & gas-related stocks and "sin" companies, leading to a low ESG rating, particularly in environmental key issues. The results echo findings of Hong & Kacperczyk (2009), showing signs that companies operating in ethically questionable businesses could yield excess returns for their investors. In particular, the authors find that there is a significant price effect on the order of 15–20% from large institutional investors "shunning" "sin" stocks (a so-called "effect of social norms on markets"). They argue that the neglect of these stocks by large institutions have affected their cost of capital significantly.

However, the results do not hold under the Norwegian factors model (alpha under the "bad" trading strategy is positive but not significant, adjusted R^2 are quite similar in the two models). The results are, therefore, not robust to the selection of asset pricing factors. We again recommend future studies to use pan-Nordic asset pricing factors to hopefully generate a better model fit.

Table 12: Regression Results for Portfolio Created Using E- Ratings.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI Environmental ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - "long" the stocks placed in the top quartile & "short" the stocks placed in the bottom quartile. *Reverse* refers to our "reverse" trading strategy, which is to "long" bottom-rated stocks and "short" top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	-0.0473	-0.0758	-0.0177	-0.0698					-0.00441	-0.0157
	(0.0846)	(0.0718)	(0.0683)	(0.0768)					(0.00276)	
Reverse1	0.0602	0.0760	0.0217	0.0885					0.000494	-0.0117
	(0.0868)	(0.0727)	(0.0697)	(0.0779)					(0.00277)	
Good1	0.0629	0.0305	-0.0470	0.656***					-0.000451	0.682
	(0.0696)	(0.0654)	(0.0843)	(0.0589)					(0.00253)	
Bad1	0.117	0.106	-0.0273	0.735***					0.00200	0.560
	(0.0821)	(0.0846)	(0.109)	(0.0593)					(0.00326)	
Main2					-0.0254	-0.135	-0.137	0.112	-0.00574*	0.0332
					(0.0685)	(0.178)	(0.135)	(0.0610)	(0.00260)	
Reverse2					0.0386	0.167	0.129	-0.113	0.00192	0.0398
					(0.0684)	(0.181)	(0.135)	(0.0628)	(0.00263)	
Good2					0.670***	0.0742	-0.330*	-0.0534	0.00239	0.606
					(0.0664)	(0.139)	(0.138)	(0.121)	(0.00264)	
Bad2					0.702***	0.225	-0.197	-0.166	0.00622*	0.579
					(0.0606)	(0.142)	(0.157)	(0.116)	(0.00294)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Consistent with the previous finding, the “long-short” strategy yields a significantly negative alpha of approximately -0.57%, under the European factors model. Again, this suggests that the results might be subject to a potential “large stocks effect”, accounting for the negative and almost zero alphas. On the other hand, we do not find any positive alphas for the strategy under the Norwegian factors model. We note that the adjusted R^2 are negative under the *Main1* and *Reverse1* regressions, suggesting that the Norwegian asset pricing factors might be a poor choice for explaining the excess returns of the two trading strategies.

Looking into the composition of the bottom-rated stocks portfolios, we find that many “sin” companies[18] are placed in the bottom-rated portfolios. An example is Swedish Match, a manufacturer of Snus and other tobacco products. This firm received a low Environmental score throughout our sample period. The firm’s average Environmental score is 3.7, and it is consequently placed in the lowest rated portfolio 78% of the months it is rated in our sample (143). Similarly, we find that Scandinavian Tobacco Group is placed in the bottom-rated portfolios 100% of the months with an average Environmental score of 3.3 (26 months).

The low environmental scores of tobacco companies could be explained by the harmful impacts of the industry on the environment. According to World Health Organization (2017), when assessing the global adverse impact of tobacco on human development, health cannot be considered in isolation from a host of other factors, of which the environment is one. Such harmful impacts could be found in terms of indoor pollution and biodiversity. Specifically, tobacco leads to indirect social and economic damage caused by the cultivation, production, distribution, consumption, and waste generated by the products (the so-called “from cradle to grave” five-stage life cycle of tobacco (World Health Organization, 2017)).

Further, we find that Carlsberg, a leading Nordic alcohol producer, also appears in the bottom-rated stocks portfolio. However, during the 144 months which it is rated in our sample period, it only appears in the lowest rated portfolio 15% of the months. Similarly, we find that Royal Unibrew is only placed in the lowest rated portfolio 16% of the months during our sample period (61 months rated).

[18] We define “sin” companies as the ones belonging to one of the “sin” industries - alcohol, tobacco, gaming/gambling, and defense.

According to a study on the environmental impact of the alcoholic beverages industry commissioned by Nordic Alcohol Monopolies (2017), the total monetized life cycle impacts amount to 320 million Euros, which is approximately 7% of the overall before-tax sales value of the alcoholic beverages sold by the Nordic Alcohol Monopolies[19] in 2014. Three among nine different environmental impact categories contribute to more than 90% of the total impact, including respiratory impacts (from breathing polluted air), global warming (from greenhouse gases), and nature occupation (loss of biodiversity), among which the two first impacts are mainly caused by the burning of fuels for energy production. Furthermore, the largest contributing life cycle stages (accounting for more than half of the total impacts) are packaging manufacturing – especially glass (even though efficient recycling in the Nordics partly alleviate the problem), agriculture fuel use, and production.

We now turn our attention to the oil and gas industry. Oil-and-gas-related activities, including exploration, production, and distribution, have traditionally been viewed negatively from environmental perspectives. According to the Norwegian Environment Agency (2016), activities in the industry have negative impacts on large areas of the sea, the seabed, and on land. They affect the environment through emissions to the atmosphere, noise from seismic surveys, and the physical footprint on the seabed. The same agency points out that the oil and gas industry is the largest source of greenhouse gas emissions in Norway. Contributing to this is a large amount of energy consumed by the production of oil and gas and transport in pipelines from the offshore fields to land terminals. In addition to this, research has shown that oil and environmentally hazardous substances discharged in produced water may affect the health and reproduction of individuals of fish and invertebrates in the oceans (Norwegian Environment Agency, 2016). Furthermore, exploration activities also affect the seabed through the placement and movement of installations and other necessary equipment such as platform legs and pipelines. Finally, Norwegian Environment Agency (2016) show that noise from seismic surveys may frighten fish and marine mammals.

All in all, these adverse environmental impacts explain why certain oil & gas com-

[19]Except for Denmark, all the Nordic countries have a state-owned off-premise retail alcohol monopoly. The monopolies include *Alko* in Finland, *Vinmonopolet* in Norway, and *Systembolaget* in Sweden.

panies will receive relatively lower E-scores from MSCI. Equinor, the largest company in the Nordics[20], received on average an Environmental score of 5.3, and is throughout our sample period never selected into the bottom rated stocks portfolio. DNO, another oil company receives an average Environmental score of 3.8 and is placed in the bottom-rated portfolio 38% of the months during our sample period (rated 56 months). Aker BP, a large Norwegian oil company, received an average Environmental score of 3.1 and was selected into the bottom-rated stock portfolio 96% of the periods when the rating was available for the company (54 months). BW Offshore, another oil and gas company, received an average Environmental score of 3.2. During the sample period, it is placed in the bottom-ranked portfolio 100% of the months it had a ranking available. However, the Environmental score of the firm is only available for nine months during the sample period. Aker, an industrial investment company with significant exposure to both oil production and oil service, received an average Environmental score of 4.5. During the portfolio construction period, it was selected in the bottom-ranked portfolio 14% of the months where there was a ranking available (51 months).

Elsewhere, Lundin Petroleum, a large Swedish oil company, received an average Environmental score of 4.1. It was placed in the bottom-ranked portfolio 30% of the months there was an available ranking (122 months). A.P. Møller – Mærsk A/S, a Danish business conglomerate with significant oil and gas activities, received an average Environmental score of 5.5. During the sample period, the stock was selected into the bottom-ranked stock portfolio 5% of the months.

Also, we observe that oil services companies generally received a higher Environmental score than the oil- and gas production companies in our observation period. Investigating some of the largest oil service companies in Norway, Akastor received an average Environmental score of 5.3 and was never selected in the bottom-ranked portfolio during the sample (rated 84 months). Similarly, Aker Solutions received an average Environmental score of 5.2 and was never selected in the bottom-ranked portfolio (49 months of ratings). Ocean Yield, a ship-owning company which also operates an FPSO-vessel producing gas, received an average Environmental score of 4.4 and during the 49 months there was a rating available for the company, it was

[20]Equinor was ranked as the largest public company in the Nordic region and placed on the Forbes 2000 list, based on Sales, Profits, Assets and Market Value (Forbes, 2018).

never selected in the bottom-ranked portfolio. Similarly, TGS & Kværner achieved an average Environmental score of 4.5 and 6.8 and was never selected in the bottom-ranked portfolio during the portfolio construction period (ratings available for TGS & Kvæner for 63 & 10 months).

Trading Strategies Built on Social Ratings

Table 13: Regression Results for Portfolio Created Using S- Ratings.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI Social ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - “long” the stocks placed in the top quartile & “short” the stocks placed in the bottom quartile. *Reverse* refers to our “reverse” trading strategy, which is to “long” bottom-rated stocks and “short” top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	0.0660	0.0842	-0.0294	-0.0444					0.000185	0.0181
	(0.0806)	(0.0628)	(0.0555)	(0.0489)					(0.00256)	
Reverse1	-0.0531	-0.0840	0.0333	0.0631					-0.00410	0.0263
	(0.0815)	(0.0633)	(0.0552)	(0.0499)					(0.00255)	
Good1	0.180*	0.166*	-0.109	0.696***					0.00287	0.645
	(0.0845)	(0.0758)	(0.1000)	(0.0595)					(0.00284)	
Bad1	0.120	0.0817	-0.0777	0.750***					0.000720	0.689
	(0.0880)	(0.0765)	(0.0893)	(0.0537)					(0.00275)	
Main2					0.0954	0.630	-0.648	-0.298	-0.0621***	-0.00111
					(0.167)	(0.544)	(0.345)	(0.200)	(0.00914)	
Reverse2					0.369*	1.218*	-0.671	-0.176	-0.0674***	0.0372
					(0.172)	(0.539)	(0.388)	(0.205)	(0.00959)	
Good2					0.843***	0.991	-0.893*	-0.385	-0.0585***	0.143
					(0.184)	(0.541)	(0.391)	(0.241)	(0.00939)	
Bad2					0.980***	1.284*	-0.904*	-0.324	-0.0612***	0.180
					(0.185)	(0.539)	(0.407)	(0.223)	(0.00951)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

MSCI Social Rating: There are in total four underlying themes covered in the Environmental pillar, namely *Human Capital*, *Product Liability*, *Stakeholder Opposition*, and *Social Opportunities*. Within these themes, MSCI ESG analysts rank firms based on 15 key issues (e.g., Labor Management, Human Capital Development, Product Safety & Quality, Controversial Sourcing, and Access to Finance) (MSCI ESG Research, 2018a). Similar to Environmental scores, the Social ratings scores are constructed from firms’ *Risks/Opportunities Exposure* and *Risks/Opportunities*

Management scores.

Consumer products related to alcohol and gaming are by many considered as sinful by many individuals and social groups in the United States and many other countries due to their addictive properties and undesirable social consequences when consumed excessively Hong & Kacperczyk (2009). To avoid undesirable consequences of such products, the Norwegian government has gone to great lengths to monopolize gambling in recent years. Similarly, a new regulation was passed in Sweden in January 2019 demanding that gaming advertisement should be moderate. Moreover, according to the Swedish newspaper Expressen, the Swedish government is planning to ban advertisement related to “dangerous gaming” such as online casino services (Svensson, 2019).

We are therefore particularly interested in investigating which Social scores gaming companies received during our sample period. Interestingly, Betsson, a Swedish company which is also one of the largest companies within the European gaming industry, is never a part of the bottom-rated portfolio (average Social score of 7). Conversely, it is a part of the highest rated stock portfolio 100% of the months it is rated (54 months). Similarly, Evolution Gaming Group received an average score of 4.9 and is never part of the bottom-rated portfolio (32 months). Investigating further, we find that the ratings within the gaming industry are mixed. NetEnt, a supplier of digitally distributed gaming systems used by some of the world’s most successful online gaming operators, is placed in the bottom rated portfolio 70% of the 50 months it is rated.

Among the firms with a high Social rating, we find, for example, Novozymes; a world leader in biological solutions with technology to enable higher agricultural yields, low-temperature washing, renewable fuel, and more. During the sample period, it is placed in the highest rated stock portfolio 91% of the months where there is an available Social rating (141 months). Neste, a Finnish oil refining company, received an average Social rating of 8.7. From their website, we find that even though it is an oil refining company, it was selected as the 3rd most sustainable company in the world on the Global 100 list (*Neste*, n.d.). Neste was placed in the highest rated portfolio in the Social ranking 98% of the months where there was a rating available (144 months).

As shown in Table 13, we do not find any abnormal returns (significantly positive alphas) from the trading strategies built from MSCI Social ratings. Specifically, under the Norwegian factors model, the alphas are almost zero and non-significant under the *Main1* and *Reverse1* regressions. There are also no abnormal returns when trading the "good" and "bad" stocks separately. We note that the top-rated stocks carry significantly positive loadings on SMB and HML, suggesting that the stocks with high Social ratings (placed in the top quartile) might be relatively smaller in size and carrying higher book-to-market ratios. On the other hand, when exploring the European factors model, we find that all four portfolios underperform with negative alphas. We also note a negative adjusted R^2 under the *Main2* regression. We offer similar explanations to the negative alphas and the low/negative adjusted R^2 as our main regressions (using overall industry-adjusted ratings). However, we remain cautious when interpreting these alphas, given the low adjusted R^2 of the European factors regressions. Finally, we note that the SMB factors load positively and significantly in the *Reverse2* and *Bad2* regressions, and that the HML betas are significantly positive in the *Good2* and *Bad2* regressions, under the European model. Again, "small firm" effects and relatively larger book-to-market ratios might explain for these results.

Trading Strategies Built on Governance Ratings

MSCI Governance Ratings: There are two underlying themes covered in the Governance pillar score, namely *Corporate Governance* and *Corporate Behavior*. These two themes include nine key issues, including Board, Ownership, Pay, and Business Ethics, for example. MSCI ESG Research (2018a) states that Corporate Governance is always material, the theme is always weighted and analyzed for all companies. According to MSCI ESG Research (2018a), the Corporate Governance Score utilizes a 0-10 scale. Each company starts with a "perfect 10" score, from which scoring deductions are applied based on the assessment of the so-called *KeyMetrics* in Board, Pay, Ownership & Control, and Accounting. Afterward, the Corporate Governance Score is derived from the sum of points associated with the *KeyMetrics*. Finally, similar to Environmental and Social pillar ratings, the final Governance scores are results of combining *Exposure* and *Management* scores.

Svenska Handelsbanken, a large Nordic bank, received an average Governance

Table 14: Regression Results for Portfolio Created Using G- Ratings.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI Governance ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - "long" the stocks placed in the top quartile & "short" the stocks placed in the bottom quartile. *Reverse* refers to our "reverse" trading strategy, which is to "long" bottom-rated stocks and "short" top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	-0.0201	-0.0634	0.000284	-0.182*					0.000852	0.0463
	(0.102)	(0.0889)	(0.0875)	(0.0820)					(0.00344)	
Reverse1	0.0331	0.0636	0.00366	0.200*					-0.00477	0.0573
	(0.102)	(0.0903)	(0.0876)	(0.0817)					(0.00344)	
Good1	0.0759	0.0746	-0.0393	0.611***					0.00358	0.522
	(0.0882)	(0.0916)	(0.115)	(0.0641)					(0.00329)	
Bad1	0.102	0.138	-0.0376	0.802***					0.000765	0.676
	(0.0869)	(0.0838)	(0.103)	(0.0600)					(0.00305)	
Main2					0.0808	0.653	-0.898*	-0.227	-0.0626***	0.00509
					(0.184)	(0.547)	(0.364)	(0.227)	(0.00947)	
Reverse2					0.384*	1.196*	-0.422	-0.248	-0.0670***	0.0443
					(0.174)	(0.558)	(0.381)	(0.209)	(0.00964)	
Good2					0.857***	1.074*	-1.109**	-0.354	-0.0582***	0.136
					(0.195)	(0.546)	(0.417)	(0.251)	(0.00953)	
Bad2					1.008***	1.345*	-0.871*	-0.365	-0.0604***	0.197
					(0.182)	(0.554)	(0.418)	(0.218)	(0.00950)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

score of 4.9 Handelsbanken was selected into the bottom-ranked portfolio 51% of the months where there was a rating available (144 months). William Demant a leading Danish company that covers all areas of hearing healthcare received an average Governance score of 4.7 and was sorted into the bottom-ranked Governance portfolio 81% of the months there was a rating available for the firm (142 months). Selvaag Bolig, a real-estate developer in Norway, also received a low average Governance score of 4.7. Selvaag Bolig was selected into the bottom-ranked portfolio 78% of the months there was a rating available for the company.

Assessing the companies which received a higher Governance score, we find, for example, Borregaard. Borregaard owns and operates one of the world's most advanced and sustainable biorefineries *Borregaard* (n.d.). It received on average a Governance score of 8.2 and was selected into the best-rated stock portfolio 67% of the months which there was a rating available for the firm (52 months). Tomra, a Norwegian company with two main business areas - Collection Solutions & Sorting solutions - received on average a Governance score of 8.4 and was selected in the top Governance portfolio all the months which there was a rating available (41 months).

The results are almost similar to the ones based on Social ratings. We also do not find any significant abnormal returns (or losses), using the Norwegian factors to explain excess returns, as shown in Table 14. In the set of European factor regressions, all alphas are negative and significant, with similarly low adjusted R^2. Additionally, we note positively significant SMB loadings in the *Reverse2*, *Good2*, and *Bad2* regressions. On the other hand, HML load negatively and significantly for both top-rated and bottom-rated stocks when using European factors.

4.2.9 Robustness Tests

As the MSCI only covers the largest stocks in the region, we acknowledge that there might be a data selection problem. That is, any abnormal returns detected could be attributed to other reasons (such as size) than the ESG ratings alone. To address this problem, we re-run the tests for all stocks in our data set. The results presented in Table 15 show a significantly negative alpha of -.06 when regressed on the European factors, indicating an underperformance of this group of stocks relative to the market (even though the adjusted R-squared for this model is quite low). When using the Norwegian factors to predict returns, we did not find any significant abnormal returns for this portfolio. In both models, we find statistically significant market betas (both lower than 1, indicating the lower risk of the portfolio relative to the market indices).

Table 15: Regression Results for All Nordic Stocks Covered by MSCI ESG

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of a portfolio consisting of all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used. The portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	N	Adjusted R^2
All1	0.0819	0.0920	-0.0698	0.711***					0.00147	144	0.737
	(0.0644)	(0.0702)	(0.102)	(0.0417)					(0.00254)		
All2					0.948***	1.040	-0.985*	-0.370	-0.0601***	144	0.168
					(0.181)	(0.539)	(0.395)	(0.234)	(0.00941)		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These results are somewhat consistent with our previous findings. The nonsignificant and minor positive, or otherwise significantly negative alphas indicate several possibilities. The first possibility is in line with our null hypothesis, which suggests that there are no significant abnormal returns generated from a "sustainable investment strategy". Another possibility is a data selection issue as we have mentioned above, given the limited coverage of MSCI ESG Ratings data sets on the Nordic stocks. The third probable reason is the flaw in our regression model caused by a lack of Nordic factors data (which might help to explain the low adjusted R^2 in the European factors model. Finally, we are constrained by a relatively limited observation period (available ESG ratings data only span from 2007 to 2018).

Next, we present results for portfolios created using ESG weighted average ratings (rather than industry-adjusted average ratings) in Table 16. We also find negative and significant alphas associated with all four portfolios, under the European factors model. No alpha is detected when Norwegian factors are used. In another robustness test, we regress excess returns of portfolios constructed from Norwegian stocks only on the same pricing factors (Table 17). We find similar results to our previous tests, with negative alphas in the European factors model, and no significant alphas in the Norwegian factors model. Market betas are significantly positive for the top-rated and bottom-rated stocks portfolios, regardless of the set of factors. These again show that our portfolios perform quite consistently with the market benchmarks.

Finally, to allow for some information delay in the portfolio construction process - fund/portfolio managers might not be able to receive the ESG ratings from MSCI instantaneously when they are released at the beginning of the month, in the next robustness test, we build the portfolios based on the last available ESG rating, instead of the ratings at the beginning of the same month. For example, at the beginning of February 2007, we rank stocks and split stocks into quartiles based on their ESG ratings at the beginning of January 2007. The portfolios are then reshuffled each month using the same approach. We are then able to obtain the monthly return series of the trading strategy from February 2017 until the end of 2018. The results are presented in Table 18. Using lagged ESG industry-adjusted ratings, we do not detect any abnormal returns for our four portfolios, using Norwegian factors. Similar to the main regressions in Table 11, we find negative alphas for all four portfolios under the European factors model.

Table 16: Regression Results for Portfolio Created Using ESG weighted average Ratings.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI ESG weighted average ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - "long" the stocks placed in the top quartile & "short" the stocks placed in the bottom quartile. *Reverse* refers to our "reverse" trading strategy, which is to "long" bottom-rated stocks and "short" top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	-0.0139	-0.0459	-0.0520	-0.124					-0.00117	0.0237
	(0.0759)	(0.0660)	(0.0630)	(0.0659)					(0.00271)	
Reverse1	0.0269	0.0461	0.0560	0.143*					-0.00275	0.0349
	(0.0760)	(0.0670)	(0.0634)	(0.0651)					(0.00270)	
Good1	0.117	0.110	-0.0806	0.661***					0.00109	0.643
	(0.0771)	(0.0751)	(0.103)	(0.0594)					(0.00282)	
Bad1	0.137	0.156	-0.0265	0.794***					0.000295	0.643
	(0.0742)	(0.0819)	(0.0980)	(0.0533)					(0.00314)	
Main2					0.0875	0.557	-0.772*	-0.241	-0.0646***	0.000201
					(0.168)	(0.509)	(0.334)	(0.197)	(0.00887)	
Reverse2					0.377*	1.292*	-0.548	-0.234	-0.0650***	0.0423
					(0.182)	(0.576)	(0.396)	(0.209)	(0.00989)	
Good2					0.857***	0.980	-0.974*	-0.372	-0.0604***	0.146
					(0.182)	(0.535)	(0.390)	(0.237)	(0.00927)	
Bad2					1.002***	1.348*	-0.862*	-0.369	-0.0606***	0.188
					(0.186)	(0.570)	(0.414)	(0.218)	(0.00971)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Regression Results for Portfolio Created Using ESG Industry-Relative Ratings - Norwegian Stocks.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on the MSCI ESG industry-adjusted ratings, under the Carhart four-factor model. Portfolios are built using Norwegian stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - "long" the stocks placed in the top quartile & "short" the stocks placed in the bottom quartile. *Reverse* refers to our "reverse" trading strategy, which is to "long" bottom-rated stocks and "short" top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	0.120	0.0611	-0.121	-0.184					-0.00539	0.0169
	(0.233)	(0.148)	(0.142)	(0.200)					(0.00667)	
Reverse1	-0.107	-0.0609	0.125	0.202					0.00147	0.0208
	(0.234)	(0.149)	(0.142)	(0.202)					(0.00664)	
Good1	-0.0685	0.108	-0.0328	0.854***					-0.0000411	0.710
	(0.116)	(0.0693)	(0.0714)	(0.101)					(0.00317)	
Bad1	-0.182	0.0469	0.0905	1.047***					0.00339	0.608
	(0.158)	(0.119)	(0.123)	(0.144)					(0.00529)	
Main2					-0.147	0.810	-0.492	-0.433	-0.0676***	0.00215
					(0.258)	(0.656)	(0.443)	(0.267)	(0.0107)	
Reverse2					0.612**	1.038	-0.828	-0.0418	-0.0620***	0.0428
					(0.221)	(0.599)	(0.480)	(0.245)	(0.0105)	
Good2					1.013***	1.104*	-0.777*	-0.139	-0.0626***	0.165
					(0.208)	(0.561)	(0.374)	(0.226)	(0.00979)	
Bad2					1.393***	1.218*	-0.945*	0.0566	-0.0598***	0.236
					(0.212)	(0.579)	(0.475)	(0.235)	(0.0102)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Regression Results for Portfolio Created Using Lagged ESG industry-adjusted Ratings.

This table summarizes the empirical abnormal returns, factor loadings, and the adjusted R^2 of different trading strategies based on *lagged* MSCI ESG industry-adjusted ratings, under the Carhart four-factor model. Portfolios are built using all Nordic stocks covered by the MSCI ESG datasets. Both Norwegian and European factors are used in the regressions. *Main* refers to our main trading strategy - "long" the stocks placed in the top quartile & "short" the stocks placed in the bottom quartile. *Reverse* refers to our "reverse" trading strategy, which is to "long" bottom-rated stocks and "short" top-rated stocks. *Good* and *Bad* refers to a portfolio containing only top-rated stocks and bottom-rated stocks,respectively. The portfolios are re-balanced monthly, based on the ESG ratings available at the beginning of the month. All portfolios are weighted based on market values at the beginning of the month. The observation period spans from January 2007 to December 2018. Standard errors are heteroskedasticity-robust.

	smbNor	hmlNor	momNor	NorRMRf	EURMktRF	EURSMB	EURHML	EURMom	Alpha	Adjusted R^2
Main1	-0.0148	-0.00685	0.0111	-0.233***					-0.00155	0.139
	(0.0888)	(0.0746)	(0.0677)	(0.0648)					(0.00267)	
Reverse1	0.0275	0.00800	-0.00713	0.252***					-0.00235	0.153
	(0.0895)	(0.0757)	(0.0681)	(0.0657)					(0.00267)	
Good1	0.0880	0.0640	-0.0179	0.630***					0.00132	0.651
	(0.0717)	(0.0723)	(0.0822)	(0.0561)					(0.00246)	
Bad1	0.109	0.0715	-0.0270	0.872***					0.000915	0.726
	(0.0808)	(0.0814)	(0.102)	(0.0547)					(0.00296)	
Main2					-0.0326	0.796	-0.646*	-0.160	-0.0625***	0.0107
					(0.166)	(0.495)	(0.316)	(0.206)	(0.00860)	
Reverse2					0.498**	1.383*	-0.520	-0.246	-0.0622***	0.0737
					(0.178)	(0.541)	(0.384)	(0.199)	(0.00955)	
Good2					0.836***	1.146*	-0.926*	-0.259	-0.0580***	0.146
					(0.187)	(0.515)	(0.376)	(0.228)	(0.00902)	
Bad2					1.101***	1.440**	-0.863*	-0.302	-0.0579***	0.225
					(0.192)	(0.536)	(0.407)	(0.217)	(0.00951)	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.10 Limitations

ESG Ratings Data

As investors place an increasing focus on ESG, several interest groups have voiced concern regarding various biases in the ESG coverage. In a recent report by Doyle, T. M. (2018), the author finds that rating agencies follow an approach that results in different biases, where one of them is that larger companies in terms of market capitalization receive better ESG ratings. Further, the author questions whether this skewness is a result of two opposing arguments. That is, do large companies have a stronger ESG alignment or are they simply able to dedicate more resources to prepare non-financial disclosures? MSCI indirectly addresses this imbalance by stating that companies with higher valuation might be more financially flexible and therefore, able to invest more in ESG related issues that could result in higher ESG scores.

Besides, the report references an analysis conducted by CSRHub[21] which finds that ESG rating agencies frequently disagree when evaluation the same firm. Credit rating agencies such as Moody's and S&P's credit ratings have a strong positive correlation of 0.9. In contrast, when comparing MSCI's and Sustainalytics[22]' ESG ratings for companies in the S&P Global 1200 Index, CSRHub found only a weak correlation of (0.32). Given these findings, a potential direction in future research is to investigate whether there is any difference in alpha generation between portfolios built on ratings from different sources. The report points out a reason for the consistency (between Moody's and S&P) is the fact that credit agencies use standardized financial disclosures. On the other hand, inconsistency across ESG agencies (such as MSCI and Sustainalytics) can be "problematic for both investors and companies working to improve their performance". The authors mention that despite the un-

[21] CSRHub is a tool that provides access to corporate social responsibility and sustainability ratings and information on 18,020+ companies from 134 industries in 141 countries. The agency claims to be the "only company to aggregate ESG datasets from the following leading analysts: ASSET4 (Thomson Reuters), CDP (Carbon Disclosure Project), ISS - IW Financial, MSCI (ESG Intangible Value Assessment, ESG Impact Monitor, GovernanceMetrics, and Carbon Tracker), Trucost and Vigeo EIRIS" (CSRHub, n.d.).

[22] Sustainalytics is a company that rates the sustainability of listed companies based on their environmental, social, and corporate governance (ESG) performance. The firm is based in Amsterdam, the Netherlands (Hale, 2016).

derstandable concerns from investors when it comes to the lack of consistency and rigor in the ratings, many large institutions nevertheless still use the rating systems to screen for or exclude investments, and in building their ESG focused mutual fund and trading strategies.

Mooij (2017) find that the multitude of initiatives and the lack of convergence between ESG providers raises questions on whether the industry's costs outweigh the benefits. Mooij further finds evidence that the industry is maturing but concludes that reporting fatigue and a lack of convergence and poor quality and transparency have made the industry more vice than virtue in the adoption of Responsible Investment (RI). Similarly, Chatterji et al. (2015) document a surprising lack of agreement across social ratings from six well-established raters. The disagreement remains after adjusting explicitly for differences in the definition of CSR held by different raters. They, therefore, conclude that the ratings have low validity.

All in all, these findings suggest that the robustness of results could be further improved by incorporating different sources of ESG ratings into the portfolios construction process. It will also be interesting to study the extent to which ratings covering Nordic stocks correlate, and whether these consistencies (or lack of consistency) in ratings would lead to any difference in abnormal returns generation.

Asset Pricing Factors Selection

As highlighted in our analysis section, the lack of access to pan-Nordic factors might have led to weaker explanatory powers of the independent variables. A suggested direction for future research is, therefore, to regress excess returns from sustainable investment strategies on pan-Nordic factors, then compare the results to the ones with Norwegian and European factors for robustness testing.

Limited Coverage of MSCI on Nordic Stocks

At the time of our study, the MSCI ESG datasets only cover the MSCI Nordic IMI with 279 constituent stocks (accounting for the index covers approximately 99% of the free float-adjusted market capitalization in each Nordic country). There is a possibility that the results in our study are biased by a large-cap portfolio effect, as we have mentioned in the analysis section.

5 Conclusion

In line with the mixed empirical evidence reported in the Literature review, we find mixed evidence on the financial costs associated with sustainable investments. From our first hypothesis, we find mixed evidence on the potential loss of returns for portfolios subjecting to a sector-based exclusionary screening of "sin" stocks in the Nordics. Specifically, we investigate whether stocks belonging to the four "sinful" industries in the Nordic region generate excess returns, by including a "sin" stocks dummy variable (*SINDUM*) in a Fama & MacBeth (1973) stock returns regression model. For the overall Nordic market, we fail to detect statistically significant results that imply excess returns associated with "sin" stocks, or in other words, a financial penalty for sustainably screened portfolios. Further, we conduct robustness tests to test for financial costs for various sub-periods. Again, we find the same results and fail to detect any significant *SINDUM* throughout the sample period. Interestingly, we detect statistically and economically significant *SINDUM* for Sweden and Finland when we run Fama & MacBeth (1973) regressions for the respective countries in the Nordics. These findings suggest that "sinful" stocks yield excess returns relative to their comparables, after controlling for other well-known factors. Therefore, there are financial costs to the negative screening of "sin" stocks in Sweden and Finland. These results are similar to the findings by Hong & Kacperczyk (2009) in their classical "sin" stocks study. We also offer various explanations for the higher risk premium of "sin" stocks, referring to Hong & Kacperczyk (2009).

Our second research model was to investigate whether stocks with low ESG ratings generate the same risk-adjusted returns as stock with higher ratings. We construct various portfolios to test this hypothesis, including breaking down the ESG-factor to subsets such as E, S & G-portfolios. For the overall ESG-factor, we fail to find any significant results from our "Main" model using Norwegian factors, indicating that stocks with higher ESG ratings do not generate higher returns than of those stocks with lower ESG ratings. However, when we apply European factors, we detect significant and negative alphas for our four portfolios. Looking at the E, S, and G- subsets portfolios, we do not detect any statistically significant alphas using Norwegian Factors. We attribute these results to a potential "large-cap" effect of stocks covered in the MSCI ESG Ratings dataset. However, using the European factors for the subset portfolios, we detect both negative and positive statistically significant alphas, depending on the strategy of the portfolio. A finding worth mentioning is a significantly positive alpha of 0.62% generated by a portfolio of Nordic stocks containing the bottom-rated quartile in terms of Environmental ratings. This mixed evidence is in accordance with our findings from the Literature review, and further echoes the finding of Edmans (2011) indicating that certain screens might improve investment returns.

We propose a few possible directions for research in this area. First of all, future academics could revisit the Carhart four-factor model with pan-Nordic factors data, which at the time of our studies, is not available. Secondly, we are constrained by a relatively limited coverage of ESG ratings on Nordic stocks (only 279 constituent listings), leading to the potential "large-cap" bias in our results. Other studies can, therefore, explore more comprehensive data sets to isolate this size effect better, and also to compare results (alpha) generated from the uses of different ESG data sources. Finally, we can expect to benefit from a larger time span of data when testing the "sin" stocks regression models, as at the time of this study, we only cover about 20 years of monthly stocks data. It would be also practical and interesting to compare the "sin" stocks regression results between the Nordics and Europe.

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6 Appendices

6.1 Weighted Average ESG Scores Across Industries

Table 19: Weighted Average ESG Scores Across Industries

Industry	Mean	Median	Min	Max
Advertising	4.8	4.9	4.4	4.9
Aerospace & Defense	5.0	5.3	3.8	5.6
Air Freight & Logistics	5.8	6.1	5.2	6.2
Airlines	5.3	5.0	4.2	6.7
Apparel Retail	7.4	7.1	7.1	7.9
Asset Management	4.6	5.1	3.2	5.3
Asset Management & Custody Banks	4.6	4.5	2.7	6.9
Auto Components	5.4	5.3	3.9	8.4
Automobiles	3.9	3.7	2.3	5.9
Banks	4.9	5.0	3.3	8.5
Banks - Emerging Markets	3.8	3.8	3.8	3.8
Banks - Europe	5.8	5.8	3.2	8.3
Beverages	6.1	6.2	4.9	7.5
Beverages & Tobacco	5.0	4.7	4.0	6.3
Biotechnology	4.8	4.8	3.6	7.6
Broadcasting & Cable TV	6.8	5.6	5.5	9.0
Broadcasting, Cable & Satellite	6.1	6.0	4.8	7.7
Building Products	6.4	6.7	3.4	8.1
Casinos & Gaming	5.2	4.8	3.5	7.3
Commercial Services & Supplies	5.7	5.8	2.8	7.9
Commodity Chemicals	3.1	3.1	2.8	3.8
Communications Equipment	7.0	7.2	4.4	8.7
Construction & Engineering	5.6	5.5	2.6	8.7
Construction & Farm Machinery & Heavy Trucks	5.8	5.7	2.3	8.8
Construction Materials	7.5	7.5	7.4	7.8
Consumer Finance	4.1	4.1	2.7	6.0
Containers & Packaging	5.8	5.8	5.2	6.8
Diversified Chemicals	4.9	4.7	4.3	7.1
Diversified Consumer Services	5.4	5.5	4.9	6.0
Diversified Financials	5.7	5.7	3.4	7.6
Diversified Financials - Europe	5.0	5.2	3.2	5.9
Electric Utilities - International	7.1	7.3	4.8	8.1
Electrical Equipment	6.4	6.3	3.9	8.8
Electronic Equipment & Instruments	4.0	4.3	2.9	5.5

Table 19: Weighted Average ESG Scores Across Industries

Industry	**Mean**	**Median**	**Min**	**Max**
Electronic Equipment, Instruments & Components	4.7	4.6	2.9	7.5
Energy Equipment & Services	5.8	5.8	1.6	8.1
Food & Drug Retailing	6.5	6.5	5.5	7.5
Food Products	5.0	4.9	2.6	6.8
Health Care Equipment & Supplies	5.3	5.3	3.4	7.1
Health Care Providers & Services	5.4	5.2	3.8	8.0
Homebuilding	6.5	6.7	5.1	7.0
Hotels & Travel	6.0	6.2	4.4	8.2
Household & Personal Products	6.8	6.7	4.9	9.4
Household Durables	5.5	5.4	3.3	8.0
IT Consulting & Services	6.0	5.9	5.9	6.2
Industrial Conglomerates	5.9	6.1	4.7	6.5
Industrial Machinery	6.0	6.1	4.2	7.8
Insurance - Europe	5.9	5.7	4.8	7.3
Integrated Oil & Gas	6.4	6.8	2.5	9.0
Integrated Telecommunication Services	5.2	5.0	3.0	8.3
Investment Banking & Brokerage	4.3	4.3	3.5	5.2
Leisure Equipment & Products	4.8	4.1	4.1	5.9
Leisure Products	5.8	5.4	3.7	7.4
Life & Health Insurance	5.5	5.6	3.8	5.9
Marine Transport	5.5	5.6	3.4	8.2
Media	5.9	5.9	4.1	7.2
Metals & Mining	5.9	6.0	5.0	6.0
Metals and Mining - Non-Precious Metals	6.2	6.3	3.5	8.4
Multi-Line Insurance & Brokerage	4.7	4.7	3.4	6.0
Oil & Gas Exploration & Production	4.7	4.9	2.5	5.8
Oil & Gas Refining & Marketing	6.1	6.8	3.6	8.4
Oil & Gas Refining, Marketing, Transportation & Storage	5.8	5.5	4.5	8.3
Paper & Forest Products	6.5	6.4	4.5	9.3
Pharmaceuticals	4.9	4.7	2.4	8.1
Professional Services	5.2	5.4	3.7	6.6
Property & Casualty Insurance	5.2	5.2	3.7	6.3
Publishing	5.0	5.1	4.3	6.4
REITs	6.8	6.5	6.2	7.8
Real Estate Development & Diversified Activities	5.3	5.0	3.4	7.4
Real Estate Investment Trusts (REITs)	6.5	6.3	5.3	8.0
Real Estate Management & Development	6.7	6.8	4.3	8.4
Real Estate Management & Services	5.9	6.1	4.1	7.1

Table 19: Weighted Average ESG Scores Across Industries

Industry	**Mean**	**Median**	**Min**	**Max**
Retail - Consumer Discretionary	5.5	5.5	3.2	7.1
Retail - Europe	6.5	6.8	5.0	7.8
Retail - Food & Staples	5.5	5.5	3.5	7.3
Road & Rail Transport	4.5	4.5	2.9	6.1
Semiconductor Equipment & Products	6.4	5.9	5.4	7.5
Semiconductors & Semiconductor Equipment	5.2	5.0	3.6	6.3
Software & IT Services	6.5	7.9	4.0	7.9
Software & Services	4.5	4.5	2.9	6.2
Specialty Chemicals	5.6	5.3	2.9	8.3
Specialty Retail	7.7	7.4	6.9	8.3
Steel	5.6	5.4	4.1	8.0
Supranationals	6.5	6.2	6.2	6.9
Supranationals & Development Banks	6.9	6.9	6.8	7.1
Surface Transport	3.8	3.7	3.3	4.3
Technology Hardware, Storage & Peripherals	4.8	4.8	3.8	5.8
Telecommunications	5.2	5.8	4.0	6.1
Textiles, Apparel & Luxury Goods	5.4	5.4	4.2	6.2
Tobacco	3.7	3.8	1.5	4.9
Trading Companies & Distributors	5.3	5.4	4.1	7.7
Transportation Infrastructure	5.6	5.5	5.4	6.9
Utilities	5.6	5.9	2.2	7.5
Wireless Telecommunication Services	5.5	5.5	4.8	6.7
Total	5.5	5.4	1.5	9.4

6.2 Industry Overview By Year

	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Advertising	12	1	12	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0
Aerospace & Defense	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	12	0	12	0	12	0	24	0	68	0
Air Freight & Logistics	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	5	0
Airlines	12	1	12	1	5	1	0	0	0	0	0	0	0	0	11	0	24	1	24	1	40	1	45	1	173	1
Apparel Retail	0	0	0	0	0	0	5	1	12	2	12	1	0	0	0	0	0	0	0	0	0	0	0	0	29	0
Asset Management	0	0	9	1	12	1	12	2	20	3	13	2	12	1	3	0	0	0	0	0	0	0	0	0	81	0
Asset Management & Custody Banks	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	1	25	1	43	1	49	1	108	2	256	1
Auto Components	21	2	28	3	24	3	24	3	19	3	24	3	22	2	35	1	54	2	50	1	67	2	77	1	445	2
Automobiles	0	0	0	0	0	0	0	0	0	0	0	0	8	1	12	0	12	0	12	0	18	0	16	0	78	0
Banks	0	0	0	0	0	0	0	0	0	0	0	0	242	19	444	17	493	14	524	14	547	13	574	11	2824	11
Banks - Emerging Markets	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0
Banks - Europe	89	8	84	8	77	8	84	11	84	11	84	10	0	0	0	0	0	0	0	0	0	0	0	0	502	2
Beverages	0	0	0	0	0	0	7	1	12	2	12	1	21	2	36	1	36	1	36	1	36	1	36	1	232	1
Beverages & Tobacco	24	2	24	2	32	3	25	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	105	0
Biotechnology	12	1	12	1	4	0	0	0	0	0	0	0	7	1	54	2	90	3	84	2	93	2	180	3	536	2
Broadcasting & Cable TV	12	1	12	1	12	1	12	2	6	1	12	1	16	1	6	0	0	0	0	0	0	0	0	0	88	0
Broadcasting, Cable & Satellite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	24	1	26	1	21	0	12	0	94	0
Building Products	22	2	20	2	12	1	12	2	12	2	12	1	18	1	44	2	82	2	84	2	90	2	140	3	548	2
Casinos & Gaming	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	12	0	20	1	30	1	60	1	129	0
Commercial Services & Supplies	46	4	42	4	36	4	18	2	9	1	12	1	14	1	52	2	96	3	107	3	126	3	138	3	696	3
Commodity Chemicals	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	12	0	12	0	12	0	0	0	38	0
Communications Equipment	24	2	24	2	24	3	24	3	24	3	24	3	24	2	6	0	0	0	0	0	0	0	0	0	174	1
Construction & Engineering	24	2	16	1	12	1	12	2	12	2	12	1	38	3	102	4	124	3	139	4	141	3	162	3	794	3
Construction & Farm Machinery & Heavy Trucks	24	2	24	2	24	3	24	3	24	3	24	3	42	3	62	2	71	2	61	2	57	1	76	1	513	2
Construction Materials	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	12	0	12	0	31	0
Consumer Finance	7	1	12	1	0	0	0	0	0	0	0	0	0	0	0	0	3	0	28	1	70	2	81	2	201	1
Containers & Packaging	4	0	0	0	0	0	0	0	0	0	0	0	0	0	13	1	24	1	24	1	24	1	24	0	113	0
Diversified Chemicals	0	0	0	0	0	0	0	0	0	0	0	0	8	1	12	0	12	0	12	0	12	0	12	0	68	0

	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Diversified Consumer Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	24	0	32	0
Diversified Financials	2	0	12	1	5	1	0	0	0	0	33	4	40	3	69	3	90	3	98	3	99	2	109	2	557	2
Diversified Financials - Europe	53	5	9	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62	0
Electric Utilities - International	11	1	12	1	12	1	12	2	12	2	17	2	1	0	0	0	0	0	0	0	0	0	0	0	77	0
Electrical Equipment	12	1	12	1	12	1	12	2	12	2	12	1	9	1	13	1	24	1	30	1	28	1	92	2	268	1
Electronic Equipment & Instruments	0	0	0	0	0	0	0	0	0	0	8	1	23	2	6	0	0	0	0	0	0	0	0	0	37	0
Electronic Equipment, Instruments & Components	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	1	42	1	54	1	52	1	108	2	276	1
Energy Equipment & Services	22	2	12	1	12	1	7	1	0	0	12	1	35	3	83	3	110	3	95	2	81	2	74	1	543	2
Food & Drug Retailing	22	2	12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0
Food Products	24	2	18	2	11	1	0	0	0	0	1	0	28	2	85	3	157	4	164	4	159	4	168	3	815	3
Health Care Equipment & Supplies	48	4	48	4	48	5	40	5	36	5	41	5	51	4	66	3	73	2	100	3	118	3	187	3	856	3
Health Care Providers & Services	12	1	2	0	0	0	0	0	0	0	0	0	0	0	2	0	16	0	34	1	54	1	72	1	192	1
Homebuilding	1	0	12	1	6	1	0	0	0	0	0	0	3	0	12	0	12	0	14	0	2	0	0	0	62	0
Hotels & Travel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	12	0	23	1	36	1	47	1	120	0
Household & Personal Products	0	0	0	0	0	0	0	0	0	0	0	0	18	1	24	1	24	1	24	1	22	1	24	0	136	1
Household Durables	12	1	13	1	24	3	24	3	24	3	24	3	24	2	28	1	56	2	60	2	60	1	48	1	397	1
IT Consulting & Services	21	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0
Industrial Conglomerates	0	0	0	0	0	0	0	0	4	1	12	1	3	0	8	0	12	0	12	0	20	0	16	0	87	0
Industrial Machinery	96	8	96	9	84	9	72	9	84	11	84	10	90	7	131	5	192	5	200	5	211	5	234	4	1574	6
Insurance - Europe	36	3	12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0
Integrated Oil & Gas	24	2	24	2	18	2	12	2	12	2	12	1	16	1	24	1	28	1	24	1	17	0	18	0	229	1
Integrated Telecommunication Services	25	2	60	5	50	5	48	6	48	7	60	7	49	4	48	2	77	2	75	2	86	2	95	2	721	3
Investment Banking & Brokerage	5	0	12	1	12	1	1	0	0	0	0	0	0	0	15	1	24	1	29	1	14	0	19	0	131	0
Leisure Equipment & Products	12	1	12	1	4	0	0	0	0	0	0	0	3	0	3	0	0	0	0	0	0	0	0	0	34	0
Leisure Products	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	13	0	24	1	24	1	45	1	115	0
Life & Health Insurance	0	0	0	0	0	0	0	0	0	0	0	0	12	1	57	2	61	2	72	2	62	1	48	1	312	1
Marine Transport	10	1	24	2	14	2	12	2	12	2	12	1	14	1	45	2	54	2	57	1	60	1	68	1	382	1
Media	0	0	0	0	0	0	0	0	0	0	0	0	13	1	29	1	24	1	24	1	24	1	26	0	140	1

	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Metals & Mining	21	2	17	2	12	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0
Metals and Mining - Non-Precious Metals	0	0	7	1	24	3	36	5	36	5	30	4	31	2	36	1	37	1	40	1	41	1	48	1	366	1
Multi-Line Insurance & Brokerage	0	0	24	2	34	4	12	2	12	2	23	3	42	3	77	3	88	2	127	3	156	4	154	3	749	3
Oil & Gas Exploration & Production	12	1	12	1	12	1	8	1	0	0	7	1	12	1	32	1	48	1	48	1	48	1	36	1	275	1
Oil & Gas Refining & Marketing	12	1	12	1	12	1	12	2	12	2	12	1	16	1	29	1	36	1	36	1	3	0	0	0	192	1
Oil & Gas Refining, Marketing, Transportation & Storage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	1	36	1	79	0
Paper & Forest Products	72	6	72	7	72	8	45	6	30	4	41	5	36	3	45	2	47	1	48	1	55	1	72	1	635	2
Pharmaceuticals	36	3	36	3	12	1	22	3	36	5	27	3	42	3	65	3	80	2	86	2	85	2	120	2	647	2
Professional Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	12	0	12	0	16	0	60	1	110	0
Property & Casualty Insurance	0	0	8	1	12	1	12	2	12	2	12	1	18	1	31	1	35	1	31	1	36	1	36	1	243	1
Publishing	19	2	24	2	12	1	12	2	12	2	12	1	0	0	0	0	0	0	0	0	0	0	0	0	91	0
REITs	0	0	0	0	0	0	0	0	0	0	0	0	6	0	6	0	0	0	0	0	0	0	0	0	12	0
Real Estate Development & Diversified Activities	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	1	106	2	161	1
Real Estate Investment Trusts (REITs)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	1	24	1	24	1	2	0	0	0	68	0
Real Estate Management & Development	24	2	24	2	14	2	0	0	0	0	0	0	6	0	72	3	177	5	207	5	19	0	0	0	543	2
Real Estate Management & Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	220	5	355	7	575	2
Retail - Consumer Discretionary	0	0	0	0	0	0	0	0	0	0	0	0	18	1	58	2	125	3	129	3	146	3	186	3	662	2
Retail - Europe	0	0	12	1	24	3	13	2	12	2	12	1	0	0	0	0	0	0	0	0	0	0	0	0	73	0
Retail - Food & Staples	0	0	0	0	0	0	0	0	0	0	0	0	14	1	30	1	39	1	47	1	48	1	48	1	226	1
Road & Rail Transport	5	0	12	1	12	1	12	2	12	2	12	1	12	1	12	0	12	0	16	0	34	1	19	0	170	1
Semiconductor Equipment & Products	14	1	24	2	24	3	15	2	12	2	12	1	9	1	0	0	0	0	0	0	0	0	0	0	110	0
Semiconductors & Semiconductor Equipment	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	31	1	23	1	24	1	24	0	108	0
Software & IT Services	3	0	12	1	4	0	0	0	0	0	0	0	8	1	6	0	0	0	0	0	0	0	0	0	33	0
Software & Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	2	109	3	89	2	126	3	254	5	618	2
Specialty Chemicals	24	2	24	2	24	3	24	3	20	3	24	3	23	2	65	3	77	2	62	2	72	2	80	1	519	2
Specialty Retail	12	1	12	1	12	1	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0

	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Steel	24	2	14	1	12	1	34	4	33	5	36	4	24	2	19	1	36	1	30	1	35	1	34	1	331	1
Supranationals	0	0	0	0	0	0	0	0	0	0	4	0	11	1	3	0	0	0	0	0	0	0	0	0	18	0
Supranationals & Development Banks	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	10	0	10	0	23	1	12	0	64	0
Surface Transport	27	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0
Technology Hardware, Storage & Peripherals	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	1	36	1	44	1	56	1	84	2	240	1
Telecommunications	35	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0
Textiles, Apparel & Luxury Goods	0	0	0	0	0	0	0	0	3	0	12	1	8	1	16	1	36	1	36	1	36	1	45	1	192	1
Tobacco	0	0	0	0	0	0	4	1	12	2	12	1	12	1	12	0	12	0	14	0	24	1	24	0	126	0
Trading Companies & Distributors	4	0	12	1	3	0	0	0	0	0	0	0	0	0	14	1	60	2	60	2	83	2	138	3	374	1
Transportation Infrastructure	6	1	12	1	12	1	6	1	0	0	0	0	0	0	0	0	0	0	1	0	6	0	0	0	43	0
Utilities	0	0	0	0	0	0	0	0	0	0	0	0	39	3	67	3	92	3	120	3	106	2	96	2	520	2
Wireless Telecommunication Services	0	0	0	0	0	0	0	0	0	0	0	0	11	1	12	0	12	0	12	0	12	0	12	0	71	0
Total	1131	100	1106	100	933	100	774	100	732	100	857	100	1303	100	2540	100	3578	100	3870	100	4304	100	5383	100	26511	100