Utilizing machine learning to examine the profitability of SRI strategies: a cross-sectional study

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Abstract:

In 2011, John H. Cochrane stated a challenge for the researchers to identify firm characteristics that provide independent information about average stock returns in the U.S (Green et al., 2017). This challenge was taken on by Green et al. (2017): they studied this so-called "factor zoo" with 94 independent firm characteristics by using the two-pass method by Fama and Macbeth (1973) in their analysis.

In this study, I follow the footsteps by Green et al. (2017) by analyzing whether ESG characteristics can provide independent information about monthly excess returns of North American stocks between December 2016 and December 2022. Although the main focus of my study is to analyze the ESG characteristics, I simultaneously inspect whether the five non-ESG firm characteristics derived from the Fama-French (2015) five-factor model can provide independent information about the excess returns in question.

Furthermore, this study provides a novel approach to Cochrane's (2011) challenge as I analyze an extensive set of 35 separate ESG characteristics and utilize machine learning methods Least Absolute Shrinkage and Selection operator (Lasso) and Principal Component Analysis (PCA) in my empirical analysis. I first conduct the Fama-Macbeth two-pass method for a model with all initial variables, and then for a model selected with the machine learning methods. I then assess the significance of the results and compare the model diagnostics between the two models. The last stage of my empirical analysis includes analyzing the results' economic significance with

Fama-French five-factor regressions on value-weighted and equally weighted portfolios sorted by the significant ESG characteristics.

Based on my empirical analysis with the Fama-Macbeth method, there exists evidence of certain ESG firm characteristics influencing North American stock returns positively: the ESG reporting scope, sustainability compensation incentives score, and product responsibility score. These results also suggest that the ESG firm characteristic social pillar score influences the stock returns negatively. However, my overall findings from both the Fama-Macbeth method and five-factor regressions on the sorted portfolios further suggest that a significant relationship exists only between the ESG characteristic product responsibility score and stock returns, although the sign of this relationship remains unclear due to mixed results.

Keywords: ESG, sustainable investing, machine learning, Fama-Macbeth, CSR, Lasso, PCA, firm characteristics, North America, SRI

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Sammandrag:

År 2011 John H. Cochrane gav en utmaning till forskare att identifiera företagskaraktärer som ger oberoende information om genomsnittliga aktieavkastningar i Förenta staterna (Green et al., 2017). Denna utmaning accepterades av Green et al. (2017) som studerade 94 företagskaraktärer med Fama-Macbeth (1973) metoden.

I min studie följer jag fotspåren av Green et al. (2017) genom att analysera om olika ESG företagskaraktärer har ett inflytande på aktieavkastningar över den riskfria räntan av nordamerikanska företag mellan december 2016 och december 2022. Trots att den viktigaste inriktningen på min studie är att analysera ESG företagskaraktärer, studerar jag samtidigt om fem andra företagskaraktärer härledda från Fama-French (2015) femfaktormodellen har ett inflytande på dessa aktieavkastningar.

Den här studien ger ett unikt perspektiv på Cochrane's (2011) utmaning eftersom jag analyserar 35 olika ESG företagskaraktärer och använder maskininlärningsmetoder Least Absolute Shrinkage and Selection operator (Lasso) and Principal Component Analysis (PCA) i den empiriska delen av studien. Jag analyserar först Fama-Macbeth resultaten för den initiala modellen, och sedan för modellen i vilken variablerna har valts med maskininlärningsmetoder. Dessutom jämför jag modelldiagnostiska aspekter mellan dessa två modeller. Till sist analyserar jag resultatens ekonomiska signifikans med Fama-French femfaktorregressioner på värdeviktade och likaviktade portföljer sorterade enligt de statistiskt signifikanta ESG företagskaraktärerna.

Resultaten med Fama-Macbeth metoden tyder på att vissa ESG företagskaraktärer har ett positivt inflytande på nordamerikanska aktieavkastningar: ESG rapporteringsomfång, och poänger på produktansvar och incitament för hållbarhetskompensation. Dessutom indikerar dessa resultat att poäng på den sociala ESG-pelaren har ett negativt inflytande på nordamerikanska aktieavkastningar. De övergripande resultaten med både Fama-Macbeth metoden och femfaktorregressioner på de sorterade portföljerna dock tyder på att en signifikant relation existerar endast mellan ESG företagskaraktären produktansvarspoäng och aktieavkastningar, trots att riktningen på relationen förblir oklar.

Nyckelord: ESG, CSR, SRI, maskininlärning, hållbar investering, Lasso, PCA, Nordamerika, Fama-Macbeth

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Table 1: Abbreviations
This table shows the abbreviations used in this study.

Abbreviation	Definition
AI	Artificial intelligence
CAPM	Capital Asset Pricing Model
CFP	Corporate financial performance
CSR	Corporate Social Responsibility
EMH	Efficient Market Hypothesis
EPS	Environmental pillar score
ESG	Environmental, social, and governance
GPS	Governance pillar score
GSIA	Global Sustainable Investing Alliance
Lasso	Machine learning method Least Absolute Shrinkage and Selection Operator; also referred as Lasso regression.
ML	Machine learning
PCA	Principal Component Analysis
PRI	Principles of Responsible Investment
RMSE	Root-mean-square of errors
RSS	Root-sum-square
SDGs	The United Nations' Sustainable Development Goals
SPS	Social pillar score
SRI	Socially responsible investment(s); also used when referring to the topic as a phenomenon
SRI investing	Investing in socially responsible investments
VIF	Variance Inflation Factor

1 INTRODUCTION

Socially responsible investing (SRI investing) has become increasingly popular during recent decades, and even more businesses and individuals are incorporating different socially responsible investment strategies into their business practices and investment decisions. As measured by Global Sustainable Investment Alliance (GSIA, 2020), in 2020 the total value of sustainable investment assets had already reached 35.3 trillion dollars, representing 36% of all professionally managed assets within the regions considered in the analysis: Europe, US, Canada, Australia, New Zealand, and Japan.

The exact definition of SRI investing has been a debated topic, and terms such as ESG investing, sustainable investing, or responsible investing can be seen used within the literature to describe the same topic. According to GSIA (2020), such terms may be used interchangeably, and the term socially responsible investing is used to describe all such investment strategies in this thesis. The term ESG refers to how environmental (E), social (S) and governance (G) aspects are integrated by, for example, companies into their business practices (Gillan et al., 2021). It is common to evaluate the ESG metrics of a company when analyzing how socially responsible it is operating. The typical belief by supporters of SRI tends to be that it is possible to “contribute to a better good while earning well”. As discovered by aggregate literature reviews by scholars such Friede et al. (2015) and Whelan et al. (2021) over thousands of studies, the previous literature suggests a positive relationship between corporate financial performance and social responsibility. The incorporation of ESG aspects may still bring challenges to both investors and businesses, which will be further discussed in this thesis.

A fundamental paradigm in finance is that riskier assets should earn higher expected returns, and one common method to estimate these possible risk premiums is the Fama-Macbeth (1973) two-pass regression method. In 2011, John H. Cochrane brought up the challenge to identify the firm characteristics that may provide independent information about stock returns, and academics such as Green et al. (2017) have taken up this challenge: they studied this so-called “factor zoo” with 94 firm characteristics by using the Fama-Macbeth (1973) method. They also analyzed the characteristic equivalents of the factors from factor models by Carhart (1997), Fama and French (2015), and Hou, Xue, and Zhang (2015). As a result, they identified 12 firm characteristics providing independent information on average U.S non-microcap stock returns between 1980 and 2014, and two firm characteristics between January 2004 and December 2014.

With the same Fama-Macbeth method as Green et al. (2017), I analyze whether specific ESG firm characteristics and/or five other firm characteristics derived from the Fama-French (2015) five-factor model can provide independent information about excess returns. Equivalent firm characteristics derived from this five-factor model have previously been found as significant by Chordia et al. (2017), with their typical signs compared to the risk factors: firm size and investment growth influencing stock returns negatively, and book-to-market ratio and profitability positively. In addition to multiple researchers finding the movements of the market influencing stock returns, the book-to-market ratio has also been found influencing stock returns positively by Green et al. (2017), Stattman (1980, cited in Daniel and Titman, 1997), and Rosenberg et al. (1985). Banz (1981) and Fama and French (1992) have also found evidence of a negative relationship between stock returns and firm size. Asset growth as the investment characteristic has also been discovered influencing stock returns negatively by Cooper et al. (2018), and operating profitability positively by Ball et al. (2015).

Due to the increasing popularity of SRI investing, I find it important to analyze the firm characteristics behind such investment strategies. In addition to finding the total ESG score as significantly and positively related to firm value and performance, Ting et al. (2019) have found evidence of some ESG characteristics influencing these indicators positively, such as ESG management score and workforce score. Additionally, Ting et al. (2019) have found evidence of the ESG shareholder score and ESG controversies score influencing firm value negatively. By also utilizing ML methods, De Lucia et al. (2020) have discovered a positive relationship between financial indicators of companies and their policies on, for example, sustainable development and diversity and opportunity. Interestingly, De Lucia et al. (2020) have also found evidence of an opposite relationship between firms and the ESG characteristics environmental management training, CSR corporate governance board committee, and number of women employees.

As with the increased popularity of aspects related to socially responsible investments, the use of machine learning (ML) methods within finance has also become more popular in the past decade (Warin & Stojkov, 2021). According to the definition by Goodell et al. (2021), machine learning can be described as a subset of artificial intelligence as it creates techniques which enable machines to notice patterns in data. In this study, I will utilize machine learning methods Least Absolute Shrinkage and Selection Operator (Lasso) and Principal Component Analysis (PCA) to avoid model diagnostics-related problems and to conduct variable selection. A somewhat similar approach has been taken by Bonacorsi et al. (2021) who analyzed the relation between the companies' risk of default and specific ESG characteristics with machine learning methods. Since the typical approaches for conducting empirical studies in finance do not tend to include machine learning methods, my study provides a novel approach to Cochrane's (2011) challenge by two main aspects: firstly, by utilizing machine learning methods in my analysis, and secondly, by including not only the ESG scores or pillar scores to the analysis but rather a much more extensive set of 35 ESG characteristics to see if they tend to influence excess stock returns.

With the Fama-Macbeth method, the results of this study support a positive relationship between the following ESG firm characteristics and North American stock returns: the ESG reporting scope, product responsibility score, and sustainability compensation incentives score. Furthermore, the results with the Fama-Macbeth method indicate the ESG firm characteristic social pillar score influencing the stock returns negatively. When further assessing the economic significance of these results with Fama-French (2015) five-factor regressions on excess returns of value-weighted and equally weighted portfolios sorted based on the significant ESG characteristics, the results suggest that only the ESG firm characteristic product responsibility score influences stock returns significantly. However, the sign of this relationship remains unclear due to mixed results, which indicates that further research on the topic is needed for more robust and generalizable conclusions.

1.1 The motivation of the research and research questions

My main motivation for this study is to give additional information for other academics, private investors, and investment managers on the question whether there are specific ESG characteristics that can be identified to provide independent information about monthly excess returns. Consequently, if there are specific ESG characteristics that tend to influence these excess stock returns positively, a value-maximizing investor or investment manager should invest more in firms with such characteristics – and especially if they are also interested in SRI investing. As Brammer et al. (2006) argue, it is important to analyze the different aspects of corporate social performance separately to gain correct conclusions of their possible impacts on stock returns. This is also why my study is an important addition to the literature as I am studying 35 ESG firm characteristics separately.

In addition to these ESG characteristics, I also analyze five other firm characteristics derived from the factors of the five-factor model by Fama and French (2015) to assess whether they can provide independent information about the excess stock returns in question. As with the ESG characteristics, I am especially interested to see if one or more of these five firm characteristics tend to influence stock returns positively – which would be a positive sign for investors to invest in firms that have such characteristics for maximizing their profits. Furthermore, my study is also an example on how machine learning methods may be utilized for empirical studies in finance.

As stated by Chordia et al. (2017), there are rather few studies that have conducted asset pricing tests using individual stocks, although there would be both theoretical and practical reasons for such analyses. Consequently, my study is also an addition to the literature of asset pricing tests for specifically individual stocks. This aspect I also study in my analysis but limit the non-ESG related firm characteristics to the ones constructed from the previously mentioned five factors of the Fama-French (2015) model, which were also studied by Chordia et al. (2017) in a similar manner. My motivation for choosing to analyze the five factors as firm characteristics instead of factors is due to the findings by Chordia et al. (2017): the results of their study suggest that regardless of the factor model, and whether the premiums are allowed to be time-varying, the firm characteristics seem to contribute more to the variation of expected stock returns. Consequently, my approach is also in line with the results by Daniel and Titman (1997) who discovered firm characteristics, rather than factor loadings, determining expected returns of companies.

For this study, I have two research questions. My first, and most important, research question is to analyze whether firms' ESG characteristics can provide independent information about excess returns of North American firms. The second research question is further focused on whether the five other firm characteristics, derived from the Fama-French five-factor model, can provide independent information about the excess returns of North American companies when simultaneously studying the ESG characteristics. In addition to these topics, I am interested to study whether machine learning methods can be used for the variable selection process and/or the improvement of model diagnostics when studying the determinants of excess stock returns - and especially the ESG characteristics as there are wide gaps in previous research for this topic.

To summarize, my study adds to both the literature on SRI investing and the more traditional asset pricing literature by studying whether certain ESG characteristics and/or the five other firm characteristics can provide independent information about excess stock returns. However, my main objective is still to study this aspect for the ESG firm characteristics. This study is also an important addition to the rapidly growing literature on the use of machine learning methods for empirical studies in finance.

1.2 The purpose of the study

In this thesis, I utilize machine learning to study whether certain ESG characteristics can provide independent information about excess North American stock returns – and if yes, are there such characteristics that contribute to generating positive excess returns?

1.3 Limitations of the study

Due to, for example, the broad topics of both socially responsible investing and machine learning, this thesis is limited in several ways. The main limitations of the study are listed below:

1) There are a vast number of machine learning methods but, in this study, only Least Absolute Shrinkage and Selection Operator (Lasso) and Principal Component Analysis (PCA) are used.

2) The data in this study is limited to North American stock market data due to its extensiveness of both ESG and other firm characteristic data. Consequently, the results of this study shouldn't be generalised to apply to other markets. The time frame for the data is limited to December 2016 – December 2022 due to the implementation of the Paris agreement. This aspect I explain more in detail in Chapter 7.1.

3) The only data source for retrieving the ESG firm characteristics and the five other firm characteristics for my empirical analysis is Refinitiv (2023). It is important to note that no other database is used to retrieve ESG values as there exist differences between the rating agencies' ways of calculating the ESG scores and sub-scores. I will explain this challenge more in detail in Chapter 2, simultaneously with the other issues that must be considered when analyzing differences in companies' ESG values. I acknowledge that the use of one or more additional databases would have been beneficial for my study but the challenges with lack of similarity in naming the tickers/stock indicators between the different databases restricted that for my large number of stocks.

4) There are many ESG characteristics on Refinitiv's database (2023), but I am limiting my analysis to only some of them due to data availability issues: there are ESG variables for which only few observations exist even for my 2177 firms. Examples of such variables are the controversies-related variables on tax fraud, child labour, privacy, or environment. Adding such variables to my data could have led to severe model diagnostical and performance-related issues. Moreover, the other non-ESG firm characteristics are limited to the five firm characteristics derived from the Fama-French five-factor model.

5) In this study, taxes or transaction costs won't be considered, which is a typical approach in financial research literature. Moreover, this aspect also leaves room for further research on the topic.

1.4 Structure of the study

As I analyze socially responsible investments in this study, I give a detailed description of the concept and further explain aspects related to socially responsible investing in Chapter 2. In Chapter 3, I discuss the topic of machine learning: I explain the machine learning methods that I utilize in this study and give general information on machine learning and its use cases in finance.

Chapter 4 covers the financial theories related to this study to give the readers' a good basis of information to further comprehend the methodology and results of the study. Previous literature on topics related to, especially, machine learning and ESG firm characteristics' possible effects on stock returns are covered in Chapter 5. Of all these studies, I present the ones that are the most similar and/or related to the purpose of my study.

I describe the methodology of this study in Chapter 6, and the data in Chapter 7. Chapters 8 and 9 include the results and model diagnostics, respectively. In Chapter 10, I further discuss the results of this study, including the findings from the machine learning methods, Fama-Macbeth two-pass regressions, and the five-factor regressions on sorted portfolios. Lastly, I state the final conclusions of this study in Chapter 11.

2 SOCIALLY RESPONSIBLE INVESTING

In this chapter, I explain the concept of socially responsible investing. Moreover, I present the closely related concepts Corporate Social Responsibility (CSR), ESG factors, and describe the different SRI strategies. To analyze these topics critically, this chapter ends with a description on the recent criticism of socially responsible investing and, especially, the ESG factors.

2.1 Corporate Social Responsibility

Like the definition of socially responsible investing, the definition of Corporate Social Responsibility has also been subject to debates due to different views of its contents. The general idea of using CSR as a framework includes the view that businesses should not only strive to maximize their profits but also consider their social responsibilities and take actions according to them.

In 1960 (pp.70), Davis famously defined CSR as "*businessmen's decisions and actions taken for reasons at least partially beyond the firm's direct economic or technical interest."* Another definition of CSR is by Carroll (1979), who states that to fully address the entire range of obligations the businesses' have for society, the definition of CSR must embody the economic, legal, ethical, and discretionary aspects of business performance. As Carroll later explained (2015), this definition included the idea that the society required from businesses that economic and legal expectations would be fulfilled. Furthermore, the ethical responsibility was expected from the businesses, and discretionary/philanthropic actions were desired from businesses (Carroll, 2015).

Moir (2001) points out that the corporate social responsibilities include a wide range of aspects such as employee relations, the environment, human rights, corporate ethics, and community relations. However, most of the CSR practices are voluntary for businesses to undertake and depend on the businesses' economic perspectives. According to Moir (2001), proponents of CSR argue that it is in businesses' self-interest to follow CSR practices to possibly achieve enhanced reputation, employee loyalty and retention. Conversely, Moir (2001) states that individuals with neo-classical views would argue that the employment of workers and tax payments should be the only social responsibilities of a business.

Due to the differing definitions of CSR as a framework, it can be seen as closely linked to and intertwining other frameworks such as SRI, sustainability, and ESG factors. In addition, CSR is closely linked to stakeholder theory and shareholder theory which I present in Chapter 3.

2.2 ESG factors

When talking about corporate social responsibility, the concept of ESG factors is often brought up. The term ESG refers to how environmental, social and governance concerns are integrated by corporations and investors into their business models and actions (Gillan et al., 2021). Correspondingly, E, S, and G are the three main categories - also defined as pillars - that are used to inspect how socially responsibly a business is operating. Each one of these three pillars includes sub-categories related to the main pillar, and detailed compositions of each pillar based on the categorisation by Refinitiv (2022) can be found from Figure 5 of Appendix 6. In this thesis, I also focus on analyzing these ESG sub-categories as specific firm characteristics.

For each company, a combined ESG score can be calculated based on the scores obtained from the E, S, and G pillars. These ESG scores can be used by, for example, portfolio managers in their portfolio formation processes to create socially responsible portfolios. Investors looking for socially responsible investments to invest in may also use these scores when evaluating how ESG-conscious a company or fund is. Understanding the concepts of ESG factors and ESG scores is also crucial for further comprehending the method and results of this thesis.

One aspect that differs ESG from the previously presented term CSR is, according to Gillan et al. (2021), that governance is included explicitly in ESG whilst CSR includes governance issues indirectly since they relate to social and environmental considerations. Thus, they state that ESG can be seen as a more expansive term than CSR, and that is also my presumption for this thesis.

2.3 Socially Responsible Investing

As discussed in the first chapter, socially responsible investing has become more popular during recent decades. Gillan et al. (2021) explain that companies have answered to the investors' increased demands of incorporating SRI aspects into business practices and investment decisions by releasing a growing number of sustainability/corporate responsibility reports. Many institutional investors and service providers are also following the Principles of Responsible Investment (PRI), which includes considering SRI aspects when making decisions and conducting investment analyses (Gillan et al., 2021). Furthermore, many investment service providers have started to incorporate ESG factors in distinct investment strategies to offer socially responsible investments (van Duuren et al., 2016).

Whelan et al. (2021) state that investing according to ESG factors also seems to provide protection during downside events such as social or economic crises. A recent example of both crises occurring simultaneously is the covid-19 pandemic, which is also included in the time frame of my study. Additionally, as Ashwin Kumar et al. (2016) argue, by integrating ESG practices in business operations, the company becomes less vulnerable to risks related to reputation, politics, and regulations. Therefore, the volatility of the cash flows decreases and profits increase (Ashwin Kumar et al., 2016).

As van Duuren et al. (2016) describe, the focus in ESG investing is on how a company performs based on the three ESG pillars. In investment companies, a portfolio manager may evaluate the potential investment objects based on their ESG scores. As an example, if a company exceeds a pre-specified ESG score threshold, it will be included in the portfolio manager's ESG portfolio. Van Duuren et al. (2016) also point out the same aspect that I mentioned in Chapter 1: that the general thesis in ESG investing is that the inclusion of ESG information does not only benefit investors but also society at a larger scale. In the more general SRI strategies, the focus is not necessarily on the ESG pillars but may instead be on other factors related to social responsibility such as whether a company follows sustainable development goals or provides sustainable energy solutions.

2.3.1 Socially responsible investing strategies

As there are many ways to define socially responsible investing, there are also many ways to classify the different SRI strategies. Nevertheless, the classification of the SRI strategies by Global Sustainable Investment Alliance (GSIA, 2020) has become the widely accepted industry standard. The classification was originally published in 2012 but has been revised in an October 2020 review by GSIA. The seven categories by GSIA's (2020) categorisation are: corporate engagement and shareholder action, norms-based screening, negative/exclusionary screening, best-in-class/positive screening, sustainability themed/thematic investing, and impact investing and community investing.

All seven categories by GSIA's (2020) classification won't be explained in detail in this thesis since the focus will be on specific ESG characteristics that construct the ESG scores. I present these characteristics more profoundly in Figure 4 of Appendix 5. However, to better comprehend the literature review in Chapter 5, explanations for the strategies negative screening, positive screening, and best-in-class screening are useful to be presented. Moreover, these different strategies can further be extended to looking at specific ESG characteristics of companies, which I do in my empirical analysis.

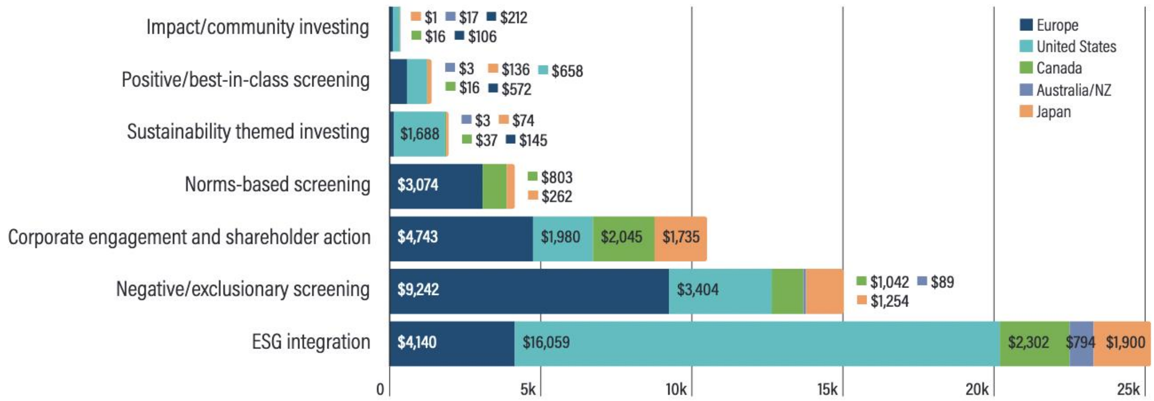
As explained by GSIA (2020), in negative screening, certain sectors, companies, countries, or other issuers are excluded from a fund or portfolio. For example, certain product categories commonly viewed as “bad” such as weapons or tobacco can be excluded (GSIA, 2020). In best-in-class screening, certain sectors, projects, or companies are selected as investments due to their superior ESG performance and scores above a certain threshold, compared to their peers in the same industry (GSIA, 2020). For example, only companies with top 10% highest ESG scores within a specific industry may be selected in an ESG portfolio based on best-in-class screening.

GSIA (2020) does not differentiate between positive and best-in-class screening but in financial literature the difference between these terms is typically that positive screening refers to picking certain types of companies based on their great ESG scores or due to otherwise integrating SRI aspects in their operations. In GSIAs (2020) review, the category ESG integration is used to describe that a company integrates ESG factors into their financial analyses, which may also be interpreted as a positive screening strategy. As I have described before, there are indeed differences in how the SRI strategies are defined and interpreted.

2.3.2 The use of different SRI strategies

From Figure 1, the popularity of these socially responsible investment strategies can be seen by different strategies and regions in 2020:

Figure 1: Sustainable investing assets by strategy and region in 2020
Illustration of the popularity of sustainable investing assets by strategy and region in 2020. Source: GSIA (2020).



In Figure 1, the asset values are expressed in billions of US dollars, and it is evident that the US has had the largest total market value of sustainable investing assets in 2020. Moreover, ESG integration has been the most popular strategy in the US in 2020 whilst norms-based screening has been the least popular strategy there. In Europe, the most popular strategy has been negative/exclusionary screening and the least popular strategy sustainability themed investing (GSIA, 2020). These SRI strategies can also partly be viewed through the specific ESG characteristics of companies on which they focus on, such as the community score variable for the strategy community investing. Consequently, the results of my study can also partially be compared to the data in Figure 1 of the different strategies' popularity in the United States and Canada.

2.3.3 Criticism of Socially Responsible Investing

Despite the positive aspects of SRI and related investing strategies that I have presented in the previous chapters, the approach has also evoked some criticism. The main points by the critics tend to focus on the costs, the differences in ESG ratings, possibility of greenwashing, and the relationship between social responsibility and corporate performance.

As mentioned, one of the main criticisms of socially responsible investing has been the approach's effect on costs. According to van Duuren et al. (2016), ESG investing may add an unnecessary burden on the investment process and consequently increase costs. This theory is supported by the findings by Kempf and Osthof (2008, cited in van Duuren et al., 2016) who state that mutual funds that conduct ESG investing tend to charge higher expense ratios. For companies, SRI integration may increase costs due to additional auditing or changes in business operations. However, SRI integration may also bring profits due to, for example, lower employee turnover rate or enhanced media representation. One reason why SRI may bring additional costs to investment companies may be that they might need to hire ESG analysts to conduct ESG screening.

Another criticism, targeted especially at the ESG scores, has been the possibility of greenwashing. Yu et al. (2020) point out a concerning fact in their study: that the ESG data that firms provide in their sustainability reports is often unaudited. This raises the question whether ESG factors – or the ESG scores calculated based on these factors – can even be reliable enough to use in investment decisions or analyses. This is also an important criticism to consider when analyzing the results of this thesis. In addition to mere greenwashing, some companies may also try to solely meet the minimum requirements to be perceived as integrating ESG factors into their businesses or complying the regulations. Consequently, certain relevant ESG-related issues may be ignored either partially or completely.

When analyzing the relevance of ESG scores and their sub-scores, one should also notice that there tends to be notable differences in how different rating agencies point individual firms' ESG factors (Christensen et al., 2022). A standardized and globally accepted framework for the scoring system would be needed to overcome this issue. Interestingly, Christensen, et al. (2022) describe that higher ESG disclosure by companies tends to lead to increased disagreements between the ESG rating agencies on the scores. This finding supports the authors' suggestion that there may be disagreements between ESG rating evaluators on which measures are more relevant to assess than others.

Since I analyze the specific characteristics constructing the overall ESG scores in this thesis, I will consider all these challenges mentioned above when discussing the results of my study. Additionally, concerns related to the relationship between corporate financial performance (CFP) and SRI practices can be dated back to Friedman's study in 1970. The typical fear is that implementation of SRI practices would decrease the overall performance of a company. As the focus in my study is on stock returns, scholars such as Gougler and Utz (2020), Statman (2006), and Lee et al. (2013) have also criticized that there does not seem to be any significant linkage between the risk-adjusted performance of portfolios and their ESG ratings. The accuracy of these claims I discuss more in the upcoming chapters, and especially along with my results.

3 MACHINE LEARNING

In this section, I explain what machine learning (ML) means as a concept and how machine learning methods can be utilized in finance. I also present in detail the machine learning methods Lasso and Principal Component Analysis (PCA) that I use in this study.

3.1 Machine learning and artificial intelligence

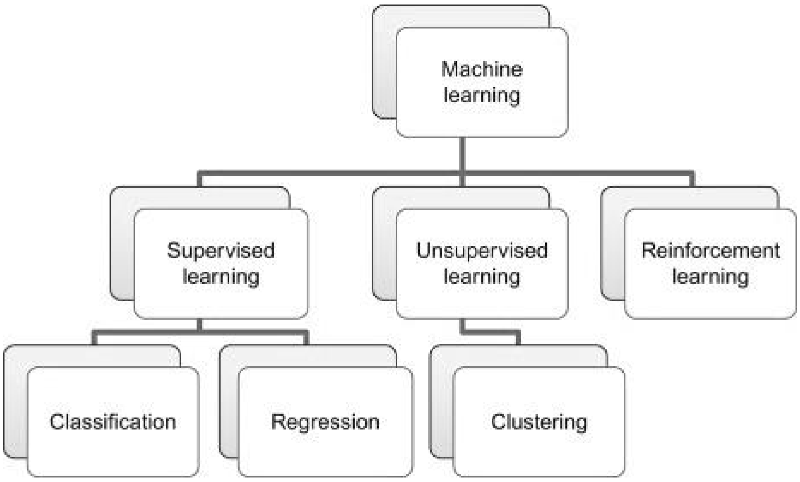
To be able to define what machine learning is, it is first important to present the term artificial intelligence (AI). There are different definitions of AI and Russell (2010) has categorized these definitions into four historically followed approaches: thinking humanly, thinking rationally, acting humanly, and acting rationally. According to Russell (2010), it is evident that AI does not just attempt to understand but also strives to create new intelligent entities. The topic of AI will not be covered in detail in this thesis, but it should be noted that AI-based methods can be used in various fields, such as in finance.

As Goodell et al. (2021) state, machine learning can be seen as a subset of AI that creates techniques which enable machines to notice patterns in data. Another well-known definition of machine learning has been given by Tom Mitchell (2006). According to Mitchell (2006), if a machine learns with respect to a task (T), performance metric (P), and type of experience (E), and the machine reliably becomes better at its performance P at task T, after gaining experience E, then the process is called machine learning.

3.2 Supervised and unsupervised machine learning

Machine learning methods can be, in general, either supervised or unsupervised. There are also other categories such as reinforced machine learning, but they won't be further discussed in this thesis. A visualization of this categorization can be seen from Figure 2:

Figure 2: Categories of machine learning
Illustration of the categorization of machine learning. Source: Shobha and Rangaswamy (2018).



In supervised learning, the outcome variable is known, and it guides the learning process (Hastie et al., 2009). Thus, the goal in supervised learning is to predict the value of an outcome variable based on the input variables, which are usually denoted as X-variables. Furthermore, the outcome variable is usually denoted as a Y-variable. Examples of supervised learning methods are Random Forests, Lasso regression, Ridge regression and linear regression.

As opposed to supervised learning, the outcome variable is unknown in unsupervised learning. Moreover, unsupervised learning attempts to describe how the data are organized or clustered - and more specifically, find the associations and patterns among input measures (Hastie et al., 2009). As Das et al. (2015) state, in unsupervised learning machines learn independently based on the input data through discovering and adopting. Consequently, unsupervised machine learning methods deal with clustering algorithms such as hierarchical clustering, k-means clustering, and self-organizing maps (Goodell et al., 2021).

3.3 Machine learning methods

There are many different machine learning methods and models to be utilized. However, in this section, I will only present the most relevant ones for the purpose of my study: the Least Absolute Shrinkage and Selection Operator (Lasso), and Principal Component Analysis (PCA). Although there has been discussion between academics on whether PCA can be categorized as a machine learning method or not, in this thesis it is still viewed as a machine learning method.

3.3.1 *Least Absolute Shrinkage and Selection Operator*

Least Absolute Shrinkage and Selection Operator (Lasso) is a supervised machine learning method that can be used for, for example, regression shrinkage and variable selection. In this thesis, it will also be used for those purposes.

In 1996, Tibshirani suggested Lasso as a new method for estimating linear regressions after pointing out two aspects in which the Original least Squares (OLS) estimates tend to perform sub-optimally: in prediction accuracy and interpretation. Moreover, Tibshirani (1996) viewed Lasso as a better option than the two typical unsupervised ML methods for improving OLS estimates, which are Ridge regression and subset selection.

As stated by Tibshirani (1996, pp.267), "*The 'lasso' minimizes the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant*". Tibshirani (1996) also points out that Lasso can be used for variable selection due to its nature of shrinking some coefficients and setting others to zero. Hence, Lasso still retains many good features of both subset selection and ridge regression (Tibshirani, 1996).

Two decades later, James et al. (2021) concluded that the results of Lasso are indeed easier to interpret than those that linear regression produces. They state that the reason to this difference is that in the final model of Lasso, the response variable will only be related to a small subset of predictors: the ones that have nonzero coefficient estimates.

The Lasso estimate is defined as (Hastie et al., 2009):

$$\begin{gathered}\hat{\beta}^{\text{lasso}} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 \\ \text{subject to} \sum_{j=1}^{p} |\beta_j| \le t. \end{gathered} \tag{1}$$

According to James et al. (2021), the main difference between the two otherwise similar methods, Lasso and Ridge, are their penalty terms. Lasso uses L1 penalty that can force certain coefficients to be exactly zero when the tuning parameter is set to be sufficiently large. In Ridge regression, L2 penalty term is used, and the coefficient estimates will only approach zero without any of them shrinking to exactly zero (James et al., 2021).

Consequently, the main tuning parameter in Lasso - t in the equation above, lambda λ if the equation is written in the Lagrangian form - should be chosen adequately to minimize the estimate of expected prediction error (Hastie et al., 2009). This tuning parameter is also the regularization parameter for Lasso. James et al. (2021) demonstrate that when the tuning parameter is set to 0, Lasso gives the least squares fit. On the contrary, when the tuning parameter is sufficiently large, the authors state that Lasso returns a null model in which the estimates for all coefficients are exactly zero.

3.3.1.1 Selecting the tuning parameter for Lasso

Cross-validation is one way to select the tuning parameter for Lasso and is used for Lasso in this thesis as well. As shown by James et al. (2021), in cross validation a grid of possible λ values is chosen and the cross-validation errors are computed for each of them. The value of tuning parameter for which the cross-validation error is the smallest is then chosen (James et al., 2021).

There are different cross-validation methods, but in this thesis the 10-fold cross validation is applied as it is commonly used with Lasso. To use the 10-fold cross-validation, the data is divided in a training data set and a test data set, which are sub-samples of the total data set. The 10-fold cross-validation is then used on the training data set, and the tuning variable selected based on the training data set is further tested with the test data set. Thus, the goal is to validate with another subset of the data that the choice of tuning parameter is indeed optimal.

3.3.2 Principal Component Analysis

As stated by James et al. (2021), Principal Component Analysis is an approach that can be used for deriving a low-dimensional set of features from many variables. Bonacorsi et al. (2021) also describe PCA as a tool to reduce the dimensions of a dataset, although it does not analyze the predictive power of each variable. PCA is still an unsupervised learning approach since it involves only a set of features $\mathrm{X}_1, \mathrm{X}_2, \dots \mathrm{X}_\mathrm{p}$, and no response variable Y (James et al, 2021). More specifically, James et al. (2021) define PCA as a technique for dimension reduction of a data matrix X, defined as $n \times p$. The first principal component then describes to which direction the observations in the data vary the most, as explained by James et al. (2021).

In my study, I strive to use PCA to improve model diagnostics and to conduct feature/variable selection in a somewhat similar manner as Bonacorsi et al. (2021). As they also describe, the largest part of the variance of the data is explained by the first principal component. Once the effect of the first principal component is removed, most of the remaining variance is explained by the second principal component, and so forth (Bonacorsi et al., 2021). In my study, I look at the highest absolute correlations between the ten first principal components and the original variables. The results can be found from Table 8 for independent variables with principal component correlations of over 0.65, which I have selected as the threshold.

The typical benefits of conducting a Principal Component Analysis include reduction of multicollinearity and overfitting. As concluded by James et al. (2021), if one has a large set of correlated variables, principal components can be used to summarize the set of variables with a smaller number of representative variables that together explain most of the data variability in the original set of variables. Due to these aspects, PCA is also a useful method for the purpose of my study, similarly as the Lasso regression method.

3.4 Machine learning in Finance

As Warin and Stojkov (2021) state in their systematic literature review, the use of machine learning methods in finance has become more popular in the past decade. Furthermore, the authors mention that there have been two methodological revolutions related to performing technical analyses of financial phenomenon. The first revolution has been the applications of machine learning algorithms to explain and forecast trends in financial markets. The second revolution has been the rise of sentiment analyses of financial market news (Warin & Stojkov, 2021).

According to a bibliometric analysis conducted by Goodell et al. (2021), there exist roughly three categories within finance in which AI and ML methods tend to be used. The first category described by the authors is portfolio construction, valuation, and investor behavior. The second category is financial fraud and distress. Lastly, the third category is sentiment inference, forecasting, and planning. Machine learning models are useful for analyses in finance since they are functionally flexible and have the computational power to decipher complex patterns in high-dimensional data environments (Goodell et al., 2021).

Moreover, Goodell et al. (2021) propose using machine learning methods to overcome the typical challenges that the traditional econometric models struggle with: detecting outliers, extracting features, performing classification, and conducting regressions with complex data. The data to be used with machine learning models in finance can come from, for example, financial documents, financial time series, news reports, or social media posts (Goodell et al., 2021). This thesis will also be an addition to the increasing number of financial research literature in which machine learning methods are utilized, belonging to the first category presented by Goodell et al. (2021).

4 THEORETICAL BACKGROUND

In this chapter, I describe the financial theories that are most relevant for the purpose of this study. Having a good understanding of these theories also helps to further comprehend the methodology and results of my study.

4.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) was invented in 1970 by Eugene Fama. According to Fama (1970), an efficient market is a market in which prices always fully reflect all available information. Based on the hypothesis, it should not be possible to attain consistent positive abnormal returns with historical information since that information would already be fully integrated in the prices if the EMH applied. Moreover, if the financial market is efficient and a new unpredictable event occurs, the effect of the event will immediately be reflected on the stock prices (Latif et al., 2011). On the contrary, if the financial market is not efficient, the effects of the new event will be reflected to the stock prices after a delay.

According to Fama (1970), the Efficient Market Hypothesis has three variations: weak form, semi strong form, and strong form. Fama (1970) states that the weak form implies that all historical information is already fully reflected in the current prices in the market. In the semi strong form of the hypothesis, the current prices in the market fully reflect all current and historical publicly available information (Fama, 1970). In the strong form of Efficient Market Hypothesis, all historical and current information are already fully reflected in the current prices – including also private information (Fama, 1970).

Most of the literature on EMH seems to suggest that markets cannot be at least strongly efficient since notable market anomalies have been reported. As also stated by Latif et al. (2011), many stock exchanges around the world have discovered that stock markets aren't functioning according to the EMH. It is still relevant to note that all empirical efficient market tests are joint tests, and to make conclusions of the existence of a specific anomaly requires the assumption that the underlying model is correct. Furthermore, data snooping may bias results of such empirical tests and cause inaccurate findings of market anomalies. For this thesis, the assumption is that markets are, at least, not strongly efficient. If markets would be completely efficient, no pricing anomalies would exist and all information on companies' SRI practices would already be fully reflected on the companies' stock prices.

4.2 Modern Portfolio Theorem

According to the inventor of modern portfolio theorem, Harry Markowitz (1952, 1959, cited in Elton & Gruber, 1997), the portfolio problem can be stated as a choice of mean and variance of a portfolio: by holding the variance constant, maximizing the expected return, and by keeping the expected return constant, minimizing the variance. By following these principles, an efficient frontier can be developed (Elton & Gruber, 1997).

As stated by Fama and French (2004), the efficient frontier is also called minimum variance frontier since it includes efficient portfolios that have minimum return variances at each level of expected return and are combinations of the risk-free asset and a single risky tangency portfolio. The investor can then choose the optimal portfolio depending on his or her level of risk aversion (Elton & Gruber, 1997). From the modern portfolio theorem, it can be concluded that the return-risk-characteristics of each portfolio on the efficient frontier depend on how diversified the portfolios are: the higher weight the risk-free asset has in an efficient portfolio, the less risky the portfolio is.

Based on the modern portfolio theorem, the Capital Asset Pricing model (CAPM) was later invented. There are different versions of CAPM, and one widely used version is the Sharpe-Lintner CAPM (Fama & French, 2004):

$$E(R_i) = R_f + \beta_{im}[E(R_M) - R_f], \; i = 1\ldots,N \quad , \tag{2}$$

in which R_f is the risk-free rate. R_M refers to the market return, β_{im} is the asset i's market beta, and $E(R_i)$ is the expected return for the asset i. As can be noted from the equation, the only risk factor in the CAPM model is the market risk, also called systematic risk. Consequently, the CAPM describes the relationship between the return of an investment and the risk premium for the investment for holding systematic risk. This risk premium in question is the excess return of the market return over the risk-free rate.

The assumptions for CAPM include that the investors are risk-averse, unlimited risk-free borrowing and lending must exist, and that the investors are only interested of the portfolios' one-period means and variances (Fama & French, 2004). Moreover, Fama and French (2004) point out that the assumptions imply that the market portfolio must be on the efficient frontier. The assumption for this thesis is that CAPM does not hold since other risk factors than solely market risk may also affect investments' performance.

4.3 Market anomalies

During the early 1980s, many finance researchers began to report an increasing number of market anomalies with respect to EMH and CAPM (Dimson, 1988). If markets were completely efficient according to the strong form of EMH, no abnormal returns would be achievable – and all returns calculated with the CAPM formula would be accurate. Thus, the theory that market anomalies exist violates both CAPM and EMH. The anomalies may occur repeatedly or only once and disappear completely.

As stated by Latif et al. (2011), market anomalies are usually categorized into three main types: calendar anomalies, fundamental anomalies, and technical anomalies. The authors explain that calendar anomalies occur during specific time periods, whilst technical anomalies refer to anomalies that may appear with the usage of technical analysis. Examples of fundamental anomalies include low price to book -anomaly, low price to earnings -anomaly, and value anomaly (Latif et al., 2011). In addition to these anomalies, certain anomalies in the financial market may also occur due to behavioral reasons related to the investors, such as irrational investing decisions. I explain these possible behavioral reasons related to SRI more in detail in Chapter 4.5.

The existence of market anomalies has been a topic in financial literature, and many recent studies tend to support the existence of such anomalies. As the assumption in this study is that markets are not fully efficient, it is also assumed that market anomalies can occur.

4.4 Theories related to value creation through social responsibility

There are two additional financial theories that are relevant for this study: stakeholder theory and shareholder theory. These theories can be seen as opposing each other, but to understand the importance of stakeholder theory for value creation through social responsibility, it is crucial to know the fundamentals of the shareholder theory.

4.4.1 Shareholder Theory

According to the shareholder theory, the executives at companies should be viewed as employees instead of employers – and thus, they should only conduct business according to their employers' desires (Friedman, 1970). In practice, this generally means maximizing the monetary profits for the shareholders.

Pfarrer (2010) explain that the shareholder theory implies that if the companies strive to maximize their profits according to their own interests, the society will also benefit.

Consequently, government and regulatory interventions should be kept at minimum (Pfarrer, 2010). Despite the focus on value maximization for shareholder, the theory does not support immoral or illegal actions: Friedman (1970) states that the executives should follow laws and other ethical rules of the society when acting according to the shareholder theory.

The shareholder theory has still raised considerable criticism during the past decades due to its core idea that companies should only focus on maximizing shareholder value without acknowledging other stakeholders in their decision-making processes. As stated by Pfarrer, (2010), there are also other popular shareholder theory -based theories such as the transaction cost economics theory and agency theory, but these theories won't be further discussed in this thesis.

4.4.2 Stakeholder Theory

On the contrary to shareholder theory, according to stakeholder theory a company should not solely consider its shareholders but also its other stakeholders when conducting business. As described by Freeman and Phillips (2002), stakeholder theory implies that the success of a company depends on how well it manages the relationships with the key groups for the company - such as customers, employees, financiers, and communities.

Stakeholder theory is commonly divided into three aspects according to the classification by Donaldson and Preston (1995): to instrumental, descriptive, and normative stakeholder theory. According to the instrumental stakeholder theory, business managers should focus on relationships with key stakeholders if the goal is to maximize shareholder value over an uncertain time frame (Freeman, 1999). According to Freeman (1999), the normative stakeholder theory simply includes the idea that managers should pay attention to relationships with key stakeholders. The descriptive stakeholder theory focuses more on describing how businesses manage or interact with their stakeholders (Freeman, 1999). As Donaldson and Preston (1995) conclude, the three aspects are mutually supportive.

Clarkson (1995) has also categorized stakeholders into primary and secondary stakeholders. Moreover, Clarkson (1995) states that the primary stakeholders are the ones whose continuing participation is crucial for the company's survival such as, typically, shareholders and investors, employees, customers, government, and suppliers. Furthermore, Clarkson (1995) argues that the company is heavily interdependent on its primary stakeholder groups. Clarkson (1995) classifies secondary stakeholders, such as the media and special interest groups, as the ones who influence or affect the company or are influence or affected by it. However, the secondary stakeholders are not engaged in transactions with the company nor essential for its survival (Clarkson, 1995).

There has also been criticism about the relationship between the stakeholder theory and CSR. As described by Freeman and Dmytriyev (2017), stakeholder theory tends to center the focus within a reasonable reach of company's activities, mainly on the company's local communities and the surrounding society, whilst CSR tends to extend the social focus of the company much further, often to as far as possible. Consequently, it is reasonable to question if it is even possible to consider all stakeholders – or even key stakeholders – as being equally important for the company when conducting business in a socially responsible way. The tensions between stakeholder theory and CSR also include questions such as which stakeholders a company should prioritize in its CSR practices, and how far a company's corporate social responsibilities should reach.

A general implication for firms is that incorporation of socially responsible practices supports the stakeholder theory as higher ESG scores tend to have an overall positive influence on different stakeholders, such as the employees and external communities through improved efforts in, for example, transparency, equality, and sustainability. Furthermore, neglecting the needs of certain stakeholder groups may affect companies' ESG scores negatively. As the possible influence of certain ESG firm characteristics on the stock returns of companies is studied in this thesis, the hypothesis by Freeman and Phillips (2002) is also partly tested.

4.5 Behavioral finance theories related to SRI

There are also some behavioral finance theories that are commonly used to explain the relationship between risk characteristics and returns of companies. The two main behavioral finance theories related to the phenomenon of socially responsible investing are prospect theory and the theory of herd behavior.

4.5.1 Prospect theory

In 1979, Tversky and Kahneman invented the prospect theory as a critique of the expected utility theorem. According to the prospect theory by Tversky and Kahneman (1979), individuals value losses and gains differently – which also makes them conduct decisions based on how they value these subjectively perceived losses and gains.

Additionally, the prospect theory implies that individuals value possible gains less than they want to avoid equivalent possible losses (Tversky and Kahneman, 1979).

The prospect theory can also be linked to socially responsible investing: as, according to the theory, investors see it more important to avoid possible losses than to seek equivalent gains, they may seek to invest in socially responsible investments due to their decreased ESG-related risks. This behavior would result in increased market values of socially responsible investments compared to the traditional investments.

4.5.2 Theory of herd behavior

As stated by Banerjee in 1992, the theory of herd behavior suggests that individuals consider the decisions made by others in their decision-making processes. In other words, people tend to do what others are doing instead of using their own information (Banerjee, 1992). This behavioral theory can also be linked to SRI investing in a way that if many individuals are investing socially responsibly, others may also want to do the same without further evaluating the act of SRI investing with their own information on the topic. However, this theory could also lead to the opposite actions: if many are disregarding the social responsibility of companies in their investment decisions, others may disregard them as well. Along the theory of herd behavior, Cao et al. (2019) studied the possible peer effects of companies' CSR practices and found strong evidence that firms tend to adopt and implement similar CSR practices as their product-market peers.

Since socially responsible investing has indeed been a recent trend, the theory of herd behavior is an interesting aspect to consider when evaluating the results of my study. The reason to this is that, when linked to the recent increase of SRI investing practices, the theory of herd behavior implies that the market value of socially responsible investments would further increase as more investors are investing in such investments - in a similar way as the value of socially responsible investments would increase according to the prospect theory.

5 LITERATURE REVIEW

In this section, I present data, methodology, and main results of the studies that are the most relevant to my thesis. These studies I further categorize according to their topics. As my study focuses on the possible relationship between ESG characteristics and stock returns, I have found only a few studies analyzing this aspect as extensively as I do – and almost none that would also utilize machine learning methods for this purpose. Consequently, in Chapter 5.1, I also present other relevant studies that use ML methods to study the ESG practices and their possible influence on firm performance at a larger perspective. In Chapter 5.2, I present the more conventional studies analyzing the possible relationship between ESG practices and stock returns, divided to studies that have found evidence of a positive relationship, and studies that have found evidence of a negative or non-significant relationship. Lastly, I present in Chapter 5.3 the two most relevant conventional studies analyzing the possible relationship between non-ESG firm characteristics and stock returns.

In some studies that I present in this section, possible differences between the separate SRI strategies from an investor's perspective are also considered. However, more research on these different strategies' possible contributions to investment performance would be needed to categorize the studies based on this aspect. It is also important to notice that although I discuss firms' ESG practices in this section, I view CSR practices and other socially responsible practices as mutually inclusive.

5.1 Studies utilizing machine learning methods to analyze the possible relationship between ESG practices and firm performance

Borgersen (2022) inspects whether ML methods, such as Lasso and XGBoost, can be used to find specific variables influencing cross-sectional stock returns. Furthermore, Borgersen (2022) applies ML regressions on a dataset of non-ESG firm characteristics, ESG firm characteristics, macroeconomic factors, and total returns on all stocks in the index S&P 500 between 2012 and 2021. Additionally, Borgersen (2022) uses Refinitiv as the main data source. As a result, Borgersen (2022) discovered that the variables selected by ML outperformed the initial variables based on goodness-of-fit criteria, and that ESG characteristics seem to influence expected stock returns slightly negatively. However, Borgersen (2022) questions the results for the ESG variables since the evaluation metrics that penalize additional variables led to different results for different models and time frames. Since the out-of-sample R squared was negative for OLS and XGBoost, Borgersen (2022) states that the relationships found by these methods are likely different from the actual ones.

Bonacorsi et al. (2022) study the possible relationship between ESG sub-factors and companies' risk of default with ML methods, such as Lasso, PCA and Random Forest, on a cross-section of 1251 European listed companies in 2019. The z-score is used as a proxy for credit risk by the authors, and the ESG variables are retrieved from MSCI ESG Manager. The authors also use Orbis and FactSet for additional financial indicators. Bonacorsi et al. (2022) show that ML can be used for variable selection, and that certain ESG sub-factors seem to explain the probability of default for a company: as an example, the companies that have a moderate proportion of revenues, rather than a large proportion, related to green building or carbon emissions show to have a higher credit risk. According to the authors, the factors decreasing a company's credit risk are hiring more skilled workers and being in a region with stricter carbon regulation or/and better data protection. One aspect that Bonacorsi et al. (2022) state as decreasing the reliability of their results is that they only found a limited selection of S and G sub-factors. This lack of ESG data disclosure by companies is also a challenge for my study.

Margot et al. (2021) utilize machine learning to study the relation between ESG features and financial performance of companies. The authors use Sustainalytics to retrieve ESG data, and Refinitiv for data of stock prices and dividends. From MSCI World Index USD, they select stocks with a ML algorithm to sector-matched and non-sector matched positively screened ESG portfolios, and in one portfolio screened over negative ESG scores. The excess returns of these portfolios and other metrics between January 2013 and March 2018 Margot et al. (2021) compare to the benchmark index, and a 30% ESG best-in-class screened portfolio. As a result, the positive ESG-screening strategy led to outperformance over all other portfolios: the benchmark, best-in-class ESG portfolio, and the portfolio screened over negative ESG scores (Margot et al., 2021). According to their findings, the authors conclude the best-in-class strategy being most likely neutral to CFP. Their results from analyzing separately excess returns of 30% best-in-class sector portfolios sorted by total ESG, E, S, and G scores also indicate that ESG factors influence stocks in distinct geographical areas and sectors differently (Margot et al., 2021). The authors conclude that some alpha exists in ESG scores, but it may only be found with non-linear and powerful methods such as machine learning.

With machine learning methods and logistic regressions, De Lucia et al. (2020) study the relation between ESG practices and firm performance, measured by ROE and ROA. More specifically, De Lucia et al. (2020) strive to use ML methods to predict the accuracy of these two performance metrics based on the ESG variables and other economic indicators. The authors analyze 1038 public European companies, with data retrieved from Refinitiv over the fiscal year 2018-2019. The findings by De Lucia et al. (2020) suggest that both ROE and ROA can be perfectly predicted by ML algorithms. Moreover, De Lucia et al. (2020) found evidence of an overall positive relationship between the companies' financial indicators and ESG practices. This finding was particularly evident for practices in, for example, sustainable development policy, and diversity and opportunity policy (De Lucia et al., 2020). Interestingly, the authors also found evidence of an opposite relationship for the ESG variables environmental management training, number of women employees, and CSR corporate governance board committee.

5.2 Conventional studies analyzing the possible relationship between ESG practices and stock returns

In this section, I present studies that analyze the possible relationship between ESG practices and stock returns. No machine learning methods are used in these studies, so I label them as more "conventional".

5.2.1 Previous literature supporting a positive relationship between ESG practices and stock returns

Verheyden et al. (2016) analyze the possible effects of ESG screening on investment performance by creating two investment universes consisting of large and mid-cap stocks: Global all and Global Developed Markets. The time frame for the analysis is between 2010 and 2015. Verheyden et al. (2016) further create six portfolios based on these investment universes – including both ESG screened and unscreened portfolios. The authors' portfolios following SRI strategies exclude either lowest 10% or 25% of the performers per industry based on their ESG scores obtained from Sustainalytics. As a result, Verheyden et al. (2016) show that for three out of the four ESG-screened portfolios, ESG screening improved risk-adjusted returns annually by around 0.16% on average. The findings by Verheyden et al. (2016) also suggest that by implementing an ESG-screening filter already before choosing the investment universe, one can create a universe of stocks that have better risk-return and diversification characteristics.

Ashwin Kumar et al. (2016) study ESG factors and risk-adjusted performance of companies. As their method, the authors use an ESG risk-premium model established to study the possible correlation between a firms' ESG practices and stock volatility. For a time period between January 2014 and December 2015, they analyze 157 companies included in the Dow Jones Sustainability Index and randomly selected 809 other companies representing the general market. From the analysis, the authors discovered that firms with higher ESG engagement exhibited lower stock volatility than their industry peers. Against the conventional view in finance that decreased risk leads to lower stock returns, Ashwin Kumar et al. (2016) found the firms that incorporate ESG practices also achieving higher returns than their peers. The authors also discovered ESG factors influencing firms in each industry differently: as an example, they found ESG factors having a positive effect on stock returns in industries of energy, food and beverage, and healthcare. A negative relationship between ESG factors and stock returns was discovered for firms operating in the industries of, for example, automobiles, insurance, and banking (Ashwin Kumar et al., 2016).

Galema et al. (2008) study ESG practices and US portfolio returns, excess stock returns, and book-to-market values between 1992 and 2006. The authors use return and accounting data from Refinitiv, and ESG data from KLD Research & Analytics, Inc. Galema et al. (2008) form SRI portfolios to study these aspects in a GMM system, in addition to conducting regression analyses such as Fama-Macbeth regressions. Based on the Fama-Macbeth regressions, the only SRI characteristic influencing excess returns directly is the employee relations, with a positive and significant effect – although only at a 10% level of significance (Galema et al., 2018). The authors argue that SRI practices have a negative influence on book-to-market ratios, and consequently, alphas in Fama-French regression models do not accurately capture the effects from such practices. Galema et al. (2008) suggest this as one reason why previous studies have not been able capture SRI alphas and argue that the relationship between SRI and stock returns is still significant. This finding was especially evident for portfolios with high scores on KLD's ESG variables environment, diversity, and product, as they influenced book-to-market ratios negatively (Galema et al., 2008).

Kempf and Osthoff (2007) analyze the relation between SRI practices and portfolio performance between 1992 and 2004, through buying stocks with high social responsibility ratings from KLD Research and Analytics -database and selling the ones with low ratings. As a result, the authors discovered that this strategy led up to 8.7% annual positive abnormal returns when measured with the Carhart (1997) four-factor model. These alphas were significant even when Kempf and Osthoff (2007) considered transaction costs. For different portfolios, the authors also use different SRI screening strategies. The largest abnormal returns were achieved through the best-in-class SRI screens, combining many SRI screens simultaneously, and buying only stocks with extreme SRI ratings (Kempf & Osthoff, 2007). The authors also analyze six KLD's ESG characteristics: community, diversity, employee relations, environment, human rights, and product. From these characteristics, Kempf and Osthoff (2007) found, for example, positive alphas for value-weighted long-short positive and best-in-class portfolios sorted based on employee relations.

5.2.2 Previous literature supporting a negative or non-significant relationship between ESG practices and stock returns

Statman (2006) compares the returns of four SRI indices to returns of the S&P 500 index between May 1990 and April 2004. These SRI indices are the Domini 400 Social Index, the Calvert Social Index, the Citizens Index, and the U.S. portion of the Dow Jones Sustainability Index (Statman, 2006). Based on the author's findings, SRI indices gained higher returns than the S&P 500 Index during the late 1990s, but worse returns compared to the S&P 500 during the early 2000s. According to Statman (2006), the null hypothesis that returns of socially responsible companies are equal to those of conventional companies cannot be rejected since none of the alphas in the Fama-French (1992) three-factor model were significant when analyzing the SRI indices.

Halbritter et al. (2015) study companies' ESG practices and stock returns with the Fama-Macbeth method, and by creating high-low market-capitalization weighted and equally weighted ESG portfolios. They construct separate portfolios for the total ESG score, the E,S, and G pillar scores, and for a score on firms' economic sustainability. The ESG data is retrieved from Refinitiv's ASSET4, Bloomberg, and KLD by the authors. The time frame for the study is as extensive as 1991-2012, although differing when using data from different ESG data providers (Halbritter et al., 2015). The authors' adjusted Fama-Macbeth regressions on the full sample suggest total ESG score, economic sustainability score, environmental pillar score, and social pillar score influencing stock returns positively. Halbritter et al. (2015) also found evidence of the government pillar score influencing stock returns negatively. However, Halbritter et al. (2015) noticed that these results were largely dependent on from which ESG rating provider the ESG data was retrieved. From the high-low portfolios and Carhart (1994) four-factor model regressions, the authors still did not find any significant relationship between the stock returns and companies ESG rating levels for the sub-scores or the total ESG score.

Van de Velde et al. (2005) study the relationship between sustainability and stock returns by constructing market capitalization-weighted portfolios based on ESG ratings. The authors retrieve corporate social responsibility scores from Vigeo, and financial data from Refinitiv. The time period of the study is from the beginning of January 2000 to the end of November 2003, and the authors use the Fama-French three-factor model for their performance analyses. Their results do not show any statistically significant evidence that high-sustainability rated portfolios would have performed superiorly to the low-sustainability rated portfolios, although possibly due to the short time horizon of the study. When analyzing portfolios constructed based on five sub-scores on human resources, environment, customers and suppliers, community and society, and corporate governance, the results remained insignificant (Van de Velde et al., 2005).

Brammer et al. (2006) study the relation between stock returns and corporate social performance of firms in the U.K. by analyzing all firms included in the FTSE All-Share Index in July 2002, and over different time periods. Brammer et al. (2016) retrieve financial data from Refinitiv, and social performance data from Ethical Investment Research Service. With multi-factor models, the authors discovered corporate social performance score influencing stock returns negatively. Furthermore, they found evidence that by holding the socially worst performing stocks, positive abnormal results can be achieved. The authors also analyze three sub-indicators of firms' social performance: the employment, environment, and community. As a result, Brammer et al. (2006) found evidence of the employment indicator influencing stock returns weakly but positively, and the environment and community measures overall negatively.

5.3 Conventional studies analyzing the non-ESG firm characteristics' possible influence on stock returns

The two studies of the non-ESG firm characteristics' possible influence on stock returns that are the most relevant for the purpose of my study are written by Chordia et al. (2015) and Green et al. (2017). More specifically, the method of my study follows to a large extent the method by Green et al. (2017), and I convert the five Fama-French (2015) factors to firm characteristics in a similar manner as Chordia et al. (2015). As I have also explained aspects of both studies in the previous chapters, I will only present short summaries of them in this chapter.

With the Fama-Macbeth method, Chordia et al. (2015) analyze bias-corrected return-premiums from regressions of stock returns on factors and firm characteristics. As their sample, the authors analyze NYSE, AMEX and NASDAQ stocks between July 1963 and December 2013. Chordia et al. (2015) study different factor models, and from these factors they also derive firm characteristics. As a result, Chordia et al. (2015) found evidence of positive beta premiums on the Fama-French five-factor model's investment and profitability factors. On the size factor, the authors found a negative beta premium, and on the market factor a less robust but positive beta premium. For the factors book-to-market and momentum, Chordia et al. (2015) did not find any reliable pricing evidence. Interestingly, no matter what the factor model was and whether the premiums were time-varying or not, the firm characteristics contributed more to expected stock returns' variation than the factors (Chordia et al., 2015). Furthermore, Chordia et al. (2015) found the coefficients on all six firm characteristics – size, book-to-market, six-month past return, profitability, and investment – being highly significant across all specifications, and with their common signs.

Green et al. (2017) take on Cochrane's (2011) challenge to study whether there are firm characteristics providing independent information of average monthly stock returns in the U.S. They study this "factor zoo" with 94 independent firm characteristics and select 1980-2014 as the time frame of the study. As Chordia et al. (2015), Green et al. (2017) use the two-step Fama-Macbeth method in their study. Furthermore, Green et al. (2015) utilize data from I/B/E/S, Compustat, and CRSP to analyze all common stocks on NYSE, AMEX, and NASDAQ that have sufficient data for the analysis. For the whole time period, Green et al. (2017) found 12 characteristics as determinants of the non-microcap average stock returns. Of these, 11 are different to the characteristics from the Fama-French five-factor, Carhart, and q-factor benchmark models, and the only exception is the book-to-market characteristic (Green et al. 2017). However, between January 2004 and December 2014, only two firm characteristics have been significant determinants of the non-microcap returns, and both positively: the number of consecutive quarters with earnings higher than the same quarter previous year, and the industry-adjusted change in the number of employees (Green et al., 2017).

5.4 Conclusions from the literature review

The results of the studies that I presented in Chapters 5.1-5.2.2 are mixed on the possible relationship between ESG characteristics and stock returns: some studies suggest a positive relationship, whilst some studies support a negative relationship or no significant relationship at all. When searching for the different studies for these chapters, I still noticed that it was more difficult to find studies suggesting that the relationship would be insignificant or negative. There are several possible reasons for these mixed results, such as differences in the ESG data providers' ratings, as demonstrated by Halbritter et al. (2015). Other such issues with ESG data I already mentioned in Chapter

2.3.3. There are also differences in, for example, the studies' time frames, geographical areas, methods, and ESG characteristics considered, which likely influence the results.

There are also several studies on how ESG factors may influence corporate financial performance at a larger scale, and scholars such as Friede et al. (2015) and Whelan et al. (2021) have conducted aggregate literature reviews of over thousands of studies and found evidence of an overall positive relationship between CFP and social responsibility. Although improved corporate financial performance does not necessarily lead to increased stock returns, these findings are also relevant to consider. However, I will not discuss them in detail in this literature review as the main focus of my study is still how the ESG characteristics may influence stock returns. The findings by De Lucia et al. (2020) also support this overall positive relationship between CFP and ESG practices.

As the studies utilizing ML methods to analyze the relation between ESG practices and firm performance that I present in Chapter 5.1 are all very recent, I find it important to critically assess the reliability of the studies. I view the studies by Margot et al. (2021) and De Lucia et al. (2020) as the most reliable since the study by Margot et al. (2021) is published on the Journal of Applied Economics and Finance, and the study by De Lucia et al. (2020) on Sustainalytics - whilst the study by Borgersen (2022) is a master's thesis and the study by Bonacorsi et al. (2022) is a working paper. Although the study by Borgersen (2022) is a master's thesis, I still find it relevant to discuss in my study as it is the only study that I have found analyzing the individual ESG characteristics' possible influence on stock returns with ML methods. There are still notable differences between my study and Borgersen's (2022) study: as an example, the author uses partly different methods and variables, and a smaller sample size in the analysis. Overall, the studies in Chapter 5.1 also seem to support the use of ML methods for analyzing the possible relationship between ESG characteristics and firm performance/stock returns.

Furthermore, the studies by Green et al. (2017) and Chordia et al. (2015) in Chapter 5.3 show that some non-ESG firm characteristics tend to influence stock returns. As found by Chordia et al. (2015), there is also evidence that at least the five Fama-French (2015) factors tend to contribute to the variation of expected stock returns, and even more as firm characteristics than as factors. My study is an interesting addition to this asset pricing literature as I utilize machine learning to study whether certain ESG characteristics can be discovered to influence stock returns.

Concluding all authors' most important findings from Chapters 5.1-5.3, the following three tables can be derived:

Table 2: Summary of the literature review for the studies utilizing machine learning methods to analyze the possible relationship between ESG practices and firm performance
This table summarizes the literature review for the studies that utilize machine learning methods to analyze the possible relationship between ESG practices and firm performance.

Author(s)	Main results
Borgersen (2022)	The variables selected with ML outperformed the set of initial variables based on goodness-of-fit criteria, and ESG variables have a slightly negative influence on expected stock returns. However, the accuracy of some of these results is questionable, as mentioned by Borgersen (2022).
Bonacorsi et al. (2022)	ML can be used for ESG variable selection, and certain ESG sub-factors seem to influence a company's credit risk. As an example, companies in regions with stricter carbon regulation exhibit lower credit risk.
Margot et al. (2021)	Positive ESG screening strategy influences stock returns the most positively compared to screening over negative ESG scores, no screening, or best-in-class screening. ESG factors influence stocks in distinct areas and sectors differently.
De Lucia et al. (2020)	ML methods can be used for predictive analyses of financial indicators ROE and ROA. Additionally, the results suggest that the overall relationship between ESG practices and these indicators is positive. Some ESG characteristics still tend to influence these indicators negatively, such as environmental management training.

Table 3: Summary of the literature review for conventional studies analyzing ESG practices' possible influence on stock returns
This table summarizes the literature review for the conventional studies that analyze ESG practices' possible influence on stock returns.

Positive relationship		**Negative or non-significant relationship**	
Author(s)	**Main results**	**Author(s)**	**Main results**
Verheyden et al. (2016)	ESG screening tends to improve risk-adjusted portfolio returns.	**Statman (2006)**	The null hypothesis that returns of SRI companies are equal to those of conventional companies cannot be rejected.
Ashwin Kumar et al. (2016)	Companies following ESG practices tend to achieve higher stock returns than their peers.	**Halbritter et al. (2015)**	Despite the evidence of some ESG characteristics influencing stock returns based on the Fama-Macbeth regressions, there is no

			significant relationship between stock returns and ESG scores when analyzing high-low portfolios sorted by the total and sub-ESG scores.
Galema et al. (2008)	SRI practices influence stock returns significantly, although alphas in Fama-French regression models do not capture the effects. When analyzing with the Fama-Macbeth method, the only ESG characteristic influencing excess returns directly is employee relations, with a positive effect.	**Van de Velde et al. (2005)**	SRI portfolios do not tend to perform statistically better than non-SRI portfolios, neither when analyzing the total sustainability rating nor the separate ESG firm characteristics.
Kempf and Osthoff (2007)	The long-short portfolio strategy of longing the SRI stocks and shorting the non-SRI stocks led to up to 8.7% annual positive abnormal returns.	**Brammer et al. (2006)**	Corporate social performance influences stock returns overall negatively. Furthermore, the results suggest a negative relationship between environmental and community indicators and stock returns, and a weak but positive one between the employment indicator and stock returns.

Table 4: Summary of the literature review for the conventional studies analyzing the non-ESG firm characteristics' possible influence on stock returns
This table summarizes the literature review for the conventional studies that analyze the non-ESG firm characteristics' possible influence on stock returns.

Author(s)	**Main results**
Chordia et al. (2015)	The six firm characteristics derived from the Fama-French (2015) model, enhanced with the momentum factor, tend to influence stock returns in the U.S. Moreover, firm characteristics tend to explain more of the variation of the expected returns than factors.
Green et al. (2017)	Between 1980 and 2014, 12 firm characteristics provided independent information of average U.S non-microcap stock returns. However, between January 2004 and December 2014, only two firm characteristics have been independent determinants of their stock returns.

6 METHODOLOGY

In this chapter, I present in detail the methodology of this study, including the two research hypotheses.

6.1 Research hypotheses

This study has two research hypotheses relating to the research questions and previous literature that I presented in the first chapter. More specifically, these hypotheses are related to the possibility of ESG characteristics and five other firm characteristics to provide independent information about stock returns. As I use the Fama-Macbeth two-pass regressions as the main method of my study, the two research hypotheses are also linked to these results. Based on the Fama-Macbeth regression results, I further assess the statistically significant ESG characteristics' economic significance with portfolio sorts, and Fama-French five-factor regressions on their excess returns.

The first hypothesis, H1, for this study is:

H1: The selected ESG characteristics can provide independent information about the excess monthly stock returns.

As has been discovered by Bonacorsi et al. (2022), some ESG characteristics seem to explain the probability of default for a company. In a similar manner, I am studying whether there are ESG characteristics that can provide independent information about the excess returns of North American companies. Some studies have also found evidence of ESG characteristics influencing stock returns positively, such as Chiu et al. (2020) who found that companies engaging in CSR reporting tend to obtain higher and positive abnormal mid- to long-term returns.

Based on the literature review I presented in Chapter 5.4, there seems to be evidence that the relationship between ESG factors and stock returns may rather be positive than negative, especially when also including studies that analyze the possible relationship between CFP and stock returns. Although corporate financial performance is not always directly comparable with stock returns, this discovery also supports studying the relationship between stock returns and ESG characteristics. As an example, the results from an aggregate literature review by Friede et al. (2015) show that in roughly 90% of studies that the authors analysed, a non-negative relationship was found between ESG factors and CFP. Moreover, this relationship was positive in majority of the studies reviewed by Friede et al. (2015), which also Whelan et al. (2021) discovered of the investment-focused studies in their literature review, as only 14% of these studies found evidence of negative performance compared to conventional investments. Ting et al. (2019) and De Lucia et al. (2020) have also discovered some ESG characteristics influencing financial indicators ROE and ROA positively, such as characteristics sustainable development policy, and diversity and opportunity policy.

Previously, slight evidence of ESG characteristics' influencing stock returns - although negatively - has been found by Borgersen (2022), also by using machine learning methods. In their study, Bonacorsi et al. (2022) were also able to use machine learning methods for ESG variable selection. Furthermore, in the study by Borgersen (2022), the regression variables selected with ML methods outperformed the author's set of initial variables. As the number of ESG characteristics that I intend to analyze in this study is large, I am also striving to see whether ML methods can be used for variable selection and/or to improve prediction accuracy for the purpose of my study. As goodness-of-fit values, I use the F-statistics, multiple R squared, and adjusted R squared. In addition to these ESG firm characteristics, I am also simultaneously analyzing five other non-ESG firm characteristics, which may provide independent information about excess returns.

The second hypothesis, H2, for this study is:

H2: When studying the possible influence of ESG characteristics on excess returns, the firm characteristics replicating the five factors from Fama-French (2015) model can provide independent information about monthly excess returns.

In a similar manner as Chordia et al. (2017), I am studying whether the five firm characteristics replicating the factors from the Fama-French (2015) five-factor model can provide independent information about monthly excess returns of North American stocks – although simultaneously when analyzing the possible influence of ESG characteristics on excess returns. As their result, Chordia et al. (2017) found all five of the Fama-French (2015) factors transformed into firm characteristics as being significant determinants of the expected stock returns. Previous studies within finance have shown that these firm characteristics tend to influence stock returns. Examples of such studies I already presented in Chapter 1 and will further discuss in Chapter 10.1, along with my results from the Fama-Macbeth method.

The two equivalent statistical hypotheses for this study can be found from Table 5:

Table 5: Statistical hypotheses for the study

This table presents the statistical hypotheses for the study.

Statistical hypotheses for the study:
$\mathbf{H1_0}$= *In either of the Fama-Macbeth models*, none of the Fama-Macbeth coefficients for the ESG characteristics differ significantly from zero.*
$\mathbf{H1_1}$= *In one or both Fama-Macbeth models*, at least one of the Fama-Macbeth coefficients for the ESG characteristics differs significantly from zero.*
$\mathbf{H2_0}$= *In either of the Fama-Macbeth models*, none of the Fama-Macbeth coefficients for the five firm characteristics differ significantly from zero.*
$\mathbf{H2_1}$= *In one or both Fama-Macbeth models*, at least one of the Fama-Macbeth coefficients for the five firm characteristics differs significantly from zero.*

** Either the full model or the one in which variables are selected with machine learning methods. Moreover, the significance of a Fama-Macbeth coefficient is assessed according to the recommendation by Harvey et al. (2016): by having an absolute t-value of 3.0 or more.*

6.2 Research method

The method of this study is mainly based on the method used in the study by Green et al. (2017). In a similar manner as Green et al. (2017), although not only for the U.S. stocks but for all North American stocks, I also use the Fama-Macbeth two-pass regression method to potentially identify firm characteristics explaining excess monthly stock returns. As I have already stated in the previous chapters, I include the Fama-French (2015) five factors in my models as firm characteristics since they have been found as significant determinants of expected stock returns by Chordia et al. (2017) with the Fama-Macbeth method. I also study the sub-characteristics of ESG scores in a similar way as Bonacorsi et al. (2021) in their study.

There are many different variables that contribute to explaining the three E, S, and G pillars, and I am interested to see if one or more of these variables could be identified to influence stock returns. The full list and explanations of the ESG characteristics included in my empirical study can be found from Appendix 5. To avoid multicollinearity in my models, I use the Variance Inflation Factor (VIF) test as a pre-selection tool for the independent variables after conducting initial data handling processes presented in chapter 7.2. As Green et al. (2017), I then remove the variables with VIF scores above seven. With this method, I already had to remove the total ESG score from the list of my independent variables – which was foreseeable due to also having E, S, and G pillar scores included. Other variables that I have removed due to high correlations are, for example, the management score, emissions score, CSR sustainability reporting variable, and resource use score. To conduct variable selection and to avoid further problems related to model diagnostics, I then use Lasso regression and Principal Component Analysis. In Chapter 3.3, I explained the detailed methods for both PCA and Lasso.

After utilizing the two machine learning methods, I conduct the Fama-Macbeth method by following the R code sample from the article "*Fama-MacBeth Regressions – Replicating Green, Hand, and Zhang*" by Rubesam (2021) with some small modifications. I conduct the Fama-Macbeth method twice: first with the model selected by ML methods, and then with the full model to study whether machine learning methods can be used to enhance the model selection process. For the statistically significant ESG characteristics based on the Fama-Macbeth method, I further assess their economic significance with value-weighted and equally weighted portfolio sorts, and conduct Fama-French five-factor regressions on the portfolios' excess returns. This process I explain more in detail in Chapter 8.4. I also use the Newey-West (1994) heteroskedasticity and autocorrelation consistent procedure in both the Fama-Macbeth regressions and the five-factor regressions on the sorted portfolios, to mitigate possible biases in the results.

As stated by Rubesam (2021), the first step in the Fama-Macbeth method used by Green et al. (2017) is to conduct cross-sectional regressions of stock returns on the independent variables for each month. As a second step, the independent variables are analyzed using the time-series averages and standard errors of the coefficients that were obtained in step one (Rubesam, 2021). It is important to note that this approach differs from the other order of conducting the Fama-Macbeth method presented by, for example, Cochrane (2001): doing first the time-series regressions and then the cross-sectional regressions. Consequently, I address this difference in the next chapter, and explain the Fama-Macbeth method more in detail.

6.3 Fama-Macbeth (1973) method

In this section, I explain the more general estimation of the Fama-Macbeth two-pass method (1973) according to Cochrane (2001), for a single-factor model.

First, beta estimates are retrieved with time series regressions for each investment i. Thus, there are as many time-series regressions as there are investments. Fama and

MacBeth use rolling 5-year regressions, but Cochrane (2001) states that one can also use the technique with full- sample betas. Then, instead of estimating a single cross-sectional regression with the sample averages, cross-sectional regressions are computed for each time period t (t=1,2...T):

$$R^{ei} = \beta' \lambda + \alpha \text{ , i = 1,2...N for each } t \tag{3}$$

Cochrane (2001) defines R^{ei} as the excess return for investment i over the risk-free rate. Then, risk premiums, λ_t, and cross-sectional regression residuals, α_{it}, are estimated as averages of the cross-sectional regression estimates, and standard deviations of the cross-sectional regression estimates are used to generate the sapling errors for these estimates. As stated by Cochrane (2001), the Fama-Macbeth method can then be extended for multiple factors, as I do in my method.

As the Fama-Macbeth approach typically starts with the time-series regressions also presented by Cochrane (2001), it is important to note that the Fama-Macbeth method by Rubesam (2021) and Green et al. (2017) conducts the analysis in a different order, starting from the cross-sectional regressions. This same ordering has also been used by Chrodia et al. (2015) to study the possible influence of five Fama-French factors on stock returns. To make the results of my study comparable, I follow the order of conducting the Fama-Macbeth method by previous literature and also start with the cross-sectional regressions.

6.4 Fama-French (2015) five-factor model

In 1992, Fama and French discovered that many of the detected anomalies in average stock returns found with the CAPM by Sharpe and Lintner (1964 and 1965, cited in Fama & French, 1996) are, in fact, related and can be captured with a three-factor model that considers two additional risk factors: a size factor (SMB) and a value factor (HML). Based on the three-factor model, Fama and French (2015) invented their five-factor model by adding factors robust-minus-weak (RMW) and conservative-minus-aggressive (CMA) to the three-factor model:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i}(SMB_t) + \beta_{HML,i}(HML_t) + \\ \beta_{RMW,i}(RMW_t) + \beta_{CMA,i}(CMA_t) + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The equation is equivalent to the CAPM but with four additional risk factors. The factors from the Fama-French five-factor model are also used in my analysis to further construct equivalent firm characteristics, and to test my results' economic significance along with portfolio sorts. I retrieve the Fama-French 5-factor model data for North American firms from the Kenneth R. French (2023) database. As French (2023) describes on the database, the five factors are created by constructing value-weighted portfolios: six such portfolios are formed on size and book-to-market ratio, six portfolios on size and operating profitability, and lastly, six portfolios on size and investment (French, 2023). In the next paragraph, I describe these variables more in detail.

The factor SMB, or size minus big, is the average return on nine small stock portfolios minus the average return on nine portfolios of large stocks (French, 2023). The factor HML, or high minus low, is the average return on the two value portfolios of which the average return on the two growth portfolios has been subtracted (French, 2023). As French (2023) states, the factor RMW, or robust minus weak, describes the average return on the two robust operating profitability portfolios, minus the average return generated by the two portfolios that have weak operating profitability. French (2023) also explains the factor CMA, or conservative minus aggressive, describing the average return on the two investment portfolios that are conservative minus the average return on the two investment portfolios that are characterized as aggressive.

7 DATA

In this chapter, I present the data used in this study. I also describe my data handling processes, and shortly discuss the descriptive statistics of my data.

7.1 Data selection

For the analysis in this thesis, monthly U.S and Canadian stock data in USD is used due to its extensiveness and availability. As GSIA (2020) has discovered, the US had at least in 2020 the largest total market value of sustainable investing assets, which I believe makes the North American stock market the most significant to study out of all the global markets regarding ESG aspects. In the full data, I have 35 ESG characteristics in addition to the five Fama-French (2015) factors transformed as firm characteristics. The definitions of the ESG variables used in this study can be found from Appendix 5.

The main data source for my study is Refinitiv (2023), from which I retrieve the ESG data and other financial data of companies. For retrieving ESG data, Refinitiv's ESG database is one of the most comprehensive ones in the industry: it covers over 85% of the global market capitalization, across over 630 different ESG metrices (Refinitiv, 2022). Additionally, the Fama-French (2015) five-factor data I retrieve from Kenneth R. French's (2023) database. The reason behind my choice of analyzing monthly returns is that daily returns tend to be noisy whilst annual returns tend to not withhold enough information. As the international treaty Paris agreement entered into force in 4th of November 2016 enhancing monitoring and reporting of the countries' climate goals (United Nations, s.a.), the time frame for my data is from December 2016 to December 2022 to have as few missing values for the ESG variables as possible.

To avoid selection biases related to data retrieving, I filtered my full set of companies to exclude the ones with stock prices of less than five dollars - which are also called penny stocks. Moreover, I excluded financial companies and very small companies with market capitalization of less than 5 million dollars at the beginning of the time period for the data. This same exclusion filter for the so-called micro-cap stocks has also been used by, for example, Cakici et al. (2022) and Lou et al. (2019). Despite being a research paper, the study by Cakici et al. (2022) is somewhat similar to mine regarding the non-ESG firm characteristics as the authors study cross-sectional return predictability in stock markets with machine learning. I also selected only firms for which total ESG scores were available at the start of the time period of my study to ensure that I have as much data of the firms' ESG-characteristics available as possible. After the data filtering processes, the final number of firms in my study is 2177, and the sample size is 158 921 monthly observations. The list of the stocks can be found from Figure 3 of Appendix 1, in which the firms are represented by their RIC indicators used in Refinitiv's (2023) database.

To analyze the most important non-ESG related firm characteristics that may provide independent information of stock returns, I transform the factors from the Fama-French five-factor model to firm characteristics. This five-factor model I presented more in detail in Chapter 6.4, and it has been often used in similar studies of socially responsible investments' financial performance. As an example, Kiymaz (2019) has studied SRI funds with multiple factor models to find if certain factors, such as ESG screening strategies, influence the funds' performance. As a result, Kiymaz (2019) noted that the Fama-French five-factor model showed the most promising results: that market, size, and operating profit as factors seem to explain SRI funds' returns. As I want to analyze these Fama-French (2015) five factors as firm characteristics in a similar way as Chordia et al. (2017), I strive to follow their transformation method as closely as possible, by still using Refinitiv (2023) as my data source.

As Chordia et al. (2017), I also describe the firm size (Sz) with the natural logarithm of market capitalization of a company. Chordia et al. (2017) transformed the factor HML to a firm characteristic by using natural logarithms of firms' book-to-market (B/M) ratios. I followed this approach and used logarithms of firms' B/M ratios on per share basis. In their study, Chordia et al. (2017) use operating profitability as the equivalent firm characteristic to the factor RMW. Similarly, I transformed that factor to a firm characteristic (Prof) by using the firms' operating profits before non-recurring incomes/expenses from Refinitiv (2023). The firm characteristic equivalent to CMA is Inv in my study: the change in total assets divided by current total assets for a firm, as in Chordia et al. (2017). The market risk premium factor, Mkt-rf, I replaced with each firm's market beta (Beta) for each month to be used as a firm characteristic. A similar estimate for this last firm characteristic has previously been used by, for example, Borgersen (2022) when estimating whether certain ESG variables explain stock returns.

7.2 Data handling processes used in this study

My data handling processes replicate closely the ones used by Green et al. (2017). I also replace the missing observations – but only for the non-indicator variables – with mean imputation, after first standardizing the firm characteristics to have a zero mean and unit standard deviation, and winsorizing all variables at the 1st and 99th percentiles. For the indicator variables, I use mode imputation by imputing the nulls for each firm with that firm's mode for the variable in question. As I stated, the winsorization and standardization practices follow Green et al. (2017) for all firm characteristics. I also winsorize the excess returns but keep them non-standardized to avoid possible challenges related to interpretability of the results. This practice follows Lins et al. (2017) as they also winsorize excess returns to study the relationship between stock returns and CSR - although they state excess returns as raw returns minus expected returns. Cai et al. (2014) also winsorize the returns when analyzing the relation between them and corporate environmental responsibility. Furthermore, Cai et al. (2014) discover that their main results are robust to winsorization, which I also find for my results from both the Fama-Macbeth method and portfolio regressions.

7.3 Descriptive statistics

From Table 6, the most important descriptive statistics for my full data can be found. For the descriptive statistics, the full data has been winsorized at the 1st and 99th percentiles and standardized for all variables except for the dependent variable, ER, as the excess returns are only winsorized.

Table 6: Descriptive statistics
This table presents the descriptive statistics for the full data. All values are presented with two decimals, and min and max indicate the minimum and maximum values, respectively.

Variable	*mean*	*sd*	*min*	*max*	*skewness*	*kurtosis*
ER	0.01	0.18	-0.94	19.81	21.95	1715.88
Beta	0	0.99	-7.93	8.43	-0.86	4.36
Sz	0	0.99	-5.9	6.81	-0.2	-0.33
B/M	0	0.98	-8.43	6.05	0.09	-0.03
Prof	0	0.99	-6.48	5.55	0.1	-0.34
Inv	0	0.98	-8.43	8.43	-0.43	14.3
GPS	0	0.99	-7.63	8.43	-0.13	-0.24
EPS	0	0.92	-8.31	8.43	0.55	2.58
SPS	0	0.99	-7.9	8.43	-0.04	0.08
DIR Controversies Score	0	0.92	-8.43	8.43	-1.3	2.35
Environmental Innovation Score	0	0.67	-8.32	8.43	0.46	7.89
Supplier ESG training Score	0	0.44	-8.41	8.43	1.4	38
ESG Reporting Scope	0	0.71	-8.43	8.43	1.18	12.92
ESG Controversies Score	0	0.8	-8.43	8.43	-1.49	5.93
DIR Inclusion Score	0	0.72	-5.84	8.43	0.98	10.04
Female on Board	0	0.97	-8.43	8.43	0.18	0.73
Climate Change Commercial Risks Opportunities Score	0	0.78	-8.01	8.43	0.82	8.61
Policy Data Privacy Score	0	0.98	-8.34	8.43	-0.11	0.67

Product Responsibility Score	0	0.98	-8.42	8.43	-0.09	0.84
Policy Water Efficiency Score	0	0.74	-8.32	8.43	0.63	7.44
Policy Customer Health Safety Score	0	0.52	-8.43	8.43	0.35	18.78
Health Safety Policy Score	0	0.94	-8.3	8.43	0.08	2.09
Human Rights Score	0	0.83	-7.89	8.43	0.92	6.9
Policy Human Rights Score	0	0.73	-8.13	8.43	1.26	12.32
Human Rights Contractor Score	0	0.73	-8.34	8.43	0.7	10.1
Equal Shareholder Rights Score	0	0.94	-8.42	8.43	-0.67	0.6
Workforce Score	0	0.99	-6.18	8.43	0.09	-0.22
Community Score	0	0.99	-8.21	8.43	-0.15	0.28
Policy Community Involvement Score	0	0.89	-8.38	8.43	0.09	2.8
CSR Strategy Score	0	0.85	-7.96	8.43	1.24	7.82
Shareholders Score	0	0.99	-8.28	8.43	-0.04	0.14
Employees Health Safety Team Score	0	0.69	-8.38	8.43	0.82	10.95
Renewable Clean Energy Products	0	0.24	-8.43	8.43	3.58	168.88
Environmental Assets Under Mgt	0	0.06	-1.42	2.65	12.77	721.57
Environmental Products	0	0.42	-8.43	8.43	1.71	55.29
Environmental Supply Chain Management	0	0.47	-8.43	8.43	1.63	43.64
SDG 5 Gender Equality	0	0.39	-2.36	8.43	4.3	139.85
Green Buildings	0	0.45	-8.43	8.43	2.24	59.84
Policy Sustainable Packaging	0	0.37	-8.43	8.43	3.28	90.71
Sustainability Compensation Incentives Score	0	0.61	-8.36	8.43	2.07	21.35
Environmental Partnerships Score	0	0.61	-8.39	8.43	0.66	16.88

As can be seen from the descriptive statistics, there are some independent variables that have extremely high kurtosis values of over 100: the indicator variables for renewable clean energy products, environmental assets under management, and SDG 5 gender equality. For these independent variables, also high skewness values can be noted: the highest value of skewness when rounded to two decimals is 12.77, for the indicator variable environmental assets under management. When the dependent variable excess returns (ER) is not standardized, it also exhibits extremely high values for both skewness and kurtosis: 21.95 for skewness and 1715.88 for kurtosis.

As there are variables with such high values for both skewness and kurtosis, the robustness of my results should be critically evaluated. To decrease possible biases, I am using Newey-West (1994) heteroskedasticity and autocorrelation consistent procedure in my Fama-Macbeth regressions and Fama-French five-factor regressions on the sorted portfolios. The overall robustness of my results I further discuss in the upcoming chapters.

8 RESULTS

In this chapter, the results of the study are presented. I start by showing the results of the machine learning methods Lasso and PCA since their results affected the models used in Fama-Macbeth regressions. In the tables presented in Chapters 8.1 and 8.2, all coefficient estimates, and standard errors are expressed as decimals. For these Fama-Macbeth regressions, I have winsorized all variables at the 1st and 99th percentiles and standardized all independent variables to have a mean of zero and unit standard deviation. This approach is explained more in detail in Chapter 7.2.

When reading the results, it is also important to note that I use abbreviations for several variables. As an example, EPS, SPS, and GPS stand for the E, S, and G pillar scores. The variables abbreviated as Beta, Sz, B/M, Prof and Inv are the firm characteristics derived from the factors of the Fama-French (2015) five-factor model. Thus, the variables are the beta for a stock (Beta), size (Sz), book-to-market ratio (B/M), profitability (Prof), and asset growth (Inv). In Chapter 7.1, I already introduced these firm characteristics more extensively. Furthermore, the detailed explanations of all ESG characteristics can be found from Appendix 5.

8.1 Results of the Lasso regression and Principal Component Analysis

For the variable selection process with machine learning methods, I winsorized and standardized all variables. The results from Lasso regression can be found from Table 7:

Table 7: Lasso regression results
This table shows the Lasso regression results, with the optimal regularization parameter of 0.01. The variables that have only dots "." as their coefficients are not selected by the regression as they are minimized to zeros.

Variable	*Lasso value*
Beta	0.03
Sz	0.08
B/M	-0.11
Prof	-0.03
Inv	0.02
GPS	.
EPS	.
SPS	-0.01
DIR Controversies Score	.
Environmental Innovation Score	.
Supplier ESG training Score	.
ESG Reporting Scope	.
ESG Controversies Score	.
DIR Inclusion Score	-0.01

Female on Board	-0.01
Climate Change Commercial Risks Opportunities Score	.
Policy Data Privacy Score	.
Product Responsibility Score	.
Policy Water Efficiency Score	.
Policy Customer Health Safety Score	.
Health Safety Policy Score	.
Human Rights Score	.
Policy Human Rights Score	.
Human Rights Contractor Score	.
Equal Shareholder Rights Score	.
Workforce Score	.
Community Score	.
Policy Community Involvement Score	.
CSR Strategy Score	-0.01
Shareholders Score	.
Employees Health Safety Team Score	.
Renewable Clean Energy Products	.
Environmental Assets Under Mgt	.
Environmental Products	.
Environmental Supply Chain Management	.
SDG 5 Gender Equality	-0.01
Green Buildings	-0.01
Policy Sustainable Packaging	.
Sustainability Compensation Incentives Score	.
Environmental Partnerships Score	.

As can be seen from Table 7, the highest Lasso coefficient is for the firm characteristic book-to-market ratio (B/M), and second highest for a firm's size characteristic (Sz). Interestingly, the Lasso regression method selects all non-ESG firm characteristics as relevant but discards many of the ESG characteristics as insignificant. As the optimal regularization parameter, the model selects a value of 0.01.

In a similar manner, from Table 8 the results from my Principal Component Analysis can be found. The values are rounded to two decimals, and I report only the variables which have principal component correlations of over 0.65 that I use as threshold for a correlation:

Table 8: Results for Principal Component Analysis, for independent variables with PC correlation of >0.65
This table presents the results for Principal Component Analysis, for the independent variables that have principal component -correlations of > 0.65.

Variable	***PC correlation***
Beta	0.90

B/M	0.89
SPS	0.84
Policy Data Privacy Score	0.74
Inv	0.67

The results in Table 8 suggest that three out of the five non-ESG firm characteristics are important to include in the model, in addition to two ESG firm characteristics: policy data privacy score and the social pillar score.

Based on the results on tables 7 and 8, the following variables are chosen for the model selected with ML methods: Beta, Sz, B/M, Prof, Inv, SPS, DIR Inclusion Score, Green Buildings, SDG 5 Gender Equality, Female on Board, Policy Data Privacy Score, and CSR Strategy Score. It is still notable that in the results for Lasso, the ESG characteristics have smaller values than the other firm characteristics – suggesting that the ESG characteristics would be less of relevance, although still selected by Lasso.

8.2 Results of the first step of the Fama-Macbeth method: the cross-sectional regressions

The first step of the Fama-Macbeth two-pass method that I use in this study includes conducting cross-sectional regressions. As I have stated earlier, I did the Fama-Macbeth method first for the model with full variables, and then for the model with variables selected by machine learning methods. In this chapter, the coefficient estimates, R-squared values, and standard errors of the regressions are expressed as decimals.

In Table 9, I present the results from the cross-sectional regression with all variables:

Table 9: Results of the cross-sectional regression with all variables
This table shows the results of the cross-sectional regression with all variables. The significance codes are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Variable	*Estimate*	*Std. Error*	*T-value*
(Intercept)	-0.0338	0.0059	-5.7390***
Beta	-0.0213	0.0033	-6.5380***
Sz	0.0236	0.0030	7.9010***
B/M	-0.0022	0.0029	-0.7480
Prof	-0.0087	0.0026	-3.3830***
Inv	0.0002	0.0023	0.0940
GPS	-0.0002	0.0030	-0.0800
EPS	-0.0020	0.0024	-0.8520
SPS	0.0006	0.0043	0.1360

Environmental Innovation Score	0.0005	0.0029	0.1880
Supplier ESG training Score	0.0014	0.0027	0.5190
ESG Reporting Scope	0.0021	0.0023	0.9080
ESG Controversies Score	0.0018	0.0025	0.7320
DIR Inclusion Score	-0.0006	0.0020	-0.3020
Female on Board	-0.0052	0.0022	-2.3930*
Climate Change Commercial Risks *Opportunities Score*	0.0001	0.0017	0.0690
Policy Data Privacy Score	0.0084	0.0033	2.5800**
DIR Controversies *Score*	-0.0004	0.0028	-0.1310
Product Responsibility Score	0.0064	0.0026	2.4560*
Policy Water *Efficiency Score*	0.0014	0.0020	0.7140
Policy Customer Health Safety Score	-0.0046	0.0031	-1.4730
Health Safety Policy Score	0.0010	0.0020	0.4730
Human Rights Score	0.0022	0.0025	0.8580
Policy Human Rights Score	-0.0020	0.0021	-0.9660
Human Rights Contractor Score	-0.0029	0.0022	-1.3470
Equal Shareholder Rights Score	-0.0015	0.0031	-0.4940
Workforce Score	-0.0026	0.0031	-0.8370
Community Score	0.0034	0.0027	1.2650
Policy Community Involvement Score	-0.0039	0.0021	-1.8840 .
CSR Strategy Score	-0.0024	0.0020	-1.1650
Shareholders Score	-0.0025	0.0022	-1.1310
Employees Health Safety Team Score	0.0005	0.0019	0.2760

Renewable Clean Energy Products	0.0028	0.0042	0.6690
Environmental Assets Under Mgt	-0.0284	0.0299	-0.9500
Environmental Products	-0.0012	0.0030	-0.3970
Environmental Supply Chain Management	0.0030	0.0024	1.2580
SDG 5 Gender Equality	0.0016	0.0019	0.8400
Green Buildings	-0.0006	0.0020	-0.3050
Policy Sustainable Packaging	-0.0026	0.0026	-1.0100
Sustainability Compensation Incentives Score	-0.0016	0.0019	-0.8400
Environmental Partnerships Score	0.0008	0.0020	0.3790

In the results shown in Table 9, the only variables in addition to the intercept that are significant even at a 0.1% level of significance are three of the five non-ESG firm characteristics: beta, size, and profitability. The variables profitability and beta seem to influence excess returns negatively, and firm size positively. As an example, one standard deviation increase in the standardized size firm characteristic is expected to increase the excess returns by around 2.36%, holding all other variables constant.

Of the ESG firm characteristics, the only variable that is significant at a 1% level of significance is the policy data privacy score, as can be noted from Table 9. Additionally, the variables female on board and product responsibility score explain the excess returns significantly at a 5% level of significance. The variable female on board has a negative relationship with excess returns, and the product responsibility score a positive one. It is still notable that majority of the ESG characteristics do not exhibit a significant relationship with excess returns based on the results in Table 9.

Additionally, the summary statistics from this cross-sectional regression model can be found from Table 10:

Table 10: Summary statistics of the cross-sectional regression with all variables

This table presents the summary statistics of the cross-sectional regression with all variables. The significance codes are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Metric	*Value*
Multiple R-squared	0.08543
Adjusted R-squared	0.06831
Residual standard error:	0.1413
F-statistic:	4.988***

The results of the cross-sectional regression model with variables selected by the ML methods are shown in Table 11:

Table 11: Results of the cross-sectional regression with variables selected by ML methods
This table shows the results of the cross-sectional regression with variables selected by ML methods. The significance codes are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Variable	*Estimate*	*Std. Error*	*T-value*
(Intercept)	-0.0342	0.0052	-6.5800***
Beta	-0.0219	0.0032	-6.7760***
Sz	0.0237	0.0030	7.9980***
B/M	-0.0018	0.0029	-0.5980
Prof	-0.0080	0.0025	-3.1750**
Inv	0.0003	0.0023	0.1260
SPS	0.0022	0.0027	0.8250
DIR Inclusion Score	-0.0011	0.0018	-0.5970
Green Buildings	-0.0007	0.0020	-0.3660
SDG 5 Gender Equality	0.0013	0.0018	0.7270
Female on Board	-0.0055	0.0021	-2.5940**
Policy Data Privacy *Score*	0.0099	0.0024	4.0400***
CSR Strategy Score	-0.0022	0.0016	-1.3710

Based on the results in Table 11, the same non-ESG firm characteristics are significant determinants of excess stock returns as in the Table 9 from the initial model with all variables, and with the same signs. Moreover, the variables beta and size are significant at a 0.1% level of significance, and profitability at a 1% level of significance. The ESG firm characteristic policy data privacy score also explains excess returns at a 0.1% level of significance and has a positive sign. The ESG firm characteristic female on board is also a significant but negative determinant of excess returns at a 1% level of significance. To conclude, the results from the model selected with ML methods are quite similar to the results from the initial model with all variables, although significance levels of some variables differ.

From Table 12, the summary statistics of the cross-sectional regression with variables selected by ML methods can be found:

Table 12: Summary statistics of the cross-sectional regression with variables selected by ML methods
The summary statistics of the cross-sectional regression with variables selected by ML methods are shown in this table. The significance codes are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Metric	***Value***
Multiple R-squared	0.07559
Adjusted R-squared	0.07047
Residual standard error:	0.1412
F-statistic:	14.75***

In Chapter 9.1, I further discuss the differences between the summary statistics of the model with all variables and the model selected with ML methods.

8.3 Final results of the Fama-Macbeth method

And lastly, the final results of the Fama-Macbeth method are shown in Table 13 for the full model, and in Table 14 for the model selected with machine learning methods. As Green et al. (2017), I present these final coefficient estimates as percentages. Moreover, I define the threshold for the significance of a Fama-Macbeth coefficient as 3.0, as recommended by Harvey et al. (2016). Additionally, Green et al. (2017) noted this approach leading to largely same inferences as adjusting two-tailed p-values on the coefficients for false detection rates that consider dependency across hypothesis tests.

Table 13: Results of the Fama-Macbeth method for the initial model with all variables, with variables that have absolute t-values of 3.0 or more
This table presents the final Fama-Macbeth results for the initial model, with variables that have absolute t-values of 3.0 or more.

Variable	***FMB Coefficient***	***T-value***
Sz	1.61	4.67
B/M	-1.31	-11.67
Prof	-0.82	-5.17
ESG Reporting Scope	0.16	3.50

Product Responsibility Score	0.11	3.07
Sustainability Compensation Incentives Score	0.21	4.10

For the model with all variables, the firm characteristics with significant Fama-Macbeth coefficients are size, book-to-market ratio, profitability, ESG reporting scope, product responsibility score, and sustainability compensation incentives score. All these variables have positive coefficients except the book-to-market characteristic and profitability characteristic. As an example, increasing the standardized ESG reporting scope characteristic by one standard deviation would be expected to result in 0.16% increase in the excess returns if all other variables would be held constant. In line with the Lasso regression results presented in Table 7, the Fama-Macbeth coefficient estimates in Table 13 are smaller for the ESG firm characteristics than for the non-ESG firm characteristics, indicating that the ESG characteristics contribute less to the variation in excess returns than the non-ESG firm characteristics.

Table 14: Results of the Fama-Macbeth method for model selected with ML methods, with variables that have absolute t-values of 3.0 or more
This table shows the final Fama-Macbeth results for the model selected with ML methods, with variables that have absolute t-values of 3.0 or more.

Variable	*FMB Coefficient*	*T-value*
Sz	1.58	4.61
B/M	-1.33	-11.23
Prof	-0.8	-4.77
SPS	-0.19	-4.65

Interestingly, the book-to-market characteristic and profitability characteristic also have significant and negative Fama-Macbeth coefficients in the model selected by ML methods, which can be seen from the Table 14. The size characteristic is also significant with a positive sign when using the model selected by ML methods. However, the main difference in the final Fama-Macbeth results between the two models is that the ESG characteristic social pillar score (SPS) has a significant and negative Fama-Macbeth coefficient when using the model selected by ML methods, but it is not significant with the initial model.

To test the robustness of my results despite the winsorization of the dependent variable, I also conducted the same Fama-Macbeth regressions with non-winsorized excess returns and discovered that the results for the second step of Fama-Macbeth method remained very similar. The only difference was that with the initial model, the t-value for product responsibility score became 2.9 so slightly less than three, making it insignificant. All other variables remained as significant and with very similar coefficient estimates and t-values as initially, so I conclude that my results are quite unaffected by the winsorization of excess returns.

8.4 Results of portfolio sorts and consequent Fama-French (2015) five-factor regressions

To assess the economic significance of my results, I constructed sorted portfolios based on the four ESG characteristics that had significant Fama-Macbeth coefficients in Tables 13 and 14. For each such ESG characteristic, I created both value-weighted and equally weighted high-portfolios, low-portfolios, and spread/long-short portfolios. More specifically, the low-rated "low" portfolios were sold short, and high-rated "high" portfolios bought long when forming the long-short portfolios. I also always formed the portfolios by dividing them into ten deciles and rebalanced the portfolios monthly. Once I had formed the portfolios, I regressed their excess returns on the five monthly Fama-French North American factors from Kenneth French's (2023) database. These five firm factors I did not winsorize or standardize, but I used winsorized excess returns to minimize the possible influence of outlier values on the results. A similar practice has also been used by Cai et al. (2014) when studying the relationship between CSR and stock returns with regressions for equally weighted and value-weighted portfolios. In addition, I conducted all regressions by using the Newey-West (1994) procedure with 12 lags. I also formed the portfolios with non-winsorized excess returns and noted that my initial main results and their levels of significance were robust to winsorization, thus not altering the conclusions of this study.

All these results from the portfolio regressions can be found from Appendix 4, and I discuss them more in detail in Chapter 10.2. From Tables 19-26, it can be noted that the only long-short portfolio with a statistically significant alpha is the value-weighted portfolio sorted by product responsibility score, as the alpha is negative and significant at a 5% level of significance with the Fama-French five-factor regression model. The t-value of a separate t-test on the excess returns of this value-weighted long-short portfolio is also statistically significant and negative at the same level of significance, as can be seen from Table 26. However, this finding of the product responsibility score influencing stock returns negatively opposes my Fama-Macbeth regression result of the product responsibility score influencing the returns positively, as shown in Table 13. By forming the different portfolios, I also discovered weak evidence of the social pillar score and sustainability compensation incentives score influencing stock returns at lower significance levels, but no evidence of the ESG reporting scope influencing stock returns – as can be seen from Table 19 since none of the alphas are statistically significant at any level of significance based on the five-factor regressions on the sorted portfolios.

At a 10% level of significance, both the value-weighted and equally weighted low-rated portfolios formed based on SPS generated positive abnormal excess returns when analyzed with the five-factor model, as can be seen from Table 21. The t-value in Table 22 from a separate t-test of the excess returns of the value-weighted portfolio of low-rated firms based on SPS is also positive and significant at a 5% level of significance. This finding that low-rated portfolios based on SPS generate positive abnormal excess returns is also somewhat in line with my Fama-Macbeth results in Table 14, which suggest that SPS is a negative determinant of stock returns. However, neither the high-rated portfolios nor long-short portfolios sorted by SPS show significant alphas when using the Fama-French (2015) five-factor regressions. Consequently, these results do not suggest that a significant relationship would exist between the social pillar score and stock returns.

From Table 23, it can be noted that at a 10% level of significance, only the equally weighted high-portfolio formed based on sustainability compensation incentive score generated positive abnormal returns with the Fama-French (2015) five-factor model. As a result, the portfolio sorts and five-factor regressions do not support a relationship between the sustainability compensation incentives score and stock returns, as no statistically significant alpha exists for either of the long-short portfolios. Moreover, none of the t-values for the excess returns of the portfolios sorted based on sustainability compensation incentives score are significant in Table 24, further supporting this conclusion.

9 MODEL DIAGNOSTICS

In this chapter, I present and discuss the model diagnostics of the study.

9.1 General model diagnostics

In a similar manner as Green et al. (2017), I also used the Variance Inflation Factor test in my study after winsorization and standardisation of my full data – although the dependent variable I left unstandardized to improve interpretability. As stated by Greene (2011, quoted in Green et al., 2017), the VIF values are used to study how much a specific characteristic is explained by a linear combination of all the other characteristics of the model. In other words, the VIF test measures how strongly a characteristic is related to the other characteristics (Green et al., 2017).

The VIF values for my full set of variables can be found from Table 15 below:

Table 15: VIF values
The VIF values for all variables are presented in this table.

Variable	VIF value
Beta	1.02
Sz	1.95
B/M	1.83
Prof	1.31
Inv	1.25
GPS	1.77
EPS	2.39
SPS	4.23
Environmental Innovation Score	1.63
Supplier ESG training Score	1.08
ESG Reporting Scope	1.98
ESG Controversies Score	1.55
DIR Inclusion Score	1.39
Female on Board	1.55
Climate Change Commercial Risks Opportunities Score	1.23
Policy Data Privacy Score	1.67
DIR Controversies Score	1.49
Product Responsibility Score	1.73
Policy Water Efficiency Score	1.36
Policy Customer Health Safety Score	1.18
Health Safety Policy Score	1.52

Human Rights Score	2.41
Policy Human Rights Score	1.62
Human Rights Contractor Score	1.40
Equal Shareholder Rights Score	1.34
Workforce Score	2.19
Community Score	2.02
Policy Community Involvement Score	1.43
CSR Strategy Score	2.22
Shareholders Score	1.39
Employees Health Safety Team Score	1.25
Renewable Clean Energy Products	1.12
Environmental Assets Under Mgt	1.02
Environmental Products	1.47
Environmental Supply Chain Management	1.25
SDG 5 Gender Equality	1.04
Green Buildings	1.13
Policy Sustainable Packaging	1.11
Sustainability Compensation Incentives Score	1.09
Environmental Partnerships Score	1.14

As mentioned by Green et al. (2017), although multicollinearity does not bias estimated slope coefficients, it still increases their standard errors. To mitigate multicollinearity, Green et al. (2017) removed all variables with VIF values of over 7, and I also follow this approach in my study. However, the highest VIF value among my variables is 4.23 for the variable SPS when rounded to one decimal – indicating that there is no need to remove any variables from my data sample.

Like Green et al. (2017), I also use Newey-West (1994) adjustments of 12 lags in my Fama-Macbeth method and portfolio regressions, to further account for possible heteroskedasticity. I also analyzed the covariance matrices to see that there are not any variables that would be very highly correlated with each other, and I defined this threshold as 0.9. Consequently, I had to remove, for example, the overall ESG score from my initial data set. There were also other ESG variables that I had to remove before even adding them to my initial models for the Fama-Macbeth method or VIF test since they either severely lacked data or were almost perfectly correlated with one or more other variables. The correlation matrix is included in Appendix 2 due to its large size.

The data handling methods and descriptive statistics for the data - that I mentioned in Chapter 7 - are also important to consider when analyzing the model diagnostics and results of my study. Specifically, as the missing variables are set to zero for the missing non-categorical variables and to modes for the categorical variables, it is notable that these processes may bias the results. The same applies to the standardisation and winsorization practices that I use for my data. However, these approaches have also been used by other academics for studies with similar purposes, such as Green et al. (2017), although Green et al. (2017) do not specifically state their approach to handling nulls in categorical variables.

The main goodness-of-fit metrics that I use to compare the Fama-Macbeth model selected by ML methods to the full model are the F-statistic, multiple R-squared and adjusted R-squared. When looking at Table 10 of the summary statistics for the cross-sectional model with all variables, the multiple R-squared is 0.085, adjusted R-squared 0.068, and F-statistic 4.988 with a highly significant p-value. As shown in Table 12, for the cross-sectional regression with variables selected by ML methods, the multiple R-squared is 0.076, adjusted R-squared 0.0705, and F-statistic 14.75 with a highly significant p-value.

When looking at these differing goodness-of-fit values, the cross-sectional model with all variables seems to perform slightly worse than the model selected with ML methods based on the values for adjusted R-squared, but slightly better based on the multiple R-squared values. As the F-statistics for both models are highly significant, they both seem to be good fits for the data based on solely that metric. It is also notable that the F-statistic value for the model selected with ML methods is much higher than that for the full model. However, as the multiple R-squared and adjusted R-squared values are very low for both models, the results also indicate that neither model succeeds to capture much variation of the excess returns. This finding is still common for the method I use, and when analyzing stock return data in general. In Table 17 in Appendix 3, I also report the result for a separate F-test between the models. According to that F-test, the full model seems to perform superiorly over the model selected by ML methods. This finding is still contradictory to the separate F-statistics of each regression. In Table 18 of the Appendix 3, I also report the RMSEs. As the value of RMSE is slightly lower for the full model, this metric also suggests that the full model has better predictive abilities than the model selected by ML methods. To conclude, the results seem to be slightly contradictory on which of the two models is more suitable for my analysis.

Additional model diagnostical test results for the full model can be found from Table 16 in Appendix 3. These tests include the Breusch-Pagan test for heteroskedasticity, Durbin-Watson test for autocorrelation, and Jarque-Bera test for normality. Based on the results for these tests, the full cross-sectional regression model does not show signs of heteroskedasticity but exhibits autocorrelation and non-normality. A possible cause of the non-normality of the data is the poor availability of ESG data, which has also been reported to cause issues in empirical studies in finance by other researchers such as Bonacorsi et al. (2022). As autocorrelation seems to be an issue for my full data, I find it beneficial to use Newey-West (1994) adjustments of 12 lags also to mitigate the possible biases caused by autocorrelation.

10 DISCUSSION OF THE RESULTS

In this section, I first discuss the results obtained with the Fama-Macbeth method and the machine learning methods. Then, I discuss the results from Fama-French five-factor regressions on the portfolios sorted based on the ESG characteristics that had significant Fama-Macbeth coefficients.

10.1 Discussion of the Fama-Macbeth regression results and ML methods

I already discussed model diagnostics in Chapter 9.1, but the main aspects to consider when analyzing the robustness of my results are related to data handling processes and high values of both kurtosis and skewness for some variables: for the non-standardized dependent variable, and for some standardized firm characteristics that do not have significant Fama-Macbeth coefficients, as can be seen from Table 6 in Chapter 7.3. In Chapter 7.2, I also explained the data handling processes in detail. As these processes and features may bias the results, they are important to critically assess, although similar data handling processes have been used by Green et al. (2017) whose order of conducting the Fama-Macbeth method I also follow in this study.

As I have stated earlier, I use the threshold recommended by Harvey et al. (2016) and report the variables with Fama-Macbeth coefficients with absolute t-values of 3.0 or more as significant. From Table 13, it can be observed that the firm characteristics that have statistically significant Fama-Macbeth coefficients with the full model are size, book-to-market ratio, profitability, ESG reporting scope, product responsibility score, and sustainability compensation incentives score. The firm characteristics profitability, size, book-to-market ratio, and social pillar score have significant Fama-Macbeth coefficients in the model selected with ML methods, as can be noted from Table 14. With these models, all significant firm characteristics except the book-to-market ratio, profitability and social pillar score seem to influence stock returns positively. The firm characteristics with the highest Fama-Macbeth coefficients for both models are the non-ESG firm characteristics size, book-to-market ratio, and profitability. Consequently, these non-ESG firm characteristics seem to influence stock returns the most statistically.

I also found evidence of some ESG characteristics influencing stock returns, such as the ESG reporting scope that measures the percentage of the company's activities mentioned in its social and environmental reports (Refinitiv, 2023). The descriptions of the other ESG characteristics with significant Fama-Macbeth coefficients are as following: the sustainability compensation incentives score measures if the senior executives' compensation is linked to CSR/H&S/sustainability targets – and if yes, to what extent (Refinitiv, 2023). Furthermore, the social pillar score measures acts related to social responsibilities of a company. Lastly, the product responsibility score measures aspects related to how well a firm is able to provide responsible goods and services (Refinitiv, 2023). Consequently, my both statistical null hypotheses of no significant Fama-Macbeth coefficients for the Fama-French (2015) factors as firm characteristics and/or the ESG characteristics can be rejected. These results are also linked to the two research questions in Chapter 1.1.

My Fama-Macbeth regression results of the social pillar score influencing stock returns negatively oppose the findings by Halbritter et al. (2015), as they found the score influencing stock returns slightly positively based on the full sample. However, the authors' Fama-Macbeth results were very much dependent on which ESG rating provider they used as data source. My findings also oppose the recent study by Cohen et al. (2023), whose results suggest that lower score on social risk for a firm influences its excess stock returns positively, as the relationship between excess returns and higher social risks seem to be negative. When analyzing over 2000 studies, the conclusion for the SPS by Friede et al. (2015) from their literature review is that the characteristic, at least, does not demonstrate significant superior positive relation to CFP. Although CFP is not directly comparable to stock returns, the findings of Friede et al. (2015) can still be seen as more in line with my results than the results by Halbritter et al. (2015) or Cohen et al. (2023). Ting et al. (2019) also discovered the social pillar score influencing firm value through Tobins' Q-metric positively, which is an interesting discovery although not either directly comparable to my results from the Fama-Macbeth method.

In line with my finding of the ESG reporting scope influencing stock returns positively based on the Fama-Macbeth regression results, Chiu et al. (2020) have discovered that firms that disclose their CSR reports tend to generate higher and positive abnormal mid- to long-term returns than the companies who do not disclose theirs. Additionally, El Ghoul et al. (2011) show that disclosure of CSR activities seems to improve firm value through reduced cost of equity. However, these findings contradict the study by Chen et al. (2018) who found evidence that firms that conduct mandatory CSR reporting in China experience a decrease in profitability after the mandate. De Lucia et al. (2020) also analyze a somewhat relatable firm characteristic to my ESG reporting scope, Number of employees in the CSR reporting, but this variable was not significant in either of their logistic regression results.

One possible reason for the ESG reporting score's seemingly positive influence on stock returns is the extensiveness of the variable as it covers aspects over all three pillars, E, S, and G. The extensiveness of the social pillar score may also be one reason for its significance based on the Fama-Macbeth results with the model selected by ML methods. As mandatory CSR reporting practices are becoming increasingly more common globally, the ESG reporting scope will be an interesting aspect to analyze in future with more available data. Some commonly criticised aspects of socially responsible investing and ESG practices that I discussed in Chapter 2.3.3 may also be related to the possibility of ESG reporting scope influencing stock returns: as an example, ESG reports can be seen as one form of greenwashing - or simply reputation building towards the market and stakeholders, as mentioned by Malik (2015).

My finding of the ESG characteristic product responsibility score having a significant and positive Fama-Macbeth coefficient is in line with the results by Jo and Harjoto (2012) as they discovered evidence of the product-dimension of Kinder, Lydenberg, and Domini's (KLD's) social-rating criteria influencing firm value positively through both Tobin's Q-metric and accounting performance, measured by the ROA. However, these findings oppose the ones by Ting et al. (2019) as they did not find Refinitiv's product responsibility score influencing the performance or valuation of firms significantly. For this same product responsibility score, De Lucia et al. (2020) did neither find any significance for either of the financial indicators ROE or ROA. Additionally, Bonacorsi et al. (2017) did not find any statistically significant relationship between the product safety/quality firm characteristic and companies' credit score.

As Chordia et al. (2017) found all five Fama-French (2015) factors as firm characteristics influencing expected stock returns, the finding of my size, book-to-market ratio, and profitability firm characteristic having significant Fama-Macbeth coefficients in both of my models is in line with their results. Interestingly, my Fama-Macbeth results for the significant non-ESG firm characteristics book-to-market ratio and size have opposing signs to the results by Green et al. (2017): when analyzing their full sample, they found evidence of book-to-market ratio influencing stock returns positively, and size negatively. Furthermore, the book-to-market ratio has been found influencing stock returns positively also by Stattman (1980, cited in Daniel and Titman, 1997), Halbritter et al. (2015), and Rosenberg et al. (1985). The firm size has previously been found influencing stock returns negatively by, for example, Banz (1981), Halbritter et al. (2015), and Fama and French (1992). Moreover, Green et al. (2017) did not find profitability, as measured by operating profitability, influencing stock returns. The findings for these firm characteristics by Green et al. (2017) are otherwise in line with the ones by Chordia et al. (2017), but Chordia et al. (2017) also found evidence of operating profitability influencing stock returns positively, similarly as Ball et al. (2015). These results still oppose mine as I discovered operating profitability influencing stock returns negatively, and the reasons to this may be that I use a sample that is shorter and more recent.

As I stated in Chapter 1, I am also interested to study whether machine learning methods can be utilized to improve model diagnostical aspects and/or to conduct variable selection when analyzing the determinants of stock returns – and especially aspects related to socially responsible investments. Bonacorsi et al. (2022) have shown that ML can be used for variable selection, and that certain ESG sub-factors seem to explain a company's probability of default. In my study, the results do not show any clear evidence that the model selected with ML methods would have performed better than the initial model. When looking at the models' summary statistics, the F-statistic for the model selected by ML methods is higher than the one for the model with all variables, although the F-statistics are highly significant for both models. The full model still seems to perform superiorly over the model selected by ML methods according to a separate F-test between the two models. The value for multiple R-squared is higher for the model with all variables, but the value for adjusted R-squared is higher for the model selected with ML methods. It is still important to note that these R-squared values are all less than 10%, which indicates that neither of the models can properly explain the variation in the excess returns. Lastly, as the value of RMSE is slightly lower for the full model, this result also suggests that the full model has better explanatory capabilities than the other model. To conclude, the values of different model diagnostical metrics show too contradicting results to properly determine which model performed overall superiorly.

Although the model diagnostical metrics do not suggest that the model selected by ML methods would have performed superiorly to the full model, I discovered the social pillar score having a significant and negative Fama-Macbeth coefficient with the model selected by ML methods despite the same coefficient being insignificant with the initial model. As the SPS was also selected by Lasso and PCA as an important variable, these findings may indicate that the model selected with ML methods still has better explanatory power due to decreased probability of issues related to overfitting. Furthermore, I was still able to utilize ML methods for both non-ESG and ESG variable selection. In addition to beta, book-to-market ratio, size, and profitability characteristics had the highest coefficients based on the Lasso regression, and all these three characteristics later had the largest negative or positive Fama-Macbeth coefficients with both models. These findings also support the use of machine learning methods for similar analyses within finance.

10.2 Discussion of the results from portfolio sorts and consequent Fama-French (2015) five-factor regressions

Despite finding statistically significant evidence of several ESG firm characteristics influencing stock returns with the Fama-Macbeth method, the results from the Fama-French five-factor regressions on the excess returns of the sorted portfolios further suggest that a significant relationship exists only between the ESG characteristic product responsibility score and stock returns. The reason to this conclusion is that none of the alphas for the other long-short portfolios were significant, although I still found weaker evidence of the other significant ESG characteristics' influence on stock returns from one or more of the sorted portfolios and consequent five-factor regressions. It is also important to note that as I have tested multiple hypotheses simultaneously, significant results may have emerged by pure chance.

For the value-weighted long-short portfolio sorted by product responsibility score, I discovered a negative alpha at a 5% level of significance, which indicates that the long-short strategy for product responsibility score tends to generate lower returns that what would be expected based on the Fama-French five-factor model. Furthermore, the separate t-test result shown in Table 26 supports this finding as the excess returns seem to differ negatively and significantly from zero. As I stated before, this discovery still opposes my Fama-Macbeth regression results of the product responsibility score influencing excess stock returns positively. Furthermore, these results differ the ones by Kempfh and Oshoff (2007) as the authors did not find any significant evidence from their sorted long-short portfolios on the SRI product indicator influencing stock returns with the Carhart (1997) four-factor model. However, the KLD product indicator that Kempfh and Oshoff (2007) used is somewhat different to Refinitiv's (2023) product responsibility score that I used, which may be one reason for the differing findings.

For social pillar score, my results suggest at a 10% level of significance that both value-weighted and equally weighted low-rated portfolios based on SPS tend to generate positive abnormal returns with the Fama-French five-factor model. The t-value in Table 22 for the value-weighted portfolio of low-rated firms based on SPS is also positive, and significant – indicating that the returns of these low-ranked companies differ significantly and positively from zero. This finding that the low-rated portfolios based on SPS tend to generate positive abnormal returns is also somewhat in line with my Fama-Macbeth results in Table 14, which suggest that SPS influences stock returns negatively. However, neither the high-rated portfolios nor long-short portfolios sorted on social pillar score show significant alphas with the five-factor regressions. Consequently, the portfolio sorts and five-factor regressions do not support a significant relationship between the social pillar score and stock returns. These findings are in accordance with the results by Halbritter et al. (2015), as they neither found social pillar score influencing stock returns significantly based on their long-short market-capitalization weighted and equally weighted portfolios regressed on the Carhart (1997) four-factor model. Moreover, Limkriangkraiet al. (2017) also constructed a long-short portfolio based on the social pillar score but neither discovered a significant alpha with Fama–French–Carhart four-factor model (Fama & French, 1993; Carhart 1997, cited in Limkriangkraiet al., 2017).

At a 10% level of significance, I also discovered the equally weighted high-portfolio formed based on sustainability compensation incentive score generating positive abnormal returns with the Fama-French (2015) five-factor model – although the other portfolios formed based on the score show insignificant alphas with the five-factor model. As I stated previously, this finding is still in line with my Fama-Macbeth results with the initial model, which suggest sustainability compensation incentives score influencing stock returns positively. However, none of the t-values for the returns of the sorted portfolios in Table 24 are significant, decreasing the robustness of these results. Since the alphas for the long-short portfolios sorted based on sustainability compensation incentives score are neither significant, the overall conclusion is that the results from portfolio sorts and consequent five-factor regressions do not support a significant relationship between the score and stock returns. I have also tried to find previous studies on the possible influence of the sustainability compensation incentives score on firm performance or stock returns, but I have not been able to find any. I have neither found any similar previous studies analyzing sorted portfolios based on the ESG reporting scope or sustainability compensation incentives score. As I explained in the previous chapters, there are still notable gaps in the ESG-related financial literature, and especially for the separate ESG firm characteristics.

My overall finding of non-significant alphas for most of the sorted long-short portfolios is in line with some of the previous studies on ESG characteristics: as an example, Van de Velde et al. (2015) studied sorted portfolios based on five ESG sub-scores, and neither found any significant relationship between the scores and stock returns. Researchers such as Gougler and Utz (2020) and Lee et al. (2013) have also criticized that there does not seem to be any significant linkage between the risk-adjusted performance of portfolios and their ESG ratings. Additionally, Lee et al. (2013) did not find a significant alpha for their high-minus-low portfolio on corporate social performance. Pedersen et al. (2021) neither discovered a significant alpha for a long-short portfolio formed based on the total ESG score, and their finding remained the same no matter which asset pricing model, such as the Fama-French five-factor model, they used to study the risk-adjusted returns.

To conclude, despite finding significant Fama-Macbeth coefficients for some ESG firm characteristics as evidence of them influencing the North American excess stock returns statistically, my results seem to lack overall economic significance: the only long-short portfolio alpha that is significant with the Fama-French five-factor regression model is the negative alpha for the value-weighted portfolio sorted based on product responsibility score, although this finding opposes my Fama-Macbeth result of the product responsibility score influencing the stock returns positively. One possibility for the differing results between the long-short strategy for the product responsibility score and the comparable Fama-Macbeth regression result is the value-weighted portfolio formation process in which the weight for each stock depends on the company's market capitalization, whilst all stocks are analyzed as equals in the Fama-Macbeth method.

11 CONCLUSIONS

In this study, my sample consists of 2177 firms, and I analyze 35 ESG variables in addition to five other firm characteristics replicating the factors from the Fama-French (2015) five-factor model. As my method, I follow Green et al. (2017) and conduct Fama-Macbeth (1973) two-pass regressions, for both a model selected with machine learning methods, and for a model with all initial variables. The results of my study suggest that certain ESG characteristics and the non-ESG firm characteristics book-to-market ratio, size, and profitability provided independent information about excess North American stock returns between December 2016 and December 2022. Consequently, I reject the two null hypotheses of no significant Fama-Macbeth coefficients for any of the Fama-French (2015) factors as firm characteristics or for any of the ESG characteristics. These two hypotheses are also linked to my initial research questions presented in Chapter 1.1. I also further assess the economic significance of the results obtained with the Fama-Macbeth method with portfolios sorted based on the significant ESG characteristics, and conduct Fama-French five-factor regressions on the excess returns of these value-weighted and equally weighted portfolios.

Based on the Fama-Macbeth method, the ESG characteristics social pillar score, ESG reporting scope, sustainability compensation incentives score, and product responsibility score tend to influence North American stock returns. My findings are still mixed on their possible influence on stock returns when analyzing the economic significance through value-weighted and equally weighted sorted portfolios on these ESG characteristics: I was able to find further significant evidence of only the product responsibility score influencing stock returns. I still discovered mixed evidence of the sign of this relationship as my Fama-Macbeth regression results suggest a positive relationship, whilst a long-short value-weighted portfolio sorted on the score generated negative abnormal returns with the Fama-French (2015) five-factor model. Consequently, more research on these ESG firm characteristics would be needed to obtain more generalizable and robust results.

In this study, I was also able to utilize the machine learning methods Lasso and PCA for variable selection. However, the results do not directly show evidence that the use of machine learning methods would have led to a model with superior explanatory power. If anything, the results of the statistical tests between the two models in Appendix 3 suggest that the model with all variables has better explanatory power than the model selected by ML methods. The other model diagnostical metrics still show mixed evidence on which model had better explanatory capabilities. Moreover, there are some aspects related to model diagnostics – such as low values of both R squared, and multiple R squared for both of my models – that decrease the robustness and reliability of my results, in addition to using data handling processes due to some missing ESG values.

For future research, other machine learning methods could be utilized in addition to Lasso and PCA to analyze the research questions of this study more in detail. Moreover, adding the firm characteristics that Green et al. (2017) found as significant in their study for their post 2003-period would be an interesting addition for future research. It would also be relevant to conduct other studies of the different ESG characteristics, and especially ones that would additionally account for the differences between industries, in a similar way as Ashwin Kumar et al. (2016) have analyzed the overall ESG performance and stock returns. As the ESG reporting practices and responsibilities for firms are constantly increasing with new legislations, in the future it will likely be possible to analyze even more extensively also the other ESG characteristics that were not included in this study, and to extend the research to also cover other geographical areas.

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APPENDIX 1: STOCKS ANALYZED IN THIS STUDY

Figure 3: Stocks analyzed in this study
This figure shows the stocks analyzed in this study, with Refinitiv (2023) as the source. The firms are represented by their stocks' RIC indicators (n = 2177).

KE.OQ	CLH.N	PSK.TO	INSW.N	FR.N	CRMT.OQ	BLMN.OQ	HIBB.OQ	VRE.N	RH.N	BLPH.OQ	MPWR.OQ
TX.N	CTSH.OQ	ATTO.N	KNX.N	HD.N	BG.N	CRDF.OQ	LGND.OQ	MAC.N	XYL.N	VUZI.OQ	MGPI.OQ
MELI.OQ	COHU.OQ	AVNS.N	GNUS.OQ	HE.N	EBIX.OQ	GOGO.OQ	LMAT.OQ	ELS.N	VAC.N	ATEX.OQ	MLAB.OQ
GPRK.N	COLM.OQ	GDDY.N	LMB.OQ	HL.N	FFIV.OQ	CEMI.OQ	LKQ.OQ	MAN.N	POST.N	XBIT.OQ	MSEX.OQ
CCO.TO	WOLF.N	TOY.TO	MRKR.OQ	HP.N	HAIN.OQ	ALEX.N	MATW.OQ	MAS.N	QUOT.N	NHTC.OQ	TELL.A
ARE.TO	DECK.N	ZD.OQ	SND.OQ	IT.N	HSII.OQ	NGVC.N	RGLD.OQ	MAR.OQ	TGLS.N	NSA.N	MSTR.OQ
CRR_u.TO	XRAY.OQ	JCI.N	BL.OQ	EL.N	DKS.N	SUN.N	RCKY.OQ	MTZ.N	BEP_u.TO	IOVA.OQ	MRTN.OQ
BCE.TO	DIOD.OQ	CYBR.OQ	CRSP.OQ	MU.OQ	GRMN.N	FIVE.OQ	RUSHA.OQ	MAT.OQ	CPRI.N	XELA.OQ	MRCY.OQ
CNR.TO	DLTR.OQ	MDT.N	TUSK.OQ	IP.N	ISRG.OQ	DKL.N	CEVA.OQ	MKC.N	PSX.N	KDNY.OQ	MYGN.OQ
CFP.TO	EBAY.OQ	CCI.N	PHUN.OQ	KR.N	JNPR.N	MANU.N	UPBD.OQ	MCD.N	GLOG_pa.N	NXRT.N	MKSI.OQ
FTT.TO	EME.N	AXTA.N	FLGT.OQ	ES.N	G.N	QLYS.OQ	GIII.OQ	MTH.N	PRGS.OQ	CDTX.OQ	MMLP.OQ
L.TO	KBR.N	VSTO.N	ACIU.OQ	PH.N	NTCT.OQ	AMBA.OQ	GIFI.OQ	MAA.N	ESRT.N	KRNT.OQ	MPAA.OQ
ENB.TO	EXPD.OQ	PFGC.N	EVBG.OQ	MO.N	NVDA.OQ	LFVN.OQ	INSM.OQ	MTD.N	FANG.OQ	BPMC.OQ	MHGU.PK
CTCa.TO	FARM.OQ	WBA.OQ	AIRG.OQ	EXC.OQ	BKNG.OQ	HY.N	IIIN.N	MTX.N	QURE.OQ	MMED.NLB	PLUS.OQ
MRU.TO	FARO.OQ	QSR.N	PTGX.OQ	RL.N	WYNN.OQ	YY.OQ	IMKTA.OQ	ALE.N	VIPS.N	KALV.OQ	SOCGP.PK
IIP_u.TO	FAST.OQ	XHR.N	PAVM.OQ	NX.N	HUN.N	PBYI.OQ	IPAR.OQ	MHK.N	TRU.N	COLL.OQ	ADC.N
SAP.TO	FUL.N	IGT.N	AE.A	SO.N	FSP.A	ATOS.OQ	GOOD.OQ	MSI.N	MATX.N	CHCT.N	AHT.N
BBDb.TO	GNTX.OQ	PGRE.N	ACU.A	PG.N	SNBR.OQ	BFAM.N	BOOM.OQ	MUR.N	PPL.TO	CRBP.OQ	AIN.N
BLX.TO	ROCK.OQ	DEA.N	AGX.N	AAL.OQ	SLAB.OQ	WES.N	GEOS.OQ	NCR.N	ABBV.N	UNIT.OQ	AIR.N
TCLa.TO	GILD.OQ	IRM.N	SVRA.OQ	WY.N	TTWO.OQ	ENTA.OQ	PATK.OQ	NBR.N	WPC.N	BZUN.OQ	AIT.N
AP_u.TO	HWKN.OQ	CC.N	CMT.A	PLD.N	DLHC.OQ	NEO.OQ	BRID.OQ	NFG.N	ETN.N	RAYa.TO	ALX.N
CPG.TO	HOLX.OQ	LIVN.OQ	CQP.A	ABT.N	OLED.OQ	KPT.TO	EMKR.OQ	NOV.N	MPLX.N	EVH.N	AME.N
CGO.TO	JBHT.OQ	LITE.OQ	DLA.A	AKR.N	UTHR.OQ	PRTA.OQ	KIRK.OQ	NYT.N	WCC.N	WING.OQ	AP.N
STN.TO	BIIB.OQ	GSM.OQ	AXDX.OQ	AES.N	CSR.N	SOT_u.TO	ANIP.OQ	NJR.N	ZTS.N	ATXS.OQ	ARL.N
NOVT.OQ	IDXX.OQ	ENR.N	CTO.N	APD.N	PRO.N	TPH.N	LAMR.OQ	JWN.N	DIR_u.TO	SIOX.PK	NSP.N
CFX.TO	INCY.OQ	ZZZ.TO	EVI.A	ANF.N	CRM.N	ARCT.OQ	DSGR.OQ	NEM.N	DOL.TO	APLE.N	ATO.N
NFI.TO	NSIT.OQ	UNH.N	GRC.N	AMD.OQ	HALO.OQ	HOT_u.TO	LCUT.OQ	NSC.N	RHP.N	APPF.OQ	AVA.N
BEI_u.TO	IART.OQ	HPE.N	GEL.N	ALB.N	ACLS.OQ	VTOL.N	JOUT.OQ	NKE.N	RPD.OQ	CFMS.OQ	AVD.N
ATS.TO	INTC.OQ	AGI.TO	GHM.N	ALK.N	BGS.N	ORMP.OQ	KAMN.N	XEL.OQ	ATRA.OQ	FSV.TO	B.N
MFI.TO	INTU.OQ	CCEP.OQ	IRDM.OQ	ALG.N	ENTG.OQ	KEL.TO	ORN.N	NWE.OQ	GBX.N	MCRB.OQ	BBW.N
PAAS.TO	IONS.OQ	H.TO	LCI.N	AEE.N	EXEL.OQ	MODN.N	OFLX.OQ	NUE.N	AMH.N	GNL.N	BCO.N
ELD.TO	ITRI.OQ	AZRE.N	EML.OQ	AEP.OQ	HOFT.OQ	INO_u.TO	SENEA.OQ	IOSP.OQ	SEAS.N	NTRA.OQ	BDC.N
IMO.TO	KLAC.OQ	BBU_u.TO	NOG.N	ARE.N	CVLT.OQ	TXMD.OQ	SGC.OQ	OXY.N	GRT_u.TO	ALPN.OQ	BFS.N
REI_u.TO	KLIC.OQ	FTV.N	NHC.A	AWR.N	PRFT.OQ	BLUE.OQ	SALM.OQ	OII.N	KOS.N	CABO.N	BHE.N
TRI.TO	LRCX.OQ	TRTN.N	EPM.A	AWK.N	ON.OQ	NRC.OQ	LSTR.OQ	OMC.N	DOOR.N	TDOC.N	BKE.N
MTL.TO	LFCR.OQ	SJ.TO	ERNA.OQ	HES.N	CMP.N	TGTX.OQ	NKTR.OQ	OHI.N	KHC.OQ	AQMS.OQ	BKH.N
NVA.TO	LECO.OQ	KMP_u.TO	INO.OQ	APH.N	ALNY.OQ	NBSE.OQ	SAIA.OQ	OKE.N	AHH.N	AVTX.OQ	BRC.N
SNC.TO	LFUS.OQ	OSK.N	KW.N	ABC.N	TNL.N	ESPR.OQ	SLP.OQ	OMI.N	SAIC.N	BW.N	BRT.N
TECK.N	SHOO.OQ	ITT.N	CMCT.OQ	AMT.N	APEI.OQ	NSTG.OQ	LSCC.OQ	PCG.N	LBTYA.OQ	BLD.N	BXC.N
GIBa.TO	MGEE.OQ	WCN.TO	OPK.OQ	ADI.OQ	TXG.TO	CWENa.N	LWAY.OQ	PPG.N	XPRO.N	OOMA.N	BZH.N
TA.TO	MTRX.OQ	ASH.N	PTN.A	ACM.N	BURL.N	LIND.OQ	NEPT.OQ	OC.N	CDE.N	SRG.N	CULP.N
EMA.TO	MGRC.OQ	CAE.TO	ALT.OQ	CF.N	FTNT.OQ	ASC.N	LNW.OQ	OXM.N	ESI.N	VTVT.OQ	CHE.N
EMPa.TO	MMSI.OQ	GOLF.N	TA.OQ	ARCH.N	GWRE.N	FOXF.OQ	NNBR.OQ	PEP.OQ	REXR.N	OLLI.OQ	CIX.A
MG.TO	MSFT.OQ	AA.N	TDS.N	ADM.N	IRWD.OQ	SIRE.N	LPSN.OQ	PFE.N	DRM.TO	PLNT.N	CNK.N
SU.TO	MCHP.OQ	LW.N	SVA.OQ	ATR.N	FN.N	MRTX.OQ	SKYW.OQ	WTRG.N	DOC.N	MCFT.OQ	CNP.N
RCIb.TO	MIDD.OQ	ASIX.N	SEB.A	EPAC.N	BCC.N	IRT.N	OMCL.OQ	PVH.N	CHP_u.TO	AGLE.OQ	CNX.N
IFP.TO	MLKN.OQ	YUMC.N	TCX.OQ	ARW.N	SPSC.OQ	PGEN.OQ	SLGN.N	PNW.N	NWSA.OQ	ZYNE.OQ	CTRA.N
CP.TO	MNRO.OQ	ATZ.TO	UMH.N	AVB.N	PANW.OQ	TNXP.OQ	SATS.OQ	PPC.OQ	WIX.OQ	APR_u.TO	CPE.N
CAS.TO	MOV.N	VVV.N	MUX.N	AZO.N	PTCT.OQ	AXGN.OQ	SBGI.OQ	PBI.N	ALLE.N	GNK.N	CPA.N
AEM.TO	ONTO.N	IQV.N	UTL.N	AVY.N	AAT.N	AAOI.OQ	RDNT.OQ	PCH.OQ	RNW.TO	BNED.N	CPK.N
MRE.TO	NATI.OQ	SBAC.OQ	AAON.OQ	AZZ.N	WDAY.OQ	MUSA.N	SHEN.OQ	PSA.N	OUT.N	IBRX.OQ	CRK.N
WFG.TO	EXLS.OQ	TRMB.OQ	ACAD.OQ	BCPC.OQ	HUBS.N	ISEE.OQ	ORLY.OQ	PNM.N	DELL.N	TRLh.V	CSV.N
HR_u.TO	WBD.OQ	SJW.N	ACOR.OQ	AVT.OQ	NLTX.OQ	REI.A	RGP.OQ	PHM.N	PAGP.OQ	PRPL.OQ	SNDA.N
MRT_u.TO	NTGR.OQ	HBM.TO	ANIK.OQ	ALV.N	AMRS.OQ	RMAX.N	HAYN.OQ	PEG.N	PRGO.N	PEN.N	CATO.N
ERF.TO	VMW.N	ULTA.OQ	ANDE.OQ	ADP.OQ	AMRC.N	VEEV.N	LAKE.OQ	PWR.N	GLOB.N	PDSB.OQ	CTS.N
BB.TO	NTAP.OQ	DXC.N	ALGT.OQ	BMI.N	LXFR.N	RNG.N	MODV.OQ	DGX.N	PINC.OQ	ACRS.OQ	CVI.N
T.TO	NDSN.OQ	FEC.TO	AMSC.OQ	BALL.N	H.N	NVEE.OQ	EYPT.OQ	RPM.N	HLT.N	RGNX.OQ	CW.N
CLS.TO	ASGN.N	BKR.OQ	AMKR.OQ	BAX.N	CNE.TO	VNCE.N	KFRC.OQ	RPT.N	KN.N	SGRY.OQ	CYD.N
CCA.TO	ORCL.N	CSIQ.OQ	AMWD.OQ	BDX.N	TVTX.OQ	MMI.N	SCSC.OQ	RRC.N	SYNH.OQ	SYBX.OQ	DAC.N
D_u.TO	PCAR.OQ	SES.TO	ALOT.OQ	BBY.N	PCG_pa.A	MGNX.OQ	SYNA.OQ	RYN.N	GEO.N	CTMX.OQ	DCO.N
FTS.TO	PZZA.OQ	CNQ.TO	AMSWA.OQ	BXP.N	TCMD.OQ	VCYT.OQ	CNXN.OQ	RRX.N	ENDPQ.PK	NVCR.OQ	DDS.N
CIGI.TO	PTC.OQ	RBBN.OQ	AMOT.OQ	BSX.N	KXS.TO	LGIH.OQ	PETS.OQ	REG.OQ	PNR.N	DSKE.OQ	DK.N
RBA.TO	PTEN.OQ	EVRG.OQ	ANGO.OQ	BYD.N	GKOS.N	PBPB.OQ	ALTO.OQ	RSG.N	WSP.TO	CSWI.OQ	DRQ.N
SSRM.OQ	PAYX.OQ	ST.N	ADES.OQ	BDN.N	HHC.N	ESBA.P	RGEN.OQ	RMD.N	PRTYQ.PK	MSGS.N	DBI.N
BIP.N	PDCO.OQ	AIM.TO	RAMP.N	BWA.N	AR.N	TCS.N	SCVL.OQ	RAD.N	SABR.OQ	PSTG.N	LCII.N
INE.TO	PEGA.OQ	AVGO.OQ	APOG.OQ	EAT.N	UNVR.N	BABA.N	RDI.OQ	RHI.N	WVE.OQ	SITE.N	DY.N
CG.TO	AGYS.OQ	NWN.N	ASTE.OQ	BMY.N	ICPT.OQ	AMC.N	CSII.OQ	ROK.N	VRTV.N	GMS.N	EBS.N
FR.TO	POWI.OQ	WRK.N	ASUR.OQ	CVS.N	HQY.OQ	KPTI.OQ	STRL.OQ	ROG.N	TMST.N	DLTH.OQ	EBF.N
NPI.TO	QCOM.OQ	DXT.TO	ATRI.OQ	CBT.N	EPAM.N	GLPI.OQ	STRS.OQ	ROP.N	KEYS.N	VYGR.OQ	ENZ.N
FM.TO	NXGN.OQ	CI.N	ATRO.OQ	CMS.N	ARMK.N	CRT_u.TO	ITRN.OQ	T.N	BHC.TO	WSC.OQ	EPD.N
LULU.OQ	DORM.OQ	VET.TO	CLDX.OQ	CDNS.OQ	INGN.OQ	VRNS.OQ	IVAC.OQ	SLG.N	VVX.N	TWNK.OQ	EPR.N
CAR_u.TO	REGN.OQ	DIS.N	AVAV.OQ	CWT.N	MEG.TO	SCTL.OQ	POOL.OQ	MRK.N	MSA.N	AXSM.OQ	AUD.N
ALS.TO	ROST.OQ	OTEX.TO	ATHX.OQ	CPB.N	TSLA.OQ	KODK.N	PENN.OQ	SLB.N	MEDP.OQ	FCPT.N	ESE.N
KEY.TO	SM.N	OFIX.OQ	ARTNA.OQ	CAH.N	SPLK.OQ	BHR.N	PDCE.OQ	MATV.N	ANET.N	KURA.OQ	ET.N
TRP.TO	SANM.OQ	PXT.TO	ATEC.OQ	CSL.N	MWA.N	EMWPF.PK	TSAT.OQ	SMG.N	AY.OQ	NMTR.OQ	EVC.N
WPM.TO	HSIC.OQ	TMHC.N	ARLP.OQ	CSX.OQ	META.OQ	ATHM.N	SPNS.OQ	SSP.OQ	QRVO.OQ	RMR.OQ	EXR.N
CSH_u.TO	SCHN.OQ	STE.N	ATNI.OQ	MODG.N	FBIN.N	CARA.OQ	STRA.OQ	SEE.N	GDI.TO	TPHS.A	EXP.N

FNV.TO	SMTC.OQ	GOLD.N	BECN.OQ	CRS.N	CRTO.OQ	CJ.TO	VIRX.OQ	SRE.N	MTY.TO	SCWX.OQ	FC.N
FVI.TO	SHYF.OQ	XRX.OQ	GRBK.N	CAT.N	HR.N	NETI.N	MDGL.OQ	SCI.N	MX.TO	NTNX.OQ	FICO.N
AC.TO	STAA.OQ	TROX.N	BCRX.OQ	CPT.N	ETSY.OQ	EGRX.OQ	MTEM.OQ	SHW.N	NCU.TO	KA.OQ	FOR.N
HLF.N	SBUX.OQ	OI.N	BRKR.OQ	CCL.N	HOUS.N	MBUU.OQ	DWSN.OQ	SSD.N	NWC.TO	OCX.OQ	FRO.N
MLCO.OQ	STLD.OQ	CSTM.N	CAAS.OQ	KMX.N	SFM.OQ	CARM.OQ	TAST.OQ	SPG.N	PBL.TO	NOMD.N	FTK.N
NTES.OQ	SRCL.OQ	OVV.N	BSET.OQ	CHD.N	CHGG.N	RVNC.OQ	LQDT.OQ	SNA.N	PEY.TO	WKHS.OQ	FUN.N
BIDU.OQ	GEN.OQ	FCR_u.TO	CDZI.OQ	CHH.N	BERY.N	FTAI.OQ	STRT.OQ	SON.N	PLC.TO	OTLK.OQ	GCO.N
EDU.N	SNPS.OQ	ODP.OQ	CCOI.OQ	CCF.A	GEVO.OQ	ALDX.OQ	INVA.OQ	LUV.N	POM.TO	GWRS.OQ	GFF.N
WNS.N	TECH.OQ	CZR.OQ	PRDO.OQ	CLX.N	MTLS.OQ	GLYC.OQ	SOHU.OQ	SCCO.N	POU.TO	EDIT.OQ	GGG.N
ICLR.OQ	TTEC.OQ	ALA.TO	BMRN.OQ	GTLS.N	SEDG.OQ	CIO.N	HTLD.OQ	SWN.N	PSI.TO	TRHC.OQ	GLP.N
CHKP.OQ	TTEK.OQ	CSCO.OQ	BLDR.N	CVX.N	TPIC.OQ	IBP.N	TITN.OQ	LSI.N	OBE.TO	CRVS.OQ	GME.N
AER.N	TNC.N	APA.OQ	CPRT.OQ	FIX.N	CPS.N	FPI.N	LXRX.OQ	SMP.N	PZA.TO	SNDX.OQ	GPC.N
QGEN.N	TSCO.OQ	STX.OQ	COKE.OQ	CLF.N	ENOV.N	OGS.N	LYTS.OQ	SWK.N	QBRb.TO	DRIO.OQ	GSL.N
CLB.N	ACIW.OQ	EDV.TO	CRAI.OQ	CMC.N	SRC.N	HRTX.OQ	DDD.N	SCL.N	SRNEQ.PK	AFIIQ.PK	GTN.N
GLNG.OQ	URBN.OQ	ADTN.OQ	CORT.OQ	NNN.N	TDC.N	EIGR.OQ	HLIO.N	SCS.N	RCH.TO	RETA.OQ	GTY.N
FLEX.OQ	VMI.N	TSE.N	DJCO.OQ	CAG.N	KDP.OQ	WATT.OQ	ADEA.OQ	SYK.N	RPI_u.TO	NTLA.OQ	AJRD.N
SIG.N	VECO.OQ	TOU.TO	CONN.OQ	COO.N	MRC.N	TRVN.OQ	TTMI.OQ	SUI.N	PRIM.N	PR.N	HAE.N
DRH.N	VRSN.OQ	PRMW.TO	CRVL.OQ	OFC.N	PM.N	ITCI.OQ	SEEL.OQ	SYY.N	RUS.TO	FWONA.OQ	HEI.N
GPRE.OQ	VSAT.OQ	CVE.TO	DGII.OQ	GLW.N	TNDM.OQ	GCI.N	AXON.OQ	TJX.N	SCL.TO	RRR.OQ	HEP.N
FLR.N	VRTX.OQ	AZPN.OQ	CVGI.OQ	CUZ.N	AGIO.OQ	PCTY.OQ	HSTM.OQ	SKT.N	SEA.TO	NGVT.N	HI.N
CBRE.N	SP.OQ	QDEL.OQ	DISH.OQ	TAP.N	ATVI.OQ	MGNI.OQ	OSIS.OQ	TFX.N	WCP.TO	NRBO.OQ	HOV.N
CUBE.N	LVS.N	DINO.N	CVCO.OQ	BIG.N	ZWS.N	PLXP.OQ	NVMI.OQ	THC.N	SIS.TO	PLSE.OQ	SVC.OQ
HT.N	WLY.N	FRT.N	CVLG.OQ	INGR.N	VRSK.OQ	AKBA.OQ	PSMT.OQ	TEX.N	SOY.TO	TPB.N	HRB.N
LL.N	WWD.OQ	DSG.TO	PTE.OQ	CCK.N	JBT.N	TNET.N	USLM.OQ	TER.OQ	SPB.TO	CLSD.OQ	EQC.N
KOP.N	HELE.OQ	PIF.TO	FONR.OQ	DAR.N	LOPE.OQ	ATEN.N	NVAX.OQ	TXN.OQ	TCS.TO	NH.OQ	HVT.N
DPZ.N	BIO.N	WELL.N	FOSL.OQ	AORT.N	TRUE.OQ	TWOU.OQ	NVEC.OQ	TXT.N	TIH.TO	COE.N	HZO.N
ATRC.OQ	CMCSA.OQ	J.N	FORM.OQ	CMI.N	WK.N	QTWO.N	NWPX.OQ	TMO.N	TOT.TO	GMRE.N	IDT.N
CE.N	FCX.N	TEAM.OQ	EXPE.OQ	DAN.N	TWLO.N	GUD.TO	SRDX.OQ	KAI.N	TWC.TO	SYRS.OQ	IEP.OQ
MDLZ.OQ	TILE.OQ	PKI.TO	FORR.OQ	DHR.N	CLW.N	TEDU.OQ	SSYS.OQ	THO.N	UNS.TO	ATOM.OQ	DIN.N
BLKB.OQ	GEF.N	KIM.N	BELFA.OQ	DRI.N	SELB.OQ	FIVN.OQ	USNA.N	TDW.N	VGCX.TO	PI.OQ	INT.N
POR.N	HUBB.N	PEAK.N	CECO.OQ	DAL.N	USFD.N	ENLC.N	USPH.N	TKR.N	WJX.TO	ELF.N	IPI.N
KRG.N	KBAL.OQ	LIN.N	CMTL.OQ	DTE.N	YNDX.OQ	BLBD.OQ	ACER.OQ	TTC.N	WN.TO	IRTC.OQ	JOE.N
DLB.N	KELYA.OQ	ENV.N	CPSI.OQ	DHI.N	LE.OQ	QTNTQ.PK	NUVA.OQ	DVA.N	WPK.TO	SD.N	KRO.N
TXRH.OQ	MERC.OQ	AOSL.OQ	CRIS.OQ	SITC.N	KMI.N	ARAV.OQ	KVHI.OQ	YUM.N	WTE.TO	CWH.N	KWR.N
WLK.N	MEI.N	CCLP.OQ	CUTR.OQ	DCI.N	NXPI.OQ	ATNM.A	NXST.OQ	WEN.OQ	XTC.TO	ADNT.N	LEE.OQ
LDOS.N	MOGa.N	PLOW.N	CVGW.OQ	DOV.N	CPX.TO	PAYC.N	RICK.OQ	TUP.N	SGY.TO	AMPY.N	LEN.N
HRI.N	AOS.N	EXPR.N	FSTR.OQ	DBD.N	GM.N	SPWH.OQ	FRPH.OQ	TGI.N	PRET.PK	IIPR.N	SR.N
CMG.N	SJM.N	RRTS.PK	GAIA.OQ	DLX.N	PBH.TO	WMS.N	SRPT.OQ	UAL.OQ	REVRQ.PK	ELC.N	LGFa.N
TMUS.OQ	PARA.OQ	CRMD.OQ	DXPE.OQ	EGP.N	LUN.TO	LEJU.N	KTOS.OQ	MRO.N	ATSG.OQ	CORR.N	LNN.N
ALGN.OQ	A.N	HNRG.OQ	CLFD.OQ	EMN.N	PXD.N	PAHC.OQ	HA.OQ	TSN.N	TFII.TO	TWI.N	LTC.N
ABG.N	ACCO.N	LMNR.OQ	CNTY.OQ	DUK.N	ABM.N	TOUR.OQ	SPTN.OQ	UNF.N	ERII.OQ	UAA.N	LXP.N
EXAS.OQ	CRI.N	WEED.TO	FIZZ.OQ	EIX.N	DHX.N	NERV.OQ	UEIC.OQ	UNP.N	NVCN.TO	UBA.N	LYV.N
MMP.N	DEI.N	CLAR.OQ	DXCM.OQ	ECL.N	SPOK.OQ	ASXC.A	PTSI.OQ	UIS.N	AXAS.PK	UFI.N	MDC.N
OIS.N	DLR.N	SIX.N	CNSL.OQ	EMR.N	SPR.N	IMUX.OQ	VLGEA.OQ	UDR.N	PHX.N	UHS.N	MCS.N
QRTEA.OQ	CYH.N	VPG.N	EXPO.OQ	AGR.N	AROC.N	LRMR.OQ	TTGT.OQ	URI.N	USM.N	UHT.N	MDU.N
IPGP.OQ	CMS_pb.N	QUAD.N	ESCA.OQ	ETR.N	CTLT.N	AGRX.OQ	VNDA.OQ	RTX.N	LXU.N	LEU.A	MED.N
ILMN.OQ	IRBT.OQ	ASMB.OQ	CYTK.OQ	EFX.N	UGI.N	CMCM.N	AVNW.OQ	UVV.N	NGS.N	VHI.N	MHO.N
EQIX.OQ	FSLR.OQ	MMYT.OQ	FLXS.OQ	EQT.N	DMRC.OQ	VNOM.OQ	MARK.OQ	SXT.N	LRN.N	VGR.N	MLM.N
RCL.N	TPX.N	HZNP.OQ	IESC.OQ	EQR.N	MD.N	TBPH.OQ	UTMD.OQ	VFC.N	PRTK.OQ	VSH.N	MLP.N
CRL.N	GPK.N	PACB.OQ	FLWS.OQ	ESS.N	AMN.N	CVEO.N	UCTT.OQ	VLO.N	AMRX.N	WMK.N	MLI.N
DOX.OQ	MYRG.OQ	SFUNY.PK	CTRN.OQ	ETD.N	COTY.N	CTRE.N	UFPT.OQ	MTN.N	SGA.OQ	WOR.N	MLR.N
DHC.OQ	THS.N	CHTR.OQ	MANH.OQ	NEE.N	LMT.N	DNOW.N	TRIB.OQ	VVI.N	OPI.OQ	GHC.N	MMS.N
SWBI.OQ	SBH.N	VRA.OQ	HEES.OQ	FMC.N	MMM.N	NEP.N	UFPI.OQ	VTR.N	NATR.OQ	WSO.N	MOD.N
SGEN.OQ	MPW.N	TAL.N	FWRD.OQ	FCN.N	CGX.TO	ARDX.OQ	USAP.OQ	RRGB.OQ	YGYI.PK	WW.OQ	MPX.N
ITGR.N	MOH.N	LAND.OQ	GDEN.OQ	FSS.N	LHX.N	AMPH.OQ	HSKA.OQ	VNO.N	ASPS.OQ	WWE.N	MTW.N
TPR.N	SHO.N	PCYG.OQ	MNST.OQ	FLS.N	MRVL.OQ	GPRO.OQ	TESS.OQ	VMC.N	SEM.N	WWW.N	MYE.N
EA.OQ	TRS.OQ	CMRE.N	EGHT.OQ	FLO.N	SXC.N	OR.TO	TZOO.OQ	WNC.N	IMV.TO	XIN.N	NAT.N
CCRN.OQ	AN.N	PCRX.OQ	CMCO.OQ	GATX.N	MOS.N	VIA.OQ	WINA.OQ	WMT.N	OMER.OQ	SPB.N	NC.N
ELV.N	LH.N	ACRX.OQ	IMAX.N	TGNA.N	ALRM.OQ	CCS.N	ACNT.OQ	WAT.N	MG.N	ACOx.TO	NEU.N
AAP.N	EW.N	UAN.N	EGLE.N	GPS.N	NOW.N	RYAM.N	MNTX.OQ	ELME.N	ADUS.OQ	ACQ.TO	NHI.N
AYI.N	NI.N	SUPN.OQ	ASRT.OQ	GIS.N	BWXT.N	VRDN.OQ	HUBG.OQ	WM.N	DG.N	ADWa.TO	NL.N
TEL.N	VZ.N	IBIO.A	IDCC.OQ	AVNT.N	BOX.N	IRMD.OQ	IAC.OQ	WTS.N	KAR.N	ARX.TO	NLS.N
CNC.N	VC.OQ	LAB.OQ	CWCO.OQ	GLT.N	RUN.OQ	SAGE.OQ	JBSS.OQ	WDC.OQ	ADN.TO	AFN.TO	NM.N
JBLU.OQ	ATI.N	ESTE.N	FCEL.OQ	GVA.N	XNCR.OQ	DBRG.N	TISI.N	WHR.N	TRNO.N	AIF.TO	NPK.N
NPO.N	LNT.OQ	RLJ.N	FELE.OQ	GWW.N	CLDT.N	LOCO.OQ	UHAL.N	WMB.N	GNRC.N	HLS.TO	NR.N
VRNT.OQ	AXL.N	THR.N	DAKT.OQ	GPI.N	AQN.TO	LNTH.OQ	HURN.OQ	WSM.N	MXL.OQ	ATD.TO	NS.N
OSTK.OQ	AWI.N	NGL.N	ACGN.OQ	GES.N	PEB.N	TSQ.N	HURC.OQ	WEC.N	NWH_u.TO	AAV.TO	NRP.N
INFN.OQ	CAL.N	MX.N	VXRT.OQ	HAL.N	GIL.TO	OCUL.OQ	GSIT.OQ	WGO.N	CALX.N	AW_u.TO	NTZ.N
ICFI.OQ	CIR.N	HII.N	NBIX.OQ	HOG.N	JKS.N	TTOO.OQ	VSEC.OQ	ADBE.OQ	SSNC.OQ	AX_u.TO	NUS.N
BKD.N	LUMN.N	FF.N	BBGI.OQ	HSC.N	SIA.TO	MDVL.OQ	INDT.OQ	DENN.OQ	WSR.N	BDGI.TO	NVR.N
XPO.N	ROIC.OQ	FENG.N	BBSI.OQ	HAS.OQ	HPP.N	OTIC.PK	CMPR.OQ	AEIS.OQ	SBRA.OQ	BDT.TO	ODC.N
RUTH.OQ	DVN.N	SAVE.N	OTTR.OQ	EHC.N	TT.N	PARR.N	XOMA.OQ	ALCO.OQ	ET.TO	BIR.TO	OGE.N
HBI.N	EOG.N	ALSN.N	OSUR.OQ	HIW.N	STNG.N	MARA.OQ	WEYS.OQ	SWKS.OQ	EXE.TO	BNE.TO	OLN.N
ORA.N	EPC.N	ZG.OQ	IMMR.OQ	HXL.N	TCN.TO	PRN.TO	ONCT.OQ	AMZN.OQ	PSIX.PK	BOS.TO	OLP.N
CROX.OQ	XOM.N	EFX.TO	ENSG.OQ	HPQ.N	PII.N	ICD.N	WERN.OQ	AMED.OQ	FRU.TO	BPF_u.TO	PAG.N
FOLD.OQ	FDX.N	USAC.N	CASI.OQ	HSY.N	LYB.N	W.N	PDFS.OQ	AMGN.OQ	HLF.TO	BRE.TO	PAA.OQ
CEQP.N	HON.OQ	CIVI.N	CENT.OQ	HNI.N	AL.N	LTRPA.OQ	ULH.OQ	ANSS.OQ	HOLI.OQ	BYD.TO	PBH.N

BR.N	HST.OQ	AMCX.OQ	CHDN.OQ	HRL.N	PD.TO	PLAY.OQ	PGTI.N	AAPL.OQ	HRX.TO	CCLb.TO	TPC.N
PODD.OQ	JACK.OQ	UI.N	DRRX.OQ	HUM.N	BAH.N	CFRX.OQ	OSPN.OQ	AMAT.OQ	ADEN.TO	CSWa.TO	PKE.N
ENS.N	JLL.N	RYI.N	COHR.N	IDA.N	STAG.N	UPLD.OQ	SILC.OQ	ARCB.OQ	KBL.TO	CEU.TO	PAR.N
PDM.N	SAFE.N	CLVSQ.PK	CGNX.OQ	ITW.N	NCLH.N	CALA.PK	SIMO.OQ	ADSK.OQ	TMD.TO	CFW.TO	RES.N
ACN.N	KFY.N	CHEF.OQ	STGW.OQ	IEX.N	TRGP.N	TARA.OQ	SCHL.OQ	BBBY.OQ	IVQu.TO	CHE_u.TO	RGR.N
ZBH.N	LII.N	TLYS.N	MCRI.OQ	IBM.N	INN.N	CHRS.OQ	YORW.OQ	AZTA.OQ	LASa.TO	CIU_pa.TO	RGS.N
X.N	MCK.N	PPTA.TO	CHRW.OQ	IFF.N	HCA.N	BOOT.N	TWIN.OQ	BFb.N	LIF.TO	CJRb.TO	ROL.N
COP.N	NRG.N	MITK.OQ	ICUI.OQ	IPG.N	DOO.TO	NVRO.N	ZBRA.OQ	CDW.OQ	LNF.TO	CJT.TO	REX.N
K.N	NWL.OQ	MTDR.N	ODFL.OQ	IVCRQ.PK	FRPT.OQ	OCGN.OQ	TCRT.OQ	CSGS.OQ	LNR.TO	CMG.TO	RS.N
O.N	PPL.N	BCOV.OQ	POWL.OQ	JBL.N	AGRO.N	SIEN.OQ	ZEUS.OQ	CACI.N	MAG.TO	CR.TO	SAH.N
R.N	PKG.N	FET.N	NCMI.OQ	JNJ.N	D.N	EVFM.PK	DZSI.OQ	CAMP.OQ	MAL.TO	CSU.TO	SAM.N
FL.N	PKI.N	PRLB.N	NATH.OQ	KALU.OQ	MPC.N	BGSF.N	WDFC.OQ	HLX.N	MDF.TO	CGY.TO	SFL.N
F.N	CXW.N	MTSI.OQ	NFLX.OQ	KBH.N	HWM.N	FGEN.OQ	WIRE.OQ	CALM.OQ	MEQ.TO	CU.TO	SGU.N
BA.N	TGT.N	GRPN.OQ	BGFV.OQ	KMT.N	COMM.OQ	EVA.N	ZUMZ.OQ	CASY.OQ	ACB.TO	CUPu.TO	SKY.N
AGCO.N	TREX.N	GNE.N	JJSF.OQ	KMB.N	GOOGL.OQ	LBRDA.OQ	WLFC.OQ	CWST.OQ	MPVD.TO	SRU_u.TO	SKX.N
MTRN.N	TYL.N	CHUY.OQ	NEOG.OQ	KRC.N	ARCO.N	ADMA.OQ	WLDN.OQ	CENX.OQ	MRC.TO	WILD.TO	SNX.N
BC.N	WST.N	ANGI.OQ	HCSG.OQ	KEX.N	BRX.N	SLNO.OQ	VIAV.OQ	CBZ.N	TCI.N	DIIb.TO	SPXC.N
KO.N	UPS.N	PBF.N	HDSN.OQ	KSS.N	VNET.OQ	MOMO.OQ	JAZZ.OQ	CAKE.OQ	TDY.N	EIF.TO	SPH.N
CAR.OQ	WAB.N	TRIP.OQ	HCCI.OQ	TBI.N	GEI.TO	BLCM.OQ	TRNS.OQ	CHS.N	TDG.N	ESI.TO	SRI.N
ED.N	FDP.N	OIG.OQ	MASI.OQ	LZB.N	APTV.N	RCKT.OQ	PLPC.OQ	PLCE.OQ	TG.N	ENGH.TO	SRT.N
DE.N	RIG.N	CSTE.OQ	HCKT.OQ	LEA.N	ATKR.N	NEWR.N	YELL.OQ	CIEN.N	TGH.N	TPL.N	STZ.N
ATGE.N	AKAM.OQ	YELP.N	HIMX.OQ	LEG.N	RARE.OQ	INSE.OQ	PLXS.OQ	CRUS.OQ	TK.N	TR.N	SUP.N
CTA_pa.N	AEO.N	HEAR.OQ	RMBS.OQ	LLY.N	NOC.N	ABEO.OQ	PLAB.OQ	CTAS.OQ	TNK.N	TRC.N	SXI.N
CL.N	THRM.OQ	TARO.N	RMTI.OQ	BBWI.N	ACHC.OQ	SUM.N	PNRG.OQ	TTI.N	TOL.N	TRN.N	SWX.N
M.N	CBRL.OQ	MACK.OQ	RBC.N	LPX.N	OEC.N	CTSO.OQ	MDRX.OQ	PKOH.OQ	GD.N	ASND.OQ	GIC.N
GT.OQ	LNG.A	GMED.N	SRGA.OQ	LOW.N	SLCA.N	UE.N	VTRS.OQ	VICR.OQ	MSM.N	VTLE.N	NVTA.N
GE.N	BJRI.OQ	MRG_u.TO	LANC.OQ	LAD.N	ALKS.OQ	SHAK.N	MNOV.OQ	MGIC.OQ	COST.OQ	SSTK.N	RAIL.OQ
FE.N	CSGP.OQ	FRGI.OQ	RGCO.OQ	MGM.N							

APPENDIX 2: CORRELATION MATRIX

	Beta	Sz	B/M	Profit	Inv	GPS	EPS	SPS	Environmental.Innovation.Score	Supplier.ESG.training.Score	ESG.Reporting.Scope
Beta	1	−0.07	0.07	−0.01	−0.01	0.06	0.08	0.06	0.05	0	0.06
Sz	−0.07	1	−0.62	0.23	0.02	0.11	0.15	0.16	0.05	0.04	0.1
B/M	0.07	−0.62	1	0	−0.2	0.06	0.04	0.03	0.03	−0.01	0.03
Profit	−0.01	0.23	0	1	−0.4	0.09	0.14	0.12	0.07	0.03	0.11
Inv	−0.01	0.02	−0.2	−0.4	1	−0.07	−0.09	−0.08	−0.05	−0.02	−0.07
GPS	0.06	0.11	0.06	0.09	−0.07	1	0.37	0.45	0.18	0.08	0.31
EPS	0.08	0.15	0.04	0.14	−0.09	0.37	1	0.55	0.45	0.17	0.48
SPS	0.06	0.16	0.03	0.12	−0.08	0.45	0.55	1	0.24	0.17	0.38
Environmental.Innovation.Score	0.05	0.05	0.03	0.07	−0.05	0.18	0.45	0.24	1	0.09	0.26
Supplier.ESG.training.Score	0	0.04	−0.01	0.03	−0.02	0.08	0.17	0.17	0.09	1	0.1
ESG.Reporting.Scope	0.06	0.1	0.03	0.11	−0.07	0.31	0.48	0.38	0.26	0.1	1
ESG.Controversies.Score	0.03	0.05	0	0	0	0.32	0.13	0.31	0.07	0.02	0.04
DIR.Inclusion.Score	0.05	0.11	0.02	0.1	−0.06	0.2	0.32	0.33	0.14	0.09	0.26
Female.on.Board	0.07	0.16	0.04	0.13	−0.1	0.45	0.42	0.44	0.21	0.1	0.28
Climate.Change.Commercial.Risks.Opportunities.Score	0.03	0.03	0.03	0.05	−0.03	0.2	0.35	0.22	0.15	0.09	0.2
Policy.Data.Privacy.Score	−0.03	−0.03	−0.04	−0.07	0.04	0.12	−0.09	0.14	−0.03	−0.02	−0.1
DIR.Controversies.Score	0.05	0.12	0.04	0.07	−0.05	0.32	0.24	0.38	0.13	0.06	0.13
Product.Responsibility.Score	0.01	0.09	0.03	0.07	−0.04	0.3	0.26	0.51	0.14	0.08	0.15
Policy.Water.Efficiency.Score	0.01	0.01	0.04	0.05	−0.04	0.16	0.29	0.2	0.17	0.11	0.29
Policy.Customer.Health.Safety.Score	0	0.05	0.02	0.04	−0.02	0.12	0.18	0.23	0.1	0.07	0.12
Health.Safety.Policy.Score	0	−0.02	0.02	−0.05	0.01	0.16	0.09	0.2	0.02	0.02	0.05
Human.Rights.Score	0.05	0.12	0.03	0.11	−0.07	0.26	0.43	0.58	0.17	0.16	0.31
Policy.Human.Rights.Score	0.05	0.06	0.03	0.04	−0.03	0.2	0.32	0.38	0.14	0.11	0.26
Human.Rights.Contractor.Score	0	0.04	0.02	0.03	−0.03	0.14	0.22	0.27	0.11	0.16	0.15
Equal.Shareholder.Rights.Score	0	0.07	−0.03	−0.08	0.04	0.17	0.08	0.2	0.05	−0.01	0.03
Workforce.Score	0.04	0.12	0.02	0.09	−0.06	0.36	0.44	0.68	0.19	0.16	0.32
Community.Score	0.04	0.13	0.03	0.08	−0.07	0.39	0.38	0.63	0.18	0.08	0.26
Policy.Community.Involvement.Score	0.01	0.01	0.03	0	−0.01	0.17	0.16	0.24	0.06	0.03	0.09
CSR.Strategy.Score	0.07	0.14	0.03	0.14	−0.09	0.34	0.53	0.43	0.25	0.11	0.67
Shareholders.Score	0.04	0.08	0.03	0.05	−0.04	0.45	0.22	0.32	0.1	0.04	0.13
Employees.Health.Safety.Team.Score	0.02	0.01	0.02	0.03	−0.02	0.13	0.22	0.2	0.12	0.12	0.2
Renewable.Clean.Energy.Products	0.02	0.03	0.01	0.02	−0.02	0.05	0.17	0.1	0.26	0.04	0.1
Environmental.Assets.Under.Mgt	0.01	0.02	−0.01	0.02	−0.02	0.02	0.04	0.02	0.06	0	0.03
Environmental.Products	0.04	0.05	0.01	0.06	−0.04	0.11	0.32	0.18	0.52	0.07	0.22
Environmental.Supply.Chain.Management	0.04	0.08	0.02	0.06	−0.05	0.14	0.34	0.25	0.15	0.12	0.23
SDG.5.Gender.Equality	0.01	0	0.02	0.05	−0.04	0.03	0.05	0.04	0.02	0.04	0.04
Green.Buildings	0.03	0.08	0	0.06	−0.03	0.12	0.28	0.17	0.11	0.06	0.22
Policy.Sustainable.Packaging	0.03	0.02	0.03	0.04	−0.03	0.1	0.23	0.14	0.13	0.08	0.19
Sustainability.Compensation.Incentives.Score	0.04	0.02	0.02	0.03	−0.03	0.25	0.13	0.12	0.07	0.04	0.1
Environmental.Partnerships.Score	0.05	0.06	0.01	0.06	−0.04	0.13	0.28	0.2	0.15	0.12	0.18

	ESG.Controversies.Score	DIR.Inclusion.Score	Female.on.Board	Climate.Change.Commercial.Risks.Opportunities.Score	Policy.Data.Privacy.Score	DIR.Controversies.Score
Beta	0.03	0.05	0.07	0.03	−0.03	0.05
Sz	0.05	0.11	0.16	0.03	−0.03	0.12
B/M	0	0.02	0.04	0.03	−0.04	0.04
Profit	0	0.1	0.13	0.05	−0.07	0.07
Inv	0	−0.06	−0.1	−0.03	0.04	−0.05
GPS	0.32	0.2	0.45	0.2	0.12	0.32
EPS	0.13	0.32	0.42	0.35	−0.09	0.24
SPS	0.31	0.33	0.44	0.22	0.14	0.38
Environmental.Innovation.Score	0.07	0.14	0.21	0.15	−0.03	0.13
Supplier.ESG.training.Score	0.02	0.09	0.1	0.09	−0.02	0.06
ESG.Reporting.Scope	0.04	0.26	0.28	0.2	−0.1	0.13
ESG.Controversies.Score	1	−0.01	0.22	0.14	0.42	0.29
DIR.Inclusion.Score	−0.01	1	0.27	0.1	−0.17	0.36
Female.on.Board	0.22	0.27	1	0.14	−0.03	0.31
Climate.Change.Commercial.Risks.Opportunities.Score	0.14	0.1	0.14	1	0.1	0.1
Policy.Data.Privacy.Score	0.42	−0.17	−0.03	0.1	1	0.07
DIR.Controversies.Score	0.29	0.36	0.31	0.1	0.07	1
Product.Responsibility.Score	0.31	0.15	0.27	0.14	0.34	0.33
Policy.Water.Efficiency.Score	0.09	0.09	0.09	0.23	0.08	0.08
Policy.Customer.Health.Safety.Score	0.05	0.09	0.11	0.08	0	0.1
Health.Safety.Policy.Score	0.28	−0.03	0.05	0.19	0.36	0.15
Human.Rights.Score	0.08	0.25	0.3	0.15	−0.08	0.15
Policy.Human.Rights.Score	0.07	0.16	0.19	0.18	0.01	0.1
Human.Rights.Contractor.Score	0.09	0.08	0.12	0.15	0.1	0.07
Equal.Shareholder.Rights.Score	0.37	−0.06	0.16	0.04	0.33	0.14
Workforce.Score	0.27	0.31	0.32	0.2	0.14	0.3
Community.Score	0.32	0.2	0.36	0.21	0.19	0.35
Policy.Community.Involvement.Score	0.2	0.08	0.12	0.18	0.19	0.25
CSR.Strategy.Score	0.04	0.32	0.35	0.18	−0.13	0.16
Shareholders.Score	0.33	0.12	0.26	0.11	0.2	0.24
Employees.Health.Safety.Team.Score	0.09	0.09	0.08	0.22	0.07	0.09
Renewable.Clean.Energy.Products	−0.01	0.06	0.07	0.02	−0.05	0.03
Environmental.Assets.Under.Mgt	0	0.03	0.04	0.01	−0.03	0.01
Environmental.Products	−0.02	0.13	0.14	0.1	−0.09	0.07
Environmental.Supply.Chain.Management	−0.02	0.18	0.18	0.11	−0.13	0.08
SDG.5.Gender.Equality	−0.01	0.05	0.03	0.01	0	−0.04
Green.Buildings	−0.01	0.15	0.13	0.1	−0.09	0.04
Policy.Sustainable.Packaging	−0.03	0.08	0.11	0.1	−0.07	0.01
Sustainability.Compensation.Incentives.Score	0.04	0.09	0.11	0.06	−0.04	0.06
Environmental.Partnerships.Score	0.03	0.17	0.14	0.15	−0.06	0.13

	Product.Responsibility.Score	Policy.Water.Efficiency.Score	Policy.Customer.Health.Safety.Score	Health.Safety.Policy.Score	Human.Rights.Score
Beta	0.01	0.01	0	0	0.05
Sz	0.09	0.01	0.05	−0.02	0.12
B/M	0.03	0.04	0.02	0.02	0.03
Profit	0.07	0.05	0.04	−0.05	0.11
Inv	−0.04	−0.04	−0.02	0.01	−0.07
GPS	0.3	0.16	0.12	0.16	0.26
EPS	0.26	0.29	0.18	0.09	0.43
SPS	0.51	0.2	0.23	0.2	0.58
Environmental.Innovation.Score	0.14	0.17	0.1	0.02	0.17
Supplier.ESG.training.Score	0.08	0.11	0.07	0.02	0.16
ESG.Reporting.Scope	0.15	0.29	0.12	0.05	0.31
ESG.Controversies.Score	0.31	0.09	0.05	0.28	0.08
DIR.Inclusion.Score	0.15	0.09	0.09	−0.03	0.25
Female.on.Board	0.27	0.09	0.11	0.05	0.3
Climate.Change.Commercial.Risks.Opportunities.Score	0.14	0.23	0.08	0.19	0.15
Policy.Data.Privacy.Score	0.34	0.08	0	0.36	−0.08
DIR.Controversies.Score	0.33	0.08	0.1	0.15	0.15
Product.Responsibility.Score	1	0.11	0.32	0.2	0.17
Policy.Water.Efficiency.Score	0.11	1	0.14	0.25	0.17
Policy.Customer.Health.Safety.Score	0.32	0.14	1	0.07	0.15
Health.Safety.Policy.Score	0.2	0.25	0.07	1	0.08
Human.Rights.Score	0.17	0.17	0.15	0.08	1
Policy.Human.Rights.Score	0.14	0.25	0.11	0.14	0.59
Human.Rights.Contractor.Score	0.14	0.26	0.16	0.23	0.41
Equal.Shareholder.Rights.Score	0.18	0.02	−0.02	0.22	0.03
Workforce.Score	0.38	0.21	0.16	0.3	0.31
Community.Score	0.36	0.2	0.15	0.25	0.26
Policy.Community.Involvement.Score	0.23	0.29	0.14	0.38	0.08
CSR.Strategy.Score	0.19	0.21	0.14	0	0.38
Shareholders.Score	0.28	0.09	0.09	0.17	0.14
Employees.Health.Safety.Team.Score	0.14	0.29	0.14	0.27	0.15
Renewable.Clean.Energy.Products	0.03	0.03	0.03	−0.03	0.09
Environmental.Assets.Under.Mgt	0	0.01	0.01	−0.01	0.03
Environmental.Products	0.08	0.11	0.1	−0.04	0.17
Environmental.Supply.Chain.Management	0.08	0.14	0.09	−0.01	0.32
SDG.5.Gender.Equality	0.02	0.02	0.04	0.01	0.05
Green.Buildings	0.06	0.15	0.05	0.03	0.16
Policy.Sustainable.Packaging	0.07	0.14	0.11	−0.03	0.13
Sustainability.Compensation.Incentives.Score	0.05	0.04	0.03	−0.01	0.11
Environmental.Partnerships.Score	0.11	0.15	0.14	0.02	0.17

	Policy.Human.Rights.Score	Human.Rights.Contractor.Score	Equal.Shareholder.Rights.Score	Workforce.Score	Community.Score	Policy.Community.Involvement.Score
Beta	0.05	0	0	0.04	0.04	0.01
Sz	0.06	0.04	0.07	0.12	0.13	0.01
B/M	0.03	0.02	−0.03	0.02	0.03	0.03
Profit	0.04	0.03	−0.08	0.09	0.08	0
Inv	−0.03	−0.03	0.04	−0.06	−0.07	−0.01
GPS	0.2	0.14	0.17	0.36	0.39	0.17
EPS	0.32	0.22	0.08	0.44	0.38	0.16
SPS	0.38	0.27	0.2	0.68	0.63	0.24
Environmental.Innovation.Score	0.14	0.11	0.05	0.19	0.18	0.06
Supplier.ESG.training.Score	0.11	0.16	−0.01	0.16	0.08	0.03
ESG.Reporting.Scope	0.26	0.15	0.03	0.32	0.26	0.09
ESG.Controversies.Score	0.07	0.09	0.37	0.27	0.32	0.2
DIR.Inclusion.Score	0.16	0.08	−0.06	0.31	0.2	0.08
Female.on.Board	0.19	0.12	0.16	0.32	0.36	0.12
Climate.Change.Commercial.Risks.Opportunities.Score	0.18	0.15	0.04	0.2	0.21	0.18
Policy.Data.Privacy.Score	0.01	0.1	0.33	0.14	0.19	0.19
DIR.Controversies.Score	0.1	0.07	0.14	0.3	0.35	0.25
Product.Responsibility.Score	0.14	0.14	0.18	0.38	0.36	0.23
Policy.Water.Efficiency.Score	0.25	0.26	0.02	0.21	0.2	0.29
Policy.Customer.Health.Safety.Score	0.11	0.16	−0.02	0.16	0.15	0.14
Health.Safety.Policy.Score	0.14	0.23	0.22	0.3	0.25	0.38
Human.Rights.Score	0.59	0.41	0.03	0.31	0.26	0.08
Policy.Human.Rights.Score	1	0.32	0.04	0.23	0.21	0.13
Human.Rights.Contractor.Score	0.32	1	0.01	0.19	0.19	0.18
Equal.Shareholder.Rights.Score	0.04	0.01	1	0.18	0.26	0.07
Workforce.Score	0.23	0.19	0.18	1	0.46	0.24
Community.Score	0.21	0.19	0.26	0.46	1	0.38
Policy.Community.Involvement.Score	0.13	0.18	0.07	0.24	0.38	1
CSR.Strategy.Score	0.28	0.15	0.04	0.37	0.29	0.07
Shareholders.Score	0.11	0.09	0.23	0.3	0.31	0.14
Employees.Health.Safety.Team.Score	0.2	0.2	0.03	0.28	0.17	0.22
Renewable.Clean.Energy.Products	0.07	0.06	−0.02	0.08	0.06	−0.01
Environmental.Assets.Under.Mgt	0.03	0.03	−0.02	0.02	0.01	−0.03
Environmental.Products	0.13	0.08	−0.04	0.14	0.1	0.01
Environmental.Supply.Chain.Management	0.22	0.26	−0.06	0.18	0.13	0.02
SDG.5.Gender.Equality	0.03	0.05	−0.11	0.04	0.01	0.01
Green.Buildings	0.14	0.08	−0.03	0.14	0.13	0.06
Policy.Sustainable.Packaging	0.09	0.02	−0.03	0.13	0.08	0.01
Sustainability.Compensation.Incentives.Score	0.07	0.04	−0.01	0.08	0.07	0.03
Environmental.Partnerships.Score	0.12	0.09	−0.03	0.19	0.15	0.13

	CSR.Strategy.Score	Shareholders.Score	Employees.Health.Safety.Team.Score	Renewable.Clean.Energy.Products	Environmental.Assets.Under.Mgt
Beta	0.07	0.04	0.02	0.02	0.01
Sz	0.14	0.08	0.01	0.03	0.02
B/M	0.03	0.03	0.02	0.01	−0.01
Profit	0.14	0.05	0.03	0.02	0.02
Inv	−0.09	−0.04	−0.02	−0.02	−0.02
GPS	0.34	0.45	0.13	0.05	0.02
EPS	0.53	0.22	0.22	0.17	0.04
SPS	0.43	0.32	0.2	0.1	0.02
Environmental.Innovation.Score	0.25	0.1	0.12	0.26	0.06
Supplier.ESG.training.Score	0.11	0.04	0.12	0.04	0
ESG.Reporting.Scope	0.67	0.13	0.2	0.1	0.03
ESG.Controversies.Score	0.04	0.33	0.09	−0.01	0
DIR.Inclusion.Score	0.32	0.12	0.09	0.06	0.03
Female.on.Board	0.35	0.26	0.08	0.07	0.04
Climate.Change.Commercial.Risks.Opportunities.Score	0.18	0.11	0.22	0.02	0.01
Policy.Data.Privacy.Score	−0.13	0.2	0.07	−0.05	−0.03
DIR.Controversies.Score	0.16	0.24	0.09	0.03	0.01
Product.Responsibility.Score	0.19	0.28	0.14	0.03	0
Policy.Water.Efficiency.Score	0.21	0.09	0.29	0.03	0.01
Policy.Customer.Health.Safety.Score	0.14	0.09	0.14	0.03	0.01
Health.Safety.Policy.Score	0	0.17	0.27	−0.03	−0.01
Human.Rights.Score	0.38	0.14	0.15	0.09	0.03
Policy.Human.Rights.Score	0.28	0.11	0.2	0.07	0.03
Human.Rights.Contractor.Score	0.15	0.09	0.2	0.06	0.03
Equal.Shareholder.Rights.Score	0.04	0.23	0.03	−0.02	−0.02
Workforce.Score	0.37	0.3	0.28	0.08	0.02
Community.Score	0.29	0.31	0.17	0.06	0.01
Policy.Community.Involvement.Score	0.07	0.14	0.22	−0.01	−0.03
CSR.Strategy.Score	1	0.17	0.2	0.1	0.04
Shareholders.Score	0.17	1	0.08	0.03	0
Employees.Health.Safety.Team.Score	0.2	0.08	1	0.04	0
Renewable.Clean.Energy.Products	0.1	0.03	0.04	1	0.12
Environmental.Assets.Under.Mgt	0.04	0	0	0.12	1
Environmental.Products	0.22	0.05	0.11	0.24	0.04
Environmental.Supply.Chain.Management	0.26	0.05	0.1	0.09	0.03
SDG.5.Gender.Equality	0.06	0.04	0.03	0.02	0.01
Green.Buildings	0.24	0.05	0.09	0.06	0.03
Policy.Sustainable.Packaging	0.2	0.04	0.09	0.03	0
Sustainability.Compensation.Incentives.Score	0.11	0.04	0.01	0.03	0.02
Environmental.Partnerships.Score	0.23	0.08	0.12	0.06	0.05

	Environmental.Products	Environmental.Supply.Chain.Management	SDG.5.Gender.Equality	Green.Buildings	Policy.Sustainable.Packaging
Beta	0.04	0.04	0.01	0.03	0.03
Sz	0.05	0.08	0	0.08	0.02
B/M	0.01	0.02	0.02	0	0.03
Profit	0.06	0.06	0.05	0.06	0.04
Inv	−0.04	−0.05	−0.04	−0.03	−0.03
GPS	0.11	0.14	0.03	0.12	0.1
EPS	0.32	0.34	0.05	0.28	0.23
SPS	0.18	0.25	0.04	0.17	0.14
Environmental.Innovation.Score	0.52	0.15	0.02	0.11	0.13
Supplier.ESG.training.Score	0.07	0.12	0.04	0.06	0.08
ESG.Reporting.Scope	0.22	0.23	0.04	0.22	0.19
ESG.Controversies.Score	−0.02	−0.02	−0.01	−0.01	−0.03
DIR.Inclusion.Score	0.13	0.18	0.05	0.15	0.08
Female.on.Board	0.14	0.18	0.03	0.13	0.11
Climate.Change.Commercial.Risks.Opportunities.Score	0.1	0.11	0.01	0.1	0.1
Policy.Data.Privacy.Score	−0.09	−0.13	0	−0.09	−0.07
DIR.Controversies.Score	0.07	0.08	−0.04	0.04	0.01
Product.Responsibility.Score	0.08	0.08	0.02	0.06	0.07
Policy.Water.Efficiency.Score	0.11	0.14	0.02	0.15	0.14
Policy.Customer.Health.Safety.Score	0.1	0.09	0.04	0.05	0.11
Health.Safety.Policy.Score	−0.04	−0.01	0.01	0.03	−0.03
Human.Rights.Score	0.17	0.32	0.05	0.16	0.13
Policy.Human.Rights.Score	0.13	0.22	0.03	0.14	0.09
Human.Rights.Contractor.Score	0.08	0.26	0.05	0.08	0.02
Equal.Shareholder.Rights.Score	−0.04	−0.06	−0.11	−0.03	−0.03
Workforce.Score	0.14	0.18	0.04	0.14	0.13
Community.Score	0.1	0.13	0.01	0.13	0.08
Policy.Community.Involvement.Score	0.01	0.02	0.01	0.06	0.01
CSR.Strategy.Score	0.22	0.26	0.06	0.24	0.2
Shareholders.Score	0.05	0.05	0.04	0.05	0.04
Employees.Health.Safety.Team.Score	0.11	0.1	0.03	0.09	0.09
Renewable.Clean.Energy.Products	0.24	0.09	0.02	0.06	0.03
Environmental.Assets.Under.Mgt	0.04	0.03	0.01	0.03	0
Environmental.Products	1	0.17	0.04	0.15	0.16
Environmental.Supply.Chain.Management	0.17	1	0.05	0.15	0.15
SDG.5.Gender.Equality	0.04	0.05	1	0.06	0.07
Green.Buildings	0.15	0.15	0.06	1	0.11
Policy.Sustainable.Packaging	0.16	0.15	0.07	0.11	1
Sustainability.Compensation.Incentives.Score	0.05	0.08	0.02	0.05	0.05
Environmental.Partnerships.Score	0.13	0.16	0.04	0.11	0.13

	Sustainability.Compensation.Incentives.Score	Environmental.Partnerships.Score
Beta	0.04	0.05
Sz	0.02	0.06
B/M	0.02	0.01
Profit	0.03	0.06
Inv	−0.03	−0.04
GPS	0.25	0.13
EPS	0.13	0.28
SPS	0.12	0.2
Environmental.Innovation.Score	0.07	0.15
Supplier.ESG.training.Score	0.04	0.12
ESG.Reporting.Scope	0.1	0.18
ESG.Controversies.Score	0.04	0.03
DIR.Inclusion.Score	0.09	0.17
Female.on.Board	0.11	0.14
Climate.Change.Commercial.Risks.Opportunities.Score	0.06	0.15
Policy.Data.Privacy.Score	−0.04	−0.06
DIR.Controversies.Score	0.06	0.13
Product.Responsibility.Score	0.05	0.11
Policy.Water.Efficiency.Score	0.04	0.15
Policy.Customer.Health.Safety.Score	0.03	0.14
Health.Safety.Policy.Score	−0.01	0.02
Human.Rights.Score	0.11	0.17
Policy.Human.Rights.Score	0.07	0.12
Human.Rights.Contractor.Score	0.04	0.09
Equal.Shareholder.Rights.Score	−0.01	−0.03
Workforce.Score	0.08	0.19
Community.Score	0.07	0.15
Policy.Community.Involvement.Score	0.03	0.13
CSR.Strategy.Score	0.11	0.23
Shareholders.Score	0.04	0.08
Employees.Health.Safety.Team.Score	0.01	0.12
Renewable.Clean.Energy.Products	0.03	0.06
Environmental.Assets.Under.Mgt	0.02	0.05
Environmental.Products	0.05	0.13
Environmental.Supply.Chain.Management	0.08	0.16
SDG.5.Gender.Equality	0.02	0.04
Green.Buildings	0.05	0.11
Policy.Sustainable.Packaging	0.05	0.13
Sustainability.Compensation.Incentives.Score	1	0.03
Environmental.Partnerships.Score	0.03	1

The correlation matrix above is presented in sections due to its large size. All variables have been winsorized and standardized expect the dependent variable as it has only been winsorized.

APPENDIX 3: RESULTS OF ADDITIONAL MODEL DIAGNOSTICS TESTS

For the tests for which the results are shown in this appendix, the excess returns were winsorized but not standardized. All other variables were both winsorized and standardized at 0.1% and 99.9%. Moreover, the tests for which results are shown in Table 16 were conducted by using the initial model with all variables.

Table 16: Tests on the assumptions for OLS
The results of the tests on the assumptions for OLS are shown in this table. Significance codes are 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Test	Value	Interpretation of the result
Breusch-Pagan	54.244	The full model does not exhibit heteroskedasticity
Durbin-Watson	2.0448***	The full model exhibits autocorrelation
Jarque-Bera	20682056673***	The full model exhibits non-normality

Table 17: F-test between the cross-sectional regression model selected by ML methods and the full cross-sectional model with all variables
This table shows the results of an F-test between the cross-sectional regression model selected by ML methods and the full model with all variables. Significance codes are 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

MODEL	RSS	SUM OF SQ	F-STATISTIC
1. SELECTED BY ML	4987.1		
2. FULL MODEL	4985.4	1.77	2.0125**

Table 18: RMSEs between the two models
This table presents the RMSEs, for the model selected by ML methods and for the full model with all variables.

Model	*RMSE*
1. Selected by ML	0.1771476
2. Full model	0.1771162

APPENDIX 4: REGRESSIONS ON VALUE-WEIGHTED AND EQUALLY WEIGHTED SORTED PORTFOLIOS

In the Fama-French five-factor regressions on sorted portfolios, for which the results are presented in this appendix, the factors from Kenneth French's (2023) database were not winsorized or standardized, and excess returns were winsorized but not standardized. Moreover, for the five-factor regression results, the t-values are reported in parentheses below the coefficient estimates.

Table 19: Regression results for portfolios formed based on ESG reporting scope
The regression results for portfolios formed based on ESG reporting scope are shown in this table. The coefficient estimates are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

ESG reporting scope, Fama-French (2015) five-factor model regression results

Value-weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.0017327 (0.7529)	1.0207878 (9.1648)***	-0.3232953 (-3.1396)**	-0.1283646 (-1.4249)	0.0230605 (0.1827)	0.0527876 (0.2260)
High-rated	0.0047146 (1.2151)	1.2284890 (5.7985)***	0.2364034 (1.8685).	-0.6421383 (-3.3627)**	-0.3056775 (-1.8163).	0.7305247 (2.3785)*
Long-short	0.0029819 (0.7685)	0.2077012 (0.9804)	0.5596987 (4.4238)***	-0.5137737 (-2.6905)**	-0.3287380 (-1.9534).	0.6777371 (2.2066)*
Equally weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.0013272 (1.2890)	1.0767354*** (26.1223)	0.7071293*** (11.7196)	0.0767836 (1.1532)	0.0458395 (0.4541)	0.2102532** (2.8603)
High-rated	0.0014291 (0.9185)	1.0059639*** (41.8322)	0.7438720*** (9.9343)	0.1727640** (2.9590)	0.1009790 (1.6404)	-0.0255957 (-0.5218)
Long-short	0.00010185 (0.1179)	-0.07077142* (-2.3828)	0.03674270 (0.6013)	0.09598043** (2.9514)	0.05513949 (0.8846)	-0.23584897*** (-3.6260)

Table 20: T-test results for portfolios formed based on ESG reporting scope
This table shows the t-test results for portfolios formed based on ESG reporting scope. The excess returns are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

ESG reporting scope, t-test results

Equally weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0096	1.2753
High-rated	0.0085	1.1718
Long-short	-0.0011	-0.8141
Value-weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0121	1.8457.
High-rated	0.0170	2.0454*
Long-short	0.0049	0.9227

Table 21: Regression results for portfolios formed based on social pillar score

The regression results for portfolios formed based on social pillar score are shown in this table. The coefficient estimates are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Social pillar score, Fama-French (2015) five-factor model regression results

Equally weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.0037791 (1.6975).	1.0001273 (21.2131)***	0.6868868 (8.3478)***	-0.0048264 (-0.0997)	0.0384297 (0.6074)	0.1810194 (2.5319)*
High-rated	0.0019172 (0.8976)	1.0917609 (19.0763)***	1.0193532 (15.7643)***	0.0798356 (0.9361)	-0.0630081 (-0.6149)	0.1100904 (0.9176)
Long-short	-0.0018618 (-0.5428)	0.0916336 (1.2479)	0.3324664 (3.0974)**	0.0846620 (0.9549)	-0.1014378 (-1.0989)	-0.0709289 (-0.4701)
Value-weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.0030450 (1.7654).	0.8913582 (19.6146)***	-0.0480491 (-0.5741)	0.1058230 (0.8885)	0.3155121 (2.6432)*	0.1603098 (0.8136)
High-rated	0.00060997 (0.1466)	1.03177507 (12.3537)***	0.24995740 (1.5558)	0.16522210 (1.1384)	0.00467914 (0.0192)	-0.20163050 (-1.1174)
Long-short	-0.0024350 (-0.5852)	0.1404169 (1.6813).	0.2980065 (1.8549).	0.0593991 (0.4093)	-0.3108330 (-1.2743)	-0.3619403 (-2.0057)*

Table 22: T-test results for portfolios formed based on social pillar score
This table shows the t-test results for portfolios formed based on social pillar score. The excess returns are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Social pillar score, t-test results

Value-weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0125	2.1497*
High-rated	0.0081	1.1293
Long-short	-0.0043	-1.0104
Equally weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0116	1.6340
High-rated	0.0088	1.0683
Long-short	-0.0027	-0.9509

Table 23: Regression results for portfolios formed based on sustainability compensation incentives score
The regression results for portfolios formed based sustainability compensation incentives score are presented in this table. The coefficient estimates are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Sustainability compensation incentives score, Fama-French (2015) five-factor model regression results:

Equally weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.00072115 (0.8782)	1.06649909 (30.9276)***	0.75279479 (9.4409)***	0.17634547 (2.4986)*	0.17740328 (2.3161)*	0.24570266 (2.4083)*

	Alpha	Mkt-rf	SMB	HML	RMW	CMA
High-rated	0.0033056 (1.8404).	1.0886391 (27.2984)***	0.7702850 (7.5365)***	0.1360721 (2.1347)*	0.0621591 (0.5601)	0.1959388 (2.3672)*
Long-short	0.0025845 (1.6203)	0.0221400 (0.7829)	0.0174903 (0.2506)	-0.0402734 (-0.9533)	-0.1152442 (-2.0326)*	-0.0497639 (-0.6604)
Value-weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	-0.00087249 (-1.0213)	0.87861637 (20.2694)***	-0.20163190 (-1.8032).	0.09229816 (0.9283)	0.22323054 (3.0433)**	0.10098030 (0.7823)
High-rated	0.00012743 (0.0491)	0.93281614 (17.8253)***	0.07274492 (0.3800)	0.11067958 (0.8427)	0.09484364 (0.7615)	0.16820971 (0.7963)
Long-short	0.00099992 (0.3855)	0.05419977 (1.0357)	0.27437682 (1.4333)	0.01838141 (0.1400)	-0.12838690 (-1.0309)	0.06722942 (0.3183)

Table 24: T-test results for portfolios formed based on sustainability compensation incentives score

This table shows the t-test results for portfolios formed based on sustainability compensation incentives score. The excess returns are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Sustainability compensation incentives score, t-test results

Value-weighted	Excess return (mean)	T-value
Low-rated	0.0083	1.5388
High-rated	0.0086	1.4592
Long-short	0.0003	0.1157
Equally weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0092	1.1988
High-rated	0.0114	1.4674
Long-short	0.0022	1.4110

Table 25: Regression results for portfolios formed based on product responsibility score

The regression results for portfolios formed based on product responsibility score are shown in this table. The coefficient estimates are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Product responsibility score, Fama-French (2015) five-factor model regression results

Equally weighted	Alpha	Mkt-rf	SMB	HML	RMW	CMA
Low-rated	0.0035613 (1.4734)	0.9984837 (16.1669)***	0.8438975 (10.8303)***	0.1110965 (1.5125)	0.1343186 (3.5207)***	0.0948100 (1.0520)
High-rated	0.0016548 (1.2271)	1.0552193 (28.0378)***	0.9971377 (12.4009)***	0.1101968 (2.1997)*	-0.0036319 (-0.0341)	-0.0019956 (-0.0298)
Long-short	-0.00190652 (-0.8202)	0.05673558 (0.7147)	0.15324018 (1.3271)	-0.00089975 (-0.0112)	-0.13795049 (-1.1460)	-0.09680559 (-0.6691)
Value-weighted	**Alpha**	**Mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**
Low-rated	0.0044236 (1.5174)	0.8961144 (20.0936)***	0.0048595 (0.0681)	0.0601383 (0.4204)	0.1945508 (1.1572)	0.0103770 (0.0526)

High-rated	-0.0034832 (-0.9991)	0.8898209 (19.1736)***	0.3110369 (3.8495)***	0.0692010 (0.6027)	0.4059456 (2.1023)*	0.1234411 (0.6203)
Long-short	-0.0079068 (-2.2679)*	-0.0062935 (-0.1356)	0.3061774 (3.7893)***	0.0090626 (0.0789)	0.2113948 (1.0947)	0.1130640 (0.5681)

Table 26: T-test results for portfolios formed based on product responsibility score
This table shows the t-test results for portfolios formed based on product responsibility score. The excess returns are as decimals, and the significance codes of t-values are: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Product responsibility score, t-test results

Value-weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0130	2.1534*
High-rated	0.0055	0.8986
Long-short	-0.0076	-2.6157*
Equally weighted	**Excess return (mean)**	**T-value**
Low-rated	0.0109	1.4688
High-rated	0.0083	1.0275
Long-short	-0.0026	-1.1844

APPENDIX 5: ESG VARIABLES USED IN THIS STUDY

Figure 4: ESG variables used in this study
This figure presents the ESG variables used in this study, in a table format. The source for the references and direct citations is Refinitiv (2023).

Variable	Explanation
Governance pillar score	The governance pillar score is the G score of total ESG score.
Environmental pillar score	The environmental pillar score is the E pillar score of total ESG score.
Social pillar score	The social pillar score is the S pillar score of total ESG score.
Environmental Innovation Score	The Environmental innovation score measures the firm's *"capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products"*.
Supplier ESG training Score	Score on whether - and if yes, how profoundly - the company provides training of ESG aspects for its suppliers.
ESG Reporting Scope	Measures the percentage of the company's activities that are covered in its social and environmental reports.
ESG Controversies Score	ESG controversies score measures a company's exposure to ESG controversies and negative events reflected in global media.
DIR Inclusion Score	Score that measures the firm's commitment and effectiveness towards effective work-life balance, disability inclusion and family-friendliness.
Female on Board	Percentage of women on the company's board.
Climate Change Commercial Risks. **Opportunities Score**	Measures whether (and if yes, how well) the company is aware that climate change can represent commercial risks and/or opportunities.
Policy Data Privacy Score	Policy data privacy score measures aspects related to the question: *"Does the company have a policy to protect customer and general public privacy and integrity?"*
DIR Controversies Score	DIR controversies score accounts for the negative impact of workforce controversies on the firm.
Product Responsibility Score	Product responsibility score *"Reflects a company's capability to produce quality goods and services integrating the customer's health and safety, integrity, and data privacy"*.
Policy Water Efficiency Score	Policy water efficiency score measures whether the firm in question has a policy to improve its water efficiency and aspects related to that.
Policy Customer Health Safety Score	*"Does the company have a policy to protect customer health & safety? - processes or initiatives in place by which it strives to market products which are fostering benefits to the consumer's*

	health & safety rather than putting it at risk-includes only products related initiatives and not services - customer security is considered for media and telecommunication companies"
Health Safety Policy Score	A score measuring aspects related to whether – and if yes, how well - the company has a policy to improve employee health & safety within the company and its supply chain.
Human Rights Score	The human rights score measures how effective a firm is towards respecting the fundamental conventions on human rights.
Policy Human Rights Score	*"Does the company have a policy to ensure the respect of human rights in general? – information to be on ensuring the respect of human rights – consider a process on general fundamental human rights"*
Human Rights Contractor Score	Human rights contractor score measures whether – and if yes, how well – the firm reports or shows the use of human rights criteria when selecting or monitoring of its suppliers or sourcing partners.
Equal Shareholder Rights Score	A score on how well the firm treats all shareholders equally.
Workforce Score	A score on the firm's efforts towards a healthy and safe workspace, work satisfaction, diversity, and equal opportunities, in addition to the development opportunities for the workforce of the company.
Community Score	The score rates a firm's commitment towards being a good citizen, respecting business ethics, and protecting public health.
Policy Community Involvement Score	Policy community involvement score measures aspects related to the question: *"Does the company have a policy to improve its good corporate citizenship?"*
CSR Strategy Score	The CSR strategy category score measures *"a company's practices to communicate that it integrates the economic (financial), social, and environmental dimensions into its day-to-day decision-making process"*
Shareholders Score	In addition to measuring the firm's use of anti-takeover devices, the shareholders score measures the effectiveness of the firm in question towards equal treatment of shareholders.
Employees Health Safety Team Score	A score on whether the company has an employee health & safety team or not, and aspects related to that.
Renewable/Clean Energy Products	Renewable/Clean energy products is an indicator variable on *"Does the company develop products or technologies for use in the clean, renewable energy – in scope, we also include data on the financing of renewable energy projects – if a utility company is deriving at least 25% of the power produced or revenue from clean technologies or energy"*
Environmental Assets Under Mgt	An indicator variable answering the question: *"Does the company report on assets under management which employ*

	environmental screening criteria or environmental factors in the investment selection process? – relevant to asset management companies – SRI and ethical funds are under our consideration"
Environmental Products	Environmental products is an indicator variable answering mainly the question: *"Does the company report on at least one product line or service that is designed to have positive effects on the environment or which is environmentally labeled and marketed?"*
Environmental Supply Chain Management	An indicator variable on*" Does the company use environmental criteria (ISO 14000, energy consumption, etc.) in the selection process of its suppliers or sourcing partners? – data can also be on existing suppliers who were selected using some environmental criteria".*
SDG 5 Gender Equality	SDG 5 Gender equality is an indicator variable with the main target of answering the question of whether the firm supports the UN's Sustainable Development Goal 5, Gender Equality.
Green Buildings	Green buildings is an indicator variable answering the question: *"Does the company report about environmentally friendly or green sites or offices?"*
Policy Sustainable Packaging	Policy sustainable packaging is an indicator variable answering the question: *"Does the company have a policy to improve its use of sustainable packaging*?" and other aspects related to that.
Sustainability Compensation Incentives Score	Sustainability compensation incentives score measures whether – and if yes, to what extent - the senior executive's' compensation is linked to CSR/H&S/Sustainability targets.
Environmental Partnerships Score	The score measures whether – and if yes, to what extent - the firm reports on partnerships or initiatives with such specialized NGOs, industry organizations, governmental or supra-governmental organizations that are focused on the improvement of environmental issues.

APPENDIX 6: ESG PILLARS

Figure 5: ESG pillars
This figure shows a table of the sub-categories and themes within E, S and G pillars, in a table format. The source of the image is Refinitiv (2022).

Pillars	Catagories	Themes
Environmental	Emmission	Emissions
		Waste
		Biodiversity*
		Environmental management systems*
	Innovation	Product innovation
		Green revenues, research and development (R&D) and capital expenditures (CapEx)
	Resource use	Water
		Energy
		Sustainable packaging*
		Environmental supply chain*
Social	Community	Equally important to all industry groups, hence a median weight of five is assigned to all
	Human rights	Human rights
	Product responsibility	Responsible marketing
		Product quality
		Data privacy
	Workforce	Diversity and inclusion
		Career development and training
		Working conditions
		Health and safety
Governance	CSR strategy	CSR strategy
		ESG reporting and transparency
	Management	Structure (independence, diversity, committees)
		Compensation
	Shareholders	Shareholder rights
		Takeover defenses

* *"These themes are not included in the scoring methodology to derive the materiality matrix, but are present in corporate ESG reporting and the Refinitiv ESG database" (*Refinitiv, 2022, pp.10)