Navigating Downside Risk: The Impact of ESG Across Sectors

Assessing the Impact of ESG scores on Value at Risk and Expected Shortfall

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Authors:

Henric Ihr & William Magnusson

Supervisor:

Anders Vilhelmsson

Abstract

This study investigates the relationship between ESG scores and downside risk across various sectors in the Nordic markets from 2018 to 2022. ESG, a widely recognized concept in finance, evaluates companies' performance based on their environmental, social, and governance practices. We examine how both the overall ESG scores and the individual pillars influence downside risk in 11 different sectors using panel regression analysis. Our findings reveal a consistent trend across the majority of sectors in the Nordics: higher ESG scores are associated with reduced downside risk. Moreover, we identify the environmental pillar as the most influential in mitigating downside risk. Interestingly, our results indicate that firms with lower ESG scores face greater penalization in terms of downside risk compared to the reduction experienced by top performers. This suggests a pronounced effect of ESG ratings on risk management practices within Nordic markets.

Keywords: *Downside Risk, ESG, Expected Shortfall, Sustainable Finance, Value at Risk*

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Contents

1 Introduction

Currently, the global financial industry is experiencing a period of transition, characterized by a dramatic increase in interest for socially and environmentally responsible investments—a movement that has emerged over the past decades. This interest is a consequence of an ambition to address the significant environmental and social problems we face in our current society, were both institutional and individual investors feel an urge to incorporate this new dimension into their investment strategies. This new trend is not solely due to social pressure, but also a result of more recent regulations (European Commission 2018). At present, regulatory pressure stems from both existing and forthcoming legislation, reflecting the significant role of the financial industry in driving the transition towards sustainability. For instance, within the EU, several regulatory initiatives are in progress to bolster transparency regarding the sustainability aspects of financial products, thereby intensifying regulatory pressure further (Brühl 2023). This pressure is evident in investors' growing ambition to more fully integrate sustainability into their investment strategies (Henriksson et al. 2019). An illustration of this shifting landscape in the financial market occurred when the world's largest institutional investor, BlackRock, disclosed that during the fourth quarter of 2021, one-third of net capital inflow was directed towards sustainable funds, amounting to 32 billion USD (Brush 2021).

To integrate these sustainability goals in a systematic and transparent manner, one of the most used approaches has been to adopt an independent labeling system for investments and corporations. An example of a rapidly growing and widespread instrument in the realm of financial sustainability labeling is the Environmental Social Governance (ESG) framework. The asset market for ESG has experienced an average of 30% annual growth between 2016 and 2021, and is estimated to amount to 53 trillion USD in 2025 (Bloomberg 2021). Considering the size of this market and the regulatory development during the recent years, ESG can be seen as a well-established type of investment, worthy of a more investigation from the perspective of risk management.

The availability of the ESG-framework and its independent rating system can in light of its core function therefore potentially offer a possibility to quantify financial performance by evaluating its affect on society, both environmentally and socially. Thus, ESG ratings are a tool to enforce financial behavior by evaluating in which degree a company affects the environment, the social well-being of affected individuals and how its governance structure is designed. A sustainable businesses can arguably inherent a negating nature towards downwards shocks in the market. The contrasting nature of this can be illustrated by comparing an environmentally friendly company with one that is not as environmentally friendly. The former is expected to be less vulnerable to both climate risks and transition risks, as it is more resilient to the impacts of climate change (Setzer & Higham 2021; Engle et al. 2020). Moreover, regarding the governance structure of a company, the OECD asserts that a company with a more responsible governance is less likely to both over-leverage and encounter litigation issues associated with poor business practices (OECD 2014).

As a result of these characteristics, one could assume that company's that inherent highly ranked ESG scores for their business practice should be advantageous in terms of risk management. Although there is a theoretical and somewhat empirical agreement on the impact of ESG ratings on downside risk (also referred to as left-tail risk) as found in earlier studies—details of which are provided in *Section 3*—the influence of these ratings on downside risk in sector-specific stocks remains largely unexamined. To date, there appears to be a lack of research analyzing how companies with varying ESG ratings are exposed to downside risks across different sectors, leaving potential sectoral differences unexplored. Furthermore, it could be enlightening to examine how the three pillars of ESG—environmental, social, and governance—individually influence downside risk. It is plausible to assume that different sectors may be differently affected by each pillar. Consequently, this study proposes to investigate both the aggregate ESG score and its individual components in order to dissect the data as thoroughly as possible. Research particularly focused on the Nordic region—encompassing Sweden, Denmark, Finland, and Norway—is also sparse. Given these gaps, this paper aims to enhance the understanding of whether and how ESG considerations could be integrated into corporate risk management strategies. Accordingly, this paper seeks to determine the influence of ESG ratings on downside risk within various sectors in the Nordic countries. The research questions we intend to address are as follows:

Q1: Do companies with a high ESG score inherent a lower downside risk relative to low rated companies?

Q2: How do the separate pillars influence the downside risk?

Given the research questions and the focus on investigating downside risk, we will employ the measures Value at Risk (VaR) and Expected Shortfall (ES) in this paper. These measures offer the possibility to generate a single number or percentage that encapsulates the overall risk in a portfolio or asset. This allows the researchers to dissect the downside risks and, consequently, answer the research question in a robust manner.

1.1 Outline

The remainder of this paper will be structured as follows: In *Section 2*, the theoretical framework will be presented, providing the theoretical basis for ESG and offering a more comprehensive review of the risk measures used. *Section 3* comprises the literature review, delineating the current research within the field and summarizing the conclusions drawn by earlier studies. *Section 4* presents the methodology employed in this paper, providing a detailed explanation of the econometric approach used to implement the models. Moreover, it also covers the data collection process, the final data selection, the settings of control variables, and provides descriptive statistics. In *Section 5* presents the results of this paper. Finally, in the last two sections, we will discuss the results, draw final conclusions based on the discussion, and provide recommendations for future research.

2 Theoretical Framework

In this section, the paper summarizes the background and development of the ESG concept. Within this subsection, the individual pillars that comprise the ESG concept will also be discussed and explained. Furthermore, this section will provide a formal description of the employed risk measures, thus offering the reader an in-depth explanation of how VaR and ES function as risk measures.

2.1 Definition of ESG

The term ESG was established in 2004 when the United Nations published the report 'Who Cares Wins' (United Nations 2004), urging major financial stakeholders to consider sustainability in their long-term objectives and strategies. Since then, the interest and importance of ESG has exponentially continued to grow. The ESG framework generally functions by rating investments and companies, where the rating suggests the degree of sustainability. A high (low) score indicates sustainable (unsustainable) ESG practices and a low (high) exposure to risks associated with ESG. More specifically, the ESG framework and rating system is built on its three constituting pillars: E (Environmental), S (Social), and G (Governance).

The environmental pillar centers on assessing the environmental ramifications of corporate operations, such as their impact on climate change, utilization of limited natural resources, and contribution to pollution. Its primary objective is to prioritize the well-being of the planet and advocate for the preservation of a sustainable environment. The social pillar pertains to the human dimension of our society, emphasizing the significance of providing all individuals with access to resources and opportunities essential for their welfare. For instance, it emphasizes the importance of diversity and inclusion in the workforce, ensuring health and safety standards for both employees and consumers, and upholding labor standards within the supply chain. The governance pillar addresses aspects related to corporate management and behavior, including board structure and actions, management compensation, adherence to ethical business models, as well as transparency and reporting standards. It focuses on ensuring robust governance practices within organizations to uphold accountability and integrity (LSEG 2023).

With the provided definitions of each separate pillar and insights from the scoring metric (LSEG 2023), variations emerge in the measurement approaches for these distinct pillars. The environmental pillar heavily leans on quantitative data, facilitated by directly measurable metrics. In comparison, the social pillar appears somewhat more abstract, yet it retains robust validity due to its reliance on certain quantitative aspects and transparency. Conversely, the governance pillar emerges as the most fragile among them, as the different criteria are challenging to quantify consistently. For instance, LSEG (2023) utilized shareholder rights and poison pills as components of the scoring metric for the governance pillar. However, the foundation of these criteria relies on the count of data-points in each subcategory building up the governance pillar. The information contributing to this pillar comprises soft values, potentially posing challenges for consistent scoring.

Currently, businesses can evaluate and measure their performance in the environmental, social, and governance criteria using the ESG framework. Various ESG data, metrics, and criteria are available to monitor and evaluate ESG performance across different industries and businesses. This information is utilized by a variety of stakeholders who depend on or have an interest in company-reported ESG data, helping them evaluate the impact of ongoing operations or choose suitable suppliers. Relying on ESG disclosure, which facilitates a consistent assessment of ESG performance, has propelled ESG reporting towards greater standardization. Currently, various third-party entities—including S&P Global, MSCI, Refinitiv, and Bloomberg—have developed their own ESG frameworks and ranking systems, streamlining evaluation in a comparable fashion (PwC 2024).

Although, Li & Polychronopoulos (2020) demonstrated that in 2019 there were 70 different firms offering some form of ESG rating, which underscores the potential for a degree of ambiguity and divergence among the available ESG ratings. Berg, Kölbel & Rigobon (2022) note a substantial divergence among providers, evidenced by correlations ranging from 0.38 to 0.71, indicating significant disagreement between providers. This variation in rating standards among different providers creates a scenario in which companies may receive different ESG ratings depending on the provider issuing the rating. This variation leads to significant challenges, particularly in determining which rating agency accurately reflects a company's ESG standards and thus, raises questions about which provider is most reliable for conducting research based on accurate and unbiased ESG ratings. Given this delicate issue, this paper will collect its data on the overall ESG score and the individual E, S, and G pillars from a single provider only. The rationale behind the choice of provider and the data collection methodology used in this study will be further discussed in *Section 4*.

The rating agencies employ both quantitative and qualitative methods to determine a company's ESG rating. Companies demonstrating responsible corporate behavior receive high ESG scores, while those engaging in irresponsible practices are assigned low ESG scores. A company is typically assigned to an overall rating category based on its ESG score, which is defined using predetermined thresholds. This categorization ensures that companies with similar scores are grouped into the same ESG rating class (LSEG 2024).

2.2 Definition and Implementation of Risk Measures

2.2.1 Value at Risk

For the purpose of this paper, the relevant risk measures must be defined. As stated earlier, the risk measure VaR is suitable to employ when assessing the left-tail risk for an asset or portfolio. There are several reasons for the support of VaR among academics and industry experts. VaR effectively captures an economic agent's total risk from a specific financial position in a single monetary figure, enabling clear and simple communication of risk levels to stakeholders (Manganelli & Engle 2001). This risk measure is comprehensive, covering all investment types because it is derived from the statistical probability of losses, represented as a certain threshold or quantile (Acerbi, Nordio & Sirtori 2001). Additionally, VaR's focus on the potential for losses is naturally appealing because it aligns with how experts and scholars typically understand risk. Due to these factors, VaR has gained recognition and extensive adoption as a method for evaluating risk. It is mathematically defined as:

$$VaR_q = \min\{l : \Pr(L > l) \leq 1 - q\} \tag{1}$$

The definition of VaR_q in accordance to Equation (1) above, states that at the q confidence level, the smallest loss l, that satisfies the condition that the probability of experiencing a loss L that is larger than l is less than or equal to $1 - q$. In simpler terms, VaR represents the maximum loss level over a specific predetermined time frame that will not be surpassed with a probability of $1 - q\%$ (Hull 2018). Furthermore, Equation (1) visualizes the mathematical definition when the underlying loss distribution F_L, is of discrete nature. However, when observing a F_L that is continuous, the definition is given by Equation (2) below:

$$VaR_q = \Pr(L > VaR_q) = 1 - q \tag{2}$$

or, equivalently:

$$\mathrm{P}(L > VaR_q) = 1 - q \tag{3}$$

By taking the inverse of the cumulative distribution function, we obtain the q-quantile of the continuous loss distribution F_L:

$$VaR_q = F_L^{-1}(q) \tag{4}$$

Due to the difference in the mathematical nature of a discrete and continuous distribution, Equation (2) and (4) instead states that at the q confidence level, VaR_q is by definition the q^{th} quantile of the loss distribution (Hull 2018).

2.2.2 Expected Shortfall

The second risk measure utilized in this paper is ES, which is also known as conditional VaR or expected tail loss. As the name suggests, ES is closely related to VaR. Fundamentally, ES is determined by taking the average of all losses in the distribution that are worse the VaR for an asset or portfolio, at a given confidence level q (Hull 2018). For a given loss distribution F_L, ES is defined by Equation (5) and applies to both discrete and continuous loss distributions (McNeil, Frey, and Embrechts 2015):

$$ES_q = \frac{E[L \cdot I_{L>VaR_q}] + VaR_q\,(1 - q - Pr(L > VaR_q))}{1 - q} \tag{5}$$

where $q \in (0, 1)$ denotes an arbitrary confidence level.

Given that F_L is continuous, we know that the VaR is given by Equation (2), and using Equation (3), it is possible to simplify Equation (5) as follows [1]:

$$ES_q = \frac{E[L \cdot I_{L>VaR_q}]}{1 - q} \tag{6}$$

Furthermore, it's important for the reader to note that within equations incorporating I, this symbol represents an indicator function, intended to specify if L exceeds VaR or not. Mathematically, the indicator function can be written in the following way:

[1] Since $\Pr(L > VaR_q) = 1 - q$, we can replace the term $\Pr(L > VaR_q)$ in Equation (5) with $1 - q$, such that the second term cancels out.

$$I = \begin{cases} 1 & \text{if } L > VaR_q \\ 0 & \text{if } L \leq VaR_q \end{cases} \tag{7}$$

Given this insight, it is possible to split up the RHS of Equation (6) in two parts, depending if the indicator function takes on the value 0 or 1. Thus, it is possible to rewrite Equation (6) to:

$$ES_q = \frac{E[L(\cdot I_{L>VaR_q} = 1)]}{1-q} + \frac{E[L(\cdot I_{L>VaR_q} = 0)]}{1-q} \tag{8}$$

In this scenario, the second term on the RHS is effectively disregarded because the indicator function is assigned a value of 0. This enables the omission of the second term on the RHS, as the indicator function dictates that $L \leq VaR_q$. Essentially, this positions the loss value beneath the critical threshold of $L > VaR_q$, rendering it excluded from the ES calculation. In essence, ES_q can thus be interpreted as the expected value of losses exceeding VaR_q. This rationale underlines why ES is sometimes referred to as the expected tail loss or conditional VaR.

To illustrate this concept, *Figure 1* displays a standard normal distribution of losses, where negative values indicate gains. This inversion (i.e., making losses positive and gains negative) effectively flips the distribution, thus visualizing the left-tail risk—which measures substantial losses—in the right tail of the distribution instead of the left tail. This practice is commonly employed when using VaR and ES in the field of risk management and explains why left-tail risk sometimes instead is referred to as downside risk. The red and blue lines denote $VaR_{99\%}$ and $ES_{99\%}$ respectively. It is observable that $ES_{99\%}$ is situated to the right of $VaR_{99\%}$, which is consistent with the theoretical framework discussed in this section.

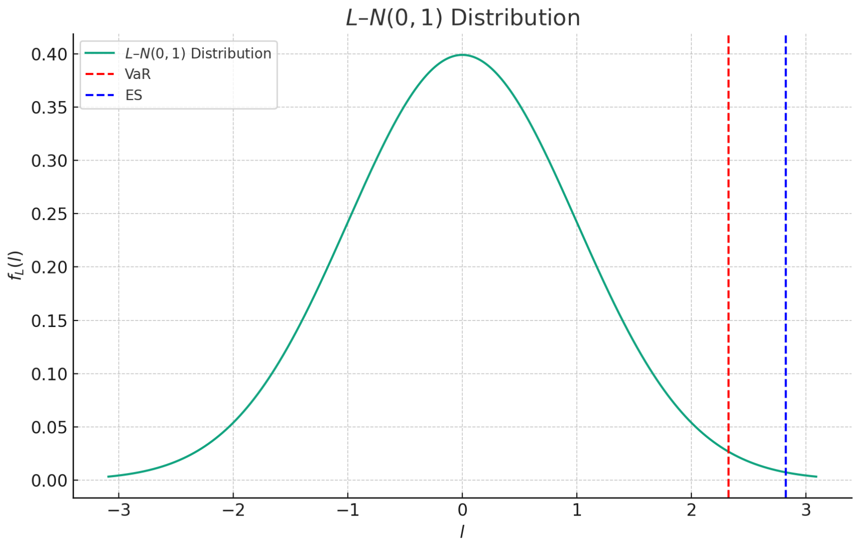

Figure 1: *$VaR_{99\%}$ and $ES_{99\%}$ given standard normal losses.*

3 Literature Review

Previous research in the field of ESG is comprehensive, concerning various aspects of the development, application, and consequences of ESG measures. However, as this paper specifically examines how downside risk is influenced by ESG scores, this section will concentrate on prior studies related to the financial implications of ESG scores, particularly regarding their potential impact on downside risk.

Early conducted research within the field suggests that adopting responsible ESG practices could alleviate the market's perception of a company's left-tail risk, thereby diminishing the anticipated occurrence of a left-tail event (Sharfman & Fernando 2008). The authors propose that adopting responsible business practices can act as insurance against left-tail risk within the context of an equity portfolio, which in turn can protect company value. Hence, the authors propose that a company could reduce its downside financial risk by achieving a more positive ESG rating as opposed to a lower one. The empirical findings from Kumar et al. (2016) suggests that robust ESG practices may reduce a company's vulnerability to reputation, political, and regulatory risks. Following this, the authors stipulate that this implies a decrease in both cash flow and profitability volatility, thus lowering the overall financial risk. In terms of risk management, these findings suggest the possibility of a negative relationship between strong ESG practices and downside risk for a company.

More recently, there has been indications that ESG ratings can influence a company's financial health, manifested through "financial or non-financial prudential risks, such as credit, market, operational, liquidity and funding risks" (European Banking Authority 2020, p.27). Research conducted by the European Banking Authority sates that risks associated with ESG factors emerge when the factors adversely affect a company's financial outcomes or its debt repayment capacity. This suggests that ESG ratings provide insight into a company's overall risk level, thereby rendering the explicit ESG-rating a potential marker for the company's riskiness (European Banking Authority 2020).

Seen in a different light, another perspective on reducing left-tail risk is presented by Shafer & Szado (2018), who suggest that positive ESG performance can lead to a more loyal customer and employee base. The authors propose that a company with a more loyal customer and employee base may be better protected against overall negative financial performance compared to a firm with less loyalty among its customers and employees. This, in turn, is assumed to mitigate unexpected harmful events to a greater degree, thereby reducing tail risk. This aligns with the findings of Kim, Li & Li (2014), who show that adequate ESG performance can mitigate the risk of stock price crashes. Furthermore, research from Minor (2011) indicates that a higher ESG rating not only tends to result in fewer adverse events over time but also that companies with high ratings incur smaller financial losses when adverse events do occur. The findings of these studies seem to further suggest that companies with a higher ESG rating experience reduced downside risk, attributed to an overall lower financial risk and more stable performance over time. Contrary to this, Zhang et al. (2021) expanded upon the research of Shafer & Szado (2018) and discovered empirical evidence suggesting the opposite, namely that firms with higher ratings often face greater tail risk.

Additional studies within the field Giese et al. (2019) and Maiti (2020) have also shown that improving ESG ratings can improve risk control and exposure. In these studies, it has been shown that portfolios built by using both the overall ESG-measure and the individual pillars E, S and G show a better overall performance. In relation to this, Hoepner et al. (2016) uncovered empirical evidence suggesting that efforts to enhance corporate ESG responsibility are linked to a decrease in downside risk, when analyzing a single institutional investor. Similarly, Sherwood & Pollard (2017) discovered that incorporating ESG information into the emerging market equity investments of institutional investors can yield both higher returns and reduced downside risks compared to non-ESG investments. Contrary to these findings, Breedt et al. (2019) discovered that when comparing portfolios composed of highly rated ESG companies to those without such a focus, there appears to be no enhanced risk-adjusted returns for the ESG-focused portfolios.

Although many of the studies mentioned above explore the relationship between ESG scores and downside risk, they have not explicitly focused their research on categorizing companies into sector-specific groups. Consequently, these studies do not examine how ESG scores might affect downside risk differently depending on the sector in which a company operates. One study that actually investigates this relationship is Jansen (2023), which examines whether ESG risk exposure influences the pricing of downside risk in sector-specific US stocks. The author demonstrates that ESG risk exposure significantly impacts the lower tail dependence of downside risk across all US sectors, leading to the conclusion that ESG risk exposure generally reduces the co-movements of downside risk in US equities. Although the author employs a different methodological approach—assessing the influence of ESG ratings on the systematic risk behavior of US equities by analyzing the tail dependency between high and low ESG-rated sector-specific portfolios and their respective sector benchmarks—it provides insightful observations about the characteristics of different industries. Generally, it appears that companies in sectors that directly serve consumers as their end customers are more vulnerable to downside risks when they do not adhere to high ESG standards.

4 Methodology and Data

In this section, we outline our methodology for examining the relationship between high and low ESG scores and downside risk among Nordic firms. Previous literature in related fields suggests that companies with higher ESG scores tend to experience reduced downside risk. To address this, our methodological approach utilizes panel regression analysis with annual observations to minimize information loss. The panel regression approach is a widely used methodology to explore both entity-specific and time-specific relationships.

4.1 Delimitation's

Due to the time constraints of our thesis and to ensure robust statistical inference, we have limited our sample to Nordic countries. This decision was made to attain a sufficiently large sample size, considering similarities in regulations regarding financial sustainability across these countries. Additionally, our research covers a five-year time horizon, spanning from 2018 to 2022, due to limited availability of ESG scores over a longer period. This time frame provided a robust sample size both in terms of duration and number of companies included.

Furthermore, we have focused our study on large cap and mid cap companies, as ESG scores for small cap companies had very low availability within our chosen time horizon. To define large cap and mid cap companies, we followed NASDAQ's definition, which considers companies with a market capitalization ranging from 150 million EUR to 1000 million EUR as mid cap, and those with a market capitalization exceeding 1000 million EUR as large cap (NASDAQ n.d). As a result of these delimitation's, all Icelandic companies were excluded from our study due to lacking data availability. Additionally, as visualized in *Figure 3*, the robustness for the companies within the Utilities sector can be considered weak considering the low amount of observations.

4.2 Sample

In our sample selection process, we began by gathering all mid and large cap firms listed on Nasdaq in the Nordics, resulting in a sample of 684 different stocks. Subsequently, we collected ESG scores from both Bloomberg and Refinitiv to assess the robustness of the scores and maximize our sample size.

To conduct a robustness check of the ESG-scores, we examined correlations among firms with scores from both data providers over our desired time-frame, resulting in 161 firms. The average correlation among these firms was approximately 0.25, with 58% of the companies exhibiting correlations higher than 0.5 and

30% higher than 0.8. These findings, while concerning, align with previous literature documenting weak correlations across ESG scores (Li & Polychronopoulos 2020).

The discrepancies in ESG scores can be attributed to variations in scoring metrics, particularly due to differences in weighting and qualitative aspects. While such differences pose challenges for ESG assessment, each scoring metric offers unique strengths. We opted to use Refinitiv data due to its superior availability and reputation for credibility in scoring metrics. Chen's (2024) research supports this choice, highlighting Refinitiv's consistent scoring over time and equal weighting against raw variables within the same sector. This criteria underscores Refinitiv's suitability for our study since their scoring metric has consistent scoring over time and within a sector, which is highly prioritized given the outline of this study.

After conducting our sample selection based on data availability, we focused on using common stocks of companies for our risk estimations. In cases where a company was listed in multiple Nordic countries, we retained the stocks from each country but removed the preferred stocks from data. This process resulted in a final sample size of 249 Nordic companies, where the geographical distribution is presented in *Figure 2* below.

Figure 2: *Number of firms in each country*

To classify all the companies into relevant sectors, we utilized the Global Industry Classification Standard (GICS)(MSCI 2023a). The main advantage with using GICS is that it is a universal and consistent classification system, which allowed us to categorize the companies into 11 different sectors based on their primary sector focus. A brief summary of the sector definitions is presented in *Table 1* and the sectors distribution in this paper is visualized in *Figure 3* below.

Sector	**Descriptions**
Communication Services	Companies involved in telecommunications, media, and entertainment services.
Consumer Staples	Companies that produce essential goods and services, such as food, beverages, and household items.
Consumer Discretionary	Companies that produce non-essential goods and services, such as automobiles, apparel, and leisure products.
Energy	Companies involved in the exploration, production, and distribution of energy resources.
Financials	Companies involved in banking, insurance, investment management, and other financial services.
Health Care	Companies involved in the production and distribution of medical equipment, pharmaceuticals, and health care services.
Industrials	Companies involved in the manufacturing and distribution of goods and services, including aerospace, defense, and machinery.
Information Technology	Companies involved in the development, manufacture, and distribution of technology products and services.
Materials	Companies involved in the extraction, processing, and distribution of raw materials and commodities.
Real Estate	Companies involved in the development, management, and leasing of real estate properties.
Utilities	Companies involved in the production, transmission, and distribution of essential services such as electricity, water, and gas.

Table 1: *Global industry sector classification definitions (MSCI 2023b).*

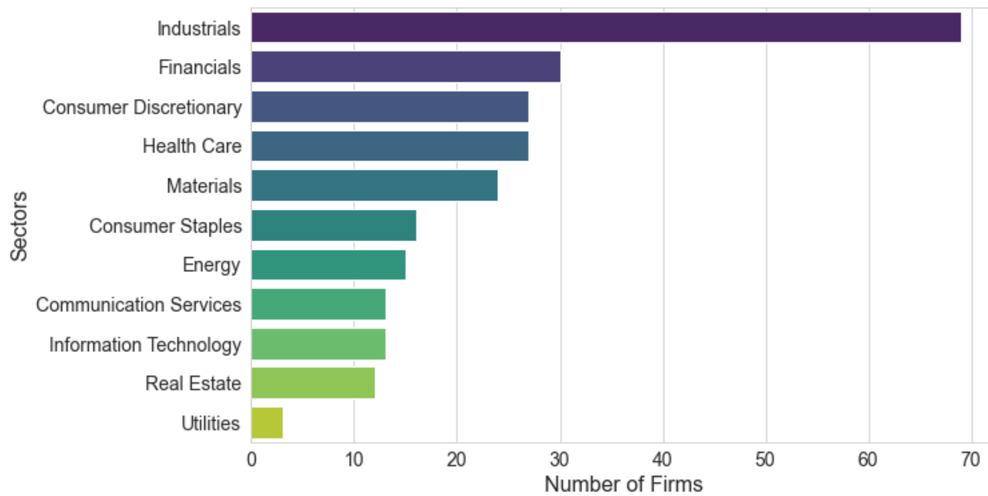

Figure 3: *Number of firms in each sector*

4.2.1 Sample Bias and External Validity

An important consideration in the data collection process for research is the assessment of any biases, which can significantly affect the validity of the study conducted. It is crucial to minimize selection bias as much as possible during data collection to ensure the sample is representative and free from bias. In the data collection process for this study, detailed further in *Section 4.2*, we compiled an initial list of all publicly traded large and mid cap companies in the Nordic region to ensure no eligible companies were omitted, thereby minimizing the risk of selection bias. Subsequently, Refinitiv was used to obtain the ESG ratings for these companies, which narrowed the sample size to 249 companies due to incomplete data for the remaining firms. Moreover, the decision to analyze the five-year period from 2018 to 2022 was not arbitrary, but was instead based on balancing the need for a substantial number of data points per company and the inclusion of as many companies as possible. This approach essentially means that the paper utilizes the entire data population that meets the inclusion criteria, given the inconsistency in ratings between different rating agencies explained more thoroughly in *Section 4.2*. Thereby, this study greatly mitigates any selection bias as the sample essentially represents the population.

Another important aspect to consider is the external validity of the sample used, which is crucial for determining whether the findings can be generalized to a broader population. This study includes the entire population that meets the specified inclusion criteria. However, this does not automatically guarantee external validity. It is important to note some limitations related to our sample data. Firstly, not all companies in the geographic location studied have an ESG score. Secondly, a significant number of companies did not meet the inclusion criteria, indicating that a large portion of Nordic large and mid cap companies do not have an ESG score. As a result, our study encompasses only a subset of all companies, which might affect the external validity of our sample. Thirdly, it is difficult to ascertain what ratings the excluded companies might have received, and therefore challenging to assess how their inclusion might have impacted the results.

Despite concerns regarding the external validity of the sample, it is important to highlight that this study utilizes as much data as is available under the circumstances. Furthermore, the issue of data availability, especially for data extending many years back, is an inevitable challenge with ESG scores, and thus beyond our control. Therefore, we believe that this sample provides as representative a picture of the influence of ESG scores on downside risk as possible. Consequently, it should be regarded as a reliable measure and indicator.

4.3 Calculations of Risk Measures

As discussed in the theoretical framework section, this paper employs VaR and ES as risk measures. Given our methodology of using panel regression with annual observations, this study applies the Basic Historical Simulation (BHS) method to estimate both VaR and ES, ensuring consistency. The BHS is a non-parametric approach that estimates VaR and ES based on the empirical loss distribution, i.e., the sample loss distribution in the data (Hull 2018).

The rationale for using a non-parametric approach rather than a parametric one is rooted in the fundamental assumptions about the data's underlying distribution. A parametric approach assumes that the data follows a specific probability distribution, making the model sensitive to these underlying assumptions. In contrast, non-parametric methods, such as BHS, do not rely on any assumptions about the data's distribution (Mentel 2013). This makes non-parametric methods particularly suitable for our study as they offer greater flexibility and robustness in the absence of specific distributional information. Furthermore, they allow for the disregarding of the underlying distribution.

BHS picks the VaR value corresponding to the confidence level given the empirical loss distribution. Therefore, the BHS directly picks the relevant loss in the sample of losses as an estimate of VaR. In a sample of T losses, the number of losses ℓ that are larger than VaR_q is by definition $(1-q)T$, given by Equation (9) (Hull 2018).

$$\Pr(L > \ell^s_{(1-q)T+1}) = \frac{(1-q)T}{T} = 1 - q \Rightarrow \text{VaR}_q = \ell^s_{(1-q)T+1} \tag{9}$$

Given this, the corresponding estimate of ES_q is therefore the average of the $(1-q)T$ largest losses, thus losses larger than VaR_q, and is given by Equation (10). In this paper we employ the confidence level q=99%, thus investigating $VaR_{99\%}$ and $ES_{99\%}$. The motivation is that we are interested in the most extreme tail events, thus applying q=99% instead of q=95% will capture the most extreme downside risk in terms of losses that the companies face.

$$\mathrm{ES}_q = \frac{1}{T(1-q)} \sum_{i=(1-q)T+1}^{T} \ell_i^s \tag{10}$$

Our choice to apply the BHS method was driven by our focus on historical data and annual observations. This method allows for direct measurement of downside risk on an annual basis, effectively capturing the fluctuations in a firm's stock performance throughout each year. For each firm, we collected daily closing stock prices from 2018 to 2022, sourced from Yahoo Finance. We calculated daily returns with the following formula to annualize them:

$$r_{i,t} = \left(\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \right) \times \sqrt{250} \times 100 \tag{11}$$

This annualization aligns the daily returns with our annual risk measures, which reflects the firm's risk profile over the preceding year. Additionally, multiplying the risk measures with 100 effectively presents the values as whole numbers. Utilizing the BHS method, known for its conservative responsiveness in rapidly changing markets, suits our methodology since we are evaluating risk annually rather than over shorter intervals.

By employing a rolling window approach, BHS evenly weights all losses within the window, thus providing an annual measure of risk for the assets. We applied this technique to calculate the VaR and ES for each company annually, ensuring that each company's specific risk metrics are accurately reflected for each year studied. The implementation of BHS, combined with the annualization of daily returns, allows us to reliably measure the annual downside risk for each firm in our study. This approach not only provides a clear view of the risk dynamics but also aligns with the yearly evaluation period, making it an ideal choice for our analysis. Below, *Table 2* presents the descriptive statistics for VaR and ES in this paper.

Table 2: Descriptive statistics of $\text{VaR}_{99\%}$ and $\text{ES}_{99\%}$

Sector	$\text{VaR}_{99\%}$	$\text{ES}_{99\%}$
Communication Services	97.93	134.42
Consumer Discretionary	104.22	144.05
Consumer Staples	71.54	104.16
Energy	125.22	166.93
Financials	79.27	108.86
Health Care	104.00	147.75
Industrials	89.73	118.41
Information Technology	92.64	125.36
Materials	83.45	109.34
Real Estate	77.86	102.04
Utilities	89.29	112.60

Table 2 illustrates the average $VaR_{99\%}$ and $ES_{99\%}$ levels for each sector. These levels are expressed as percentages of annual returns, as explained earlier in this section and represented in Equation 11. To present the values as whole numbers rather than decimals, the risk measures are multiplied by 100.

4.4 Dummy Variable Construction

Since this study investigates whether high ESG scores correlate with reduced downside risk in the Nordics, we employ interacted dummy variables that classify firms within their respective sectors based on high ESG scores for each year. This classification involves comparing ESG scores with those of sector peers, enabling us to identify firms that have relatively high scores compared to sector standards. Moreover, employing interacted sector dummy variables in this approach enables us to bypass the need for a base group, as the interaction mitigates perfect negative correlation among the dummies. Consequently, we evade the pitfalls of the dummy variable trap. We believe this approach enhances the measurement quality of the subsequent panel regression by allowing for comparisons of firms within the same industry rather than against an overall average derived from aggregated ESG scores across all sectors. The reasoning behind this sector-specific approach is the assumption that fundamental differences exist in the potential for conducting sustainable business practices across sectors. This assumption is confirmed by *Figure 4*, which illustrates that firms operating in the Financial sector typically have lower overall ESG ratings than those in the Materials sector.

This difference is presumably due to the nature of their operations, thereby justifying this sector-specific approach. This method is similar to the practice in multiple-based corporate valuation, where a firm's valuation is based on key ratios in comparison to those of similar firms within the same sector.

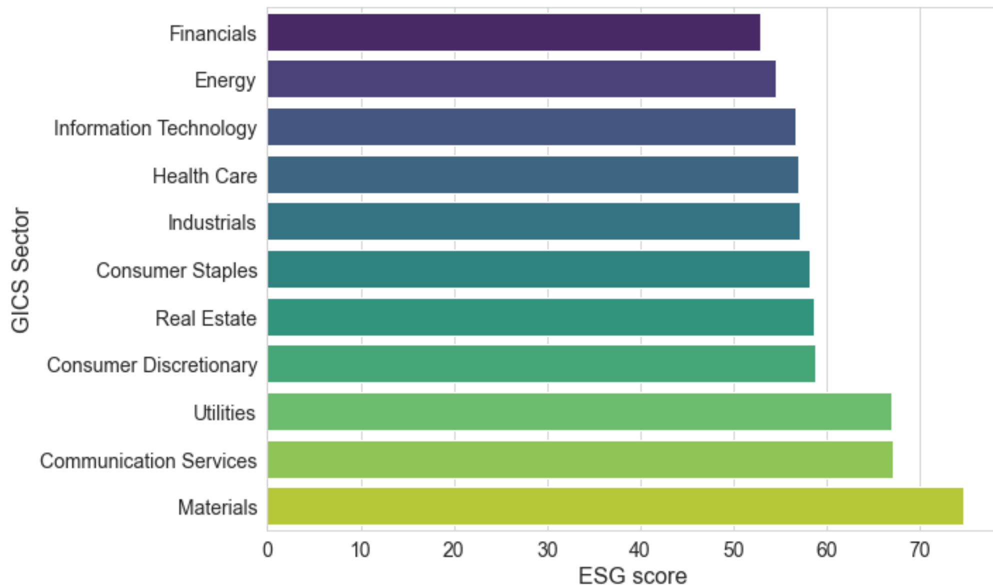

Figure 4: *Average ESG Score for each Sector*

This approach also aligns with the diversification principle in financial theory, which posits that investors aim to construct diversified portfolios by investing in firms that excel within their respective sectors (Markowitz 1952). A well-diversified portfolio should include firms from a variety of sectors to mitigate risk. Therefore, it is not relevant to compare firms across different sectors, as such comparisons do not provide a basis for determining whether a firm excels within its own sector.

To further analyze the impact of ESG scores, we create dummy variables for the overall ESG measure as well as for its individual pillars: environmental, social, and governance. This approach, motivated by previous research (Crespi & Migliavacca 2020), allows us to explore how different aspects of ESG are perceived and weighted in the market. By examining both the composite score and its constituent elements, we aim to identify potential variations in market reactions across these dimensions.

In constructing our dummy variables, we employ various thresholds to enhance the robustness of our study. For our first threshold, we classify firms based on whether their ESG scores exceed the mean score for each year.

$$\text{Dummy Industry}_i = \begin{cases} 1 & \text{if ESG-score}_{ijt} > \text{Mean ESG score}_{it} \\ 0 & \text{if ESG-score}_{ijt} \leq \text{Mean ESG score}_{it} \end{cases} \tag{12}$$

where:

- i represents the specific industry.
- j represents the firm.
- t represents the specific year.

Additionally, we use quantiles, setting thresholds at the 30th and 70th percentiles. This approach enables us to evaluate the impact of firms that rank within the top 30% and top 70% in terms of scores in each sector, consequently three different thresholds will be employed in this paper.

4.5 Control Variables

To isolate the relationship between ESG scores and downside risk, this paper will incorporate control variables into the regression. The use of these control variables is intended to account for other financial factors that may impact a company's downside risk, thereby influencing the dependent variable and, consequently, the outcome of this study. By including appropriate control variables, this paper aims to isolate the effect of ESG scores on downside risk by considering variables that capture information about the annual overall volatility, idiosyncratic risk characteristics, systematic risk, the size effect, capital structure, and profitability. Moreover, this approach mitigates the risk of omitted variable bias in the regression and therefore reduces the risk of endogeneity and biased results in the model. The control variables employed in this study are presented and discussed in the following sections.

4.5.1 VIX

We incorporate the VIX index as a control variable in our regression analysis. VIX, or the CBOE Volatility Index, serves as a measure of predicted volatility for the S&P 500 index. Its calculations is based on option prices, providing insights into market sentiment and perceived risk levels. A higher VIX value indicates greater market stress and volatility.

To assess the relevance of VIX for our study covering Nordic markets, we examined the correlations between Nordic indexes and the S&P 500. Our analysis revealed strong correlations, with all Nordic indexes exhibiting correlations of 0.9 or higher, and OMX30 showing a particularly high correlation of 0.97 with the S&P 500. These findings support the inclusion of VIX as a control variable for market volatility in our regression model.

Ticker	OSEBX	SP500	OMX30	OMXC25	OMXH25
OSEBX	1.0	0.9	0.86	0.84	0.85
SP500	0.9	1.0	0.97	0.98	0.92
OMX30	0.86	0.97	1.0	0.96	0.96
OMXC25	0.84	0.98	0.96	1.0	0.91
OMXH25	0.85	0.92	0.96	0.91	1.0

Figure 5: *Correlation Matrix of indexes in the Nordics and SP500*

We obtained VIX data from Yahoo Finance, and to incorporate it into our regression, we calculated the average VIX level for each year from 2018 to 2022. This process yielded five observations that captured the annual volatility levels for the years examined. These average VIX values were then assigned to each entity in our dataset. This variable measures the level of market uncertainty experienced in a given year and does therefore capture variations in time. We therefore anticipate a positive relationship between VIX and the levels of VaR or ES. Higher VIX values would correspond to increased volatility and risk, potentially leading to higher VaR and ES levels.

4.5.2 Market Capitalization

The inclusion of market capitalization as a control variable stems from its correlation with a company's risk profile. It is a well-documented observation in financial markets that large-cap companies tend to be more stable and exhibit less volatility than mid cap companies, an effect known as the size effect (Banz 1981). Therefore, by incorporating market capitalization into this study, the analysis can control for the inherent differences in risk profiles that are associated with company size. The data on market capitalization were sourced from Refinitiv and were consistently collected in euros to ensure uniform classification.

Three additional factors related to control variable market capitalization include liquidity, diversification, and visibility. The first factor, liquidity, acknowledges that larger companies typically enjoy higher liquidity, meaning their stocks can be bought or sold quicker and with less impact on the stock price (Amihud & Mendelson 1991). This characteristic can potentially reduce downside risk, as less liquid stocks may undergo more substantial price fluctuations during market downturns. The second factor, diversification, acknowledges that large companies typically operate across a broader range of activities, which can mitigate firm-specific risks and thereby reduce downside risk (Markowitz 1952). Lastly, larger companies generally attract more attention from investors, analysts, and the public, increasing scrutiny (Merton 1987). Such visibility can intensify the pressure to uphold robust ESG practices and can lead to stronger market responses to ESG-related developments. Based on the above discussion, this paper expects a negative relationship between market capitalization and downside risk. Therefore, using this control variable will help isolate the size effect from the impact of ESG scores.

4.5.3 Debt to Equity

Unlike broader leverage metrics that may encompass all assets, the debt-to-equity ratio (D/E) specifically focuses on the extent of debt used relative to equity. This metric provides insights into debt management and risk, particularly illustrating how debt levels correlate directly with financial health risks (Barclay & Smith 1995). Therefore, a high D/E ratio could be a indicator of financial risk, potentially leading to greater financial distress. Moreover, Faulkender & Wang (2006) argue that such high leverage levels make companies more susceptible to economic downturns and interest rate fluctuations. These risks heighten the probability of significant financial downturns, thus affecting the downside risk. Consequently, this paper includes the D/E ratio as a control variable to capture the effect of capital structure on downside risk. By controlling for the D/E ratio when analyzing the impact of ESG scores on downside risk, it is possible to discern how much of the risk profile attributed to varying ESG scores is actually due to the debt level, rather than the actual sustainability practices.

4.5.4 Return on Equity

The inclusion of Return on Equity (RoE) as a control variable is pertinent in this study as it assesses management's efficiency in utilizing the firm's assets to generate profits. This metric not only measures a firm's ability to derive profits from its shareholders' equity but also reflects operational effectiveness (Cummins & Zi 1998). The data for this variable was collected from Bloomberg. By accounting for RoE, this paper can consider the influence of management efficiency on a firm's risk profile, which is relevant since efficient use of equity could be assumed to be associated with enhanced risk management practices. Furthermore, different sectors may have varying average RoE's due to their specific operational characteristics. Based on this implication, including RoE as a control variable could help to distinguish between sector performance and the impacts of varying levels of RoE, thereby isolating these effects from the influence of ESG scores. By definition, a higher RoE indicates that a firm is using its assets more efficiently, thereby reducing the risk of poor financial performance. Consequently, this paper hypothesizes a negative relationship between RoE and downside risk.

4.5.5 Leverage

Financial leverage, calculated as the ratio of average total assets to average total common equity, is an appropriate control variable in regression models that analyze downside risk, since this variable accounts for the effect of a company's capital structure on its risk profile. Essentially, this ratio measures the extent to which a firm uses debt to finance its operations, thus indicating the degree of financial leverage. A higher ratio not only can amplify returns but also increases the company's financial risk (Baxter 1967). In the context of downside risk, considering leverage is important because firms with higher leverage are likely to experience more significant fluctuations in their net asset values. Such fluctuations imply greater volatility in earnings and cash flows, which in turn, can affect downside risk (Baxter 1967). Therefore, including financial leverage in the regression model allows us to separate the impact of capital structure from the influences of other variables. Thus, it helps isolate the effects attributable to ESG scores, enabling a more precise analysis of how this factor independently affects downside risk. The data for financial leverage, like that for RoE, was collected from Bloomberg. Based on the theoretical and empirical implications of possessing higher financial leverage, this paper expects a positive relationship between financial leverage and downside risk.

4.5.6 Firm Specific Beta

Including a firm specific control variable that captures the firm's market risk is appropriate for this analysis, as it can quantify and reflect the potential volatility associated with its exposure to systematic risk. This is of interest in the regression analysis conducted in this paper, as it enhances the ability to isolate the risks associated with individual firms' exposure to systematic risk, thereby enabling a more precise isolation of the effects of ESG scores. A suitable measure to employ as a control variable in this context is firm specific Beta stemming from the Capital Asset Pricing Model, which captures a firm's exposure to systematic risk and serves as a fundamental link between market conditions and individual company performance. This measure provides insight into how volatile a firm is expected to be relative to the overall market (Fama & French 2004). Although, some research (Östermark 1991) has shown that the Beta coefficient is unable to exhaustively represent the economic forces of capital asset pricing, especially in the Scandinavian countries, indicating a mitigated the capability of the measure to accurately capture a firm's exposure to systematic risk. Understanding the risk dynamics associated with ESG factors necessitates a robust analytical framework. By including firm specific Beta as a control variable in the regression, this paper addresses the issue of varying individual riskiness among the firms in our dataset, thereby allowing for a more precise determination of the impact that ESG scores have on downside risk.

4.6 Variable Summary

To facilitate the understanding of the variables used in this paper, *Table 3* provides a comprehensive summary and a brief description of each variable. It is important for the reader to note that the dummy variables included represent both the sector and whether a company is highly rated within the ESG frameworks—namely ESG as whole, E, S, and G—across all thresholds discussed in *Section 4.4*. Moreover, since this paper applies three different thresholds for classifying a score as high, there are a total of 12 different sector dummy classes indicating high ratings, each containing the 11 sectors examined in this paper. Additionally, as this analysis covers both VaR and ES, there are 24 distinct categories of sector dummy variables, leading to 24 separate regressions conducted in this study.

Variables	**Descriptions**	**Source**
Sector Dummy high ESG	Dummies capturing sector and high ESG score	(a)
Sector Dummy high E	Dummies capturing sector and high E score	(a)
Sector Dummy high S	Dummies capturing sector and high S score	(a)
Sector Dummy high G	Dummies capturing sector and high G score	(a)
VIX	The observed mean level of the VIX-index for a given year	(c)
Market Capitalization	Capturing Market Capitalization for a given company and year (euros)	(a)
Debt to Equity	Capturing the D/E ratio for each company and year	(b)
Return on Equity	Capturing RoE for a given company and year	(b)
Leverage	Captures the leverage of a given company and year	(b)
Firm specific Beta	Captures the Beta for a given company and year	(b)

Table 3: Summary of variables used in the regressions. (a) Thomson Reuters Eikon, (b) Bloomberg and (c) Yahoo Finance. Period of interest: 2018-2022

4.7 Panel Regression

A common challenge in research is that methodological approaches suitable for answering the research question often cannot be used due to the unavailability of counterfactual information. Seen in the light of our research question, it is not possible to know what outcomes would have been observed if a company had a low score, given that it has a high score today. Ideally, if such information were available, this paper could precisely measure the effects of high sustainability awareness on downside risk. However, given the gap between this ideal and reality, we must opt for less accurate, albeit suitable, methodological approaches that align with the research question posed in this paper. Given that this paper exclusively utilizes historical data for components used to calculate downside risk measures and ESG scores, it adopts an econometric approach that compares the downside risks of companies within the same sector based on their high or low ESG scores (including E, S, and G scores) over time. This method should simultaneously adjust for endogenous economic information and firm specific characteristics to isolate the effect that the sustainability measures are expected to have on downside risks. Thus, the study employs panel regression analysis to explore the relationship.

Applying panel regression analysis requires determining the appropriate model structure, which should align with the research question posed and the characteristics of the dataset. This dataset encompasses information from companies across 11 distinct sectors over a five-year span, from 2018 to 2022, incorporating both cross-sectional and time-series data. Given the data, the most extensive panel regression model that can be set up is a two-way specification, allowing for the measurement of both time and entity-specific effects. This model setup creates the need of an additional choice, namely choosing to measure fixed or random effects, denoted as μ_i and ν_t in Equation (13) below. The fixed effects are parameters we can estimate, whilst random effects are errors (random variables) following a distributional function similar to a usual error term (Roberts & Whited 2013). Thus, the nature of this data allows the conceptualization of the following regression model:

$$y_{i,t} = \alpha + \beta_h x_{i,t} + \gamma_w x_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \tag{13}$$

where:

- β represents a specific sector.
- γ represents a specific control variable.
- μ represents entity-specific effects.
- ν represents a time-specific effects.
- $i = 1, \ldots, N$ indexes the companies.
- $t = 1, \ldots, T$ indexes time.
- $h = 1, \ldots, H$ indexes the sector dummies.
- $w = 1, \ldots, W$ indexes the the control variables.

However, given that there is no variation over time — since companies do not switch sectors within the observed time frame—there exists an entity-specific homogeneity. Consequently, modeling time-series variation is not only unnecessary but could also induce econometric problems, such as multicollinearity. Multicollinearity arises when independent variables in a regression model are highly correlated, which, in this case, is due to the static nature of sector allocation for companies throughout the period under consideration. In the context of a regression, multicollinearity causes biased estimates of coefficients. Considering this implication, our model should not measure entity specific effects, thus leaving out the variable μ_i.

Since each company has one annual observation over the years 2018-2022, we have 249 time-series consisting of 5 observations. The annual values of the independent variables in the regression, $x_{i,t}$, can vary (due to the fact that ESG scores and the values of the control variables can vary over time), and therefore are time-specific heterogeneous. This is obviously of interest since this enables the measurement of how high ESG (or E, S, and G scores independently) affect the downside risk. Although the panel data exhibits time-specific heterogeneity, our primary interest does not lie in how ESG scores fluctuate over time, nor whether this constitutes a fixed or random effect. Our focus is solely on the potential trend between ESG scores and downside risk. Consequently, it is justifiable to exclude time-specific effects, ν_t from our model, as they do not provide relevant information for our analysis.

Given the fact that this paper will not analyze entity-specific nor time-specific effects, it instead pools the entire data foundation, resulting in a pooled OLS. An issue with this approach is that one would expect that there could exist a dependency structure in time between observations for the same company, which could create dependent standard errors due to the intragroup correlation. In simpler terms, this problem arises due to the fact that observations within the same company are likely to be more similar to each other than to observations from different companies. To address this potential problem, the paper employs clustered standard errors which is used to obtain robust and efficient estimates standard errors that account for within cluster correlation. This is necessary to ensure the assumption of independence, and in more technical light, this will prevent overstating the statistical significance of coefficients due to within-group correlation (StataCorp 2013). This methodological approach enables the paper to solely analyze the effects that the sustainability measures have on downside risk, adjusted for endogenous and exogenous economic information by the control variables. The panel regression formula applied is therefore simplified to the following:

$$y_{i,t} = \alpha + \beta_h x_{i,t} + \gamma_w x_{i,t} + \varepsilon_{i,t} \tag{14}$$

To further clarify the implementation of the regressions conducted in Stata, we present two examples below focusing on VaR and ES, as specified in Equation (15) and Equation (16) respectively. As illustrated, all control variables are included as well as the interacted dummy variables. The sector dummies represent the classification of high ESG scores relative to the sector. These regressions are performed repeatedly with sector dummies for ESG, E, S, and G, as well as for different thresholds. This results in 24 different regressions. Below we illustrate generalized expressions for the regressions conducted in the study, where *High Score* indicates a high sustainability score for the measure used in the regression.

$$\begin{aligned}
\text{VaR}_{99\%} = {} & \beta_0 + \beta_1\text{VIX} + \beta_2\text{Market Cap} + \beta_3\text{D/E} + \beta_4\text{RoE} + \beta_5\text{Leverage} + \beta_6\text{Firm Specific Beta} + \\
& \gamma_1\text{Industrials}_{\text{ High Score}} + \gamma_2\text{Financials}_{\text{ High Score}} + \gamma_3\text{Consumer Discretionary}_{\text{ High Score}} + \\
& \gamma_4\text{Health Care}_{\text{ High Score}} + \gamma_5\text{Materials}_{\text{ High Score}} + \gamma_6\text{Consumer Staples}_{\text{ High Score}} + \\
& \gamma_7\text{Energy}_{\text{ High Score}} + \gamma_8\text{Communication Services}_{\text{ High Score}} + \gamma_9\text{Information Technology}_{\text{ High Score}} + \\
& \gamma_{10}\text{Real Estate}_{\text{ High Score}} + \gamma_{11}\text{Utilities}_{\text{ High Score}} + \epsilon_i
\end{aligned} \tag{15}$$

$$
\begin{aligned}
\mathrm{ES}_{99\%} = {} & \beta_0 + \beta_1 \mathrm{VIX} + \beta_2 \text{Market Cap} + \beta_3 \mathrm{D/E} + \beta_4 \mathrm{RoE} + \beta_5 \text{Leverage} + \beta_6 \text{Firm Specific Beta} + \\
& \gamma_1 \text{Industrials}_{\text{ High Score}} + \gamma_2 \text{Financials}_{\text{ High Score}} + \gamma_3 \text{Consumer Discretionary}_{\text{ High Score}} + \\
& \gamma_4 \text{Health Care}_{\text{ High Score}} + \gamma_5 \text{Materials}_{\text{ High Score}} + \gamma_6 \text{Consumer Staples}_{\text{ High Score}} + \\
& \gamma_7 \text{Energy}_{\text{ High Score}} + \gamma_8 \text{Communication Services}_{\text{ High Score}} + \gamma_9 \text{Information Technology}_{\text{ High Score}} + \\
& \gamma_{10} \text{Real Estate}_{\text{ High Score}} + \gamma_{11} \text{Utilities}_{\text{ High Score}} + \epsilon_i
\end{aligned}
\tag{16}
$$

4.8 Statistical Tests and Robustness Check

When conducting research using a quantitative methodology, it is important to ensure that the model applied to the sample data is free from statistical pitfalls that could alter the results. This is crucial because such issues can render the findings less reliable and make it difficult to draw valid inferences from the results. In line with this, we have already addressed how this paper tackles potential issues related to heteroscedasticity in *Section 4.7*. It states that this potential issue is mitigated by employing clustered standard errors.

To address the potential issue of multicollinearity, we employed the methodological approach present in *Section 4.7*, thus once again mitigating the risk of introducing multicollinearity in our regressions. To double-check, we conducted a Variance Inflation Factor (VIF) test to examine the correlation structure between the independent variables in the regression. The results from the VIF test indicate that the scores range between 1 and 2, where scores above 10 are generally considered indicative of multicollinearity within the regression model (García et al. 2016). Given these results, we conclude that there is no evidence of multicollinearity in our employed model.

An additional approach to ensure the robustness of our regression model involves analyzing the adjusted R^2 in the conducted regressions. We are using adjusted R^2 rather than R^2 since it adjusts for the usage of multiple explanatory variables in a regression. The rationale behind this is to mitigate the risk of omitted variable bias, thereby reducing the potential for endogeneity in our model. Endogeneity may arise if the model lacks explanatory variables that are crucial for accurately predicting the dependent variable (Roberts & Whited 2013). While it is technically challenging to control for problems associated with omitted variables bias, we argue that a reasonably high adjusted R^2 suggests that a sufficient number of explanatory variables are included in the regression. Although a high adjusted R^2 indicates that the dependent variables can explain the independent variable, a to high adjusted R^2 would also raise concerns. This is due to the that there is assumed to be some stochastic elements and randomness in the variation in the dependent variable, and therefore a too high adjusted R^2 would indicate that something is misspecified. With this in mind, including a balanced number of relevant independent variables in the regression enhances the model's robustness and significantly reduces the risk of endogeneity.

In this context, it is essential to recognize that empirically testing for endogeneity is not feasible. As a result, there is no definitive statistical method to completely eliminate the risk of endogeneity in an econometric model. This implies that our model could inherit unobserved heterogeneity, which occurs when characteristics not captured by observable variables influence the outcomes or the explanatory variables, thus introducing endogeneity into the model (Roberts & Whited 2013). By definition, such sources of endogeneity are unmeasurable and uncontrollable, making it impossible to fully rule out their presence in our model. Given this, it is plausible that factors influencing both ESG scores and the downside risk of a firm indicate a relationship between the two. Since this relationship may be influenced by unobserved factors, we could face unobserved heterogeneity, which renders the relationship non-causal.

In an ambition to ensure robust findings, we employ three different thresholds to analyze the impact of high sustainability scores, providing us with an additional opportunity to assess the robustness of our model. The rationale behind this approach is that while we predefined the mean as a reasonable threshold for this study, there is no definitive evidence supporting the use of the mean as the optimal threshold. Therefore, we also create thresholds based on the 30th and 70th percentiles. By employing these different thresholds, we aimed to assess the sensitivity of our results to varying thresholds. If the results are consistent across these various thresholds, it suggests that the findings are robust, as consistency indicates an absence of randomness in the results. The results will be presented and further discussed in *Section 5*.

5 Empirical Result

In this section, we will present the results from the regressions employed based on our model specification. As stated earlier, this paper conducts 24 regressions since we use different thresholds to classify what constitutes high scores, and analyze the overall ESG measure as well as the environmental, social, and governance pillars individually. Due to the large number of tables required to present all regressions and results, we intend to visualize and discuss the findings by presenting parts of the regression output. This approach will exemplify what the output looks like and explain how to interpret it, and regarding the tables not presented in this section, we refer to the Appendix. Furthermore, given our research question, we do not focus on the absolute values of the coefficients observed in the regression. This since our primary interest lies in determining whether sustainable business practices in different sectors reduces downside risk. Therefore, we will mostly concentrate on the signs of the significant coefficients in the tables presented in this section.

This section initially presents some descriptive statistics which eases the interpretation of the results from a panel regression in this paper. This is followed by sections that summarizes the result in both quantitative and qualitative aspects. The quantitative summary focuses on the overall trend and the qualitative discloses sector specific results. Lastly, we discuss the results robustness in light of the potential issues mentioned in *Section 4.8.*

5.1 Descriptive Statistics and Regression Results

Table 4 below displays a regression output example, specifically the regressions conducted with VaR as the dependent variable. The three columns represent results from different regressions based on the three distinct thresholds, which are specified at the top of the table. Initially, the interacted sector dummy variables are listed; the first 11 variables capture sector-specific information, and the following six variables are the control variables used in the model. As noted at the bottom of *Table 4*, asterisks indicate that a variable's coefficient is statistically different from zero, with the significance levels varying based on the number of asterisks next to the coefficient value. In this paper, the threshold p-value for a variable to be considered statistically significant is 5% (denoted by two asterisks), a common practice in research.

In terms of regression analysis, a negative sign on a significant variable indicates that this variable reduces downside risk, while a positive sign suggests an increase in downside risk. To interpret the coefficient values, consider the example of the first interacted dummy variable for the mean percentile threshold, which pertains to the Consumer Staples sector and has a coefficient value of approximately -25,75. This value indicates that there is a decrease in VaR by 25,75 percentage points compared to the average in the sector, all else equal. To further clarify this example, consider the values for VaR and ES presented in *Table 2* in *Section 4.3.* As *Table 2* visualizes, the average annual VaR for the Consumer Staples sector is 71.54. In comparison, a firm classified as having a high ESG score within this sector (compared to the mean threshold) would on average face an annual VaR of 45.79, reflecting a reduction of 25.75 percentage points (71.54 - 25.75 = 45.79) in downside risk on annual basis. Consequently, a positive sign on a variable would imply the opposite effect, indicating an increase in downside risk by the coefficient value in percentage points, all else equal. This logic applies to all interacted dummy variables presented in *Table 4*, as well as to all other regressions conducted in this paper.

Table 4: $VaR_{99\%}$ as the dependent variable and dummies for ESG

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-24.0926*** (4.5273)	-25.7498*** (4.0163)	-25.7272*** (3.2465)
Industrials $_{\text{High Score}}$	-9.1029** (3.5777)	-8.6594*** (2.9498)	-6.2501 (3.5389)
ConsumerDiscretionary $_{\text{High Score}}$	5.4263 (5.9850)	5.5019 (5.7631)	9.0128 (7.8815)
HealthCare $_{\text{High Score}}$	0.2912 (6.0213)	-0.8110 (7.1899)	1.9011 (4.2021)
Materials $_{\text{High Score}}$	-12.6123*** (4.2036)	-11.3187*** (4.0634)	-8.6962 (4.5754)
Financials $_{\text{High Score}}$	-16.6611** (6.7684)	-17.9345*** (5.5041)	-13.6504** (6.2039)
RealEstate $_{\text{High Score}}$	-16.4604*** (5.8358)	-13.9659** (6.8970)	-14.3561*** (5.1865)
CommunicationServices $_{\text{High Score}}$	-14.3057* (7.6049)	-15.3999* (8.5417)	-12.6252 (15.0700)
InformationTechnology $_{\text{High Score}}$	-12.9095** (5.4363)	-16.4041*** (4.3210)	-9.9102*** (3.5279)
Utilities $_{\text{High Score}}$	-10.7151 (7.0032)	-10.0051 (6.2887)	-20.7209*** (4.9109)
Energy $_{\text{High Score}}$	18.2014* (9.5195)	19.9118** (9.0805)	13.8883** (5.5024)
VIX	3.4913*** (0.1619)	3.5083*** (0.1632)	3.4791*** (0.1604)
D/E	0.0007 (0.0006)	0.0007 (0.0006)	0.0009 (0.0005)
Market Cap	-0.0004*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)
Leverage	-0.0032 (0.4050)	-0.0639 (0.3614)	-0.1337 (0.3720)
ROE	-0.4508*** (0.1105)	-0.4571*** (0.1108)	-0.4693*** (0.1133)
Firm Specific Beta	-0.6088 (2.4602)	-0.5835 (2.4648)	0.3131 (2.5275)
Constant	30.2853*** (5.1691)	28.5380*** (5.0482)	26.4879*** (5.0380)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.4275	0.4259	0.4040

High Score indicates a high ESG score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Regarding the control variables, the coefficients should be interpreted as follows: a negative sign indicates a decrease in VaR, while a positive sign indicates an increase. For example, in the regression for the 30th percentile shown in *Table 4*, there are three significant control variables, namely VIX, Market Cap, and RoE. The VIX displays a positive coefficient, suggesting that higher overall average annual volatility increases the VaR. Conversely, Market Cap and RoE feature negative coefficients, indicating a negative relationship between VaR and both company size and RoE. Again, this logic applies to all control variables presented in *Table 4*, as well as to all other regressions conducted in this paper.

5.2 Quantitative Summary of Panel Regressions

As mentioned in the former section, *Table 4* only shows a portion of the total results. Therefore, *Table 5* is provided below to summarize all the panel regression results in this paper. It includes outcomes for both VaR and ES as dependent variables, modeled against the interacted sector dummy variables and the control variables detailed in *Table 4*. It also specifies the number of interacted sector dummy variables that are statistically different from zero. Additionally, *Table 5* records the instances where a significant interacted sector dummy variable exhibits a positive coefficient, which is contrary to the hypothesis of this study. Finally, it enumerates the significant control variables and highlights any that display signs opposite to those anticipated.

Table 5 shows that when using VaR as the dependent variable, the number of significant interacted sector dummy variables are relatively consistent across the overall ESG measure, the environmental pillar, and the social pillar, with six to eight dummy variables significantly different from zero. Regarding the governance pillar, fewer variables significantly differ from zero across all thresholds compared to the other measures. Notably, the results for the 70th percentile threshold consistently feature slightly fewer significant interacted sector dummy variables compared to the other two thresholds, who consistently show approximately the same number of significant variables. The aforementioned trend, wherein the 70th percentile threshold exhibits the fewest significant variables, also holds when conducting the panel regression with ES as the dependent variable. Once again, there is no notable difference between the 30th percentile and mean thresholds.

Although there are some minor differences in the results depending on the threshold used, the overall picture presented by *Table 5* suggests that our findings are robust, as the number of significant variables does not vary substantially across different thresholds. However, in terms of the difference in significant ESG, environmental, social, and governance interacted sector dummy variables, the most notable divergence is that the environmental pillar produces the most significant variables, while the governance pillar produces the fewest.

Regarding the signs of the coefficients for significant interacted dummy variables, *Table 5* indicates that one variable with a positive coefficient appears in approximately half of the regressions. It is important to note that no more than one coefficient exhibits this positive sign in any given regression, suggesting that it could be the same sector dummy consistently showing the positive coefficient value (this will be further discussed in the upcoming section). This could indicate a contrasting trend for this specific sector compared to the remaining sectors. Moreover, *Table 5* also shows that three control variables consistently appear as significant in all regressions, and all exhibit the coefficient signs expected according to *Section 4.5*. Given the output from *Table 4*, the three significant control variables are VIX, Market Cap and RoE. Furthermore, this consistency supports the robustness of the results. Additionally, the fact that these variables display the expected signs in accordance to *Section 4.5* suggests that the model used in the panel regression is correctly specified.

Table 5: Summary of regressions, number of significant variables at α=5%

Number of significant sector dummies with:	**30th percentile**	**Mean**	**70th percentile**
$\mathbf{VaR_{99\%}}$ as dependent variable			
ESG	6	7	6
E	8	7	5
S	7	7	4
G	5	4	4
$\mathbf{ES_{99\%}}$ as dependent variable			
ESG	5	6	5
E	8	7	4
S	5	6	5
G	6	6	3
Positive sign* using $\mathbf{VaR_{99\%}}$ as dependent variable			
ESG	0	1	1
E	0	0	1
S	0	1	0
G	1	1	1
Positive sign* using $\mathbf{ES_{99\%}}$ as dependent variable			
ESG	0	0	1
E	0	0	1
S	0	1	1
G	1	1	0
Number of:			
Significant control variables	3**	3**	3**
Significant control variables with unexpected sign	0	0	0

* Positive sign indicate increase in VaR/ES for high sustainability scores

** same control variables are significant in every regression

5.3 Qualitative Summary of Panel Regressions

To further clarify the results from the panel regressions conducted in this paper, we present *Table 6* and *Table 7* below. They disaggregate the two first sections of *Table 5*, thus visualizing which sectors that are statistically significantly different from zero. Since ES and VaR are intertwined by construction, as detailed in *Section 2*, it is worthwhile to examine the regression results for both VaR and ES, both individually and collectively, across each of the four sustainability indicators employed. This approach facilitates the possibility to analyze the consistency between the two risk measures, thus ensuring the robustness in the measurement of downside risk.

By examining the regressions involving the overall ESG measure, we notice that there is one less significant variable for each threshold for ES compared to VaR. When reviewing *Table 6* and *Table 7*, it becomes evident that the sector dummy variables significant across all three thresholds are nearly identical for both VaR and ES. Regarding the consistency of statistically significant interacted dummy variables between VaR and ES, we find the following: For the 30th percentile threshold, four dummy variables—Consumer Staples, Industrials, Materials, and Real Estate—are significant for both VaR and ES. For the mean threshold, five dummy variables—Consumer Staples, Industrials, Materials, Financials, and Real Estate—are significant. For the 70th percentile threshold, three dummy variables—Consumer Staples, Materials, and Real Estate—are consistent across both dependent variables. Therefore, the interacted dummy variables that are significant across all thresholds for both VaR and ES are Consumer Staples, Materials, and Real Estate. Additionally, Industrials is significant for both VaR and ES in two of the three thresholds.

Regarding the regressions concerning the environmental pillar, the lower two thresholds display the same number of significant interacted dummy variables, whereas for the 70th quantile threshold, ES has one less significant variable compared to VaR. When examining the two tables, it is clear that for the first two thresholds, the dummy variables that are significant are nearly identical for both VaR and ES. This pattern continues for the 70th quantile threshold, with the exception that fewer interacted dummy variables are significant compared to the other two thresholds. The only interacted dummy variable that is significant across all thresholds for both VaR and ES is Consumer Staples. However, the sectors Financials, Utilities, and Real Estate are significant in five out of six regressions, while the remaining sectors are significant in the majority of the regressions.

For the social pillar, the difference in the number of significant interacted dummy variables within the same threshold for VaR and ES is at most one. In the case of VaR, the sectors Consumer Staples, Materials, Financials, and Information Technology are significant across all thresholds. For ES, Consumer Staples, Materials, and Real Estate are significant throughout all thresholds. Therefore, the sectors consistently shown to be significant for the social pillar are Consumer Staples and Materials.

Lastly, regarding the governance pillar, we observe a trend similar to that of the other sustainability measures. The difference in the number of significant interacted dummy variables within the same threshold for VaR and ES is at most one, except for the mean threshold where the difference increases to two. Despite this, the dummy variables that are significant for this threshold highly overlap, as indicated by the tables. For VaR, the sectors Consumer Staples, Real Estate, and Energy are significant across all three thresholds. For ES, Consumer Staples and Real Estate remain significant across all thresholds.

Presented in *Table 8*, we have summarized the number of times each interacted dummy sector variable occurred as significant at $\alpha = 5\%$ to further enhance the comprehensibility of the result. This table involves all the regressions with both VaR, ES and the different thresholds, thus summarizing the findings for all regressions in this paper. The analysis reveals that the interacted sector dummies for Health Care, Consumer Discretionary and Communication Services rarely show significant differences from zero in the conducted regressions, suggesting that companies in these sectors do not experience effects on downside risk as a result of sustainable business practices. Although these interacted sector dummy variables do exhibit significant coefficients in some regressions, the infrequency and variability of significant outcomes across different thresholds lead us to interpret that these sectors are not impacted by the sustainability measures employed in this study.

To summarize the findings, this section has demonstrated a clear pattern in our panel regression results, showing consistent significance across the majority of the regressions for certain sectors, and a high degree of consistency between the results for VaR and those for ES. Specifically, the interacted sector dummy variable for Consumer Staples has been significant in all regressions conducted in this paper. Additionally, sectors such as Real Estate, Materials, Financials and Industrials have also been significant in the majority of the regressions conducted. The only anomaly observed relative to the expectations of the regression outcomes before conducting them concerns the Energy sector. As discussed in the previous section, one interacted sector dummy variable exhibited a positive sign when significant, which occurred in 13 out of 24 regressions. This variables was the interacted dummy variable for the Energy sector, indicating that the downside risk increases when sustainability scores are high within this sector.

Table 6: Summary of regressions, significant sector dummy variables at $\alpha = 5\%$

Significant sector dummies with:	**30th percentile**	**Mean**	**70th percentile**
$\text{VaR}_{99\%}$ as dependent variable			
ESG	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • InformationTechnology	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • InformationTechnology • Energy	• ConsumerStaples • Materials • Financials • RealEstate • InformationTechnology • Energy
E	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • CommunicationServices • InformationTechnology • Utilities	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • CommunicationServices • InformationTechnology	• ConsumerStaples • Financials • InformationTechnology • Utilities • Energy
S	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • CommunicationServices • InformationTechnology	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • InformationTechnology • Energy	• ConsumerStaples • Materials • Financials • InformationTechnology
G	• ConsumerStaples • HealthCare • Materials • RealEstate • Energy	• ConsumerStaples • Materials • RealEstate • Energy	• ConsumerStaples • RealEstate • Utilities • Energy

Table 7: Summary of regressions, significant sector dummy variables at $\alpha = 5\%$

Significant sector dummies with:	**30th percentile**	**Mean**	**70th percentile**
$\mathbf{ES_{99\%}}$ **as dependent variable**			
ESG	• ConsumerStaples • Industrials • Materials • RealEstate • Utilities	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • Utilities	• ConsumerStaples • Materials • RealEstate • Utilities • Energy
E	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • CommunicationServices • InformationTechnology • Utilities	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • CommunicationServices • Utilities	• ConsumerStaples • RealEstate • Utilities • Energy
S	• ConsumerStaples • Industrials • Materials • RealEstate • InformationTechnology	• ConsumerStaples • Industrials • Materials • Financials • RealEstate • Energy	• ConsumerStaples • ConsumerDiscretionary • Materials • RealEstate • Energy
G	• ConsumerStaples • ConsumerDiscretionary • HealthCare • Materials • RealEstate • Energy	• ConsumerStaples • ConsumerDiscretionary • HealthCare • Materials • RealEstate • Energy	• ConsumerStaples • RealEstate • Utilities

Table 8: Summary of panel regressions

Sector	Number of times significant
ConsumerStaples	24
RealEstate	22
Materials	19
Financials	14
Industrials	13
Energy	13
InformationTechnology	11
Utilities	11
CommunicationServices	6
ConsumerDiscretionary	3
HealthCare	3

Number of times the interacted sector dummies occurs significant at α=5%

5.4 Robustness of Empirical Results

To validate our model and results, we conduct robustness checks. Firstly, our robustness check involved using multiple thresholds for constructing our dummy variables, as discussed more thoroughly in *Section 4.8*. Our overall findings exhibited relative consistency, particularly in the results obtained using the 30th percentile and the mean as thresholds. The number of significant variables and the specific variables identified as significant were largely similar across these thresholds. However, the results obtained using the 70th percentile threshold displayed some differences. While there was an overall trend of fewer significant variables, the noteworthy aspect is that the variables that were significant is consistent with the ones using other thresholds. We will delve into the reasons for these discrepancies in the *Section 6*.

Our second approach to conducting a robustness check on the model involved examining the impact of control variables. This serves as a robustness check because it assesses the expected direction of influence for each control variable. As previously mentioned, we included six control variables, three of which were found to be significant at a significance level of $\alpha = 5\%$. These significant variables were VIX, RoE and Market Cap. Importantly, all of these variables exhibited the expected signs.

In accordance to results presented in *Section 5.1*, a higher average value of VIX resulted in a higher downside risk on average for all firms. This aligns with our expectations, since higher uncertainty typically leads to increased downside risk. Similarly, a higher RoE was associated with lower downside risk, indicated by the negative sign, which is consistent with the notion that firms with higher RoE perform well and are rewarded by the market, thus experiencing lower downside risk. We also expected Market Cap to have a negative sign, as larger firms are often perceived as more stable and experience less market volatility. This reasoning stems from our initial expectations in *Section 4.5*, specifying how these control variables are assumed to affect downside risk.

However, three control variables did not show a significant impact. While this might raise concerns about the validity of the model, it is important to note that the absence of significance could be attributed to various factors, such as the choice of measurement or the variables actual impact on the level of VaR and ES. For example, the variable capturing leverage, defined as the ratio of average total assets to total average common equity, may not directly affect risk measurement levels. Additionally, the lack of impact from the firm specific Beta variable, which was included to capture market risk, was surprising and somewhat concerning, as higher levels of firm-specific Beta would typically be expected to increase downside risk. As discussed in *Section 4.5.6*, this can be attributed to the low explanatory power of Beta in CAPM for Scandinavian companies, suggesting that this result actually should not be considered surprising.

Regarding D/E, the control variable was incorporated to capture the effect that capital structure could have on downside risk. Based on the expectations presented earlier in *Section 4.5.3* we assumed that a higher value on this key ratio would increase VaR or ES, hence having a positive relationship. Our empirical results do not showcase this relationship, and the reason behind this could be attributed to the fact that the optimal capital structure could differ across the different sectors, based on their nature of operations.

We opted to retain even the non-significant control variables in the models. This decision was made because, although these variables did not show a significant relationship towards downside risk, they contribute to capturing noise and thereby isolating the effects of sustainability scores. In this manner, the inclusion of control variables enhances the robustness and consistency of the interacted sector dummies.

To further enhance the robustness, we employed two distinct risk measures, as explained in *Section 2.2* and *Section 4.3*. Our rationale stemmed from a desire to analyze potential disparities in VaR and ES, to see if there are some difference in the tail events compared to the exact level in VaR. Our analysis unveiled a harmonious alignment between the results obtained from VaR and ES, indicating consistent outcomes. This coherency suggests a consistency in distribution, implying small deviations in kurtosis across sectors, hence the results from VaR and ES becomes similar. Had there been significant variations in kurtosis among sectors, the robustness of our findings would have been compromised, leading to discrepancy in our results. However, the similarity in outcomes reinforces our judgement that certain sectors exhibit a trend of reduced downside risk when companies maintain high sustainability scores. Thus, given the consistency between VaR and ES, we conclude that the measurement of the the downside risk is robust.

The final procedure in conducting the robustness check in this paper was to evaluate the adjusted R^2. The results indicate that the model is robust, since the regressions adjusted R^2 values are in the range of 0.32 to 0.43, as shown in *Appendix A*. This suggests that the control variables can explain a significant portion of the variation in the dependent variable, thereby mitigating potential endogeneity issues as discussed in *Section 4.8*.

With respect to the aspects discussed in this section, we consider the model to be robust. This is because all significant control variables exhibited the expected signs, aligning with theoretical expectations. Additionally, the adjusted R^2 values are relatively high, indicating that our independent variables can explain the dependent variable in a satisfactory degree. Moreover, the employed risk measures are correctly specified and showcase consistent results. Furthermore, given the model specification which mitigates the risk of heteroscedasticity and multicollinearity, we feel ensured that these potential pitfalls are eliminated. Above all, the results obtained using different thresholds show relative consistency.

6 Analysis and Discussion

The results observed in this paper largely align with our initial expectations, which are grounded in both the theoretical foundations and previous research on the effects of sustainable business practices on downside risk. We found that a majority of the analyzed sectors are affected to some degree by sustainability performance measures, as evidenced by a reduced downside risk associated with high sustainability scores. The notable exception is the Energy sector. In an effort to decompose the results thoroughly, this section will initially discuss and analyze our results in relation to both the theoretical framework outlined in *Section 2* and the literature review, detailed in *Section 3*. Following this, we will analyze the sector-specific results and discuss anomalies and further questions that arise from our findings. Lastly, we discuss the potential of ESG measures as being tools for risk management.

6.1 The ESG Measure and its Constituting Pillars

In accordance with *Section 2.1*, the theoretical foundation of the ESG measure suggests that companies operating sustainably could reap benefits in terms of downside risk compared to those that do not emphasize sustainability in their business practices. This assertion is broadly supported by previous research in the field, as detailed in *Section 3*. Therefore, both theoretical and empirical studies indicate that adherence to ESG standards could lead to superior outcomes for companies engaged in sustainable operations, since a high overall ESG score suggests low exposure to the risks associated with ESG factors. Additionally, regulatory pressure from both existing and forthcoming legislation adds another dimension to the implications of having a high ESG score, as this new legislation increasingly requires firms to conduct and disclose their sustainability reporting transparently, presented in *Section 1*.

Given this brief recap of the motivation underlying our research and hypothesis formulation, the results of this paper largely aligns with the existing theory behind the construction of the overall ESG measure. Clearly, not all sectors exhibit significant results which implies that sustainability measures do not affect all sectors. Although, the measure seems to effectively capture the risks quantified by its rating system, which is based on the three constituent pillars for some sectors. The findings suggest that firms with high scores experience reduced downside risk compared to those with lower scores in the Nordic countries, after adjusting for other factors using the employed control variables.

As detailed in *Section 4.4*, we employed various quantiles to construct our dummy variables, ensuring the robustness of our model. The ensuing discussion of our findings in *Section 5.4* not only underscore the robustness of our model, but also revealed an unexpected outcome: the 70th percentile, our upper threshold, yielded weaker results compared to other quantiles. Initially, we anticipated that companies with the highest scores would exhibit lower downside risk. Our findings instead suggest that it tends to penalize firms with low scores more than it rewards top performers. This observation aligns with previous literature presented in *Section 3*, stating that neglecting sustainability factors can lead to increased risk exposure.

As presented in *Section 5*, the environmental pillar is the sustainability measure that produces the most significant interacted sector dummy variables. It is followed by the overall ESG measure and the social pillar, with the governance pillar producing the fewest significant interacted sector dummy variables. The fact that the overall ESG measure neither produces the most nor the fewest significant variables is unsurprising, given that it is a weighted average of the three constituting pillars. This result further strengthens the robustness of the results presented in this paper. Instead, an interesting implication of our results is that the environmental pillar appears to be more important in reducing downside risk compared to the other two pillars.

To understand this implication, it is important to revisit the construction differences of the individual pillars. As mentioned in *Section 2.1*, there are variations in how the pillars are measured because they assess different aspects, which are quantifiable to varying degrees. The environmental pillar is based on the most quantitative framework, while the governance pillar relies least on strictly quantitative framework, making it the most subjective and, therefore, potentially the least robust pillar by construction. Given this understanding of how the pillars are constructed, our panel regression results might reflect these differences. Thus, there are two clear potential reasons why the environmental pillar shows more significant results compared to the two remaining pillars: either due to the nature of the pillar score construction or because the environmental pillar is inherently more significant with respect to downside risk.

Although the construction of the pillars may account for some differences, it is important to emphasize that, based on our results, the most straightforward and fair conclusion is that the environmental pillar has the most profound mitigating effect on downside risk. This suggests that risks explicitly associated with environmental considerations, such as climate risks and transition risks, are of greater importance than the governance risks related to poor business practices, which could lead to issues like over-leveraging or litigation problems, or risks captured by the social pillar. One explanation for this result could be that the risks associated with environmental considerations are perceived to be the most urgent and impactful. Since a high score within this pillar theoretically implies that a firm possesses a mitigating nature against downward market shocks according to Setzer & Higham (2021) and Engle et al. (2020), the firm is assumed to be less vulnerable to climate and transition risks due to its high score. Therefore, this assumption could explain our results in combination with the increasing global attention on environmental issues. Thus, it makes environmental sustainability a critical factor in investment decisions, as also stated by Henriksson et al. (2019), since it can provide an insight into a firms overall risk level (European Banking Authority 2020). Moreover, investors and regulators seem to increasingly value firms that can demonstrate resilience to environmental risks in accordance Giese et al. (2019), which likely contributes to the observed significance of the environmental pillar in reducing downside risk.

6.2 Analysis of Sector Specific Results

Regarding the relationship between sector-specific characteristics and downside risk, we did not observe a coherent pattern indicating why specific sectors seem to show that high sustainability scores decreases the downside risk for companies operating in them. In light of this analysis, Jansen (2023) discovered that sectors that directly serve end consumers are more vulnerable to downside risk when possessing poor ESG scores, opposed to companies operating in sectors who typically sell their products or services to other companies. We found this observation intriguing, and upon examining our results, we found partial evidence supporting Jansen's (2023) results. For instance, the Consumer Staples sector exhibited a significant negative relationship in all 24 regressions, making it the sector that demonstrated the largest impact on reducing its downside risk through inheriting high sustainability scores. Consumer Staples comprises companies offering non-cyclical essential consumer products like food and beverages, directly serving consumers as their end customers. The relationship observed in this sector could also be attributed to findings by Shafer & Szado (2018), who suggest that higher sustainability scores tend to create a more loyal customer and employee base. This loyalty can reduce the risk of unexpected financial events, thereby lowering downside risk.

Additional sectors such as Real Estate, Materials, Financials and Industrials also display strong results, although these sectors not directly serve consumers as end their customers. Conversely, the Consumer Discretionary sector, which encompasses cyclically sensitive consumer products like restaurants and hotels, exhibited the weakest relationship of all the sectors. These two observations in our result are notable counterexamples to Jansen's (2023) findings, since they do not show a trend regarding sector specific characteristics. In conclusion, our findings do not definitively support the notion that high sustainability scores for sectors directly serving end consumers reduce downside risk.

In contrary to our other results, the Energy sector stood out and showcased the opposite trend, since the sector witnessed higher downside risk for high sustainability scores. This observation led us to delve deeper into why this sector exhibited the opposite trend. Firstly, the definition of the Energy sector by London Stock Exchange Group (2023) indicated that everything included in the sector is related to either oil, gas, or coal, which is fossil fuels that could not be classified as environmentally friendly. This could be a contributing factor to the sector having the second-lowest average ESG score, as visualized in *Figure 4* in *Section 4.4*. Since the nature of operations in this sector per definition is harmful to the environment, it weakens the legitimacy and scores of the strongest pillar according to our findings, the environmental pillar. Consequently, investors might place less weight on the ESG score in a sector that is inherently bad for the environment.

Sharfman et al. (2008) found that responsible business practices, with consequently high sustainability scores, serve as a protective shield against downside risk. If investors were to put less weight in ESG scores, the sustainability scores would not serve as a protective shield, and the main determinant of the downside risk would be the performance of the companies. Consequently, companies in this sector that attempt to transition to a more sustainable business model might inherit higher ESG scores, but could lose competitive power since the transition could lead to poorer short-term performance due to higher expenses in the transition period. Thus, the downside risk for companies in this sector with higher sustainability scores would be greater, which could explain the result for the Energy sector.

6.3 ESG as a Risk Management Tool

As *Table 4* and subsequent regressions presented in *Appendix A* suggest, there is potential for considerable economic gains from utilizing ESG scores to reduce downside risk. This study finds that firms with high ESG scores, relative to a sector-specific threshold, can reduce their VaR and ES by 10 to 30 percentage points annually, depending on the sector. It is important to note that these findings do not apply universally across all sectors, as not all exhibit significant results. However, the overall findings of this study provide incentives for firms to consider ESG scores in assessing and mitigating downside risk. Furthermore, this result aligns with the discussion in *Section 1*. It highlights the growing influx of capital into sustainable investments and the increasing efforts by investors to integrate sustainability into their investment strategies, emphasizing the importance of incorporating sustainability measures, such as ESG, in financial decision-making. Therefore, the results of this paper suggest that there are compelling reasons to view the ESG framework and its pillars as valuable tools in risk management.

Although, it is important to consider the risk of unobserved heterogeneity in the model, as discussed in *Section 4.8*. The section explains that it is impossible to exclude the influence of unobserved factors that may simultaneously affect both downside risk and ESG scores, potentially leading to a spurious correlation where high ESG scores appear to correlate with lower downside risk, suggesting a non-causal relationship. One possible source of this heterogeneity could be managerial competence, which is challenging to measure and therefore not included as a variable in this study. Managerial competence is a factor that could affect the model because competent managers may both mitigate downside risk and value sustainable business practices, creating a correlation between high ESG scores and lower downside risk. This introduces the risk that the observed relationship might actually be driven by an unobserved factor, such as managerial competence, rather than the direct impact of high ESG scores. Nevertheless, our results are consistent with the theoretical framework and previous studies in the field, affirming that the relationship between high ESG scores and lower downside risk is grounded in established theory and empirical evidence. Consequently, the risk of unobserved heterogeneity influencing this relationship is likely minimal.

Concerning the utility of ESG as a protective measure against downside risk, our findings suggest it is indeed valuable. As discussed in *Section 2.1*, although ESG metrics come with inherent limitations due to their scoring methods and the precision of criteria within each pillar, they nevertheless offer important insights into the environmental, social, and governance qualities of companies. Thus, despite the imperfections in their design, these measures serve as significant indicators of potential downside risk in a firm. Furthermore, this result aligns with the discussion in *Section 1.* This is notably evident in the rising flow of capital from the rapidly expanding sustainable funds sector, which includes substantial contributions from major institutional investors such as BlackRock. In conclusion, our results therefore indicate that adherence to the ESG framework could serve as an effective risk management tool across a broad range of sectors.

7 Conclusion and Further Research

The shift toward a sustainable future for our planet requires participation from all members of society. For quite some time, the interest in addressing the environmental and social challenges we face has been firmly established in both political and societal debates, which have emphasized the importance of the global financial industry joining the movement toward sustainability. In recent years, the concept of the ESG framework has gained widespread recognition and adoption within the financial industry. It is used to classify how sustainable a business or investment is, facilitating the introduction of bonds and funds with a sustainability focus. However, there has been little emphasis on understanding how these classifications impact the riskiness of an asset.

In this paper, we aim to address the gap in existing research regarding the effects of a high sustainability focus on downside risk. We do this by examining whether high scores within the ESG framework and its constituting pillars can influence sector-specific downside risk in the Nordic countries during the years 2018 through 2022. Our goal is to develop a deeper understanding of the ESG framework and its impact on financial downside risk. To ensure robust results, this paper employs three different thresholds to classify high sector-specific sustainability scores. Additionally, it utilizes two widely recognized risk measures, Value at Risk and Expected Shortfall, to calculate downside risk. Additionally, numerous control variables, which are assumed to affect downside risk, are included to strengthen the model and isolate the effects of the sustainability measures.

Our findings indicate that companies with high scores within the sustainability measures employed generally experience reduced downside risk compared to firms in the same sector with low scores. When analyzing the effects of a high overall ESG score, this paper concludes that such scores tend to reduce downside risk in some sectors, while in others, they have no effect. However, there is one exception: the Energy sector, which exhibited a higher downside risk despite having a high ESG score. Moreover, the environmental pillar emerged as having the most significant effect on reducing downside risk, while the governance pillar showed the least significant results, indicating that it has the smallest impact on reducing downside risk among the three pillars. In conclusion, this study highlights that high scores within the ESG framework, particularly in the environmental pillar, can mitigate downside risk. These findings suggest that it may be of interest to incorporate such factors into risk management strategies within firms, presenting a compelling case for future research and application.

The future of sustainable finance is poised for significant advancement driven by escalating regulatory pressures. The forthcoming years are expected to witness a substantial increase in data availability, propelled by new transparency regulations across the world. For future research endeavors, it would be intriguing to delve into the underlying reasons why the downside risk associated with ESG factors varies across different sectors. It would be interesting to understand why certain sectors are more profoundly affected than others, and identifying the distinguishing characteristics contributing to this divergence, presents an intriguing avenue for exploration.

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Appendix A-C

A: Regression Results from Stata

All regressions conducted in this study that are not presented in *Section 5* can be found below.

Table 9: $VaR_{99\%}$ as the dependent variable and dummies for the Environmental Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
Consumer Staples$_{\text{High Score}}$	-24.0891*** (4.6299)	-22.2263*** (4.5161)	-20.7407*** (4.6601)
Industrials$_{\text{High Score}}$	-12.5282*** (3.4646)	-8.4813*** (3.0718)	-4.8778 (3.3356)
Consumer Discretionary$_{\text{High Score}}$	-0.7612 (5.8362)	3.0228 (7.4251)	4.6996 (9.7845)
Health Care$_{\text{High Score}}$	-3.7428 (5.2976)	-6.7104* (3.8290)	1.9502 (4.7527)
Materials$_{\text{High Score}}$	-14.8577*** (4.2715)	-10.4263** (4.2151)	-9.4997 (5.8767)
Financials$_{\text{High Score}}$	-25.9316*** (5.2872)	-20.7574*** (5.7395)	-16.0862** (6.5059)
Real Estate$_{\text{High Score}}$	-19.4419*** (5.7453)	-15.4364** (6.1297)	-11.4620 (9.3750)
Communication Services$_{\text{High Score}}$	-23.0292*** (7.6652)	-19.4445** (7.9599)	-16.7266 (9.0892)
Information Technology$_{\text{High Score}}$	-17.5501*** (5.3736)	-17.9416*** (4.2255)	-18.1246*** (4.7166)
Utilities$_{\text{High Score}}$	-15.3176** (6.3508)	-11.6691* (6.1401)	-20.8180*** (4.9353)
Energy$_{\text{High Score}}$	7.8441 (6.5031)	14.7025* (8.1504)	14.3960*** (5.3497)
VIX	3.4862*** (0.1601)	3.5032*** (0.1614)	3.4882*** (0.1611)
D/E	0.0009* (0.0005)	0.0008 (0.0006)	0.0010 (0.0006)
Market Cap	-0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)
Leverage	0.0020 (0.3444)	-0.0451 (0.3587)	-0.1143 (0.3747)
ROE	-0.4449*** (0.1091)	-0.4549*** (0.1116)	-0.4644*** (0.1138)
Firm Specific Beta	-0.1525 (2.3972)	-0.7156 (2.4609)	0.0084 (2.4597)
Constant	32.8326*** (5.0186)	29.4328*** (5.1408)	26.6955*** (5.0563)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.4335	0.4220	0.4038

High Score indicates a high Environmental score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: $VaR_{99\%}$ as the dependent variable and dummies for Social Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-26.4465*** (4.3361)	-29.2199*** (3.4678)	-26.6197*** (3.4961)
Industrials $_{\text{High Score}}$	-12.3860*** (3.4994)	-10.5586*** (2.8149)	-6.5883 (3.5458)
ConsumerDiscretionary $_{\text{High Score}}$	5.7012 (6.1179)	8.2503 (6.5146)	9.3615 (8.7824)
HealthCare $_{\text{High Score}}$	-0.8443 (5.5820)	-3.6795 (4.0901)	0.5847 (4.6938)
Materials $_{\text{High Score}}$	-17.2544*** (4.2486)	-15.7464*** (4.1617)	-12.9034*** (3.7390)
Financials $_{\text{High Score}}$	-17.1581*** (6.0265)	-17.5854*** (5.2884)	-16.4823*** (5.3504)
RealEstate $_{\text{High Score}}$	-22.5267*** (6.2406)	-19.0583*** (6.8774)	-10.4192 (8.9135)
CommunicationServices $_{\text{High Score}}$	-15.6364** (7.7895)	-13.3017* (7.4880)	-10.0432 (14.2329)
InformationTechnology $_{\text{High Score}}$	-15.1251*** (5.3619)	-18.0575*** (4.3733)	-16.1516*** (5.6785)
Utilities $_{\text{High Score}}$	-0.7744 (7.2156)	8.1290 (7.1421)	3.4449 (3.7176)
Energy $_{\text{High Score}}$	9.7168 (6.6754)	14.8319** (6.4288)	19.8979 (11.4869)
VIX	3.4877*** (0.1591)	3.4903*** (0.1594)	3.4789*** (0.1610)
D/E	0.0008 (0.0006)	0.0007 (0.0006)	0.0007 (0.0006)
Market Cap	-0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)
Leverage	-0.0990 (0.3805)	-0.0886 (0.3689)	-0.1312 (0.3492)
ROE	-0.4555*** (0.1088)	-0.4601*** (0.1106)	-0.4693*** (0.1121)
Firm Specific Beta	-0.3202 (2.4194)	-0.8991 (2.4586)	0.4177 (2.5523)
Constant	32.1831*** (5.0884)	30.1041*** (5.0274)	26.4961*** (5.0240)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.4333	0.4314	0.4093

High Score indicates a high Social score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Table 11: $VaR_{99\%}$ as the dependent variable and dummies for Governance Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-19.1878*** (4.6581)	-21.7647*** (4.0535)	-23.0574*** (3.0194)
Industrials $_{\text{High Score}}$	-4.3600 (3.4465)	-4.3836 (3.1078)	-7.1666 (3.7082)
ConsumerDiscretionary $_{\text{High Score}}$	9.8728* (5.1605)	7.7620 (5.2125)	1.1776 (5.0038)
HealthCare $_{\text{High Score}}$	11.8600** (5.8208)	9.9795 (6.5325)	-2.4081 (5.1236)
Materials $_{\text{High Score}}$	-8.8412** (4.0977)	-9.1870** (3.8670)	-6.9004 (5.8961)
Financials $_{\text{High Score}}$	-7.8266 (6.0940)	-5.4322 (5.8363)	-9.6484 (5.7190)
RealEstate $_{\text{High Score}}$	-15.4500*** (4.4555)	-15.5754*** (4.0453)	-13.9155*** (2.8069)
CommunicationServices $_{\text{High Score}}$	-9.7497 (8.9225)	-7.7025 (10.1121)	-18.3469 (10.4691)
InformationTechnology $_{\text{High Score}}$	-2.0206 (6.6187)	-4.3508 (5.2293)	-8.0752 (4.5963)
Utilities $_{\text{High Score}}$	1.2303 (10.2884)	-7.0993 (5.7107)	-20.1360*** (5.2730)
Energy $_{\text{High Score}}$	25.1580*** (9.1499)	31.2538*** (10.0145)	22.8891** (11.0389)
VIX	3.5019*** (0.1609)	3.5345*** (0.1620)	3.4860*** (0.1629)
D/E	0.0007 (0.0006)	0.0009 (0.0006)	0.0010 (0.0006)
Market Cap	-0.0004*** (0.0001)	-0.0004*** (0.0001)	-0.0004*** (0.0001)
Leverage	-0.0756 (0.3977)	-0.1673 (0.3686)	-0.1962 (0.3494)
ROE	-0.4463*** (0.1106)	-0.4487*** (0.1114)	-0.4761*** (0.1128)
Firm Specific Beta	-1.1241 (2.5198)	-0.5248 (2.5366)	-0.8577 (2.5951)
Constant	27.0596*** (5.2478)	25.8391*** (4.9910)	28.1979*** (5.0965)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.4275	0.4230	0.4045

High Score indicates a high Governance score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Table 12: $ES_{99\%}$ as the dependent variable and dummies for ESG

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-27.4353*** (7.4815)	-30.8144*** (6.6220)	-34.6307*** (5.5620)
Industrials $_{\text{High Score}}$	-13.8794** (5.4182)	-13.2795*** (4.6886)	-8.4812 (5.7272)
ConsumerDiscretionary $_{\text{High Score}}$	9.4778 (7.8226)	10.3801 (7.0973)	15.6912 (9.4941)
HealthCare $_{\text{High Score}}$	8.4116 (9.0183)	4.9359 (9.8498)	13.1862 (7.1638)
Materials $_{\text{High Score}}$	-18.5293*** (6.5195)	-16.3067** (6.4851)	-16.5492** (6.5057)
Financials $_{\text{High Score}}$	-18.8695* (10.7765)	-21.8335** (8.7601)	-15.1152 (9.4395)
RealEstate $_{\text{High Score}}$	-26.4411*** (7.0349)	-23.5963*** (7.7374)	-19.8768** (8.5204)
CommunicationServices $_{\text{High Score}}$	-21.7745* (11.3710)	-22.4517* (12.9469)	-11.5832 (22.5567)
InformationTechnology $_{\text{High Score}}$	-15.6504* (9.0716)	-17.6731* (9.8854)	-4.9461 (11.0487)
Utilities $_{\text{High Score}}$	-22.0516** (10.8968)	-21.7389** (9.8570)	-30.9282*** (5.3974)
Energy $_{\text{High Score}}$	30.3193* (17.2395)	30.9143* (16.4085)	20.4114** (9.2933)
VIX	4.3608*** (0.2672)	4.3756*** (0.2696)	4.3420*** (0.2662)
D/E	0.0008 (0.0008)	0.0008 (0.0008)	0.0011 (0.0008)
Market Cap	-0.0006*** (0.0002)	-0.0005*** (0.0002)	-0.0006*** (0.0002)
Leverage	-0.0431 (0.5918)	-0.1045 (0.5325)	-0.2012 (0.5470)
ROE	-0.6631*** (0.1615)	-0.6732*** (0.1619)	-0.6913*** (0.1655)
Firm Specific Beta	-3.4091 (3.7559)	-3.2180 (3.7473)	-1.5882 (3.8641)
Constant	51.9894*** (8.6442)	49.9364*** (8.6559)	46.6538*** (8.5721)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.3531	0.3487	0.3291

High Score indicates a high ESG score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Table 13: $ES_{99\%}$ as the dependent variable and dummies for Enviorment Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-23.2730** (9.3240)	-23.7678*** (8.5856)	-25.7800*** (8.1718)
Industrials $_{\text{High Score}}$	-18.4047*** (5.3981)	-13.5070*** (4.8300)	-7.9306 (5.6250)
ConsumerDiscretionary $_{\text{High Score}}$	2.7139 (8.8123)	6.9561 (10.4793)	8.5010 (13.9620)
HealthCare $_{\text{High Score}}$	0.4568 (7.8766)	-2.8142 (6.9727)	13.9674 (9.3574)
Materials $_{\text{High Score}}$	-21.4492*** (6.6913)	-16.5212*** (6.2377)	-14.6804 (9.4843)
Financials $_{\text{High Score}}$	-33.1039*** (8.4682)	-25.6100*** (9.2808)	-18.5698 (9.8090)
RealEstate $_{\text{High Score}}$	-29.1864*** (6.8799)	-23.6654*** (7.1689)	-22.6331** (9.4054)
CommunicationServices $_{\text{High Score}}$	-31.3016*** (11.7182)	-26.4187** (12.1490)	-26.5598 (14.5039)
InformationTechnology $_{\text{High Score}}$	-19.9683** (8.7617)	-18.4568* (9.6594)	-19.5987 (13.0647)
Utilities $_{\text{High Score}}$	-28.7868*** (9.9080)	-23.9334** (9.6685)	-31.4123*** (5.4324)
Energy $_{\text{High Score}}$	12.2188 (10.3099)	24.8084 (15.4026)	19.3302** (8.5187)
VIX	4.3494*** (0.2665)	4.3685*** (0.2667)	4.3566*** (0.2659)
D/E	0.0011 (0.0007)	0.0009 (0.0008)	0.0013 (0.0008)
Market Cap	-0.0005*** (0.0002)	-0.0005*** (0.0002)	-0.0006*** (0.0002)
Leverage	0.0010 (0.5115)	-0.0770 (0.5303)	-0.1815 (0.5519)
ROE	-0.6595*** (0.1601)	-0.6707*** (0.1629)	-0.6832*** (0.1664)
Firm Specific Beta	-2.4202 (3.7126)	-3.2541 (3.7880)	-2.4945 (3.7106)
Constant	54.8557*** (8.3464)	50.8969*** (8.6694)	47.7464*** (8.4239)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.3520	0.3435	0.3292

High Score indicates a high Enviormental score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Table 14: $ES_{99\%}$ as the dependent variable and dummies for Social Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-29.7929*** (7.4813)	-34.4947*** (6.5966)	-34.7759*** (5.6843)
Industrials $_{\text{High Score}}$	-18.1260*** (5.4354)	-15.7586*** (4.5786)	-8.4829 (5.9495)
ConsumerDiscretionary $_{\text{High Score}}$	8.8156 (8.9624)	10.7985 (8.3132)	20.5460** (9.8117)
HealthCare $_{\text{High Score}}$	7.9130 (8.3481)	2.0432 (6.5028)	12.4941 (7.8764)
Materials $_{\text{High Score}}$	-24.7854*** (6.6590)	-22.3535*** (6.7812)	-16.8918*** (6.0801)
Financials $_{\text{High Score}}$	-19.5917** (9.8601)	-20.8491** (8.6943)	-14.9262 (8.9510)
RealEstate $_{\text{High Score}}$	-34.3300*** (7.1654)	-31.3449*** (7.6885)	-19.8532** (8.9600)
CommunicationServices $_{\text{High Score}}$	-23.0472** (11.6266)	-20.6951* (11.1639)	-10.7346 (21.5574)
InformationTechnology $_{\text{High Score}}$	-19.3059** (8.8608)	-20.2811* (10.4026)	-11.6928 (14.2211)
Utilities $_{\text{High Score}}$	-6.6793 (11.4026)	7.5444 (14.5475)	-1.2540 (7.2887)
Energy $_{\text{High Score}}$	13.2533 (9.6308)	23.3793** (11.3725)	31.4356** (15.8358)
VIX	4.3542*** (0.2644)	4.3550*** (0.2668)	4.3457*** (0.2679)
D/E	0.0009 (0.0008)	0.0008 (0.0008)	0.0007 (0.0008)
Market Cap	-0.0005*** (0.0002)	-0.0005*** (0.0002)	-0.0005*** (0.0002)
Leverage	-0.1706 (0.5575)	-0.1451 (0.5419)	-0.2094 (0.5188)
ROE	-0.6718*** (0.1601)	-0.6754*** (0.1619)	-0.6910*** (0.1641)
Firm Specific Beta	-2.8188 (3.7073)	-3.8086 (3.7442)	-1.7683 (3.8684)
Constant	54.5326*** (8.2607)	52.3489*** (8.5630)	46.5702*** (8.5407)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.3543	0.3508	0.3331

High Score indicates a high Social score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

Table 15: $ES_{99\%}$ as the dependent variable and dummies for Governance Pillar

Sector	0.3 Quantile Dummies	Mean Dummies	0.7 Quantile Dummies
ConsumerStaples $_{\text{High Score}}$	-20.6417*** (7.0186)	-25.1200*** (6.6338)	-26.8101*** (6.9290)
Industrials $_{\text{High Score}}$	-5.5950 (5.0984)	-6.4694 (4.7336)	-10.6715 (5.8104)
ConsumerDiscretionary $_{\text{High Score}}$	19.9004** (7.8265)	16.9181** (8.4260)	8.6898 (9.6397)
HealthCare $_{\text{High Score}}$	27.0848*** (8.4581)	25.0209*** (9.5727)	8.6844 (10.5478)
Materials $_{\text{High Score}}$	-13.2061** (5.9974)	-14.5230*** (5.4905)	-12.8583 (8.5335)
Financials $_{\text{High Score}}$	-3.5881 (9.7427)	-1.5505 (9.2271)	-8.0951 (8.1747)
RealEstate $_{\text{High Score}}$	-20.1858*** (5.7096)	-22.1353*** (5.3450)	-22.0141*** (4.9600)
CommunicationServices $_{\text{High Score}}$	-12.5293 (13.4589)	-9.4515 (15.4012)	-24.1952 (14.1197)
InformationTechnology $_{\text{High Score}}$	2.6328 (10.3031)	1.1333 (9.2484)	-1.4181 (11.6191)
Utilities $_{\text{High Score}}$	-0.4473 (17.5625)	-12.7229 (10.8839)	-23.6128** (11.7731)
Energy $_{\text{High Score}}$	38.1747** (16.8464)	49.7099*** (18.6069)	42.5522 (21.6972)
VIX	4.3769*** (0.2648)	4.4264*** (0.2656)	4.3558*** (0.2703)
D/E	0.0008 (0.0008)	0.0010 (0.0008)	0.0012 (0.0008)
Market Cap	-0.0007*** (0.0002)	-0.0007*** (0.0002)	-0.0006*** (0.0002)
Leverage	-0.1606 (0.5709)	-0.2459 (0.5279)	-0.2720 (0.5070)
ROE	-0.6526*** (0.1586)	-0.6476*** (0.1602)	-0.6924*** (0.1649)
Firm Specific Beta	-3.9800 (3.8958)	-3.1964 (3.9098)	-3.6146 (3.9770)
Constant	45.8990*** (8.8704)	44.7693*** (8.6163)	48.7409*** (8.6344)
Observations	1,245	1,245	1,245
Adjusted R-squared	0.3571	0.3545	0.3320

High Score indicates a high Governance score compared to other firms within the same sector given the threshold.

Clustered standard errors in parentheses refer to firm specific variation

*** p<0.01, ** p<0.05, * p<0.1

B: Summary of Regressions with Unexpected Sign

The table below visualizes which sectors exhibit an unexpected sign for significant interacted sector dummy variables and also identifies the control variables that are significant across all regressions.

Table 16: Summary of regressions, number of significant variables at $\alpha = 5\%$

Significant sector dummies with:	**30th percentile**	**Mean**	**70th percentile**
Positive sign* using $\mathbf{VaR_{99\%}}$ as dependent variable			
ESG	-	Energy	Energy
E	-	-	-
S	Energy	Energy	-
G	Energy	Energy	Energy
Positive sign* using $\mathbf{ES_{99\%}}$ as dependent variable			
ESG	-	-	Energy
E	-	-	Energy
S	-	Energy	Energy
G	-	-	-
Number of:			
Significant control variables	VIX, Market Cap, ROE(**)	VIX, Market-Cap, ROE(**)	VIX, Market-Cap, ROE(**)
Significant control variables with unexpected sign	-	-	-

- Indicates no Variables

* Positive sign indicates an increase in VaR/ES for high sustainability scores

** same control variables are significant in every regression

C: List of Companies

The table below lists all companies included in this paper and the respective stock exchanges in which they are listed.

Company	**Country**	**Company**	**Country**
AAK AB	Sweden	Bergman & Beving AB	Sweden
Abb Ltd	Sweden	Betsson AB	Sweden
Afry AB	Sweden	Bilia AB	Sweden
Akastor ASA	Norway	Billerud AB	Sweden
Aker ASA	Norway	Biogaia AB	Sweden
Aker BP ASA	Norway	Biotage AB	Sweden
Aker Solutions ASA	Norway	Boliden AB	Sweden
Aktia Bank Abp	Finland	Bonava AB	Sweden
Alfa Laval AB	Sweden	Bang & Olufsen A/S	Denmark
Alimak Group AB	Sweden	Borregaard ASA	Norway
ALK-Abello A/S	Denmark	Bravida Holding AB	Sweden
ALM. Brand A/S	Denmark	Bufab AB	Sweden
Ambu A/S	Denmark	Bure Equity AB	Sweden
AP Moeller - Maersk A/S	Denmark	BW LPG Limited	Norway
Arjo AB	Sweden	BW OFFSHORE LIMITED	Norway
Assa Abloy AB	Sweden	Camurus AB	Sweden
ASTRAZENECA PLC	Sweden	Cargotec Corp	Finland
Atea ASA	Norway	Carlsberg A/S	Denmark
Atlas Copco AB	Sweden	Castellum AB	Sweden
Austevoll Seafood ASA	Norway	CATENA MEDIA P.L.C	Sweden
AUTOLIV, INC.	Sweden	Caverion Oyj	Finland
Avanza Bank Holding AB	Sweden	Caverion Oyj	Finland
Axactor ASA	Sweden	CellaVision AB	Sweden
Axfood AB	Sweden	Citycon Oyj	Finland
B2 Impact ASA	Norway	Clas Ohlson AB	Sweden
Bavarian Nordic A/S	Denmark	Cloetta AB	Sweden
Beijer Ref AB	Sweden	Coloplast A/S	Denmark

Company	Country	Company	Country
CTT Systems AB	Sweden	Fortum Oyj	Finland
Dampskibsselskabet Norden A/S	Denmark	FRONTLINE PLC	Norway
Danske Bank A/S	Denmark	GAMING INNOVATION GROUP INC.	Sweden
Demant A/S	Denmark	Genmab A/S	Denmark
DFDS AS	Denmark	Getinge AB	Sweden
Dios Fastigheter AB	Sweden	Gjensidige Forsikring ASA	Norway
DNB Bank ASA	Norway	GN Store Nord A/S	Denmark
Dometic Group AB	Sweden	Golden Ocean Group Limited.	Norway
DSV A/S	Denmark	Granges AB	Sweden
Dustin Group AB	Sweden	Grieg Seafood ASA	Norway
Elanders AB	Sweden	H & M Hennes & Mauritz AB	Sweden
Electrolux AB	Sweden	Hansa Biopharma AB	Sweden
Elekta AB	Sweden	Hexagon AB	Sweden
Elisa Oyj	Finland	Hexpol AB	Sweden
Elkem ASA	Norway	Hoist Finance AB	Sweden
Entra ASA	Norway	Holmen AB	Sweden
Epiroc AB	Sweden	Hufvudstaden AB	Sweden
Equinor ASA	Norway	Humana AB	Sweden
Essity AB	Sweden	Husqvarna AB	Sweden
Europris ASA	Norway	Industrivarden AB	Sweden
Evolution AB	Sweden	Indutrade AB	Sweden
Fabege AB	Sweden	Intrum AB	Sweden
Fastighets AB Balder	Sweden	Inwido AB	Sweden
Finnair Oyj	Finland	ISS A/S	Denmark
FLEX LNG LTD.	Norway	JM AB	Sweden
FLSmidth & Co A/S	Denmark	Jyske Bank A/S	Denmark
Fortnox AB	Sweden	Kemira Oyj	Finland

Company	**Country**	**Company**	**Country**
Kesko Corporation	Finland	Nibe Industrier AB	Sweden
KINDRED GROUP PLC	Sweden	Nilfisk Holding A/S	Denmark
Kinnevik AB	Sweden	Nkt A/S	Denmark
KONE Corporation	Finland	NNIT A/S	Denmark
Konecranes Abp	Finland	Nobia AB	Sweden
Kongsberg Automotive ASA	Norway	NOKIA	Finland
Kongsberg Gruppen ASA	Norway	Nokian Tyres plc	Finland
L E Lundbergforetagen AB	Sweden	Nolato AB	Sweden
Leroy Seafood Group ASA	Norway	Nordea Bank Abp	Finland
Lindab International AB	Sweden	Nordic Semiconductor ASA	Norway
Loomis AB	Sweden	Norsk Hydro ASA	Norway
Lucara Diamond Corp.	Sweden	NORTHERN DRILLING LTD.	Norway
Lundin Mining Corporation	Sweden	Norwegian Air Shuttle ASA	Norway
Meko AB	Sweden	Novo Nordisk A/S	Denmark
Metsa Board Oyj	Finland	Novozymes A/S	Denmark
Metso Oyj	Finland	Nyfosa AB	Sweden
Millicom International Cellular SA	Sweden	Oersted A/S	Denmark
Modern Times Group MTG AB	Sweden	Oriola Oyj	Finland
Mowi ASA	Norway	Orion Oyj	Finland
Munters Group AB	Sweden	Outokumpu Oyj	Finland
Mycronic AB	Sweden	P/F Bakkafrost	Norway
NCC AB	Sweden	Pandora A/S	Denmark
Nederman Holding AB	Sweden	Pandox AB	Sweden
Nel ASA	Norway	Peab AB	Sweden
Neste Oyj	Finland	Per Aarsleff Holding A/S	Denmark
Netcompany Group A/S	Denmark	PGS ASA	Norway
New Wave Group AB	Sweden	Ponsse Plc	Finland

Company	Country	Company	Country
Probi AB	Sweden	SkiStar AB	Sweden
Prosafe SE	Norway	Solar A/S	Denmark
Protector Forsikring ASA	Norway	Spar Nord Bank A/S	Denmark
Ratos AB	Sweden	Sparebank 1 SR Bank ASA	Norway
RaySearch Laboratories AB	Sweden	SSAB AB	Sweden
REC Silicon ASA	Norway	Stillfront Group AB	Sweden
Resurs Holding AB	Sweden	STOLT-NIELSEN LIMITED	Norway
Rockwool A/S	Denmark	Stora Enso Oyj	Finland
Royal Unibrew A/S	Denmark	Storebrand ASA	Norway
Saab AB	Sweden	Subsea 7 SA	Norway
SalMar ASA	Norway	Svenska Cellulosa Aktiebolaget SCA	Sweden
Sampo Oyj	Finland	Svenska Handelsbanken AB	Sweden
Sandvik AB	Sweden	Sweco AB	Sweden
Sanoma Oyj	Finland	Swedbank AB	Sweden
SAS AB	Sweden	Swedish Orphan Biovitrum AB	Sweden
Scandi Standard AB	Sweden	Sydbank A/S	Denmark
Scandic Hotels Group AB	Sweden	Tele2 AB	Sweden
Scandinavian Tobacco Group A/S	Denmark	Telefonaktiebolaget LM Ericsson	Sweden
Scatec ASA	Norway	Telenor ASA	Norway
Schibsted ASA	Norway	Telia Company AB	Sweden
Schouw & Co A/S	Denmark	TGS ASA	Norway
Sectra AB	Sweden	Thor Medical ASA	Norway
Securitas AB	Sweden	Thule Group AB	Sweden
Selvaag Bolig ASA	Norway	Tietoevry Oyj	Finland
Skandinaviska Enskilda Banken AB	Sweden	Tokmanni Group Oyj	Finland
Skanska AB	Sweden	Tomra Systems ASA	Norway
SKF Inc	Sweden	Topdanmark A/S	Denmark

Company	**Country**
TORM PLC	Denmark
Trelleborg AB	Sweden
Troax Group AB	Sweden
Tryg A/S	Denmark
UPM-Kymmene Oyj	Finland
Uponor Oyj	Finland
Valmet Corporation	Finland
VBG Group AB	Sweden
Veidekke ASA	Norway
Vestas Wind Systems A/S	Denmark
Vitrolife AB	Sweden
Volati AB	Sweden
Volvo AB	Sweden
Wallenius Wilhelmsen ASA	Norway
Wallenstam AB	Sweden
Wartsila Oyj Abp	Finland
Wihlborgs Fastigheter AB	Sweden
WithSecure Oyj	Finland
XXL ASA	Norway
Yara International ASA	Norway
YIT Oyj	Finland
Zeal Global Services Limited	Norway