Comply or Die: A Study of ESG Factor Returns and Volatility in the Nordic Countries from 2016 to 2022

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ABSTRACT

Using corporate environmental, social and governance (ESG) reporting data from 611 publicly traded firms in the Swedish House of Finance's Nordic Compass database, we estimate stock return and volatility exposures to an ESG factor during the period 2016-2022 in the Nordics. Using a Fama-Macbeth methodology, we find that during this time in the Nordic Countries exposure to an ESG factor is compensated with a risk premium and a volatility reduction in a Fama French 4 Factor model. However, we find that the premium of this factor decreases during periods of high market volatility, which may be an explanation as to why the literature provides mixed results as to the existence of such a factor. Our results indicate that the return of an ESG factor might be improved by increasing exposure during periods of low volatility and decreasing exposure during periods of higher volatility.

Keywords: ESG Factor, Nordic Compass, Fama-Macbeth, Volatility Management

JEL Classification: G11, G12, G15, G39

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I – Introduction

Environmental, Social, and Governance (ESG) factors represent a company's performance on non-financial metrics such as the environment, social responsibility, and corporate governance. ESG factors have gained an increasing interest in the finance industry due to their potential impact on a company's financial performance and risk profiles. This thesis aims to investigate the relationship between ESG factors, stock returns, and volatility in the Nordic countries during the period 2016-2022.

To furnish researchers and practitioners with insights into the investment potential of ESG factors in the Nordic region, this paper examines the relationship between ESG compliance, stock returns and volatility. Several studies have documented the relationship between ESG factors and financial performance. For example, research has shown for a prolonged period that companies with strong ESG performance are more likely to have lower costs of capital and better risk profiles (Graham & Harvey, 2001) ;(Eccles et al., 2014) ;(Derwall et al., 2011). Moreover, studies have shown for a long time that investors are increasingly considering ESG factors when making investment decisions (Edmans A., 2011). While some researchers have found evidence supporting the existence of a positive relationship between ESG factors and financial performance, others have not found any such relationship (Cornell & Damodaran, 2020). One possible explanation for these mixed findings is that the relationship between ESG factors and financial performance is not constant over time and may vary with market conditions (Bauer et al., 2005).

To analyze and explore these discrepancies, our paper seeks to answer the following questions: *Does compliance with ESG and exposure to an ESG factor impact stock returns and volatility in the Nordic countries? Does this relationship vary over time and with the movements of the wider market? Can this information be applied dynamically to improve portfolio returns?*

We answer these questions by creating ESG ratings following standard industry methodology but using ESG compliance data from the Swedish House of Finance's (SHoF's) Nordic Compass database. These ratings will then in turn be used to conduct a portfolio analysis on ESG sorted portfolios and to conduct a modified Fama Macbeth regression (in accordance with Fama and Macbeth, 1973) on an ESG factor in a Fama French four factor model. Conducting these analyses, we find that ESG exposure is compensated with a statistically significant risk premium and a volatility reduction throughout the period. We find that the effect is more persistent with volatility than it is for returns, but that both effects vary during extreme market conditions.

Finally, a question arises as to how investors can use this information. Assuming ESG factor exposure can reduce volatility and provide a new risk premium, and that they do so best during periods of low market volatility, then a strategy of volatility management is likely to be particularly effective on this factor. Applying Moreira and Muir's (2017) volatility management strategy, we find that a strategy of increasing exposure during periods low volatility and decreasing during periods of high volatility could reliably increase the returns of the ESG factor during the period.

Our novel contributions to the body of literature are threefold. First, we use raw ESG compliance data curated by the Swedish House of Finance (SHoF) to generate proprietary ratings, as opposed to standardized ratings. Secondly, we provide the latest evidence of the performance of ESG as an investment strategy and increased firm compliance to ESG requirements up to the end of last year, in the Nordic countries. Thirdly, we investigate the possibility of improving ESG investing outcomes with a volatility management strategy. Our study suggests that ESG factors may be a useful tool for managing portfolio risk, and that investors may be able to achieve higher returns during periods of low market volatility by investing in high-ESG companies.

II – Literature Review

Environmental, Social, and Governance (ESG) investing has gained increasing attention in recent years as investors seek to align their financial goals with their values. Alessandrini & Jondeau (2020) explore optimal strategies for ESG portfolios, finding that these portfolios can outperform conventional portfolios in terms of risk-adjusted returns. Similarly, Lioui & Tarelli (2022) find evidence of an ESG factor that contributes to risk-adjusted returns. However, other studies have found mixed results when analyzing the impact of ESG on investment performance.

One factor that may impact the efficacy of ESG investing is the lack of standardized ESG ratings. The Stanford Graduate School of Business (Larcker, Pomorski et al 2022) notes that ESG ratings are a "compass without direction," as there is no standardization in how companies are rated. This lack of standardization can make it difficult for investors to compare ESG performance across companies and sectors. Furthermore, the paper expounds on the negative implications caused by the divergence of ESG ratings, including the potential to confuse investment decisions by giving unreliable information about the ESG quality of firms and reducing the incentive of companies to improve their ESG performance by sending unreliable signals about how their ESG initiatives are assessed by third-party observers.

Further studies suggest that while ESG information is material to investment performance, which information is material probably varies systematically among countries (e.g., a country where water pollution is a serious issue versus a country where corruption is a more serious issue), industries (e.g., an industry affected dramatically by climate change versus an industry affected by violations of human rights in the supply chain), and even company strategies (e.g. companies that follow differentiation versus those that follow a low-price strategy) (Amal-Zadeh A., Serafeim G. 2018)

Another challenge for ESG investing is the potential trade-off between impact and financial performance. Berk & Van Binsbergen (2021) find that impact investing, which seeks to achieve a positive social or environmental outcome in addition to financial returns, can result in lower financial returns compared to traditional investing. This finding is consistent with the "exit vs. voice" framework presented by Broccardo et al. (2020), which argues that boycotting companies or divesting from industries with poor ESG performance may have limited impact on the behavior of those companies.

Recent geopolitical and macroeconomic factors have called the accuracy of ESG classifications into question. Prior to Russia's invasion of Ukraine, many investors considered defense companies as "non-ESG." Afterward, many did a hasty U-turn, rewriting their investment policies to redefine defense as ESG (Edmans, 2023). Edmans (2023) concludes that ESG is both extremely important and nothing special. It is extremely important since it affects a company's long-term shareholder value but should not be put on a pedestal compared to other intangible assets that affect both financial and social value, such as management quality, corporate culture, and innovative capability.

Pedersen et al. (2021) find that ESG screening can lead investors who maximize their Sharpe ratio to choose a portfolio with lower ESG scores than those chosen by unconstrained investors who accept investments in low-ESG assets. This provides interesting insights into ESG portfolio construction and

’Screening’ as an effective technique. The paper additionally finds that the authors’ proxy for G offers a better ESG-Sharpe ratio tradeoff as compared to their E & S proxies, perhaps because good G predicts strong future fundamentals, while attracting modest investor demand, leading to relatively cheap valuations and positive returns. With those insights, Pedersen et al (2021) were able to construct an ESG efficient frontier. The idea being that a portfolio’s average Sharpe ratio can be optimized for a desired average ESG score, but that at a certain point increasing the score comes at the expense of the Sharpe ratio. We will compare part of our results to Pedersen et al’s (2021) ESG-efficient frontier later in this paper.

Bolton & Kacperczyk (2021) additionally find that a carbon premium cannot be explained through a sin-stock divestment effect, suggesting that investors are pricing in carbon risk. Divestment takes place in a coarse way in a few industries such as oil and gas, utilities, and automobiles, and is entirely based on scope 1 emission intensity screens. Notably, they find no carbon premium associated with emission intensity. However, the authors find a robust, persistent, and significant carbon premium at the firm level for all three categories of emission levels and growth rates. This finding contradicts the conclusion drawn by (Blitz & Fabozzi, 2017), who theorize that abnormally high raw returns of sin stocks can be fully explained by recently introduced asset pricing factors—in particular, the two new quality factors of Fama and French, profitability, and investment.

Besides returns, there is also a body of research about the volatility properties of ESG. If ESG compliance signals seriousness on the part of companies, then it would stand to reason that these more compliant firms should exhibit lower volatility and even safe-haven properties. Several studies have analyzed the volatility of ESG stocks during the Covid-19 crisis to test this. In China, (Zhou & Zhou, 2020) analyzed the volatility of ESG leaders and laggards within 5-, 10- and 30-day windows before and after the first lockdown of Wuhan in January 2020. Those researchers found that the ESG leaders experienced lower volatility than the laggards, and that this effect dissipated at wider windows.

In the west the evidence is less clear. Rubbaniy et al. (2022) conducted a wavelet coherence analysis on various market fear indexes and the returns of ESG indexes during a 62-day period of time during the COVID crisis. Results varied depending on what fear index was used. Using covid-specific fear indexes, such as the global covid-19 fear index (GFI), ESG seemed to exhibit safe-haven properties. Using a more common index, the CBOE’s VIX Volatility Index, the opposite was established. Perhaps this goes to show that the pandemic was anything but a “normal” crisis, but it leaves readers of Rubbaniy et al. (2022) unsure whether these ESG safe-haven properties exist. Closer to home, Albarbari and Rosenberger (2022) in a master’s Thesis at the Stockholm School of Economics investigated ESG effects during the covid crisis through the lens of fund flows. They found that sustainable funds in the European Union outperform and have greater inflows in normal conditions, but during a crisis, capital leaves these funds.

Seeing how evidence from China (Zhou and Zhou 2020), the United States (Rubbaniy et al 2022), and Europe (Albarbari and Rosenberger 2022) does not tell the exact same story about ESG and volatility, it behooves us not only to look at ESG factor returns in our study, but also volatilities, and how any effects may or may not vary over time. Outside of the Covid crisis specifically, the literature seems to be more uniform. Dunn et al. (2017), Melas (2016) and Chan et al. (2020) for example all found that ESG correlates to lower volatility, and that the minimum-volatility factor correlates with ESG. We have not found any papers contradicting that. Therefore, in this study we expect higher ESG and exposure to the ESG factor to result in lower volatility in general, but whether it has "safe-haven” properties is less clear.

Regarding the existence of investment factors in general, the Fama French 3 Factor model (FF3) is well known. Fama and French in their famous 1993 (Fama & French, 1993) paper discovered that besides market beta, stocks are compensated with risk premia for exposure to the size and value factors. In other words, firms can also be compensated with risk premia for being of a smaller size and having a higher book to market ratio. Since then, researchers have looked for other factors which are compensated with risk returns, such as momentum and the previously mentioned quality factors.

A test of factors which has been commonly used since then is the Fama Macbeth regression, derived from a methodology developed by Eugene Fama and James Macbeth in their 1973 paper (Fama & Macbeth, 1973). Using a Fama Macbeth (1973) methodology, we will evaluate the existence of an ESG factor in the Nordics in an FF3 + 1 model. One of the first applications of Fama Macbeth methodology to an ESG factor we could find was by (Halbritter & Dorfleitner, 2015). Halbritter and Dorfleitner (2015) had mixed results when applying a Fama Macbeth methodology, with significance for an ESG factor created using ratings from Morningstar's Asset4 database but no significance for factors created from Bloomberg's or KLD's ESG ratings. Halbritter and Dorfleitner (2015) seemed to confirm that there is a problem of inconsistent ratings standards.

More recently, Lioui and Tarelli's (2022) applied a methodology partly inspired by Fama Macbeth and found that an ESG factor was significant across all ratings providers, though with different explanatory power. We will draw from Lioui and Tarelli (2022) as part of our methodology. Others have also tried to apply Fama Macbeth methodology to test the ESG factor, with different results. To name an example, (Naffa & Fain, 2022) do not find a significant factor, though those researchers ran their analysis across 48 countries. (Sagbakken & Zhang, 2022) meanwhile failed to find a "sin factor" in Europe.

Due to these conflicting theories on the efficacies of adopting ESG strategies, we also reference (Moreira & Muir, 2017) as a main inspiration for this paper. (Moreira & Muir, 2017) argue that volatility-managed portfolios can outperform traditional long-only portfolios. To construct such portfolios, they propose a simple algorithm that considers the expected volatility of each asset and rebalances the portfolio accordingly. Specifically, at the beginning of each period, the investor selects the set of assets with the highest Sharpe ratio, where the Sharpe ratio is defined as the excess return over the volatility of each asset. The investor then weights these assets by their inverse volatility and holds them until the next rebalancing period. The results of the paper suggest that the volatility-managed approach is a promising avenue for ESG investors seeking to optimize their portfolios.

III - Methodology

III.1 Method Summary

We detail our methodology below but for the benefit of the reader we provide a summary as follows:

Raw ESG ratings will be computed for individual firms using data from Nordic Compass, which will be used to generate size-industry controlled ESG-Z scores, which in turn will be used to create an ESG factor. The ESG factor and the ESG scores will be used for five empirical tests.

For the first two tests, stocks will be sorted into 10 evenly sized portfolios according to their ESG-Z scores. Monthly returns and volatilities will be calculated and plotted for these ten portfolios. The first test evaluates if the differences in volatility and returns between the top and bottom three ESG decile portfolios vary according to the movement of the market in general, as represented by the OMXS30 index.

1. *Portfolio Differences: For there to be a result the general market return and volatility should affect the differences in return and volatility between the top and bottom ESG portfolios. Expressed as a null hypothesis and an alternative hypothesis:*
    a. H_0: $\beta_{\sigma,\,mkt} = 0 \;\&\; \beta_{R,\,mkt} = 0$
    b. H_A: $\beta_{\sigma,\,mkt} \neq 0 \;\&\; or\; \beta_{R,\,mkt} \neq 0$

The second test attempts to apply a linear model. A regression will be run to determine if a linear model on ESG can be applied to explain the return and volatility of these deciles. The hypothesis we attempt to answer is as follows:

2. *ESG Decile portfolios linearity – For there to be a result the linear effect of ESGClass on portfolio volatility or return must be equal to 0. Where $\beta ESGClass_{n,t}$ represents the slope coefficient of ESGClass.*
    a. H_0: $\beta ESGClass_{n,t} \;=\; 0$
    b. H_A: $\beta ESGClass_{n,t} \;\neq\; 0$

The third test is the Fama Macbeth regression set, which in the first instance will determine if firms are compensated with an ESG return risk premium during the test-period. A regression will also be run to determine if exposure to the ESG factor has any effect on firms' volatility. The Fama Macbeth regression will be run yearly, as well as throughout the whole period, so any variations across years can be seen.

3. *Fama Macbeth Regressions – For there to be a result, the effect of ESG factor exposure betas on firm returns or volatilities must not be equal to zero, where $\overline{\beta}_{n,\,T,\,ESG}$ is the coefficient of the ESG factor in a regression model predicting firm returns and volatilities.*
    a. H_0: $\overline{\beta}_{n,\,T,\,ESG} \;=\; 0$
    b. H_A: $\overline{\beta}_{n,\,T,\,ESG} \;\neq\; 0$

The fourth test evaluates whether the strategy of volatility management, that is scaling factor exposure to factor volatility as outlined by Moreira and Muir (2017), works on the ESG factor and other factors in the Nordic context.

4. *Volatility Management: The effect of the volatility management strategy is in the intercept of the regression $f^{\sigma}_{t+1} = \alpha + \beta \cdot f_{t+1} + \varepsilon$. If the strategy is effective, alpha will be greater than 1 when this is applied to the ESG factor.*
    a. H_0: $\alpha = 0$
    b. H_A: $\alpha > 0$

The fifth and final test zooms in on the narrow windows around the Covid crisis and the Ukraine crisis, following the method of Zhou and Zhou (2020) to determine if ESG has any effect on firm volatility during the most acute phase of these major market events.

5. *Window Volatility: For ESG to have reduced volatility during these events, the variable ESGf, a dummy variable noting whether a firm belongs to the top or bottom ESG quarter, must be statistically significant and negative.*
    a. H_0: $\beta_{ESGf} = 0$
    b. H_A: $\beta_{ESGf} < 0$

We will now proceed to break down the methodology and the empirical tests mentioned above in detail.

III.2 Creating Raw ESG Ratings

To construct an ESG rating, we first convert binary variables into a 0-100 scale by assigning a score of 100 to positive outcomes and a score of 0 to negative outcomes. These binary variables are then reclassified as qualitative variables, e.gs., include Injury Disclosure, Health & Safety policy, etc. (Check Table 15, for a detailed list of the variables used).

For the quantitative variables, we create new variables using existing variables. We create these new variables for the purposes of comparability and consistency. For example, to measure the carbon intensity of a company, we divide GHG emissions by the company's sales in euros that year, in the following manner:

$$carbon\_intensity = GHG \text{ emissions}/Sales$$

Where $carbon\_intensity$ is the new, created variable and GHG emissions & $Sales$ are existing variables, provided to us in the Nordic Compass dataset. The reason some variables are calculated as intensities is to control for size when considering a variable like GHG emissions.

We then replicate this process for each quantitative variable for each company to generate yearly observations. We then normalize the quantitative data (e.g., include carbon intensity, CEO compensation, etc.) into a 0-100 scale using the formula:

$$NormalizedScore = \frac{(Xi - \min(X))}{\max(X) - \min(X)} \cdot 100$$

Where; $min(X)$ value and $max(X)$ values represent the minimum and maximum values in the data.

We then rescale quantitative variables depending on their classification. We employ a '*good*' and '*bad*' classification for variables. Let us reconsider the carbon intensity variable. A higher carbon intensity score indicates that the company is excessively polluting in proportion to its industry and sales. It should therefore be punished for this, by receiving a poor score on carbon emissions. Therefore, we rescale the score as:

$$carbon\_intensity\ score\ =\ 100 - NormalizedScore$$

Conversely, if the variable is good, we let the score remain as it is. For example, let us consider the variable $percent\_female\ employees\ =\ female\_employees/total\_employees$. A company with a higher percent of female employees will score better on the 'Social' criteria and should be rewarded with a higher score. The exact operation conducted on each variable in the Nordic Compass database is shown in Table 15 of the appendix.

After all quantitative and qualitative variables are assigned a 0-100 rating, we assign equal weights (½) to the qualitative and quantitative data types, to reflect their importance in the overall score of a particular type. Nordic Compass specifies which variables are considered E, S or G variables. We therefore compute a rating for each of these types for a given firm n in a year t in the following way:

$$E_{n,\,t} = \left(w \cdot QTS_{E,\,n,\,t}\right) + \left((1-w) \cdot QLS_{E,\,n,\,t}\right)$$

$$S_{n,\,t} = \left(w \cdot QTS_{S,\,n,\,t}\right) + \left((1-w) \cdot QLS_{S,\,n,\,t}\right)$$

$$G_{n,\,t} = \left(w \cdot QTS_{G,\,n,\,t}\right) + \left((1-w) \cdot QLS_{G,\,n,\,t}\right)$$

Where; w is the weight assigned to quantitative variables, (QTS) is the average 0-100 scale rating of all quantitative variables for a particular type, and (QLS) is the average 0-100 scale ratings of all qualitative variables of a given type.

At this point, to create the raw ESG scores we assign equal weights (1/3) to each of the three Environmental, Social and Governance pillars.

$$RawESG_{n\,,\,t}\ =\ \frac{1}{3}E_{n,\,t} + \frac{1}{3}S_{n,\,t} + \frac{1}{3}G_{n,\,t}$$

Our methodology is constructed by loosely referencing the MSCI ESG Ratings Methodology (ESG Research LLC, 2023). However, there are a few key differences between our methodology and the methodology employed by MSCI. The MSCI ESG ratings aim to measure a company's resilience to long-term, financially relevant ESG risks. Our methodology is more punitive as we seek to measure a company's adherence to ESG reporting and practices, via the data available to us in the Nordic Compass database. The MSCI assessment is industry relative, using a 7-point AAA – CCC scale. Finally, while our ratings and MSCI use the same ESG pillars, MSCI further identifies 10 ”themes” and 35” key-issues “. Some examples include the 'Toxic emissions and waste' key issue, under the 'Pollution and Waste' theme of the Environmental pillar. A limitation that we face in our ratings construction is the lower number of firms – the data provided by Nordic compass gives us an average of ~350 firms per year as compared to the 1200+ firms that MSCI covers. We are therefore unable to be as comprehensive in slicing our Dataset as MSCI. As shown in Table 11 in the appendix, keeping the original number of industries would have boosted the diversification parameter and reduced the ESG parameter of our raw ESG scores.

When creating an ESG ratings methodology, it is essential to acknowledge that it may not capture all aspects of a company's ESG performance. Firstly, some ESG factors are challenging to measure, and creating a standardized system that covers all ESG risks is challenging (Larcker et al. 2022.) Secondly, ESG data relies on voluntary disclosure by companies, and some firms may be hesitant to reveal information that could harm their reputation (Cornell & Damodaran, 2020). Furthermore, the quality of ESG data varies across different regions, industries, and companies, which makes it difficult to ensure uniformity in ratings. Lastly, ratings agencies can face conflicts of interest since they may have a financial stake in the companies they rate. Despite these limitations, the methodology we employ is a reasonable approach to creating ESG ratings. By using a 0-100 scale, creating comparable variables, and assigning equal weights to qualitative and quantitative data, the methodology ensures that each variable receives a fair rating, and the final ESG score provides a comprehensive overview of a company's ESG performance.

III.2 a Setting z-Scores

The raw ESG score by its nature is a summation of implemented reporting and ESG policies and outcomes such as carbon emissions and women's representation in the workplace. Reasonable expectations of raw ESG scores are therefore different for different industries and different size companies. We control this in the following way, taking inspiration from Lioui and Tarelli (2022). For industry, firms are sorted into five industry groups[1]. For size, firms are sorted into large or mid-sized cohorts based on their exchange classifications[2].

This results in ten size-industry cohorts in each year. Within each size-industry cohort a firm n's z-score (or industry and size-controlled score) is its placement on a standard normal distribution with a mean μ of 0 and standard deviation σ of 1, as Lioui and Tarelli (2022) do and is common practice.

Mathematically this means the ESG z-score for a firm n in size-industry-year cohort c is calculated as follows.

$$ESG_{z,\,n,\,c} = \frac{RawESG_n - \mu_c}{\sigma_c}$$

Where RawESG denotes the firm's raw ESG score from 0-100 in that year, μ_c denotes the mean raw ESG score of the firms in the cohort, and σ_c denotes the standard deviation of the firms in the cohort.

Besides the intuitive understanding that ESG ratings should be controlled for size and industry, as is common practice, we note that larger firms tend to have higher raw ESG scores (see table 9 in the appendix, for descriptive statistics of raw ESG scores across size).

ESG Z-scores are what will be used to create ESG deciles and the ESG factor throughout the study.

[1] Nordic Compass provides industry codes for firms, but there are 73 unique industry classifications in the dataset for the 611 firms in our universe of stocks. This would be too many classifications to provide any meaningful industry normalization. For this reason, we narrowed these to 5 industry groups.
[2] Stock exchanges in the Nordic countries (with the exception of Norway) list firms as large, mid or small by market cap. Nordic Compass provides these classifications in their ESG data, so we use these classifications to create size cohorts. There were only four "small" firms in the dataset, which we reclassified as mid.

III.3 Stock and Portfolio Returns and Volatility

In this study, the return factor of a stock *i* on a given trading day *t* is calculated as the closing price, plus any potential dividends, divided by the previous trading day's closing price as follows.

$$\left(1 + R_{i,\,t}\right) = \frac{P_{i,\,t} \ + Div_{i,\,t}}{P_{i,\,t-1}}$$

During a certain period, such as a year or month, the total return of a stock is calculated as the product of the firm's return factors in that period. This makes the implicit assumption that dividends are reinvested in the security and would be reinvested in any factor portfolios, as is common practice.

The return of a specific portfolio on a specific day, such as an ESG-decile or a Value-ESG grouping, is calculated as the average return of the firms in that cohort at that time. Then the portfolio's monthly return, when required, is calculated as the product of its return factors during that month.

Stock volatility is calculated as the standard deviation of daily returns during a specific calendar month, scaled to a monthly timeframe in the following manner.

$$\sigma_{n,\,T} \ = \ \sqrt{21} \cdot \sqrt{\frac{1}{N} \sum \left(R_{i,\,t} - \overline{R}_{i,\,T}\right)^2}$$

The reason for multiplication by $\sqrt{21}$ is to scale the daily volatility to a monthly volatility, and a month normally contains 21 trading days. When calculating a portfolio's volatility in each month, we determine the average of the volatilities of the stocks in that portfolio during the month.

When calculating a stock's average volatility throughout a year, as we will do for the Fama Macbeth regressions, we calculate the average of its monthly volatilities throughout the period and rescale annually.

The volatility of a factor is calculated in the same way as for a stock (I.e., the standard deviation of its daily returns during a calendar month). Factor volatilities are required for our volatility management strategy.

III.4 Size, Value and Market Factors

A regularly updated database of Fama French factor returns in the Nordic Countries is not available[3]. Since we our methodology requires that we add the created ESG factor to a Fama French 3 Factor model from 2016 to 2022, we decided to create size and value factors within our universe of Nordic stocks. To do this we follow the method of Aytug et al (2020).

Those researchers constructed Fama French 4 factor returns for the Swedish stock market from the years 1983-2019 on behalf of the Swedish House of Finance. The size and value factors are constructed on a 2x3 portfolio sort. Two size categories, big (top 20% of market cap) and small (bottom 80% of market cap) are

[3] The Swedish House of Finance has a database of Swedish Fama French factor returns in their Finbas database, but this data only lasts until 2019. For this reason we decided to create a size and value factor out of our universe of stocks.

created. Three value categories, value (top 30% book to market ratio), growth (bottom 30% book to market ratio) and neutral (the remainder) are also created.

Grouping	Composition
Small Growth (SG)	Below 80^{th} percentile of market cap - Below 30^{th} percentile of book to market ratio
Small Neutral (SN)	Below 80^{th} percentile of market cap - Between 30^{th} and 70^{th} book to market ratio percentiles
Small Value (SV)	Below 80^{th} percentile of market cap - Above 70^{th} percentile of book to market ratio
Big Growth (BG)	Above 80^{th} percentile of market cap - Below 30^{th} percentile of book to market ratio
Big Neutral (BN)	Above 80^{th} percentile of market cap - Between 30^{th} and 70^{th} book to market ratio percentiles
Big Value (BV)	Above 80^{th} percentile of market cap - Above 70^{th} percentile of book to market ratio

The return of the size factor (SMB) on any given day is the average return on the 3 small portfolios minus the average return of the 3 big portfolios, as follows.

$$SMB = \frac{SG + SN + SV}{3} - \frac{BG + BN + BV}{3}$$

Where SG refers to the return of the Small Growth portfolio, SN refers to the return of the Small Neutral portfolio, etc.

The return of the value factor (HML) is the average return of the 2 value portfolios minus the average return of the 2 growth portfolios, as follows.

$$HML = \frac{BV + SV}{2} - \frac{BG + SG}{2}$$

III.5 ESG Portfolios and Factors

Once ESG scores are created stocks can be sorted into percentiles based on those ratings. Since ESG data from Nordic Compass is updated annually, this can be done annually. For our first series of regressions regarding portfolio differences, we split our stocks into deciles, which results in roughly 30 to 45 firms per ESG decile. The reason for this portfolio analysis is to see if a gradual increase in ESG scores corresponds to effects on return and volatility such as those seen in Pedersen et al., 2021, or if they are more linear.

To create the ESG factor, however, we sort stocks into ESG-thirds. To create the ESG factors itself we then adopt a 2 x 3 sort of ESG and Value, taking inspiration from Lioui and Tarelli (2022) who also do a value sort.

Grouping	Composition
Top Growth (3G)	Above 66^{th} percentile of ESG Z-score - Below 30^{th} percentile of book to market ratio
Top Neutral (3N)	Above 66^{th} percentile of ESG Z-score - Between 30^{th} and 70^{th} book to market ratio percentiles
Top Value (3V)	Above 66^{th} percentile of ESG Z-score - Above 70^{th} percentile of book to market ratio
Bottom Growth (1G)	Below 33^{rd} percentile of ESG Z-score - Below 30^{th} percentile of book to market ratio
Bottom Neutral (1N)	Below 33^{rd} percentile of ESG Z-score - Between 30^{th} and 70^{th} book to market ratio percentiles
Bottom Value (1V)	Below 33^{rd} percentile of ESG Z-score - Above 70^{th} percentile of book to market ratio

The ESG factor's return on any given day is then finally calculated as the difference in the average return of the three top-ESG portfolios and the three bottom-ESG portfolios.

$$ESG = \frac{3G + 3N + 3V}{3} - \frac{1G + 1N + 1V}{3}$$

Where 3G corresponds to the average return of growth stocks in the top ESG-third, 1V corresponds to the average return of value stocks in the bottom ESG sixth, etc. The reason a value sort is undertaken instead of a size sort is that size is already considered in the construction of the ESG ratings themselves.

III.5 a. ESG Decile Portfolios

The first phase of our study seeks to determine whether high-ESG portfolios have lower volatilities and/or higher returns than low-ESG portfolios. We also seek to recreate the observation by Pedersen et al (2021) of an ESG efficient frontier, albeit from a different angle.

To do this we use the previously constructed ESG z-scores to create annual ESG-decile portfolios for the time-period 2016-2022. Each portfolio's monthly return and volatility is calculated. This leaves us with return volatility observations for 840 ESG-decile months. The worst 10% firms in each year end up in decile 1, the second worst in decile 2, etc. Since ESG scores are calculated annually, in accordance with the method we outlined so far, the composition of the decile portfolios changes substantially each year.

We will plot the average monthly outcomes of these decile portfolios, calculating their average monthly Sharpe ratios, returns and volatilities throughout the period. These outcome statistics will be presented in table 2 and plots will be analyzed in section VI, our interpretation of the empirical results.

III.5 b. Portfolio Differences over Time

We first wished to evaluate how the differences in the decile portfolios' volatilities and returns, if they exist, change depending on market conditions. Therefore, we run two ordinary least squares regressions of the following form.

$$\overline{\sigma}_{1,2,3,t} - \overline{\sigma}_{10,9,8,t} = \alpha + \beta \cdot \sigma_{Mkt,t} + \varepsilon_t$$

$$\overline{R}_{10,9,8,t} - \overline{R}_{1,2,3,t} = \alpha + \beta \cdot R_{Mkt,t} + \varepsilon_t$$

We determine the difference in the average return and volatility of the three best (10, 9, 8) and worst (1, 2, 3) ESG portfolios to see if it interacts with general market movements. In this case, we define the market as the Stockholm OMX 30 index.

$\overline{\sigma}_{1,2,3,t} - \overline{\sigma}_{10,9,8,t}$ denotes the difference in volatility between the groups in month t. $\sigma_{Mkt,t}$ denotes the volatility of daily returns of the OMX 30 index during month t.

$\overline{R}_{10,9,8,t} - \overline{R}_{1,2,3,t}$ denotes the difference in return between the groups in month t. $R_{Mkt,t}$ denotes the return of the OMX 30 index during month t.

The reason we elect to apply this to the top and bottom ESG-thirds is because the ESG factor itself, which we will investigate later is constructed using thirds. Therefore, this analysis can inform any variations across years we find with the ESG factor's risk premium and volatility effect in the Fama Macbeth regressions. The null hypothesis would therefore be that the general market volatility or return has no effect on its respective difference. The results of this regression are presented in Table 3.

III.5 c. ESG Decile Rank

After plotting out average monthly outcomes of the ESG decile-portfolios, we then conduct a time series analysis of their monthly excess returns and volatilities through the period. The purpose is to determine if the ranking (1-10) of the ESG deciles, which we denote as ESGClass below, predicts the excess return and volatilities of these portfolios in a linear fashion, when controlling for other characteristics of the portfolios. To do this we run two ordinary least squares regressions of the following form.

$$\sigma_{n,t} = \beta \cdot size_{n,t} + \beta \cdot value_{n,t} + \beta \cdot Beta_{n,t} + \beta \cdot ESGClass_{n,t} + \eta + \varepsilon_t$$

$$R_{n,t} - r_{f,t} = \beta \cdot \overline{\overline{\beta}}_{size,n,t} + \beta \cdot \overline{\overline{\beta}}_{value,n,t} + \beta \cdot \overline{\overline{\beta}}_{mkt,n,t} + \beta \cdot ESGClass_{n,t} + \eta + \varepsilon_t$$

$\sigma_{n,t}$ is the volatility of ESG-decile portfolios *n* during month *t. Size* is the average of the natural logarithm of market capitalization (in Euros) of the firms in ESG-decile-portfolio n at month t[4]. Value is the average book to market ratio of the firms in decile-portfolio n at month t. Beta is the average market beta of the stocks in portfolio n at month t. η denotes a monthly fixed effect. ε denotes the residual.

Meanwhile for the return regression $R_{n,t} - r_{f,t}$is the excess return above the risk-free rate of ESG-decile-portfolio n in month t. $\overline{\overline{\beta}}_{factor,n,t}$ denotes the average factor exposure beta (with the factors being size, value and the OMXS30 market index) of the firms in decile n at month t. All other variables in the return regression have the same meaning as in the volatility regression.

Besides our dependent variable and our controls, we have the decile itself, referred to here as ESGClass. We use the decile's numerical ranking as the variable for this, with decile 10 being the highest ESG decile and 1 the lowest.

Our hypothesis is that there will be statistically significant negative coefficients on volatility, since, as we discussed in the literature review, the effect of ESG on volatility seems to be clear. We do not have a set hypothesis for returns, but the existence of an ESG factor would be supported if the ESG-class variable had a statistically significant positive coefficient there. The results of these regressions are reflected in table 5.

III.6 Fama Macbeth Regressions

The next step after our two sets of baseline regressions is to run Fama Macbeth regressions. As a reminder, a Fama Macbeth regression evaluates the exposure of stocks to specific factors by running two sets of regressions. The first set of regressions estimates factor exposure betas for each asset during a time period. The second set of regressions then evaluates all asset returns for each of T time periods against the previously estimated betas to determine the risk premium for each factor in each period. We

[4] See appendix for details of how size, value and Beta are calculated here.

ran a modified version of that same method on an FF3 Plus 1 model. It is important that we explain these modifications, as they are quite substantial.

The first modification is that we will be calculating the factor betas of individual firms instead of portfolios, and the analysis will be done using firm data. Normally a Fama Macbeth analysis is done by calculating the factor betas of portfolios. The reason we opt for individual firms instead is because we are more interested in analyzing the outcomes of individual firms, since we create and map the ESG compliance of individual firms in our dataset. Implications for portfolio construction and asset management themselves are instead treated in the regressions on ESG decile portfolios, and the volatility management regressions (explained in the next section).

The second modification is that we will be calculating stock factor exposure betas annually, such that each firm will have one set of betas per year. Normally a Fama Macbeth regression only calculates one set of betas per asset or portfolio. The reason we calculate annual betas is because the ESG scores are calculated annually, due to the nature of Nordic Compass's data. We also believe that ESG compliance has drastically increased among firms throughout the period, which we will discuss in the interpretation of our results. If a large section of firms increases their ESG compliance, it would be reasonable to assume that their exposures to the ESG factor should change, and that the exact composition of the ESG factor should also change. Therefore, firm factor betas should be calculated annually even though it may be uncommon to do so.

The third modification is that we will proceed to break down factor risk premia results per year, as well as present them in aggregate. Normally a Fama Macbeth regression does not split risk premia results by time. The reason we do this is that we wish to see if and how factor exposure effects may have varied over time. This can in turn be compared to the ESG compliance/ratings data, which we do in the interpretation of our empirical results. Since ESG ratings themselves are inextricably linked to the ESG factor, factor risk premium variation can be compared to ratings variation. This is best done on an annual basis because the ESG ratings are calculated annually.

Finally, the fourth modification is that we also evaluate the effect of exposures on volatility, not just returns. Normally a Fama Macbeth regression does not take particular interest in volatility effects, mainly focusing on factor risk premia. However, since volatility is a subject of our analysis, and these results can be compared to the decile portfolios tests (more on those below), we would like to evaluate the effects of factor exposures on firm volatility throughout the period.

Thus, our regression occurs in two steps, with the first step being to estimate exposure betas for each stock and factor during each year. The return of stock n on day t is regressed as follows, to determine asset betas during specific years. This is done for all stocks in the dataset.

$$R_{n,t} = \alpha + \beta_{n,ESG} \cdot R_{ESG,t} + \beta_{n,Value} \cdot R_{Value,t} + \beta_{n,size} \cdot R_{size,t} + \beta_{n,mkt} \cdot R_{mkt,t} + \varepsilon_t$$

The result is one set of return betas, which we also call factor exposure betas, *for each stock during each year*. Then, we run the following regressions on a stock's annual excess returns and volatilities, using the estimated factor betas.

$$R_{n,T} - r_{f,T} = \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon_T$$

$$\sigma_{n,T} = \gamma + \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon$$

Where $R_{n,T} - r_{f,T}$ is stock n's total excess return (i.e., return net of the average risk-free rate) during year T, $\sigma_{n,T}$ is stock n's volatility in year T, γ is the volatility or return premium for exposure to the respective factor, and $\overline{\beta}$ is the return beta estimate of stock n on a specific factor during year T. For there to be a result, γ_{ESG} (the risk premium and volatility effect of ESG factor exposure) must be statistically significant.

We run two versions of this regression set, one for the entire period and another year by year. The purpose of the year-by-year regression is to see if the return and volatility premia vary in any way from year to year, which helps for comparison with results in table 3. The results of the whole-period regression are reported in table 6 a), the results of the year-by-year return regression are reported in table 6 b), and the results of the year-by-year volatility regression are reported in table 6 c).

III.7 Volatility Management of an ESG Factor

We investigate the possibility of applying volatility management as a strategy for the ESG factor. We follow the method of Moreira and Muir (2017). Those researchers originally proposed this strategy in the context of a Fama French 5 Factor Portfolio. The idea of a volatility management strategy is to decrease exposure to a portfolio or factor when its volatility is increasing and increase exposure when its volatility is decreasing. According to the strategy, volatility-managed portfolios are constructed by scaling the excess return by the inverse of its conditional variance. Each month the strategy increases or decreases risk exposure to the portfolio according to variation in variance, according to the formula below.

$$f_{t+1}^{\sigma} = \frac{c}{{\sigma_t}^2} \cdot f_{t+1}$$

where f_{t+1}^{σ} denotes the volatility managed excess return of a given factor during month t+1. f_{t+1} denotes the normal excess return of the factor during month t+1. ${\sigma_t}^2$ denotes the variance of the factor during month t.

c controls the average exposure of the strategy up until that point. In other worse, c is equal to the average variance of the factor until month t. Therefore, when the factor's variance in month t is higher than the historical average before month t, the volatility managed portfolio underweights the factor and likewise when the variance is lower than the historical average, it is overweighted.

The effectiveness of the strategy is investigated by running a time-series ordinary least squares regression of the volatility managed portfolio's excess return on the factor's standard excess return.

$$f_{t+1}^{\sigma} = \alpha + \beta \cdot f_{t+1} + \varepsilon$$

For the strategy to be deemed effective, the intercept α must be positive and statistically significant. We intend to test this strategy on the factors in our FF3 + 1 model. In other words, a regression of the strategy will be run for each factor respectively. We do this so the effect of volatility management on the ESG factor can be compared to the effect it has on other factors in the Nordic countries.

Our hypothesis is that the intercept for the ESG factor should be positive and statistically significant. This is because information in Europe, a closer market to Sweden, indicates that capital leaves high-ESG firms during crisis periods (Albarbari and Rosenberger, 2022). Therefore, it should be prudent to underweight the ESG factor during high volatility periods.

III.8 Crisis Volatility: Covid vs Ukraine

As discussed in our literature review, evidence regarding volatility during the Covid crisis was inconsistent between China, the United States and Europe. While we will evaluate volatility effects in general and, analyze yearly variation in the Fama Macbeth regressions, and compare to market effects in the portfolio differences regressions, as a final complement to this we would like to replicate a section of Zhou and Zhou's (2020) method, with some modifications.

As the reader will recall from the literature review, those researchers evaluated the effect of ESG on volatility within very narrow windows before and after the start of the Covid. We will replicate a part of their method, with the following regression:

$$WVOL_{n,\,t} = \beta \cdot ESGf_n + \beta \cdot Beta_n + \beta \cdot Lev_n + \beta \cdot Cash_n + \beta \cdot Logsales_n + \varepsilon_n$$

Where $WVOL_{n,t}$ refers to the standard deviation of firm n's daily stock returns in a t-day window, $ESGf_n$ is a dummy variable for whether a firm n is in the top ESG quartile (determined using our ESG Z-scores), $Beta_n$ is firm n's market beta, as calculated in previous regressions, Lev_n is firm n's liabilities to assets ratio, $Cash_n$ is firm n's cash to assets ratio, and $Logsales_n$ is the natural logarithm of firm n's annual sales in euros. This regression compares the top and bottom quartile of ESG firms, so the middle two quartiles are not observations in these regressions.

A specific date is set as the center date of the window, marking the beginning of the crisis period, with the window being t-days before and after the date. Zhou and Zhou (2020) set the date as the declaration of a lockdown in the city of Wuhan. The covid crisis started later in Europe. We set the center date as March 12th, 2020. We then evaluate volatility in a 5-day, 15-day and 30-day window (meaning three regressions). The reason to evaluate the effect across several windows is to see if any effect dissipates or strengthens as the window widens. With these regressions around the Covid crisis, we can compare the most acute crisis volatility results directly to Zhou and Zhou (2020) and see if there is any similarity between the Nordics and China in acute volatility. Since more time has elapsed since Zhou and Zhou's (2020) original study, we also run these regressions around the beginning of the Ukraine war, a major negative market event in Europe. The date for this is set as February 24th, 2022, the beginning of the Russian invasion of that country.

For there to be a result, the dummy variable $ESGf$ must have a statistically significant coefficient. If ESG possesses safe-haven properties, this coefficient should be negative.

IV – Data Description

As previously mentioned, we gather ESG data from the Nordic Compass database, offered by the Swedish House of Finance (SHoF)[5]. Nordic Compass compiles ESG data from company annual reports from 2014 to 2021. However, data is only compiled by SHoF's staff during the year after annual reports. For example, 2021's ESG data would only have been actionable during 2022. For this reason, we push all ESG data up

[5] SHoF's website provides more information on the database and its data collection process here: https://www.hhs.se/en/houseoffinance/data-center/nordic-compass-shofs-esg-database/

one year, such that ESG data compiled for 2021 is the data used for ESG sorts during calendar year 2022. This means that ESG data and ratings can be applied from 2015 to 2022.

However, there is only ESG data from 253 firms from 2014's annual reports in Nordic Compass. We prefer there to be at least 300 firms per year available. This way there are always at least 30 firms per ESG decile or and 100 per ESG third, enough to keep results of decile regressions and factor construction robust. 2014's ESG data applies to trading year 2015, so we will only be analyzing stock, portfolio and factor returns from calendar years 2016 to 2022 in this study.

Nordic Compass provides gvkey and ISIN identifiers for their firms, which we use to request stock price and balance sheet data from Compustat Global database, accessible through Wharton Research Data Services (WRDS). We gather daily stock price data from Compustat's global Security Daily database for the firms in Nordic Compass from 2016 to 2022, using both gvkey and ISIN identifiers to ensure that each firm only has one security on a given trading day (for example to prevent multiple share classes from having an effect), and to guarantee that the same firms are being analyzed as those specified in Nordic Compass.

We gather annual balance sheet data from Compustat's Global Fundamentals Annual database to calculate book to market ratios. The reason we apply annual data and not quarterly data is because our ESG ratings data is also annual. This way, for Value and ESG, which are used to create our ESG-factor, are done using the same data frequency.

Market Index data for the Stockholm OMXS30 index can be gathered from any public source. We decided to download this data from the Nasdaq Nordic website[6], since the firms in this index trade on Nasdaq Stockholm. As mentioned, we recognize that this is only the market index for Sweden, but since this is the most widely recognized market index for the Nordic countries, from the largest Nordic country, to which all other Nordic countries will be highly correlated, we find this acceptable.

We collect data on the Swedish risk-free rate from Statistics Sweden's Short- and Long-Term Interest Rates dataset[7]. We choose the interest rate on 3-month Treasury Discount Notes as the risk-free rate, scaling it to monthly timeframes when needed. Again, we recognize that using one country's government bonds for the risk-free rate of the entire Nordic market can present comparability issues. However, since all Nordic countries (save Iceland) have been applying zero interest rate policy until 2022, Sweden is the largest Nordic country, and Nordic and European monetary policies are highly correlated, we find this acceptable.

[6] Available here: https://www.nasdaqomxnordic.com/indexes/historical_prices?Instrument=SE0000337842

[7] This dataset can be found on Statistics Sweden's website. Statistics Sweden is the Swedish government agency responsible for managing statistics. They source this information in turn from the Riksbank: https://www.scb.se/en/finding-statistics/statistics-by-subject-area/other/general-statistics/sveriges-ekonomi/pong/tables-and-graphs/short-and-long-term-interest-rates-1989-/

V. Empirical Results

Descriptive statistics of ESG scores

Following the method which we outlined the first step is to calculate raw ESG scores and the ESG Z-scores. These scores will then in turn be used to allocate stocks to ESG decile portfolios and to create the value-ESG sorts which are used to create the ESG factor. Annual descriptive statistics for these ratings are shown below.

Table 1

		Raw ESG Score Statistics				ESG Z-Score Statistics			
year	Number of Firms	Mean	Std Dev	Min.	Max.	Mean	Std Dev	Min.	Max.
2015	252	53.57	15.34	14.53	79.08	0	0.99	-2.76	2.08
2016	365	51.55	16.12	15.69	80.48	0	0.99	-3.09	2.32
2017	411	48.05	15.56	0.98	73.64	0	0.99	-3.08	3.01
2018	475	45.28	15.65	7.80	72.00	0	0.99	-3.15	2.56
2019	426	45.34	14.46	12.67	70.70	0	0.99	-2.55	2.56
2020	473	48.78	12.90	17.61	72.28	0	0.99	-3.12	2.56
2021	489	52.43	12.79	13.86	72.37	0	0.99	-3.70	2.13
2022	440	54.49	12.71	13.68	78.87	0	0.99	-3.81	1.98

Table 1- Summary statistics of raw and z-score ESG ratings we calculated for the firms in the Nordic compass database, annually.

As can be seen, the mean raw rating decreases somewhat from 2015 to 2018, before it starts rising. The main reason for the initial decrease is that data from more firms with poorer compliance became available during these years. For example, the worst raw ESG rating ever occurred in 2017. We do not believe that a firm decided to comply with fewer ESG reporting requirements that year than it did before, such that the rating *became* 0.98. For this reason, the average raw ESG score does not tell a very interesting story for the first few years.

However, the standard deviation of raw ESG scores does. As the standard deviation decreased from 2015 to 2022, we can infer that the distribution of raw ESG ratings has become narrower. In the skewness and kurtosis statistics (available in Table 12 in the appendix) we can also see that the distribution became more negatively skewed as well. This implies that many firms are catching up in their compliance.

V.1 ESG Decile-Portfolio Outcomes

Table 2 below reports the average, maximum and minimum monthly outcomes of the ESG decile sorted portfolios from 2016 to 2022. These figures show that the top ESG decile has a lower average volatility and greater average return than the bottom ESG decile. Its Sharpe ratio is therefore higher. However, the maximum Sharpe ratio is held by ESG decile 6.

Table 2

	Average Statistics						Maximum Statistics		Minimum Statistics	
Decile	Raw ESG	ESG-Z	Number of firms	Return	Vol	Sharpe	Return	Vol	Return	Vol
1	30.47	-1.84	37.42	0.58%	3.86%	1.20	11.15%	10.03%	-11.43%	1.65%
2	32.72	-1.06	37.46	0.46%	3.47%	1.15	8.70%	8.18%	-10.82%	1.53%
3	37.24	-0.70	37.40	0.42%	3.66%	1.14	11.68%	8.86%	-11.29%	1.40%
4	43.95	-0.31	37.45	0.49%	3.75%	1.34	11.26%	10.59%	-11.77%	1.32%
5	50.75	0.03	37.43	0.63%	3.69%	1.25	12.37%	8.97%	-13.14%	1.24%
6	56.80	0.30	37.45	1.09%	3.73%	1.70	9.58%	10.27%	-12.08%	1.54%
7	58.61	0.53	37.40	0.89%	3.96%	1.40	11.87%	10.13%	-9.00%	1.07%
8	61.23	0.74	37.42	0.89%	3.76%	1.54	11.22%	9.93%	-10.61%	1.55%
9	62.37	0.99	37.43	0.78%	3.68%	1.45	10.67%	9.30%	-11.16%	1.42%
10	63.16	1.44	37.39	0.71%	3.69%	1.46	11.78%	9.58%	-11.24%	1.70%

Table 2: Average monthly ESG Decile Portfolio outcomes. The sample is 10 ESG decile sorted portfolios across 84 months (7 years) from 2016 to 2022, with average outcomes as well as maximum and minimum outcomes. All figures besides ESG ratings and number of firms are reported on a monthly scale.

That the maximum Sharpe ratio is not held by the very top ESG portfolio appears to confirm the existence of an ESG efficient frontier, as described by Pedersen et al (2021). Since the higher ESG deciles, 8, 9 and 10, have higher Sharpe ratios than the lower ESG deciles, this also implies that on average, an ESG factor should have positive returns and lower volatility throughout the period.

Table 3 – Portfolio Differences vs Market Outcomes

Table 3 reports the results of the OLS regressions

$\overline{\sigma}_{1,2,3,t} - \overline{\sigma}_{10,9,8,t} = \alpha + \beta \cdot \sigma_{Mkt,t} + \varepsilon_t$ **(1)**

$\overline{R}_{10,9,8,t} - \overline{R}_{1,2,3,t} = \alpha + \beta \cdot R_{Mkt,t} + \varepsilon_t$ **(2)**

where $\left(\overline{\sigma}_{1,2,3,t} - \overline{\sigma}_{10,9,8,t}\right)$ refers to the difference between the average volatility of the bottom three portfolios (low-ESG portfolios) and the average volatility of the top three portfolios (high ESG portfolios) during month t, $\left(\overline{R}_{10,9,8,t} - \overline{R}_{1,2,3,t}\right)$refers to the difference in average monthly returns of the same, and $\sigma_{Mkt,t}$and $R_{Mkt,t}$refer to the volatility and return of the OMXS30 index during month t. Standard errors are corrected for heteroskedasticity.

The columns differentiate the two regressions, with column (1) showing the results of the volatility difference regression, and column (2) showing the results of the return difference regression.

Table 3

Variables	(1) Volatility Difference	(2) Return Difference
Intercept	0.130 (0.081)	**0.279**** **(0.147)**
$\boldsymbol{\sigma_{Mkt,\,t}}$ or $\boldsymbol{R_{Mkt,\,t}}$	**-0.036***** **(0.018)**	**0.049*** **(0.031)**
Observations	84	84
Adjusted R-squared	0.056	0.034

*Note: Sample period 84 months from 2016 to 2022. Robust standard errors are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

First, we can interpret column 1. The statistically insignificant intercept implies that a persistent difference in volatility between the groups of portfolios cannot be seen. A significant coefficient of -0.036 for market volatility however implies that this difference comoves with the market, such that when market volatility goes down higher ESG portfolios have better volatility than low ESG portfolios.

We interpret column 2 in a similar manner. There does seem to be a general difference between the monthly returns of the top three portfolios and the bottom three. The top three portfolios had on average a 0.279% higher monthly return than the bottom three during the period, according to the intercept. Additionally, the coefficient 0.041 on our market return variable implies that the difference increases during times of high market returns and decreases during times of low market returns.

From these two regressions we can see preliminarily that if an ESG return factor and volatility effect does exist, its effect is more pronounced during low volatility, high return periods for the index and diminishes during high volatility, low return periods. The results of these regressions can be seen more intuitively in figures 1 and 2 below.

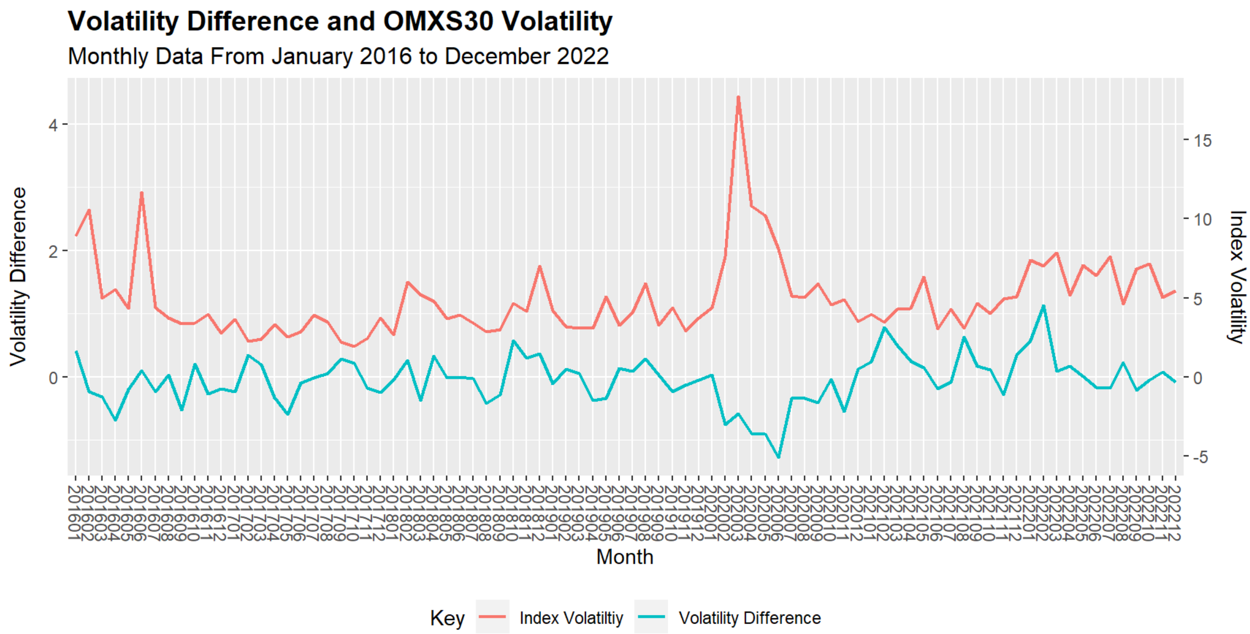

Figure 1*- Difference between the average volatilities of the bottom three and top three ESG decile portfolios, from 2016 to 2022, monthly, overlaid with monthly OMXS30 volatility throughout the same period. These are the same observations which produced the results in Table 3, column 1*

The clearest indication of a correlation for volatility (Figure 1) is that in March 2020 there was a large volatility spike while the volatility difference reached its lowest level, meaning that the low-ESG stocks had lower volatility in March and April 2020.

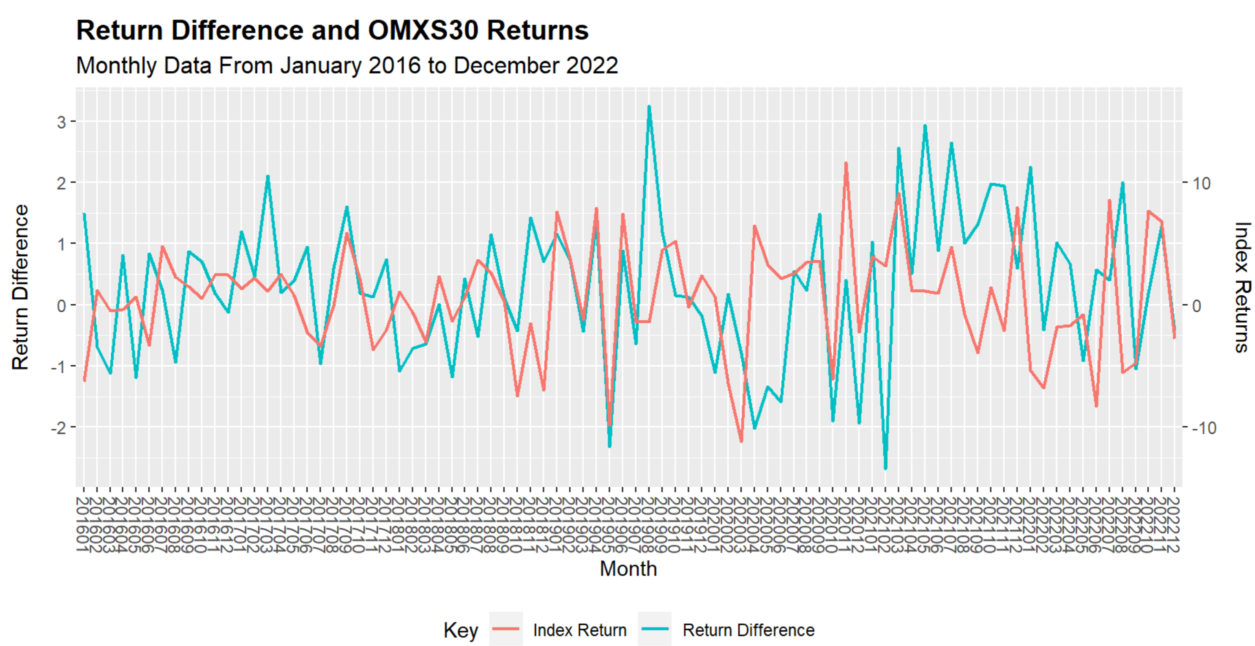

Figure 2- *Difference between the average returns of the top three and bottom three ESG deciles, from 2016 to 2022, overlaid with monthly OMXS30 returns throughout the same period. These are the same observations which produced the results in Table 3, column 2*

The return difference (Figure 2) meanwhile fluctuates around the zero-line more often. Some positive correlations can be seen, however. For example, the return difference declined drastically in the beginning of 2020, while the index did the same. The regression results in table 3 also indicate this. So, again, the return effect of ESG exposure seems more dependent on the general market environment.

V.1 a. ESG Decile Ranking – The Linear model

While the initial results indicate that the difference in the volatilities of the top and bottom three ESG decile portfolios varies with the market, we ought to investigate more closely whether moving up ESG ranks really improves return and volatility outcomes. While we saw in the raw outcomes in Table 2 that in general the higher ESG decile portfolios had better Sharpe ratios than the lower ESG decile portfolios, raw outcomes do not control for portfolio characteristics such as size, value or market exposure. So, as we explained in our methodology they are used as control variables in the linear model.

A breakdown of the average factor betas of the ESG decile portfolios, as presented in Table 4 below, can show us why this might be necessary.

Table 4

ESG Decile Portfolio	Market Beta	Size Beta	Value Beta
1	0.60	-0.28	-0.13
2	0.53	-0.14	-0.10
3	0.56	-0.16	-0.05
4	0.58	-0.28	-0.06
5	0.57	-0.34	0.00
6	0.62	-0.55	0.06
7	0.66	-0.60	0.08
8	0.63	-0.58	0.18
9	0.62	-0.50	0.11
10	0.60	-0.35	0.07

Table 4 – Shows the average factor beta of the firms in each ESG decile portfolio from 2016 to 2022.

The greatest variation can be seen in the size factor betas. While we controlled for firm size in the creation of our ESG Z-scores, some deciles seem to lean more towards larger firms and indicated by the negative size factor beta (since the size factor longs small firms). There are also differences in the market and value betas.

Table 5

Table 5 reports the results from the following regressions on the ESG decile portfolios

$$\sigma_{n,t} = \beta \cdot size_{n,t} + \beta \cdot value_{n,t} + \beta \cdot Beta_{n,t} + \beta \cdot ESGClass_{n,t} + \eta + \varepsilon_t \quad \textbf{(1)}$$

$$R_{n,t} - r_{f,\,t} \;=\; \beta \cdot \overline{\overline{\beta}}_{size,\,n,\,t} + \beta \cdot \overline{\overline{\beta}}_{value,\,n,\,t} \;+\; \beta \cdot \overline{\overline{\beta}}_{mkt,\,n,\,t} \;+\; \beta \cdot ESGClass_{n,\,t} \;+\; \eta \;+\; \varepsilon_t \quad \textbf{(2)}$$

Where $\sigma_{n,\,t}$ refers to ESG portfolio n's volatility in month t and $R_{n,t} - r_{f,\,t}$is ESG decile-portfolio n's excess return in month t. $size_{n,\,t}$is the average of the natural logarithm of the market capitalization in euros of the firms comprising portfolio n in month t. $value_{n,\,t}$is the average of the book to market cap ratio of the firms comprising portfolio n in month t. $Beta_{n,\,t}$is the average OMXS30 market beta of the firms comprising portfolio n in month t. $\overline{\overline{\beta}}_{factor,\,n,\,t}$ is the average factor beta (for size, value and the market) of the firms in decile-portfolio n in month t. $ESGClass_{n,\,t}$is the rank/number of ESG portfolio n in month t. A monthly fixed effect is added, and standard errors are clustered across time.

The columns refer to the different regressions, with column (1) referring to a regression on portfolio volatility, and column (2) referring to a regression on portfolio returns.

Table 5

Variables	(1) $\boldsymbol{\sigma_{n,t}}$	(2) $\boldsymbol{R_{n,t} - r_{f,t}}$
Size / Size Beta	**-0.097***** **(0.034)**	**-1.293***** **(0.220)**
Value / Value Beta	-0.009 (0.064)	-0.484 (0.452)
Market Beta	**4.483***** **(0.360)**	**-2.358***** (0.973)
ESG Class	**-0.015***** **(0.004)**	0.025 (0.017)
Observations	840	840
Adjusted R-squared	0.215	-0.090

*Note: The sample is of 840 ESG class portfolio months from 2016 to 2022 (7 years * 10 portfolios * 12 months). Total no. of firms = 611. Standard errors clustered across time are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold. Monthly fixed effects are not reported in this table.*

First an analysis of the volatility results, column (1). As reported on the fourth line of the table the ESG portfolio's class reduces its volatility in a statistically significant manner. According to the results, between the worst ESG group (rank 1) and the best group (rank 10), on average throughout the period you could expect to see a monthly volatility difference of 0.135%. Scaled to annualized volatility, this would be an average volatility reduction of 0.46% throughout the period. Regarding our control variables, high beta stocks are generally expected to have higher volatility on average. It makes sense therefore that a higher average beta of the ESG portfolio would increase volatility with a positive coefficient. Likewise larger firms generally have lower volatility, so a negative coefficient on our size variable is also reasonable.

For returns, column (2) no statistically significant effect was established for our ESG portfolio rank. Exposure to the size factor was significant, with a negative coefficient. It may we worth noting this because this is opposite to the expected results for a size factor (for example as defined by Fama and French, 1993), where smaller firms should generally have higher returns. This will be a recurring theme in our Fama Macbeth Regressions. We also note a negative effect on returns for the decile's average firm market beta. That would be consistent with Betting Against Beta factors that other researchers have found. However, the model had a negative adjusted R-squared, meaning a linear model like this is not good at explaining differences in returns.

This gives us the expectation moving forward that exposure to an ESG factor, if it exists, has a much greater effect on volatility than on returns. It also informs us that ESG's relationship to volatility is much more linear than it is for returns.

V.2 Fama Macbeth Regressions

Moving away from ESG decile portfolios now, we evaluate the relationship from another perspective, the Fama Macbeth regressions. As detailed in our method, we will see if firms' exposures to the factors in our FF3 + 1 model have effects on their returns and volatilities throughout the period. Table 6 a) will show the results of the regressions across the period and tables 6 b) and 6 c) will show these results year-by-year, so we can see any variations.

Table 6 a)

Table 6 a) shows the results of the following OLS regressions in the Fama Macbeth model.

$$R_{n,T} - r_{f,T} = \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon_T \quad \textbf{(1)}$$

$$\sigma_{n,T} = \gamma + \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon \quad \textbf{(2)}$$

Where $R_{n,T}$ represents the total return of firm n during year T and $\sigma_{n,T}$ represents the volatility of the same. In both regressions $\overline{\beta}_{n,T,factor}$ represents the estimated exposure of firm n to a given factor in year T. The columns differentiate the two regressions. Column 1 shows the result on returns. If a coefficient is significant, this implies that the factor existed and provided a risk premium during the period. Column 2 shows the result on volatility. If a coefficient here is significant, it implies that the factor had a significant effect on volatility and provided either a volatility discount or premium.

Table 6 a)

Variables	(1) $\boldsymbol{R_{n,T}}$	(2) $\boldsymbol{\sigma_{n,T}}$
Intercept	n/a	**21.589 ***** **(0.421)**
$\overline{\boldsymbol{\beta}}_{ESG}$	**7.721***** **(0.995)**	**-2.135***** **(0.258)**
$\overline{\boldsymbol{\beta}}_{Value}$	**-7.414***** **(1.288)**	**-0.902*** **(0.466)**
$\overline{\boldsymbol{\beta}}_{Size}$	**-7.543***** **(1.236)**	**4.573***** **(0.253)**
$\overline{\boldsymbol{\beta}}_{Mkt}$	**14.86**** **(1.413)**	**8.961***** **(0.606)**
Observations	2,635	2,635
Adjusted R-squared	0.078	0.300

*Note: Sample period 2,635 firm years from 2016 to 2022. No. of firms = 611. Robust standard errors clustered across time are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

Throughout the period larger firms and growth stocks seemed to show better returns, as the negative coefficients on size and value factor exposures indicate. The negative coefficient on the size factor confirms the relationship we noticed in Table 5. We note that this is different from the general, long term risk premia of the size and value factors which Fama and French found in their original paper, among others. Reasonably, there is a positive market risk premium throughout the period.

The ESG factor, our object of inquiry, has a significant risk premium here. From these coefficients alone however, it is hard to tell a complete story. Part of our hypothesis is that the ESG factor's value varies over time, and we can investigate that more closely in table 6 b).

The story for volatility seems clearer. Exposure to the ESG factor reduces firm volatility, which is consistent with results in table 5. Exposure to the value factor, meaning strong balance sheets, also reduces stock volatility. Meanwhile exposure to the size factor (small firms) and a higher market beta increase volatility, which is consistent with what anyone would expect. The relatively high R-squared of 0.300 also makes sense.

Consistent with the results in table 5, these results indicate that exposure to an ESG factor, if it exists, has a much greater effect on volatility than on returns, and that that effect on volatility is negative.

Table 6 b)

Table 6 b) shows the results of the following regression. ESG factor risk premia by year

$$R_{n,T} - r_{f,T} = \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon$$

All variables have the same meaning as in Table 6 a), except that we are now only regressing returns, and doing to for each year separately. The purpose of this is to see if the risk factor premia vary in an interesting manner over time. Each column in the table below shows the risk premium of each factor during a specific year.

Table 6 b)

	Calendar Year						
Variables	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
$\overline{\boldsymbol{\beta}}_{ESG}$	**9.414**** **(4.739)**	**8.328***** **(2.922)**	1.962 (2.035)	**8.858***** **(3.231)**	-3.224 (3.523)	5.838 (4.282)	**16.915***** **(2.560)**
$\overline{\boldsymbol{\beta}}_{Value}$	4.109 (4.664)	3.287 (2.796)	**-16.140***** **(3.392)**	**-19.399***** **(3.278)**	-18.640 (12.543)	0.139 (4.521)	**-8.399***** **(3.998)**
$\overline{\boldsymbol{\beta}}_{Size}$	**-10.903 ***** **(3.101)**	**-8.962***** **(2.694)**	**-7.988***** **(2.297)**	**-6.744**** **(3.060)**	-0.827 (3.523)	**-16.191***** **(3.240)**	**-7.322***** **(2.641)**
$\overline{\boldsymbol{\beta}}_{Mkt}$	**29.867***** **(3.868)**	**19.420***** **(2.442)**	**-11.325***** **(1.705)**	**31.410***** **(2.516)**	**35.040***** **(6.101)**	**43.544***** **(3.563)**	**-16.414***** **(1.831)**
Obs.	314	350	402	353	398	421	397
Adj. R2	0.171	0.1433	0.206	0.361	0.279	0.2646	0.4368

*Note: Based on firm returns and factor exposures from 2016 to 2022. No. of firms/observations per year specified in table. Total no. of firms = 611. Robust standard errors are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

The ESG factor's risk premium was not statistically significant in all years. A particular pattern cannot be discerned, but we note that 2018 (an ESG-insignificant year) was a year when Nordic markets declined and 2020 and 2021 were years when investors were preoccupied with the pandemic and its effects. We propose interpretations of this when we analyze the results in section VI.

Throughout the period larger firms appeared to outperform smaller firms, as shown by the statistically significant negative coefficients for the size factor. Growth stocks outperformed value stocks in a statistically significant manner for only three of seven years. Understandably, the market risk premium is more significant throughout the period. 2018 and 2022 were bad years for the stock market at large, so the market risk premium was negative during those years.

Table 6 c)

Table 6 c) shows the results of the following regression.

$$\sigma_{n,T} = \gamma + \gamma_{ESG}\,\overline{\beta}_{n,T,ESG} + \gamma_{Value}\,\overline{\beta}_{n,T,Value} + \gamma_{size}\,\overline{\beta}_{n,T,size} + \gamma_{mkt}\,\overline{\beta}_{n,T,mkt} + \varepsilon$$

All variables have the same meaning as in Table 6 a), except that we are now regressing factor betas against stock volatility and doing to for each year separately. The purpose of this is to see if the factor volatility effects vary in an interesting manner over time. Each column in the table below shows the volatility effect of each factor during a specific year.

Table 6 c)

	Calendar Year						
Variables	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Intercept	**19.866*** (1.040)**	**17.681*** (0.636)**	**19.356*** (0.831)**	**20.543*** (0.809)**	**27.043*** (4.015)**	**19.905*** (0.815)**	**25.073*** (1.135)**
$\overline{\boldsymbol{\beta}}_{ESG}$	**-2.434*** (0.704)**	**-2.658*** (0.545)**	**-3.066*** (0.408)**	**-2.591*** (0.764)**	-0.018 (0.561)	**-3.021*** (0.513)**	**-1.574*** (0.409)**
$\overline{\boldsymbol{\beta}}_{Value}$	**2.853*** (0.870)**	**-3.768*** (0.596)**	**-3.453*** (0.580)**	-1.097 (0.716)	1.242 (2.529)	**-5.264*** (0.463)**	**-6.346*** (0.642)**
$\overline{\boldsymbol{\beta}}_{Size}$	**2.087*** (0.613)**	**4.892*** (0.531)**	**3.396*** (0.500)**	**4.055*** (0.582)**	**3.939*** (0.557)**	**6.716*** (0.423)**	**5.057*** (0.520)**
$\overline{\boldsymbol{\beta}}_{Mkt}$	**11.573*** (1.616)**	**4.804*** (0.942)**	**8.769*** (1.065)**	**6.312*** (1.042)**	**11.694* (4.793)**	**5.856*** (1.061)**	**11.350*** (1.217)**
Obs.	314	350	402	353	398	421	397
Adj. R2	0.369	0.496	0.405	0.364	0.265	0.575	0.537

*Note: Based on firm returns and factor exposures from 2016 to 2022. No. of firms/observations per year specified in table. Total no. of firms = 611. Robust standard errors are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

Volatility effects appear to be much more consistent over time. The ESG factor is consistently significant and reduces volatility, except during 2020. As could be seen in figure 1, 2020 was the year with the most extreme market volatility of the period, so it would be consistent with our previous results that 2020 would be the one year when exposure to the ESG factor would not reduce volatility. The fact that the volatility effect does not subside as easily as the risk premium effect in table 6 b), is again consistent with our previous results that ESG reduces volatility more than it increases returns.

V.3 Volatility Management

Table 7 shows the results of the following regression

$$f_{t+1}^{\sigma} = \alpha + \beta \cdot f_{t+1} + \varepsilon$$

where f_{t+1} represents the excess return of a factor in month t+1, f_{t+1}^{σ}represents the volatility managed excess return of the ESG factor in month t+1, and α, the intercept in the regression, represents the additional excess return provided by the volatility management strategy. The volatility management strategy is applied from 2016 to 2022 on a monthly basis. This results in 83 observations, instead of the normal 84, because the volatility management strategy requires knowledge of the previous month's volatility to determine weighting, and so can't be applied to the first month January 2016.

The regression is run separately for each of our four factors. The individual columns show the results of each factor individually.

Table 7

Variables	(1) ESG	(2) Value	(3) OMX30	(4) Size
$\boldsymbol{\alpha}$	**0.105 *** **(0.077)**	0.132 (0.129)	0.144 (0.432)	**-0.148**** **(0.074)**
$\boldsymbol{f_{t+1}}$	**1.137***** **(0.092)**	**0.824***** **(0.076)**	**1.113***** **(0.127)**	**1.205***** **(0.218)**
Observations	83	83	83	83
Adjusted R-squared	0.773	0.701	0.631	0.635

*Note: Sample period 83 months from 2016 to 2022. Robust standard errors are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

The coefficient for the ESG factor, f_{t+1}, being 1.137 means that on average, the strategy overweights the factor by 13%. The intercept coefficient being 0.105 implies that the volatility management strategy increases, in a statistically significant manner, the returns of an ESG factor strategy by 0.105% per month. The fact that the coefficient is positive means that increasing exposure to the ESG factor during periods of lower volatility and decreasing exposure to the ESG factor during periods of higher volatility, should increase the factor's returns. These results can perhaps be seen more intuitively in Figure 3 below.

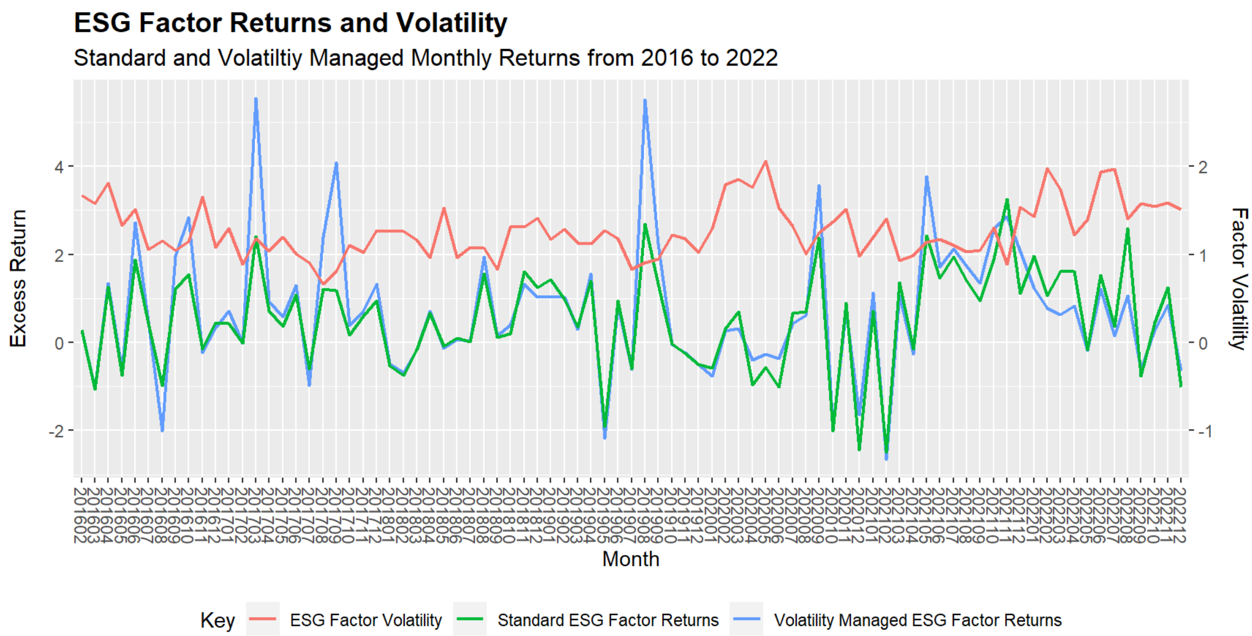

***Figure 3**- ESG factor excess returns, volatility, and volatility managed excess returns (applying Moreira and Muir's 2017 strategy) from February 2016 to December 2022, monthly. These are the same observations which produced the results in table 7.*

As can be seen in Figure 3, when factor volatility is lower the volatility management strategy overweights the portfolio. Since the ESG factor generally seems to have higher returns when its volatility is lower, this strategy manages to exploit spikes in the ESG factor's returns. A good indication that the strategy is effective is that the volatility managed returns (the blue curve) deviate from standard factor returns (the green curve) to the upside much more than they do to the downside. It can also be noted that the strategy did not work in 2022, with managed returns being lower than standard returns.

The volatility management strategy does not seem to work with the Value Factor and the market index. Meanwhile, the strategy reliably reduces the return of the size factor by 0.148% per month. Seeing as the size factor has a negative risk premium throughout our period, however, this means the volatility management strategy would generate improved returns on an inverse size factor.

V.4 Window Volatility

Table 8

Table 8 shows the results of the following regression

$$WVOL_{n,\,t} = \beta \cdot ESGf_n + \beta \cdot Beta_n + \beta \cdot Lev_n + \beta \cdot Cash_n + \beta \cdot Logsales_n + \varepsilon_n$$

Where; WVOL refers to the standard deviation of firm n's daily stock returns in a t-day window, ESGf is a dummy variable for whether a firm n is in the top ESG quartile vs the bottom quartile, Beta is firm n's market beta, as calculated in previous regressions, Lev is firm n's liabilities to assets ratio, cash is firm n's cash to assets ratio, and logsales is the natural logarithm of firm n's annual sales in euros.

Table 8

Variables	Covid Crisis, March 12th, 2020			Ukraine Crisis, February 24th, 2022		
	WVOL 5	WVOL 15	WVOL 30	WVOL 5	WVOL 15	WVOL 30
Intercept	**2.114*** (0.249)**	**2.383*** (0.147)**	**2.087*** (0.130)**	**1.913*** (0.217)**	**2.009*** (0.170)**	**1.952*** (0.155)**
ESGf	0.160 (0.102)	0.024 (0.058)	-0.019 (0.054)	**-0.169* (0.102)**	**-0.142* (0.072)**	**-0.143** (0.068)**
Beta	**0.926*** (0.338)**	**1.047*** (0.223)**	**1.139*** (0.210)**	**0.950*** (0.171)**	**0.978*** (0.134)**	**1.001*** (0.135)**
Lev	0.068 (0.250)	-0.156 (0.143)	-0.009 (0.129)	-0.237 (0.230)	-0.090 (0.159)	-0.099 (0.158)
Cash	**0.739* (0.393)**	0.279 (0.207)	0.278 (0.170)	**0.994*** (0.273)**	**0.812*** (0.202)**	**0.860*** (0.192)**
Logsales	-0.022 (0.024)	-0.014 (0.012)	-0.012 (0.010)	0.005 (0.029)	-0.017 (0.021)	**-0.037* (0.022)**
Obs.	199	199	199	197	197	199
Adj. R2	0.058	0.173	0.234	0.238	0.359	0.405

*Note: Regressions against stock volatility in 5-, 15- and 30-day windows around March 12th, 2020, and February 24th, 2022. No. of firms/observations per year specified in table. Robust standard errors are reported in parentheses. (***, **, *) indicate significance at the 1%, 5% and 10% level. Significant coefficients are in bold.*

As can be seen, being in the top or bottom ESG quartile had no statistically significant effect on volatility during any windows around the Covid crisis. This directly contradicts the results of Zhou and Zhou (2020), implying that their observation was a Chinese phenomenon and not a Scandinavian one. This is also consistent with the plot in Figure 1 showing that around the covid crisis low ESG portfolios had drastically lower volatility than high ESG portfolios. Notably, only market beta explained firm volatility during the covid crisis, and variables such as leverage, or size had no effect. This is also consistent with our Fama Macbeth regression results in Table 6 c), namely that 2020 was the only year in which firms' ESG factor exposure had no effect on their volatility whatsoever.

Meanwhile in the Ukraine crisis firm volatility was clearly reduced by being in the top ESG quartile vs the bottom. This is again consistent with the Fama Macbeth regression results where exposure to the ESG factor gave statistically significant risk premia and volatility reductions in 2022. Other variables also had volatility effects in the Ukraine crisis, such as cash on hand and sales.

VI – Interpretation of Empirical Findings

VI.1 Control Variables – Size and Value in the Nordics

Before analyzing and interpreting the target of this study, the ESG factor, we would like to briefly discuss the results of our control variables. In the portfolio analysis and Fama-Macbeth regressions we included the size factor, the value factor, and market beta as control variables and as a part of the FF3 + 1 model. Besides these results being interesting in themselves, they also set the stage for analyzing the larger market environment in which the ESG factor has been operating throughout the period.

The effect of market beta is not surprising. The regressions show that as market beta increases, both the returns and volatility of firms increase. In line with standard CAPM theory since Sharpe (1964) or Lintner (1965), as firms or portfolios have increased exposure to the general market, they move up the securities market line and increase their returns at the cost of increased volatility. In the year-by-year Fama Macbeth regression, exposure to the market brought with it a negative risk premium in 2018 and 2022, but this is not surprising as stock markets across the west declined during those years. In short, our results regarding market beta are uncontroversial.

The impact of size and value on returns in our sample, however, is counterintuitive and deserves comment. Value did not have a significant effect on ESG decile returns. In the Fama Macbeth regressions exposure to the value factor was significant throughout the period, but it had a negative risk premium. In the year-by-year breakdown we see that growth outperformed value and presented a statistically significant risk premium in 2018, 2019 and 2022. Meanwhile the size factor had a consistently negative and statistically significant risk premium throughout the period, in almost all years.

While Fama and French (1993) established that value stocks should outperform growth stocks over time, it is no secret that growth has outperformed value in general over the past decade. Several studies have investigated the "death of value", (Arnott et al., 2021) and (Fama & French, 2020). The first sentence of the abstract of Fama and French (2020) reads "Value premiums, which we define as value portfolio returns in excess of market portfolio returns, are on average much lower in the second half of the July 1963-June 2019 period". From this perspective it makes sense that exposure to the value factor had a negative effect on firm returns in our sample.

With all this being said, the value factor would be expected to exhibit a risk premium in 2022 (a chaotic year for markets in the Nordics), but it was negative there too in our sample. While extensive research on last year's stock market has yet to come out, asset managers such as JP Morgan (Romahi et al. 2023) show that Value strategies have outperformed globally in the last year. This is hard to explain. This may have to do with our stock universe. Since the value factor was created using the 611 companies with ESG information in Nordic Compass, almost all firms are large or mid-sized. The small growth stocks in the Nordics that would likely have crashed the most last year, are absent. This would make our value factor less extreme than one considering all stocks. Another perspective is that the negative risk premium improved significantly, being around –19% in 2019, but only around –8% in 2022. Even in our stock universe, Value as a factor improved in 2022.

Declarations of the death of the size factor have not been as forthcoming in the literature, but in our sample larger firms clearly outperform smaller firms. This is consistent with observations by asset managers. JP Morgan (Romahi et al. 2023) notes that large cap firms in the United States have outperformed smaller cap firms in the past decade. Closer to home, a statistically significant "reverse size effect" (i.e., an inverse size factor) has been observed in Sweden and the Nordic countries as far back as data has been available by Stöcker and Wilke (2016) in a master's thesis at the Stockholm School of Economics. While this contradicts the common Fama and French (1993) size factor, at this time and in the Nordics, it is entirely expected that larger firms should outperform smaller firms. It is not lost on us that larger firms also have greater ability to comply with ESG. While we control firm size in our ESG ratings and factor creation, this consistent reverse size effect implies with our other results that a very large firm with good ESG compliance should be the ultimate winner right now in the Nordic countries.

At this point we have not discussed the volatility effects of the size and value factor reported in Table 6 a) and Table 6 c). Exposure to the size factor increased volatility and exposure to the value factor reduced it during the period. These effects are much more intuitive and require less explanation. Larger firms should be more liquid and hence less volatile than smaller firms. Therefore, exposure to the size factor increases a firm's volatility. Meanwhile a firm with a stronger balance sheet should be less at risk of financial distress. Therefore, exposure to the value factor should reduce volatility.

VI.2 ESG Deciles

Our results in ESG decile-portfolio regressions for volatility are both statistically and economically large. As detailed in the results in Table 5, moving up to the top ESG decile from the bottom reduces portfolio volatility by 0.46% annually. The results in Table 3 meanwhile indicate that the difference in volatility does correlate with general market conditions. The volatility results here are consistent with previous literature, such as (Dunn et al., 2017) and (Chan et al., 2020), indicating that higher ESG scores are correlated with lower volatility for firms in general.

The results for the return are the opposite of those for volatility. In Table 5 the model had very poor explanatory power (negative in fact!), meaning return and ESG do not have a linear relationship. However, in Table 3 we could see that the difference in return between the top three and bottom three ESG deciles, like volatility, does vary with market return in a statistically significant manner, increasing when the market shows higher returns and decreasing when it shows lower returns. In other words, the return effect of moving up the ESG deciles is fickler (if it exists), and more dependent on market conditions.

The ESG-Efficient Frontier: Deciles vs the ESG Factor

The fact that moving up ESG deciles does not increase returns in a linear fashion indicates that the ideal investment strategy is not for the investor to simply maximize the ESG score of his holdings. However, it does not eliminate the existence of a factor since factors do not look at sliding scales, but instead are calculated as a difference between extremes. With the results in table 2 clearly indicating return and volatility of the top and bottom ESG-deciles are different, the results from the ESG-decile portfolio analysis support the idea that an ESG factor might exist.

The results of our Fama Macbeth regression can establish more clearly whether a factor exists. Before that though, it may be worth looking at the Sharpe ratios of the ESG deciles. Calculating the average annualized Sharpe ratio of each ESG decile, we can produce the figure below from the results in Table 2.

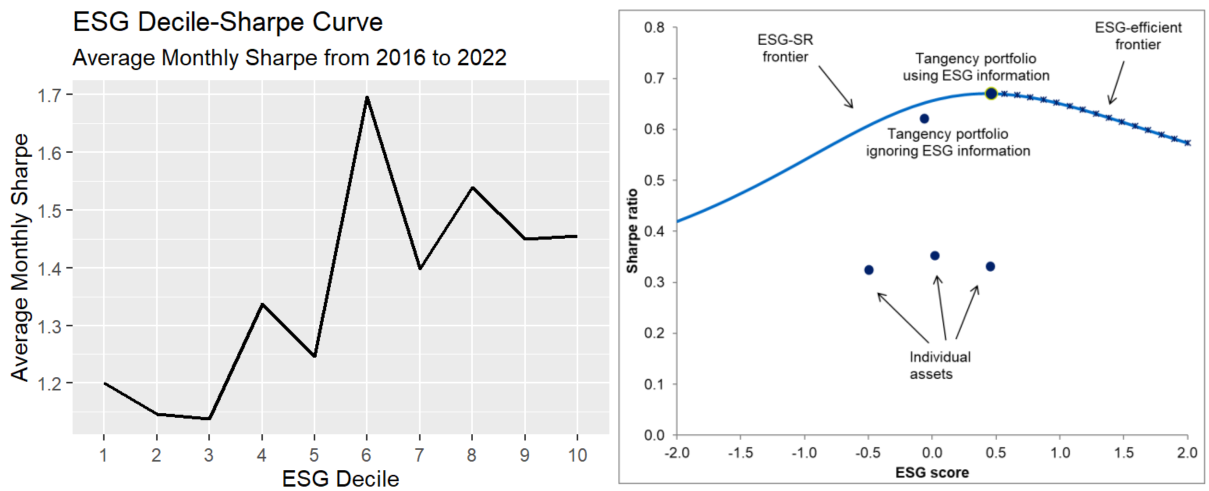

Figure 4 – *Left: The average monthly Sharpe ratio (annualized) of ESG decile-portfolios from 2016-2022. Right: Pedersen et al's (2023) representation of the ESG-efficient frontier in their paper, for comparison.*

Figure 4 could be considered an ESG-Sharpe frontier and compared to results by Pedersen et al (2021). Those researchers investigated the possibility of creating an "ESG-Efficient frontier" (the paper's namesake) whereby investors would optimize a utility function between ESG and the portfolio's maximum possible Sharpe ratio. The outcomes of this optimization can be mapped to a curve of ESG rating on the x-axis and maximum Sharpe ratio on the y-axis. The curve takes the form of a shallow inverse parabola, such that at some ESG rating you reach the maximum possible Sharpe ratio, and increasing ESG after this point comes at the expense of Sharpe ratio. This section of the curve is called the ESG-efficient frontier. Pedersen et al (2021) found in their exercise that the ESG efficient frontier starts at a point slightly above the average ESG rating. For comparison we provide a representation of Pedersen et al's (2021) frontier above.

In Figure 4 we find a very similar ESG-efficient frontier, though admittedly a bit more jagged than Pedersen's (2021). The ESG decile with the highest average Sharpe ratio during the period was 6, just above the bottom half. From there, to move up the ESG decile scale comes at the expense of the Sharpe ratio. An investor cannot maximize his Sharpe ratio by only investing in firms with the highest ESG compliance.

However, we can also clearly see in Figure 4 that the top ESG-third (or top three ESG-deciles) all had higher Sharpe ratios than the bottom ESG-third on average during the period. Since our ESG factor is created as a long-short strategy from ESG thirds, Figure 4 visualizes that an ESG factor is more likely to exist than a simple linear relationship between ESG and returns or Sharpe. With that, we can move on to analyze the results of the Fama Macbeth regressions.

VI.3 Fama Macbeth

Does an ESG factor exist?

The results of the Fama Macbeth regression in our FF3 + 1 model indicate that on average, throughout the period, exposure to the ESG factor provided an annual risk premium of 7.721% and an annualized volatility reduction of 2.135%, as per table 6 a). Across the entire period the model has greater explanatory power for volatility than it does for returns, but these effects are both economically and statistically significant. The results are consistent with our ESG decile results.

The effect of exposure to the ESG factor is not completely consistent across all 7 years of our study. The factor's risk premium was only statistically significant in four out of seven years. The volatility reduction is more consistent, being statistically significant across all years at a level between 1.5% and 3%. The only exception to the volatility effect was 2020, when it was statistically insignificant. That the volatility effect was much more persistent than the return effect is again consistent with the results in our decile portfolio regressions.

However, we have clearly shown that an ESG effect on returns and volatility was present in the Nordic countries from 2016 to 2022. Why would this be the case? And why would it vary over time? We evaluate three popular explanations for the ESG factor and an alternative explanation (besides general market conditions) as to why the effect might vary over time.

Why an ESG factor should exist: Investor Demand

Investor demand is a critical driver of the growth of ESG investing in the Nordics. Investors are increasingly interested in investing in companies with strong ESG profiles. One reason for this interest is that ESG investing has been shown to offer competitive risk-adjusted returns. In a study of over 2,000 academic papers on ESG investing, researchers found that the majority of studies showed a positive correlation between strong ESG practices and financial performance. (Serafeim & Trinh, 2020)

Furthermore, the report by the Nordic Investment Bank (*NIB on Sustainable Finance at 2019 ICMA Conference - Nordic Investment Bank*, 2019) indicates that the Nordic countries have a strong institutional framework to support sustainable and responsible investment practices. For example, the Nordic countries have some of the world's most stringent corporate governance regulations, which ensure that companies are held accountable for their environmental and social impacts. This institutional framework has helped to create an ecosystem in which ESG investing can thrive, as investors can trust that companies are being held to high ESG standards.

Overall, the growing interest in ESG investing among Nordic investors, combined with the long history of socially responsible investing in the region and the strong institutional framework supporting sustainable and responsible investment practices, may have contributed to the emergence of an ESG factor in the Nordics.

Why an ESG factor should exist: Competitive Advantage

Companies with strong ESG practices may enjoy a competitive advantage in the marketplace because they are better positioned to meet the evolving needs and expectations of customers, employees, and other stakeholders. For example, companies that prioritize environmental sustainability may be better positioned to take advantage of the growing demand for green products and services. This is particularly relevant in the Nordics, where there is a high level of environmental awareness and consumer demand for sustainable products and services. Companies that can meet these demands may be more likely to attract customers and gain market share.

Similarly, companies with strong social and governance practices may be better positioned to attract and retain top talent, which could translate into better overall performance. A company with a strong ethical and values-based culture may be more attractive to potential employees, particularly younger generations who prioritize social and environmental responsibility in their career choices. This can help companies to recruit and retain top talent, which is critical for long-term success.

Research supports the idea that companies with strong sustainability practices outperform their peers over the long term. A study by Harvard Business School (Serafeim & Trinh, 2020) found that companies with strong sustainability practices had better financial performance than their peers, both in terms of stock price performance and accounting performance. This study suggests that companies with strong sustainability practices are better positioned for long-term success and may be more resilient in the face of economic and market uncertainties.

Overall, companies with strong ESG practices may benefit from a competitive advantage in the marketplace, including the ability to meet evolving customer and employee expectations, attract and retain top talent, and achieve better long-term financial performance.

Why an ESG factor should exist: Risk Management

Companies that prioritize ESG considerations are considered to be better at managing risks. In particular, companies with strong ESG practices are better positioned to manage environmental, reputational, and regulatory risks. By addressing these risks proactively, companies can avoid legal and regulatory penalties and protect their brand and reputation. In addition, companies that prioritize sustainability may be better able to adapt to disruptive events such as economic shocks or natural disasters.

The World Economic Forum has conducted research (Abou-Jaoudé, N. 2023) on the relationship between sustainability and risk management. Their study found that companies with strong ESG practices are better able to weather economic shocks and other disruptive events, such as the COVID-19 pandemic. The study argues that companies that prioritize sustainability are better able to respond to challenges and adapt to changing circumstances. This may be because companies with strong ESG practices are better positioned to identify risks and opportunities and to respond quickly and effectively to changing conditions.

Overall, the evidence suggests that companies that prioritize ESG considerations are better positioned to manage a range of risks, including environmental risks, reputational risks, and regulatory risks. By taking proactive steps to address these risks, companies can avoid the costs that come with failing to comply.

That companies are taking this seriously, and increasing their compliance, could also be a reason for variations in the effect of the ESG factor. We will investigate this in the next section.

A reason why effects may vary over time: Increased Compliance

A potential reason why the ESG factor might have had varying statistical significance is changes in firm compliance to ESG. We opted for a ratings methodology that ultimately ranked firms within industry-size cohorts, placing them on a standard normal distribution, but the raw scores on which that is based is essentially an index of absolute ESG compliance. It could stand to reason that if more firms are complying with ESG requirements the importance of the ESG factor would wane.

The fact that more firms are setting ESG requirements is clearly supported in the literature. For example, the consulting firm PWC (O'Connor P et al. 2022) have noted that the imposition of certain requirements, such as linking CEO compensation to ESG outcomes, has doubled in the past two years. This has raised calls for the "end of ESG". Notably Edmans (2023) argued that ESG is widely accepted and that it is now essentially a component of long-term value. ESG investing in Edman's (2023) perspective is "no longer niche investing, but just investing".

We would like to remind the reader of the descriptive statistics of ESG ratings presented in Table 1. The standard deviation of raw ESG scores decreased drastically in 2019 and 2020. The ESG-Z statistics, as well as the skewness and kurtosis statistics in the appendix, also implied that the distribution became more negatively skewed. We can visualize this by plotting the probability density function of raw ESG scores and ESG-Z scores in Figure 5, below.

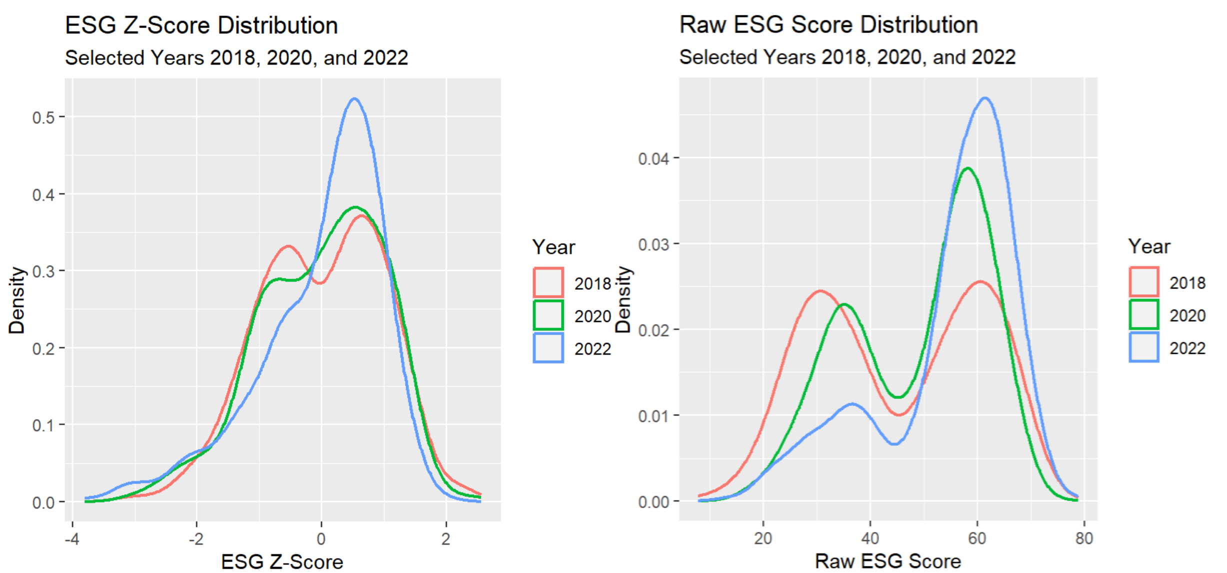

***Figure 5 -** Raw and Z-score ESG density distributions in 2018, 2020 and 2022. Left: ESG Z-score density distribution. Right: Raw ESG score density distribution.*

From this sample, we can see that the distribution of raw ESG scores in 2018 was more even and had equally large contingents of high scoring (around a raw ESG of 60) and low scoring (around raw ESG 30) firms. In 2022, the contingent of low scoring firms is much smaller, and the contingent of high scoring firms is much greater. This is evidence that a greater number of firms are "catching up" in their raw ESG compliance. The trend is the same in the distribution of Z-scores, though less pronounced because the Z-scores intentionally normalize the distribution of scores within industry-size-year cohorts.

The effect of these increasing ESG scores appears to be that firms in the Nordic countries have increased their exposure to the ESG factor. The average firm's ESG beta was –0.29 in 2016, rising to a high of 0.15 in 2021 (see these figures in the appendix, table 12). The ESG factor is created by being long the top ESG-third and short the bottom third; that the average factor beta is increasing means that the middle third is increasing its exposure to the ESG factor. This is again consistent with the fact that the ESG-ratings distribution has become negatively skewed.

In layman’s terms, most firms are catching up and clustering around higher ESG ratings as they seek to improve their compliance and catch any premium that the market may allocate to this compliance. Considering that this trend accelerated in 2019-2020 it would be reasonable that the ESG factor was significant in three of four years before 2020 and only in one of three years after 2019 in the Fama Macbeth regression. If the distribution is narrower, the differences are smaller and therefore investors don’t react to them as much.

This also conforms with an explanation from Pástor et al (2021). Those researchers analyzed ESG investing through the lens of an equilibrium model. In this model, the equilibrium is a situation in which investor opinions on ESG are homogeneous and investors are not focused on it. The researchers were able to demonstrate that in this equilibrium state an ESG long-short portfolio would have 0 to negative returns, but in a situation where ESG has the attention of investors the factor instead sees positive returns (Pástor et al. 2021).

Taking this perspective, it could be argued that investor opinions on ESG are becoming homogenized, as the narrowing raw ESG distribution indicates. Additionally, the reader would recollect the headlines of 2020 and 2021 - the pandemic. This could leave investors distracted from other considerations, like ESG. For example, we can see in Table 4 b) that all return factors besides the market trend were ignored in 2020. Taking the perspective of Pástor et al (2021), it would make sense that the factor would become less significant over time.

While it seems clear that most firms in the Nordic countries have taken a comply-or-die approach to ESG, this does not explain 2022. If anything, compliance reached its zenith last year, while the ESG factor’s risk premium also reached a high. Therefore, what may be the underlying cause or explanation for this situation? More research will presumably be published later this year, but the market downturn in 2022 in the Nordics was less acute and had more to do issues that directly relate to ESG investing such as energy policy. It would stand to reason that the debate and discussion around ESG would have become livelier and therefore from Pástor et al’s (2021) perspective ESG returns would increase.

Since 2022’s ESG ratings were created from 2021 ESG data, as per our methodology, we do not know how the 2022 invasion of Ukraine has affected compliance yet. In a few months' time post the writing of this paper, the Swedish House of Finance will compile data from 2022’s ESG reporting. We expect the trends we established above to continue. Put differently, after the pandemic we expect the distribution of ESG scores to become even narrower, and even more negatively skewed.

VI.4 Volatility Management

That ESG might possess safe-haven properties or the opposite, procyclical properties, is the theory we have tested the most in this study. Results from our ESG factor portfolios, in particular Table 3 and Figures 1 and 2, implied that the ESG effects were pro-cyclical, increasing when the market index performed better. Meanwhile, per our Fama Macbeth regressions, the ESG factor had a statistically insignificant risk premium during 2018 (a down year for markets) and 2020 (the year with the highest volatility).

The factors of Market, Value, Size, and ESG behave differently during the period of 2016-2022, as seen in Table 13 showing their monthly and annualized outcomes. The ESG factor has the highest mean excess return and the highest Sharpe ratio, indicating that ESG compliance and exposure to ESG factors can provide a risk premium and reduce volatility in a portfolio. On the other hand, the Size and Value factors show negative mean excess returns and negative Sharpe ratios, indicating that investing in smaller or undervalued companies may not yield positive returns or provide a risk premium. The Market factor shows a positive mean excess return but a relatively low Sharpe ratio, indicating that market exposure can provide positive returns, but not necessarily reduce volatility.

The volatility management test in this study therefore sought to determine whether volatility management is an effective strategy for investing in ESG. Moreira and Muir (2017) were able to show that in the past century, for stocks listed in the United States, the returns of Fama French factors, among others, can be improved by volatility management, by essentially reducing exposure when the factor's volatility is high and increasing it when it is low.

The results of volatility management are easy to interpret. Since the intercept in Table 7, column 1, is positive and statistically significant, the strategy works on the ESG factor. According to the results, volatility management increases the returns of the ESG factor by 1.26%, annually. Compared to the other factors, the ESG factor benefits more from this strategy than the market index or value factor, but less than does the inverse size factor.

This is partly consistent with the results of the Fama Macbeth regressions. The insignificant results in that regression from 2018 and 2020 suggest that the ESG factor does not possess safe-haven properties during market downturns or high volatility periods. However, the significant result in 2022 suggests that reducing exposure during that year (since volatility would have been higher) would have been unwise. As was noted in Figure 3, which plots the observations which produced the results in Table 7, the volatility management strategy would not have increased ESG returns in 2022. However, in aggregate volatility management would have worked on the ESG factor in the Nordic countries from 2016 to 2022.

There are several implications of our findings for investors and policymakers. Earlier results suggested that ESG investing is unlikely to be a safe-haven strategy, but it can still be profitable during market downturns when combined with volatility management. Investors who want to use ESG investing as a strategy should therefore consider implementing volatility management to improve their returns.

Regarding other factors, interestingly volatility management only worked on the size factor (which is consistent with Moreira and Muir, 2017), but not on value or the market (which is inconsistent with Moreira and Muir, 2017). Considering the V-shaped market recovery in the aftermath of the Covid crash, this is understandable since the strategy would have advised investors to reduce exposure at the bottom of that crash. It could also be a Nordic idiosyncrasy since Nordic markets are generally more volatile than those of the United States.

Our study invites scope for further research. Future studies could investigate the effectiveness of volatility management for the ESG factor in other regions. Additionally, future studies could investigate the effectiveness of other risk-management strategies, such as value-at-risk or conditional value-at-risk, for the ESG factor. Further research could also investigate whether combining multiple ESG factors based on different metrics, rather than just one, with volatility management can improve returns even further.

VI.5 Window Volatility results

Replicating part of the method of Zhou and Zhou (2020) we could also determine if being in the top vs bottom ESG quarter had any volatility effect on firms during the most acute phases of market downturns. We elected to analyze the Covid crisis, set as March 12th, 2020, and the Ukraine invasion, set as February 24th, 2022. The results of this regression could have been guessed based on the results in Figure 1, namely that during the Covid volatility spike the volatility effect of ESG disappeared but it did not in 2022. It could have also been intimated from the results in Table 6 c), where the volatility effect of exposure to the ESG factor was statistically insignificant during 2020.

Nevertheless, in Table 8 we clearly see that there was no statistically significant volatility effect during any of the Covid volatility windows, but there clearly was during the Ukraine volatility windows. This directly contradicts the results in Zhou and Zhou (2020), where those researchers found a significant volatility reduction during the Covid crisis window for firms in China. This in our mind settles the debate we brought up in the literature, namely that evidence from China (Zhou and Zhou 2020) and the west (Rubbaniy et al, 2022) was contradictory. What Zhou and Zhou (2020) discovered was a uniquely Chinese effect. ESG behaved differently in the Nordics during the Covid crisis.

That ESG had a volatility effect in the immediate crisis window around February 24th, 2022, is consistent with the other evidence we have brought to bear in this paper. 2022 was a good year for ESG compliance, as the risk premium of the ESG factor was the greatest in that year. It may also speak to the difference between the two events more generally. The Covid crisis was more acute, and stocks reached higher levels of volatility, whereas last year's bear market was less acute and longer lasting. For that reason, then, it makes more sense that ESG saw a dip in 2020 but had an effect in 2022.

VII – Conclusion

In this paper we investigate the effects of ESG compliance and exposure to an ESG factor in the Nordic Countries from 2016 to 2022. Through a battery of empirical tests, we plot and evaluate the average return and volatility outcomes of ESG decile-portfolios, apply Fama-Macbeth methodology, investigate the possibility of volatility managing exposure to the ESG factor by replicating Moreira and Muir (2017), and evaluate ESG volatility effects in crisis windows by replicating the method of Zhou and Zhou (2020).

Our results show that the highest ESG stocks tend to have better Sharpe ratios than the lowest ESG stocks, but not the highest Sharpe ratios of all. This supports the notion of an ESG efficient frontier existing, as proposed by Pedersen et al. (2021). Our results also indicate through our modified application of Fama and Macbeth's 1977 method that exposure to an ESG factor has provided a risk premium and a volatility reduction for Nordic firms throughout the period, with the effect more prevalent in earlier years. The ESG factor provided an annual risk premium of 7.721% and a volatility reduction of 2.135% during the period, which is economically and statistically significant.

We find some evidence that the ESG effects vary over time, with return effects correlating to the market index and ESG interacting differently in the immediate aftermath of the Covid and Ukraine crises respectively (as per our replication of Zhou and Zhou, 2020). Our application of the volatility management strategy of Moreira and Muir (2017) in this context suggests that ESG as a strategy should be invested in when its volatility is low.

As a continuous theme throughout the paper, we find that ESG effects are much stronger and more persistent on firm volatility than they are on returns, with the exception of the Covid crisis. Our underlying data also clearly indicates that a greater proportion of firms are increasing their compliance with ESG requirements and catching up to the leaders now than at the beginning of the period. This may have also interacted with the ESG factor, explaining its variability between years.

The empirical findings provide insights into the impact of ESG factors on the returns of firms in the Nordics, as well as the relationship between ESG scores and volatility. The results suggest that larger firms with good ESG compliance are likely to be the ultimate winners in the Nordic countries, at this point in time. The findings also raise questions about the safe-haven theory of ESG and suggest that further research is needed to fully understand the relationship between ESG scores and volatility. We note that moving up ESG deciles (i.e., investing in firms with higher ESG scores) does not increase returns in a linear fashion, suggesting that the ideal investment strategy is not simply to maximize ESG scores.

To this end, Naffa & Fain's (2022) factor methodology may prove useful for future research. By constructing pure ESG equity factor portfolios rated on a five-point scale, their method filters out secondary factor effects and measures the risk-adjusted performance of the pure ESG factors. The ESG PFPs may function as sustainability indices used for the calculation of investment portfolio tilt to ESG factors and for the quantification of the performance attribution of the ESG factor tilt. In addition, Naffa and Fain address statistical issues such as sample selection bias and endogeneity by using a GMM distance IV estimator. Further research could employ this methodology to investigate the relationship between ESG scores and returns more rigorously, and to gain a deeper understanding of the nature of the ESG factor in investment returns.

These empirical findings have significant implications for investors and policymakers. Investors who seek to integrate ESG factors into their investment strategies should be aware of the non-linear relationship between ESG scores and returns and the potential impact of market conditions on the return effect of ESG investing. Policymakers should note that ESG reporting/compliance is drastically increasing among firms, as companies are clearly piling into this trend.

In conclusion, the empirical findings suggest that ESG factors can impact the returns of firms in the Nordics, and exposure to the ESG factor can provide a risk premium and reduce volatility in a portfolio. Of course, further research is needed to fully understand the relationship between ESG scores and volatility, as well as the existence and nature of an ESG factor in investment returns. Investors and policymakers should be aware of the non-linear relationship between ESG scores and returns and the potential impact of market conditions on the return effect of ESG scores.

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IX - Appendix

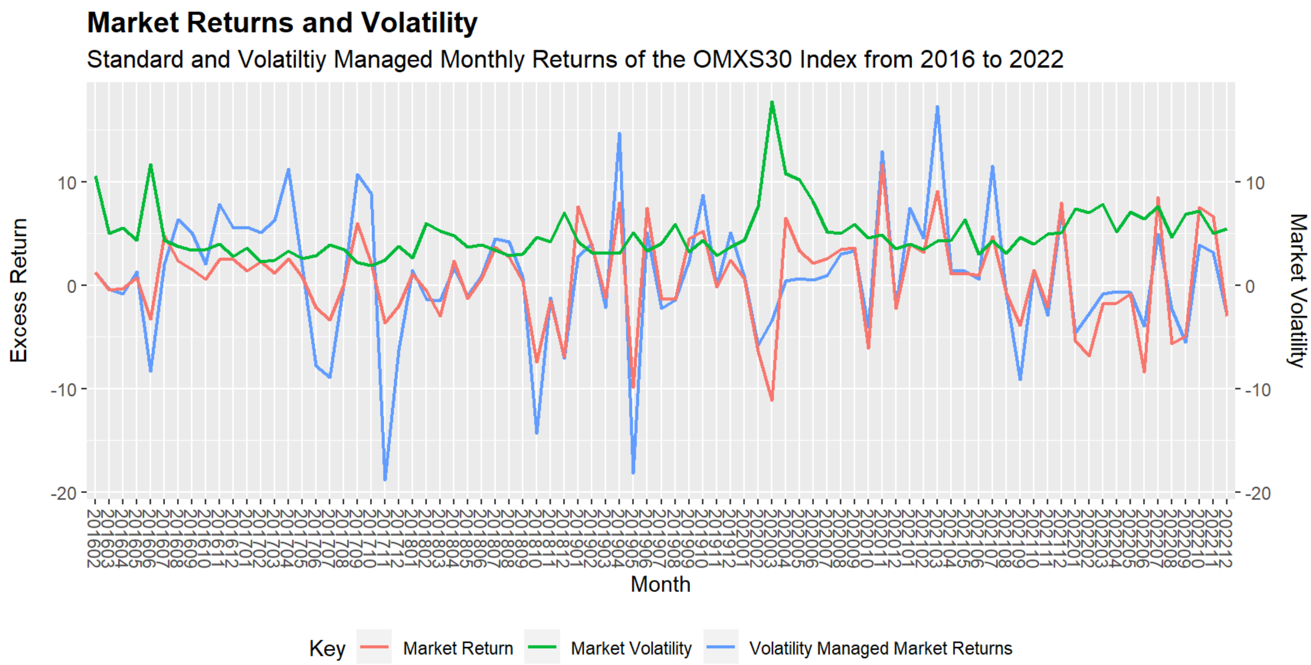


Figure 6 – Shows the outcomes of the volatility management strategy on the OMXS30 index. This graph is structured in the same way as Figure 3, i.e., a line shows the normal factor excess returns, the factor's volatility, and the volatility managed returns. As can be seen, the volatility management strategy clearly would go excessively long during negative-return months towards the beginning, which likely explains why the strategy failed to generate alpha in this instance.

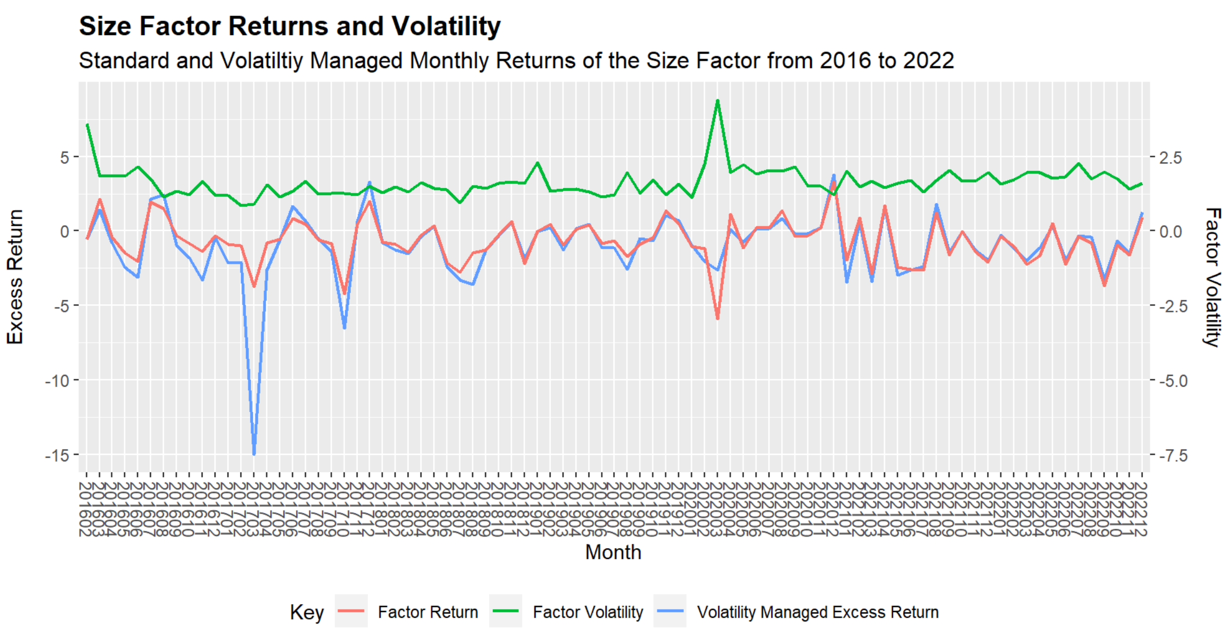


Figure 7 – Shows the volatility management outcomes on the Size factor. The strategy was able to generate a statistically significant alpha (negative) on the size factor, as we know from Table 7. We can

see that that mostly came from one event in March 2017, when it would have been particularly wise to overweight an inverse size factor. Also notice that the returns of this factor are generally below 0, which is consistent with our other evidence.

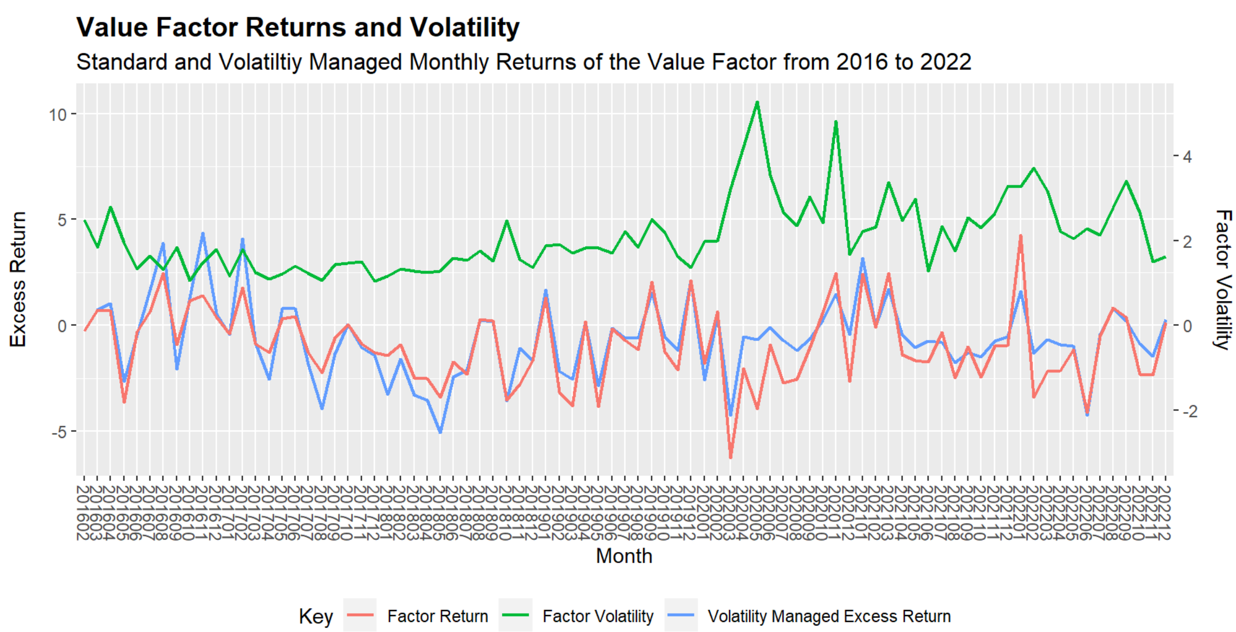


Figure 8 - Shows the volatility management outcomes on the value factor. As we know from Table 7 the strategy did not produce statistically significant alpha for this factor. This was likely due to volatility managed returns being worse than standard returns in 2017 and early 2018.

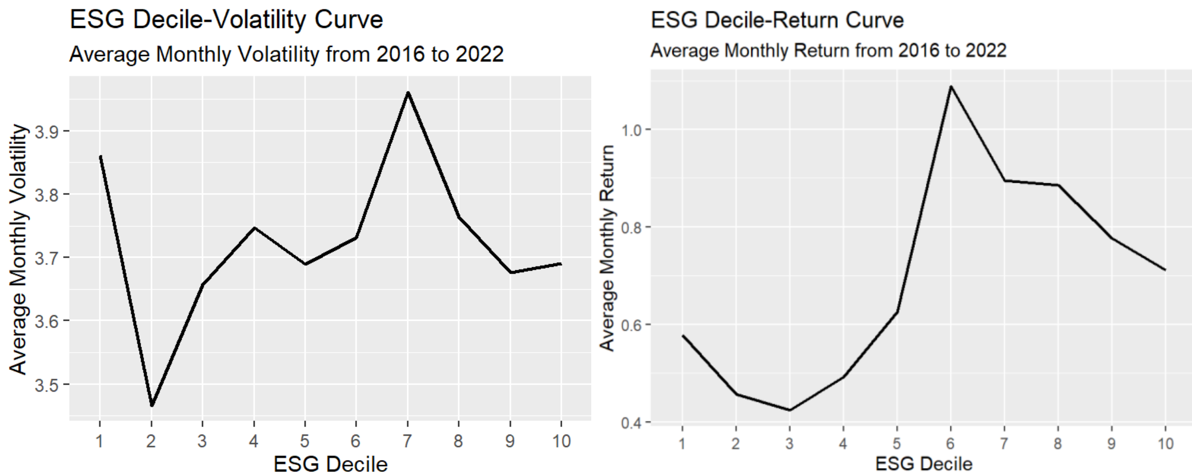


Figure 9 – Left, average monthly volatility outcomes within ESG decile groups. Right, average monthly returns of ESG decile groups/portfolios. These are the return and volatility components of the ESG efficient frontier (ESG-Sharpe curve) presented in Figure 6. You may notice that the average monthly returns vary more than the volatilities.

segment	Mean ESG	σ ESG	Number of Firm Years	Min ESG	Max ESG
Large	57.29811	11.52797	1554	19.48507	80.48295
Mid	43.06432	14.04851	1777	0.98055	78.87256

Table 9 – Descriptive statistics of size segments, irrespective of year. The larger firms are able to get larger ESG scores, of course. This is why it was important to control for size cohorts in the creation of ESG Z-scores, to control size in our decile regressions, and to consider the size factor in our factor analysis regressions.

Industry Groups	Mean ESG	σ ESG	Firm years	Min ESG	Max ESG
Banking, Finance and Insurance	48.8293	14.39874	696	17.12963	78.42125
Consumer Goods & Services	53.40497	13.37963	659	0.98055	78.87256
HealthCare and Pharmaceuticals	44.25375	15.45133	363	14.26426	80.48295
Industrials	50.97882	14.53557	1295	11.15449	79.08462
Telecom and Technology	44.98681	15.24018	318	15.42637	76.76562

Table 10 – Descriptive statistics of our five industry groups and their ESG ratings. Across seven years, this allows for at most 185 and at least 45 firms per industry per year. In combination with size cohorts, having more industry groups than this would have created too much of a diversification factor and too little of an ESG factor for the study to be valuable. 73 separate industries, as per Nordic Compass's original dataset would have been untenable for this reason.

Group	segment	year	Mean ESG	Firms	σ ESG	Min ESG	Max ESG
BFI	Large	2015	53.13163	34	14.22908	26.76493	78.42125
BFI	Large	2016	57.69525	37	13.03984	33.21237	74.85352
BFI	Large	2017	51.22596	47	12.15442	24.63991	67.66313
BFI	Large	2018	50.18528	46	13.66788	19.48507	70.46153
BFI	Large	2019	50.26878	45	11.31709	26.92744	70.69741
BFI	Large	2020	55.415	53	10.44086	24.88268	68.43529
BFI	Large	2021	60.11994	45	7.529226	36.67378	70.62699
BFI	Large	2022	60.13218	63	8.51721	27.68169	71.71836
BFI	Mid	2016	40.80311	37	14.9828	17.12963	68.29353
BFI	Mid	2017	38.73413	40	12.95718	21.54999	66.15998
BFI	Mid	2018	37.10258	56	12.57932	21.22582	69.26925
BFI	Mid	2019	37.62432	44	13.02721	18.85788	57.38291
BFI	Mid	2020	42.76077	58	12.79939	18.50746	66.13476
BFI	Mid	2021	48.37529	54	12.71306	19.29436	67.55608
BFI	Mid	2022	47.30676	37	14.2089	18.5291	63.85824
CG&S	Large	2015	61.14549	30	10.13433	38.83588	77.02166
CG&S	Large	2016	61.62079	29	11.69944	35.27101	77.57258
CG&S	Large	2017	60.55987	32	9.926503	37.26008	72.44403
CG&S	Large	2018	56.34211	37	12.85765	26.879	71.12601
CG&S	Large	2019	53.77106	38	13.90214	22.54276	68.31863
CG&S	Large	2020	56.50657	33	8.83897	28.95204	67.45229
CG&S	Large	2021	60.82673	40	7.579961	35.36163	71.43947
CG&S	Large	2022	58.74569	41	10.19685	25.55617	72.98005
CG&S	Mid	2015	47.49162	11	15.84857	17.18916	67.4079
CG&S	Mid	2016	54.4579	47	11.89292	28.98268	72.25764
CG&S	Mid	2017	47.46217	48	15.10919	0.98055	70.54638
CG&S	Mid	2018	44.38428	60	14.90352	7.797619	68.8401
CG&S	Mid	2019	46.53072	51	13.97487	12.66913	67.74832
CG&S	Mid	2020	48.1822	56	12.31527	17.61482	72.28418
CG&S	Mid	2021	53.39187	55	11.24957	24.72652	65.99235
CG&S	Mid	2022	54.29961	51	12.43427	25.75005	78.87256
HC&P	Large	2015	59.05762	14	13.34474	36.42925	74.98823
HC&P	Large	2016	62.37615	15	9.669173	43.25764	80.48295
HC&P	Large	2017	56.13616	17	12.91093	37.39713	72.45178
HC&P	Large	2018	51.15887	19	14.54006	25.14968	66.75268
HC&P	Large	2019	50.29271	20	12.03933	28.73246	65.23074
HC&P	Large	2020	56.31859	18	7.185883	42.35431	66.5626
HC&P	Large	2021	58.04471	19	9.060304	30.99117	71.67467
HC&P	Large	2022	54.55399	31	12.90582	20.05937	73.36305
HC&P	Mid	2016	35.2872	24	12.7334	17.54543	64.85163
HC&P	Mid	2017	39.21184	25	10.07193	19.93722	59.82568
HC&P	Mid	2018	32.88101	33	10.6883	14.26426	57.2109

HC&P	Mid	2019	30.18958	32	8.695469	18.49588	52.48353
HC&P	Mid	2020	36.16585	37	12.71692	19.89688	68.69256
HC&P	Mid	2021	38.84146	40	12.37835	21.95302	63.7711
HC&P	Mid	2022	41.66292	19	14.57971	20.86833	64.63613
I	Large	2015	60.29801	66	12.78621	24.97054	79.08462
I	Large	2016	62.82811	62	12.1634	25.27057	77.06537
I	Large	2017	60.30502	67	10.73629	34.5918	71.8398
I	Large	2018	58.06644	79	11.59576	21.55757	72.00397
I	Large	2019	53.38098	83	12.64845	21.11194	69.9586
I	Large	2020	56.10047	86	9.708685	29.64952	68.6788
I	Large	2021	59.66312	81	8.47301	33.62624	70.48171
I	Large	2022	60.33873	95	8.234355	33.86956	74.62202
I	Mid	2015	45.74609	68	15.56541	14.52682	70.23248
I	Mid	2016	44.52191	84	15.33309	15.68713	74.06712
I	Mid	2017	40.66509	96	14.95649	12.17857	70.87337
I	Mid	2018	39.23703	99	13.49898	11.15449	65.37033
I	Mid	2019	40.29212	74	12.0299	23.27573	68.77763
I	Mid	2020	44.85325	88	10.96547	17.62313	63.71627
I	Mid	2021	47.98299	106	11.44629	13.86111	72.36737
I	Mid	2022	49.85128	61	12.4906	13.67521	69.36437
T&T	Large	2015	58.81218	15	13.41705	33.30241	76.76562
T&T	Large	2016	60.15038	13	11.39523	32.47915	73.58837
T&T	Large	2017	60.50358	14	11.7651	29.23665	73.63798
T&T	Large	2018	53.03629	17	14.89686	24.02025	68.10007
T&T	Large	2019	52.44048	16	11.39542	31.86992	70.04385
T&T	Large	2020	55.69858	15	8.26148	37.55259	68.63361
T&T	Large	2021	60.3493	18	9.345723	25.81568	71.85808
T&T	Large	2022	54.10993	24	11.66401	29.30084	69.81905
T&T	Mid	2015	38.44578	14	11.92587	24.57848	63.20806
T&T	Mid	2016	36.78149	17	8.460153	22.18086	54.80068
T&T	Mid	2017	33.91669	25	8.845079	21.73526	60.53606
T&T	Mid	2018	32.46624	29	10.6088	15.42637	55.98182
T&T	Mid	2019	32.95174	23	10.26932	21.81152	53.1619
T&T	Mid	2020	39.04772	29	11.64281	25.38024	60.17939
T&T	Mid	2021	41.53754	31	13.81506	20.87807	61.62308
T&T	Mid	2022	39.03589	18	13.10335	22.0452	58.83738

Table 11 – Descriptive statistics for each industry size year cohort. ESG-Z scores are calculated within these groups.

For space we used abbreviations for industry groups. BFI = Banking Finance and Insurance, CG&S = Consumer Goods and Services, HC&P = Healthcare and Pharmaceuticals, I = Industrials, T&T=Telecom and Technology.

year	ESG beta	Market Beta	Size Beta	Value Beta
2016	-0.29418	0.673411	0.389147	-0.04442
2017	0.008192	0.650554	0.516958	-0.1752
2018	0.03166	0.677227	0.428336	-0.30965
2019	-0.08626	0.645886	0.367126	-0.13738
2020	-0.01291	0.612208	0.531844	0.030045
2021	0.159317	0.724693	0.726901	-0.17131
2022	0.033009	0.792905	0.646609	-0.01249

Table 12 – Average factor exposure estimates for stocks per year.

	ESG Z score statistics		Raw ESG Score statistics	
Year	Kurtosis	Skewness	Skewness	Kurtosis
2015	2.51	-0.53	-0.53	2.04
2016	2.57	-0.41	-0.35	1.90
2017	2.73	-0.27	-0.21	1.92
2018	2.57	-0.22	-0.07	1.64
2019	2.49	-0.26	-0.18	1.69
2020	2.80	-0.44	-0.43	1.93
2021	3.75	-0.89	-0.79	2.53
2022	4.02	-1.07	-1.07	3.31

Table 13 – Skew and kurtosis of raw ESG and ESG Z distributions for each year. While we already visualized the distribution using Figure 5, these numbers can quantify the increasing negative skew of ESG score distributions.

	Monthly Outcomes			Annualized Outcomes		
Factor	Mean Excess Return	Mean Volatility	Sharpe Ratio	Mean Excess Return	Mean Volatility	Sharpe Ratio
ESG	0.540	1.272	0.425	6.483	4.406	1.471
Size	-0.684	1.639	-0.418	-8.212	5.676	-1.447
Value	-0.939	2.088	-0.450	-11.271	7.232	-1.558
Market	0.618	4.909	0.126	7.422	17.005	0.436

Table 14 – Mean monthly excess return, volatility, and Sharpe ratio outcomes of the four factors analyzed in the FF3 + 1 model. We provide the raw monthly numbers to the left, and annualized versions of these to the right.

Control Variables

Since we apply a Fama French Three Factor model to our regression, we have to create size and value factors. This of course requires us to calculate the firms' market capitalizations and book to market ratios. We also calculate individual stock beta with the OMXS30 Index for our baseline set of regressions. Here we will detail how these are calculated.

Market Capitalization

Market Capitalization is equal to the share price multiplied by the number of shares outstanding at any given time. Since there are multiple different currencies in the Nordic countries we convert all market capitalizations to Euros, and then calculate the natural logarithm of this, in the following manner.

$Logsize = \ln\left(\frac{P \cdot Shares}{EUR}\right)$, where P is the closing share price (variable name "prccd" in Compustat) on a given day, Shares refers to the number of shares outstanding (variable name "cshoc" in Compustat), and EUR refers to the Euro exchange rate of the currency the shares trade in.

We applied an average euro exchange rate throughout the period for simplicity since Nordic currencies are relatively stable and there were very few firms trading in other currencies. The average exchange rates were as follows.

SEK – 10.5	MXN – 21	DKK – 7.45
EUR – 1	CHF – 1.1	GBP – 0.88
NOK – 10	BRL - 5	ARS – 90
CLP – 10	ISK – 800	

Book to Market Ratio

Book to market ratio was defined as follows.

$$Value = \frac{Book\,Value\,of\,Equity}{Market\,Capitalization}$$

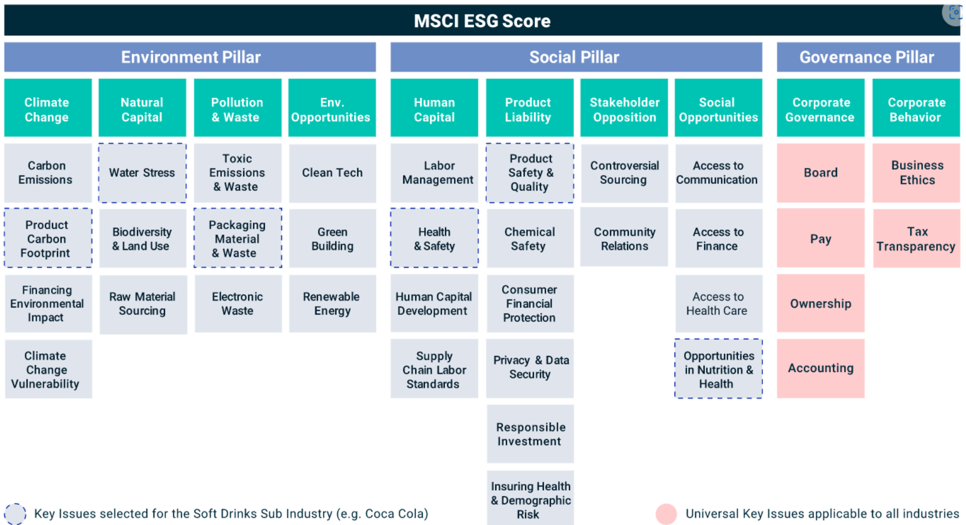
Book value of Equity was calculated as total assets minus total liability (variable names "at" and "lt" in Compustat). Market Capitalization was defined as closing price ("prccd") multiplied by shares outstanding ("cshoc"). We did not need to apply the exchange rates to this calculation, as balance sheet reporting and trading currencies are the same for the firms in our stock universe.

Beta

In our ESG decile portfolio regression set we calculate a stock i's factor betas during a given calendar year as the covariance of the stock with the market (or the factor in question) divided by the variance of the market as follows.

$$Beta_i = \frac{Cov(r_i\,, r_m)}{Var(r_m)}$$

MSCI Key Issues Framework



As stated in the ratings construction methodology the MSCI ESG score is constructed using 3 pillars, 10 themes and 35 key issues. The governance pillar is standardized across industries. In the above example 3 key issues are selected within the E & S pillars for the 'Soft drinks Sub Industry'. This image further highlights the differences between our ratings methodology and the method employed by MSCI

Table 15 - Variables in Nordic Compass Set

The Nordic Compass dataset contains 109 variables. The database classifies these as "general", "Environmental", "Governance" and "Social" datapoints. We list all variables below, their type (qualitative or quantitative) and if they were used in the computation of E, S and G scores, as per our methodology.

General Variables

comp_name	Company Name
ticker	Ticker
year	Year
gvkey	Gvkey
org_number	Organization number (from 2019)
isin	ISIN (from 2019)
finbas_id	Finbas Companyid (from 2019)
segment	Segment
industry	Industry
supersector	Supersector
supersector_icb	Supersector ICB Code
hq_country	Headquarters Country

Environmental Datapoints

Variable Code	Variable Description	Inclusion?	Type
ceo_sust_statem	CEO/Chair/Executive Sustainability Statement	Included in $RawESGn$	*Qualitative Variable*
reported_curr	Reported Currency	Included in $RawESGn$	*General Variable*
sales	Sales (MEUR YE)	Included in $RawESGn$	*Quantitative Variable. Included in multiple 'created' variables*
env_policy	Environmental Policy and Assessment	Included in $RawESGn$	*Qualitative Variable*
ep_targets	Targets associated with Environmental Performance	Included in $RawESGn$	*Qualitative Variable*
env_impact_red	Steps taken to reduce negative environmental impact	Included in $RawESGn$	*Qualitative Variables*
energy_consump	Total Energy Consumption (GJ)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "energy intensity"*
incr_renew_en	Increased usage of renewable energy	Included in $RawESGn$	*Qualitative Variable*
disclosure_raw	Disclosure of raw material consumption	Included in $RawESGn$	*Qualitative Variable*
resource_target	Targets associated with Efficient use of Resources	Included in $RawESGn$	*Qualitative Variable*
water_withdraw	Total Water Withdrawal (1000 cubic meter)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "water intensity"*
water_disclose	Disclosure of Water Discharges	Included in $RawESGn$	*Qualitative Variable*
ghg_emis	Total GHG Emissions (kilotonnes)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "carbon intensity"*
transport_emis	Transportation Emissions (CO2, NOx, CO, HC, SO2, CH4, particulates in kilotonnes)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "transport intensity"*

Social Datapoints

Variable Code	Variable Description	Inclusion?	Type
board_es_resp	Board of Directors responsible for Environmental/Social performance	Included in $RawESGn$	*Qualitative Variable*
board_es_comp	Board compensation linked to Environmental/Social performance	Included in $RawESGn$	*Qualitative Variable*
exec_es_resp	Senior Executives responsible for Environmental/Social performance	Included in $RawESGn$	*Qualitative Variable*
exec_es_comp	Senior Executive compensation linked to Environmental/Social performance	Included in $RawESGn$	*Qualitative Variable*
exec_cbb_esg	Senior Executive with Core Business Background in charge of ESG	Included in $RawESGn$	*Qualitative Variable*
exec_nocbb_esg	Senior Executive without Core Business Background in charge of ESG	Included in $RawESGn$	*Qualitative Variable*
div_es_resp	Environmental/Social responsibility at the divisional level	Included in $RawESGn$	*Qualitative Variable*
years_es_report	Number of years of reporting on ESG	Included in $RawESGn$	*Quantitative Variable*
audit_es_report	External audit of ESG reporting	Included in $RawESGn$	*Qualitative Variable*
num_employees	Number of Employees (year-end)	Included in $RawESGn$	*Quantitative Variable*
tot_sal_exp	Total salaries and remuneration expense (MEUR)	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "average employee salary"*
female_emp	Number of female employees	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "percentage of female employees"*
female_exec	Number of female Senior Executives	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "Percentage of female executives"*
board_size	Board Size including employee representatives	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "Percentage of female board members"*
female_board	Number of full-member females on the Board	Included in $RawESGn$	*Quantitative Variable. Used to create 'good'*

			variable "Percentage of female board members"
pay_eq_report	Reporting on male/female pay equality	Included in $RawESGn$	*Qualitative Variable*
equal_policy	Equal Opportunity Policy or Statement	Included in $RawESGn$	*Qualitative Variable*
edu_spending	Training & Education spending (hours/employee)	Included in $RawESGn$	*Quantitative Variable*
edu_policy	Training & Education policy for employees	Included in $RawESGn$	*Qualitative Variable*
injury_disclose	Disclosure of types of Injury and by region and/or Gender	Included in $RawESGn$	*Qualitative Variable*
accidents	Accidents per millions hours worked (LTI)	Not included in $RawESGn$	Not included to maintain Industry comparability.
fatalities	Number of fatalities of employees and contractors on the job	Not included in $RawESGn$	Not included to maintain Industry comparability.
health_policy	Not included to maintain Industry comparability. Health & Safety Policy	Included in $RawESGn$	*Qualitative Variable*
health_assess	Health & Safety Risk Assessment	Included in $RawESGn$	*Qualitative Variable*
pandemic_policy	Pandemics Policy	Included in $RawESGn$	*Qualitative Variable*
su_guidelines	Supplier Guidelines	Included in $RawESGn$	*Qualitative Variable*
su_aud_disclose	Disclosure of percent of Suppliers visited and audited	Not included in $RawESGn$	Not included to maintain Industry comparability.
su_eva_disclose	Disclosure of Supplier Evaluation Procedures	Included in $RawESGn$	*Qualitative Variable*
su_lab_assess	Supplier assessment for labor practices	Included in $RawESGn$	*Qualitative Variable*
su_hr_assess	Supplier assessment for human rights	Included in $RawESGn$	*Qualitative Variable*
su_env_assess	Supplier assessment for environmental impact	Included in $RawESGn$	*Qualitative Variable*
whistleblower	Whistleblower mechanisms / hotlines	Included in $RawESGn$	*Qualitative Variable*
corrupt_policy	Anti-Corruption Policy or Statement, including extortion and bribery	Included in $RawESGn$	*Qualitative Variable*

hr_policy	Human Rights Policy or Statement	Included in $RawESGn$	*Qualitative Variable*
ethics_policy	Code of Conduct / Ethics Policy	Included in $RawESGn$	*Qualitative Variable*
loc_imp_assess	Social impact assessments on local communities	Included in $RawESGn$	*Qualitative Variable*
loc_dev_prog	Local community development programs	Included in $RawESGn$	*Qualitative Variable*
com_investment	Community Investments as percent of Sales	Included in $RawESGn$	*Quantitative Variable*

Governance datapoints

Variable Code	**Variable Description**	**Inclusion?**	**Type**
ceo_not_chair	Separate CEO and Chairman of the Board	Included in $RawESGn$	*Qualitative Variable*
chair_ind_mgmt	Chairman of the Board Independent of Company and Senior Management	Included in $RawESGn$	*Qualitative Variable*
chair_ind_ms	Chairman of the Board Independent of Major Shareholders	Included in $RawESGn$	*Qualitative Variable*
pres_director	Lead / Presiding Director	Included in $RawESGn$	*Qualitative Variable*
ceo_statem	sed	Included in $RawESGn$	*Qualitative Variable*
ind_directors	Number of Independent Directors	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "Percentage of independent directors"*
emp_reps	Number of Employee and/or Union Representatives on Board	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "Percent of employee/union board reps"*
nomcom	Number of Members on Nomination Committee	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "Percent of nomcom board members"*
nomcom_no_board	Number of Members of Nomination Committee not on the Board	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "Percent of*

			nomcom non-board members"
nomcom_ind_ms	Number of Nomination Committee Board members, independent of company and major shareholders	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "Independent nomcom board members"*
nomcom_dep_ms	Number of Nomination Committee Board members, independent of company, dependent on major shareholders	Not included in $RawESGn$	Not included to maintain Industry comparability.
nomcom_dep_co	Number of Nomination Committee Board members dependent on company	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "percentage of dependent nomcom board members"*
majority_dir	Majority Voting Policy for election of Directors	Included in $RawESGn$	*Qualitative Variable*
ind_dir_rc	Number of Independent Directors on Remuneration Committee	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "percentage of independent remcom directors"*
members_nc	Number of Members of Remuneration Committee	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable "percentage of independent remcom directors"*
ind_dir_ac	Percent Independent Directors on Audit Committee	Not included in $RawESGn$	Not included to maintain Industry comparability.
audit_fees	Audit Fees (MEUR)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "Audit fees as a percent of revenue"*
non_audit_fees	Non-Audit Fees (MEUR)	Included in $RawESGn$	*Quantitative Variable. Used to create 'bad' variable "non-Audit fees*

			as a percent of revenue”
ceo_comp	CEO compensation (MEUR)	Included in $RawESGn$	*Quantitative Variable. Used to create ‘bad’ variable “CEO compensation as a percent of revenue”*
earn_per_share	Earnings Per Share diluted (EUR)	Not included in $RawESGn$	Not included as it's not an ESG variable
ceo_share_co	CEO Share based compensation	Included in $RawESGn$	*Quantitative Variable. Used to create ‘good’ variable “CEO compensation as a percent of sales”*
board_duration	Board Duration years	Not included in $RawESGn$	Not included to maintain Industry comparability.
board_meetings	Board Meetings Per Year	Not included in $RawESGn$	Not included to maintain Industry comparability.
board_attend	Board Meeting Attendance in percent	Not included in $RawESGn$	Not included to maintain Industry comparability.
block_votepower	Block shareholders voting power in percent	Not included in $RawESGn$	Not included to maintain Industry comparability.
unequal_voting	Unequal voting rights	Included in $RawESGn$	*Qualitative Variable*
gri_compliance	GRI Compliance	Included in $RawESGn$	*Qualitative Variable*
gri_level	GRI Level (Discontinued 2015)	Not included in $RawESGn$	Not included due to discontinued data
gri_score	GRI Score (Discontinued 2015)	Not included in $RawESGn$	Not included due to discontinued data
gri_ext_assur	GRI External Assurance	Included in $RawESGn$	*Qualitative Variable*

Extra compensation (governance) data points (introduced from 2019)

Variable Code	**Variable Description**	**Inclusion?**	**Type**
ceo_f_salary	CEO fixed salary (from 2018)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of CEO's total compensation*
ceo_var_salary	CEO variable salary/cash bonus (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of CEO's total compensation*
ceo_sh_award	CEO LTI/share-based award (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of CEO's total compensation*
ceo_pension	CEO pension (cost) (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of CEO's total compensation*
ceo_other_comp	CEO other comp. (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of CEO's total compensation*
ceo_tot_comp	CEO total comp. (from 2019)	Included in $RawESGn$	*Quantitative Variable*
ceo_during_year	Number of CEO during the year (from 2019)	Included in $RawESGn$	*Quantitative Variable with a penalty for greater than 1 CEO/year*
mgmt_f_salary	Mgmt. fixed salary (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of management's total compensation.*
mgmt_var_salary	Mgmt. variable salary/cash bonus (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of management's total compensation.*
mgmt_sh_award	Mgmt. LTI/share-based award (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of management's total compensation.*

mgmt_pension	Mgmt. pension (cost) (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of management's total compensation.*
mgmt_other_comp	Mgmt. other comp. (from 2019)	Included in $RawESGn$	*Quantitative Variable, measured as a percent of management's total compensation.*
mgmt_tot_comp	Mgmt. total comp. (from 2019)	Included in $RawESGn$	*Quantitative Variable*
tot_exec	Total Number of Executives during the year (excl. CEO) (from 2019)	Included in $RawESGn$	*Quantitative Variable. Used to create 'good' variable, "percent of female executives"*
max_var_pay	Max variable pay (from 2019)	Not included in $RawESGn$	Not included to maintain Industry comparibility