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Green Choices, Grey Areas: Risk Management and Investor Behavior in the ESG Landscape

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Doctoral Dissertation

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1. INTRODUCTION

Environmental, Social, and Governance (ESG) factors have taken central place in the modern financial landscape. As investors, regulators, and society place greater emphasis on sustainability and ethical business practices, companies are compelled to prioritize ESG values. While ESG scores have been broadly used to assess and compare companies on their ethical, social, and environmental impact, the empirical implications of these scores, particularly in the realm of financial performance, risk management and investor behavior, remain subjects of robust academic inquiry.

The introduction of ESG scores has enabled comparability across companies in terms of their levels of responsibility and organizational compliance, offering an avenue for investors to formulate strategies aligned with responsible dimensions. Today, multiple firms engage in determining and selling ESG ratings using various methodologies, leading to potential differences in calculation methods, sector weighting, and basic variable definitions. Broadly, without claiming completeness, the 'E' dimension tracks an entity's ecological footprint, capturing water usage, waste management practices, and carbon emissions. The 'S' component describes the relationship between the company and its stakeholders (e.g., suppliers, consumers, community, employees) and sheds light on the quality of employee health protection measures. The 'G' aspect, on the other hand, encompasses elements like corporate culture, data management practices, the quality of internal audits, corruption levels, and executive remuneration.

The ESG classification system was first adopted and developed by the data provider Eiris and KLD in the 1980s. Later, MSCI started the objective of assessing all publicly-listed companies based on these responsible principles. Nowadays, the assessment technique and frequency may vary depending on the numerous ESG data providers (Berg, Koelbel and Rigobon [2022]).

ESG rating agencies evaluate the sustainability performance of numerous companies, utilizing a variety of data sources. Some ratings rely solely on non-financial information, while others integrate both financial and non-financial data for a holistic assessment of long-term value and sustainability. Over the past decade, the ESG rating industry has experienced substantial growth and undergone consolidation, marked by mergers among existing agencies and the entry of financial rating and information providers.

The major players among ESG rating agencies are Reuters Refinitiv, ECP, FTSE Russell ESG Ratings, MSCI ESG Research, ISS-oekom, RobecoSAM, Sustainalytics, and Video EIRIS. Each agency uses its unique approach, however due to limited transparency, the exact criteria behind ratings might not be fully disclosed. Based on the descriptive analysis of Escrig-Olmedo et al. (2019), during the assessment process and calculation methodologies, the three pillars (environmental, social and governance) are not equally balanced at each of the agencies. While MSCI and FTSE Russell are using the same weights for the different pillars, Sustainalytics and Refinitiv apply different weighting schemas. Furthermore, Refinitiv and MSCI integrates financial information in their ESG score but FTSE and Sustainalytics do not. The paper also concludes, that all of the agencies evaluate sustainability, recognize the present needs and expectations of stakeholders, as well as the requirements of future generations, however none of them have life-cycle thinking. This means, that while measuring sustainability, rating agencies are not considering the effective management of impacts arising from neither upstream nor downstream of the company activities.

Although ESG-based portfolio management and investing are increasingly growing and becoming popular, criticisms have been raised regarding the lack of unified, regulated definitions for ESG metrics. Due to the various definitions and methodologies employed by different rating agencies, the same company may have different ESG scores depending on which agency's data is used. Berg, Koelbel, and Rigobon (2022) states that 56% of the ESG rating disagreement among different agencies are coming from the fact that they measure different things. For example, one agency measure labor practices based on workforce turnover, while the other counts the number of labor related court cases. 38% of the disagreement is coming from scope divergence, which means that agency ratings are based on diverse attributes, just like one agency includes lobby activity while another does not. The rest of the disagreement is coming from the weight divergence, which emerges when agencies assign different importance to attributes, like giving more weight to labor practices than lobbying in the final rating. The combined contributions of scope, measurement, and weight divergence complicate the interpretation of differences between two ESG ratings.

According to Fiaschi et al. (2020), the disagreement and subjectivity among rating agencies can be bridged through the use of a corporate wrongdoing index. The current ratings may offset negative actions (such as causing harm or emitting pollutants) by incorporating positive actions (such as charitable donations). The authors suggest focusing solely on negative actions, quantifying them, and creating an index, thereby obtaining a more objective and accountable measure of corporate responsibility. The authors also criticize the lack of accountability in rating agencies due to the methodology and the absence of validation. They argue that a rating should exhibit temporal consistency, along with the transparency of both the data used and the calculation methodologies.

In this dissertation, we utilize the Reuters Refinitiv overall ESG score and the individual E, S and G scores, which are measured on a 0 to 100 scale. A high score signifies outstanding relative ESG performance and a significant level of transparency in publicly disclosing essential ESG data, while firms with the lowest ratings are the laggards relative to peers and a lack of transparency in publicly reporting crucial ESG data. The ESG pillar score is a cumulative measure relative to the category weights, which differ by industry for both environmental and social categories. The weight of the governance pillar is constants through industries. The pillar scores are made up by weighting boolean data points ("Is there a water efficiency policy in place within the company?") and numerical data points by percentile ranking considering industry group relevancy as well.

Table 1 contains a description of the Refinitiv ESG variables. The table contains the most important list of variables within environmental, social, and governance factors.

Table 1. The main themes covered by the Reuters Refinitiv ESG variables.

ESG-variables	Main themes
Environmental (*E*)	Waste – pollutant emission
	Energy – water usage
	Innovations
Social (*S*)	Human rights
	Data security
	Diversity and inclusion
	Workplace conditions
	Health and safety
Governance (*G*)	Corporate Social Governance (CSR-strategy)
	Commitment of company leadership to best governance practices
	Consideration of the interests of the company's stakeholders

Source: Refinitiv [2022].

Refinitiv provides one of the most extensive ESG databases in the industry, covering over 90% of the global market cap with a range of more than 630 ESG metrics dating back to 2002. This comprehensive dataset allows for the seamless integration of ESG factors into portfolio analysis, screening, equity research, and quantitative analysis. ESG scores transparently and objectively evaluate a company's relative ESG performance, commitment, and effectiveness based on reported data across 10 main themes such as emissions, human rights and so on. The scores are available for over 15,500 global companies, utilizing percentile rank format for easy interpretation. The methodology considers industry benchmarks, tailoring scores to a company's sector and country of incorporation for environmental, social, and governance categories. The approach avoids defining 'good,' allowing data to determine industry-based relative performance within established criteria and a robust data model. Emphasizing data-driven assessments, the methodology minimizes biases related to company size and transparency, with key calculation principles underpinning ESG scoring.

ESG scores offer a comprehensive evaluation of a company's ESG performance, considering reported information related to ESG pillars and incorporating ESG controversies from global media sources. The primary goal is to adjust the ESG performance score by discounting it based on negative media narratives. This adjustment accounts for the impact of significant ESG controversies in the overall ESG score. Such controversial ESG events can include tax fraud, industrial accidents affecting the public or employees, customer/user issues, data protection concerns for customers or employees, insider trading, violation of shareholder rights, etc.

In cases where companies face ESG controversies, the ESG score is computed as the weighted average of ESG scores and ESG controversies scores for each fiscal period, with recent controversies reflected in the most recent completed period. Conversely, when companies are not involved in ESG controversies, the ESG score aligns with the ESG score (Refinitiv [2022]).

The ESG rating landscape is constantly evolving, with calls for greater standardization and transparency. Regulatory changes and industry collaboration could enhance the accuracy and consistency of ratings.

Asset and portfolio managers began allocating their investments in line with some kind of responsible strategy already in the last century. Initially, a dominant approach involved excluding certain industries from their investment universe (e.g., tobacco or weapons), but with the advent of ESG scores, numerous funds and indices were born considering these responsibility criteria, such as the S&P 500 ESG Index (USD) and MSCI ESG Leaders Indices. Investors might choose these specific products for varying objectives: some seek to support a better long-term mission with their investment, others focus on risk management, and yet some anticipate above-benchmark returns from ESG-aligned baskets (MSCI [2022 a, b]).

The rise in ESG-based investments is evident from the report by US SIF (The Forum for Sustainable and Responsible Investment), which indicates that one in every three dollars invested in the United States is allocated following some form of responsible guideline. This figure has been sharply increasing since the early 2010s, both in Europe and the USA. Consequently, since the mid-2010s, investors have placed escalating emphasis on investments based on ESG, be it for long-term responsibility objectives or yield-risk optimization (US SIF [2021]).

Since the strengthening trends towards sustainability and responsibility, corporate governance practices have progressively transitioned from the view that the primary and sole business objective is shareholder value maximization. Due to this emerging trend, consideration of stakeholder interests has moved to the forefront. In summary, companies are no longer solely focused on maximizing the benefit for shareholders; it's crucial for them to also represent the interests of the broader stakeholder group. Stakeholders, beyond shareholders, can encompass customers, suppliers, employees, and communities associated with the company in some manner. As the value of a company is no longer determined solely based on shareholder benefits, it raises the question of whether asset valuation models, which only consider shareholder value, should be reassessed. ESG scores hence can serve as a good proxy for determining the value of these stakeholders (Shrivastava and Zsolnai [2020], Márkus [2024]).

The current academic consensus (detailed in the next sub-chapters) regarding the risk-return characteristics of responsible investments suggests a more positive relationship between ESG scores and financial performance, while a mixed association is observed between ESG scores and stock returns. This is still a subject of vigorous debate. Additionally, a significant portion of the literature in the field of risk management finds a negative relationship, both in terms of credit and market risk as well as operational risk, indicating that issuers and companies with higher ESG scores face reduced downside, reputational or default risk.

Overall, it is evident that firms with higher ESG scores tend to exhibit lower CDS spreads, alongside favorable credit ratings and a reduced probability of default. Studies have also explored the positive impact of ESG scores on a firm's market risk, including measures such as Value-at-Risk, beta, and idiosyncratic risk, which assess potential financial loss in adverse market conditions. While a relatively small number of studies have comprehensively addressed how effective ESG management correlates with lower operational risk, the current results suggest a negative correlation for proxies of operational losses.

In the following, we delve into the most significant research findings in detail and emphasize those areas where conclusions differ from previous studies or where there is relatively limited research available to form a consensus. By focusing on these grey areas, this dissertation can assist in complementing the current literature.

1.1. THE CURRENT DEBATE ON THE EFFECT OF ESG SCORES ON CORPORATE FINANCIAL PERFORMANCE

The literature has extensively explored the relationship between a company's ESG score and its corporate financial and accounting performance. Understanding the connection between a company's ESG score and its financial and accounting performance is crucial for making informed decisions, managing risks, ensuring long-term sustainability, and aligning with evolving market trends and stakeholder expectations.

A substantial proportion of these articles identify a positive association between ESG and financial performance. Friede, Busch and Bassen (2015) provide a meta-analysis summarizing more than 2000 studies, concluding that the majority of the papers show positive correlation between ESG performance and financial performance (financial performance here is defined as corporate fundamental value, operational, and accounting performance). Orlitzky, Schmidt and Rynes (2003) find during an integrative rigorous meta-study, that companies who actively invest in social responsibility, particularly based on aspects reflected in their reputation, are more likely to see positive financial outcomes, especially when measured by traditional accounting methods and not by market performance. Cheng, Ioannou and Serafeim (2013) analyze a broad sample of firms, and their research reveals that companies with superior corporate social responsibility (hereafter CSR[1]) performance encounter lower capital constraints through higher transparency and better stakeholder engagement. Other studies arrive at the same conclusion investigating the phenomenon from different angles (Barnett and Salomon [2012], Khan, Serafeim and Yoon [2016]).

On the other hand, there have been contrasting findings, and it remains questionable whether there is a positive relationship between performance measured by stock returns. Eccles, Ioannou and Serafeim (2014) reveal that high ESG performer companies tend to outperform in terms of stock returns. Based on a new quantitative model developed by Kumar et al. (2016), it shows that lower volatility of equity returns was also paired with

[1] While ESG and CSR both address the ethical and sustainable aspects of business operations, they are not exact synonyms. However, both concepts have gained significant attention in recent years, reflecting a growing recognition of the importance of ethical, sustainable, and responsible business practices hence we will use both measures to express the company’s responsible intention (Gillan et al. [2021]).

higher risk-adjusted returns. A study of Verheyden, Eccles and Feiner (2016) shows that using ESG filters, particularly a 10% best-in-class approach, significantly improves risk-adjusted returns in global and developed markets portfolios. The findings of Khan et al. (2016) indicate that companies with favorable ratings on material sustainability issues demonstrate a significant stock outperformance compared to those with poor ratings in the same category. However, there is no significant outperformance observed for companies with good ratings on immaterial sustainability issues when compared to those with poor ratings in the same category.

In contrast, Cornell and Damodaran (2020) argue that ESG is good for the society but cannot provide excess stock returns. Halbritter and Dorfleitner (2015) also support the previous conclusion by applying an ESG portfolio approach using the Carhart four factor model on a large dataset between 1991 and 2012 and did not find any abnormal returns related to sustainable investing. Cornell (2021) further emphasizes, that however highly rated ESG companies are able to reduce their cost of capital, due to the risk-return tradeoff, they realize lower expected return. Lööf, Sahamkhadam and Stephan (2022) confirm the conclusion of Cornell during turbulent market conditions. Their research horizon is narrowed to the COVID-19 Pandemic period and during this time they reveal that while high CSR stocks can lower their downside risk, also have lower upside potential therefore support Cornell's risk-return trade-off hypothesis.

Table 2. Summary table of the literature review, featuring articles that describe the relationship between ESG performance and financial performance.

Article (Author and Year)	Scope	Connection between ESG score and Scope	Method
Friede, Busch and Bassen (2015)	Financial performance	Positive	Meta-analysis
Orlitzky, Schmidt and Rynes (2003)	Financial performance	Positive	Meta-analysis
Cheng, Ioannou and Serafeim (2013)	Financial performance	Positive	Regressing the Kaplan and Zingales index by five accounting variables
Barnett and Salomon (2012)	Financial performance	Positive	Regressing ROA by CSR measures
Khan, Serafeim and Yoon (2016)	Financial and stock performance	Positive	Calendar-time portfolio regression and panel regression
Eccles, Ioannou and Serafeim (2014)	Financial and stock performance	Positive	Propensity score matching
Kumar et al. (2016)	Stock performance	Positive	Correlation between ESG performance and volatility of stock returns
Verheyden, Eccles and Feiner (2016)	Stock performance	Positive	Portfolio filtering approach
Cornell and Damodaran (2020)	Stock performance	Negative	Qualitative analysis
Halbritter and Dorfleitner (2015)	Stock performance	Negative	Portfolio approach
Cornell (2021)	Stock performance	Negative	Qualitative analysis
Lööf, Sahamkhadam and Stephan (2022)	Stock performance	Negative	Correlated random effect regression

Table 2 summarizes the processed literature on the relationship between ESG performance and corporate financial and stock market performance, with particular emphasis on the methodology employed and the conclusions drawn.

As Cornell (2021) highlights, two factors determine the expected return of high ESG rating companies, these are investor preferences and their risks. We believe that the inconsistent outcomes observed in the literature regarding the relationship between ESG and anticipated stock returns can be attributed to the lack of pure rationality among investors when establishing their preferences and managing their portfolios.

Most of the research about ESG and stock returns is inconclusive because they do not account for the already documented psychological effects. Rational investor theory, a cornerstone of traditional finance, posits that individuals act in their best interest to maximize utility, making decisions based on all available information and without the interference of emotions. However, in many cases, behavioral finance has already provided answers, where the traditional finance could not have, particularly in non-ESG contexts (Kahneman and Tversky [1984], Shefrin and Statman [1985], Odean [1998], Barberis, Huang and Santos [2001]). Within this field, the examination of gain-loss asymmetry (reference point effects as discussed in Wang, Yan, and Yu [2017]) has yielded insights. It is plausible that this asymmetry holds significant relevance in the context of ESG evaluation as well. Investors may have different approaches to risk and financial decisions, and it's worth considering whether this holds true for ESG considerations.

Behavioral finance offers a unique perspective on the understanding of stock returns by highlighting the psychological factors and biases that can influence investment decisions. Traditional finance models, such as the Efficient Market Hypothesis (EMH), assume that all investors are rational and that they have access to and process all available information correctly. However, real-world observations often contradict these assumptions. Traditional models often fail to explain various stock market anomalies, such as the momentum effect or the value premium. Behavioral finance provides explanations based on investor psychology for why stocks might exhibit patterns not predicted by standard financial theories. Furthermore, while traditional finance suggests that mispriced assets should be quickly arbitraged away, behavioral finance points to factors like limits to arbitrage (due to constraints on certain investors) and investor psychology as reasons why mispricing can persist (Ritter [2003]).

Behavioral finance's importance in understanding stock returns lies in its ability to provide a more holistic view of market dynamics. By accounting for human emotions and biases, it presents a more comprehensive framework for understanding price movements, market anomalies, and investor behavior. Recognizing these biases can lead to better ESG investment strategies and a deeper understanding of stock market dynamics.

1.2. THE CURRENT DEBATE ON THE EFFECT OF ESG SCORES ON RISK MANAGEMENT

With the global shift towards sustainable development and the increasing importance of corporate social responsibility, ESG factors have become mandatory elements of modern risk management practices for businesses as well. By understanding the complex interplay between ESG scores and various forms of risk, companies can make better decisions, mitigate potential issues, and ultimately improve their creditworthiness, market performance, and operational resilience. This benefits not only the company itself but also investors, stakeholders, and the wider society. In order to better understand and comprehend the impacts of ESG scores on corporate risks, categorizing risks by type such as credit, market, and operational risks, and dissecting them separately, we highlight the most significant and comprehensive research findings individually.

Starting with the credit risk aspect we can conclude, that the vast majority of the relevant studies found negative correlation between ESG scores and credit risk indicating that ESG considerations can serve as valuable indicators of creditworthiness. By incorporating ESG criteria into investment strategies, investors aim to reduce exposure to companies with higher environmental and social risks, potentially mitigating credit risk in their portfolios. In the following, we highlight research article findings regarding the connection between different credit risk measures (like CDS spread, probability of default, credit rating) and ESG/CSR scores.

Goss and Roberts (2011) find that companies with CSR issues pay 7 to 18 basis points higher spread on their loans than their more responsible counterparts. However, the authors document varied response to optional CSR investments: low-quality borrowers that voluntarily spend on CSR face increased loan costs, whereas lenders show no preference concerning CSR investments made by high-quality borrowers. According to Barth, Hüber and Scholz (2022), one standard deviation increase of ESG scores reduces the CDS spreads of European and US firms. They find a U-shaped risk mitigation effect of ESG improvement among companies in different ESG quantiles. Firms with average ESG score can reduce their CDS spreads by 8% while ESG over and underperformers by 3% and 4% respectively if their ESG score improves by one standard deviation.

Jiraporn et al. (2013) and Attig et al. (2013) conclude the same by investigating the connection between CSR-scores and credit ratings. They show that more socially responsible firms enjoy favorable credit ratings and hence lower financing costs through their higher credit ratings. Next to the credit spreads and credit ratings, while those are somehow related, CSR also strongly reduces the probability of default (Sun and Cui [2014]).

Outside of the developed markets, the cost of borrowing shows the same relation with ESG in China. Green certificates, green bonds and CSR all have negative effect on interest rate costs, indicating that issuers with green certificates face lower borrowing costs and hence lower credit risk compared to their non-green similar counterparts (Li et al. [2020]). With an international data sample covering 14 years of observations in 36 countries, Do (2022) concludes the same negative association between CSR and default probability. According to the study, the effect is even stronger regarding long-term probabilities than in the short run. Moreover, the association gets stronger among different countries where the capital markets and legal circumstances are weaker.

The association between ESG and market risk, as price volatility, tail and downside risk are also negative, according to the majority of the studies. Responsible firms can relatively reduce their market related losses compared to non-responsible companies. The subsequent articles discuss the correlation between ESG scores and widely acknowledged market risk metrics such as Value-at-Risk, market beta, and idiosyncratic risk.

According to the paper of Hoepner et al. (2018), engagement in responsible practices can lower firms' downside risk, measured by Value-at-Risk. The downside protection and risk reduction have the most effect when companies are focusing primarily on climate-related topics. Relative to control firms, the authors show 9% reduction in Value-at-Risk measures for high ESG performers. Sassen, Hinze and Hardeck (2016) also investigates the systematic, non-systematic and hence, the total risk of firms' relation to their corporate social performance (CSP). They detect on a large, European dataset between 2002 and 2014 that high performance in CSP lower the total and non-systematic risk. They further shade their findings. Overall, idiosyncratic risk is the more sensitive to the environmental factor (E factor), while firm total risk and systematic risk are decreased only in the environmentally exposed industries. In addition, they find negative association between the social factor (S factor) and firm risk measures, but cannot find any significant relation between the governance factor (G factor) and market risk of firms.

Jo and Na (2012) further exploit the negative correlation between CSR and firm risk by industries with an extensive dataset representing US companies between 1991 and 2010. According to their results, companies within controversial industry can benefit more in risk reduction compared to non-controversial industry players by incorporating CSR strategies into their strategies because CSR engagement has more powerful effect on the alcohol, tobacco, gambling etc. firms than on the non-controversial companies.

Lastly, operational risk, often overlooked in the shadow of market or credit risks, plays a fundamental role in the day-to-day functioning and long-term success of an organization. In an era marked by technological advancements, regulatory changes, and global interconnectedness, the importance of understanding and effectively managing operational risks has never been more paramount.

In the academic literature, there is limited discussion concerning the relationship between ESG scores and operational risk. This can be attributed to at least two reasons. Firstly, the identification of operational risks emerged later than that of market or credit risks. Secondly, measuring operational risks is considerably more challenging than observing market or credit risks. In many instances, researchers cannot rely on actual loss data for their studies because of the harder observable nature of operational loss data. Instead, they attempt to approximate indicators of risk stemming from operations, using metrics such as the standard deviation of ROA (Return on Assets), ROE (Return on Equity), or the variance of the annual revenue of the firm.

Under the aforementioned limitations, Zhao, Song, and Chen (2016) show on the Chinese market that A-listed firms can reduce their operating risk if they complete their ESG fulfillment. Operational risk as a container includes various categories of risks originating from completely different natures, like failed processes, systems, policies, or events therefore it could be necessary to exploit the relationship between responsibility and risk within these subcategories as well. There is a lack of comprehensive studies that mutually exclusively and collectively exhaustively explore the relationships between ESG scores and operational risk categories. Harjoto (2017) examines the severity and frequency of only the corporate fraud as an operational risk related to CSR performance and find a negative correlation between the two.

Table 3 summarizes the processed literature on the relationship between ESG performance and credit, market, and operational risk, with particular emphasis on the methodology employed and the conclusions drawn.

Table 3. Summary table of the literature review, featuring articles that describe the relationship between ESG performance and various risk types.

Article (Author and Year)	**Scope**	**Connection between ESG score and Scope**	**Method**
Goss and Roberts (2011)	Credit risk (loan spread)	Negative	Heckman selection, IV regression
Barth, Hüber and Scholz (2022)	Credit risk (CDS spread)	Negative	Quantile regression, fixed effect panel regression
Jiraporn et al. (2013)	Credit risk (credit rating)	Negative	OLS regression and 2SLS regression
Attig et al. (2013)	Credit risk (credit rating)	Negative	Ordered probit model
Sun and Cui (2014)	Credit risk (probability of default)	Negative	Newey-West regression
Do et al. (2022)	Credit risk (probability of default)	Negative	Fixed effect regression, propensity score matching
Li et al. (2020)	Credit risk (loan spread in China)	Negative	Linear regression
Hoepner et al.	Market risk (downside risk)	Negative	Stacked regression approach
Sassen, Hinze and Hardeck (2016)	Market risk (total and idiosyncratic risk)	Negative	Panel data regression

Article (Author and Year)	Scope	Connection between ESG score and Scope	Method
Jo and Na (2012)	Market risk (total and idiosyncratic risk)	Negative	Spearman correlation and fixed effect regression
Zhao, Song, and Chen (2016)	Operational risk (Leverage and standard deviation of annual income)	Negative	Linear regression
Harjoto (2017)	Operational risk (corporate fraud)	Negative	Heckman selection, propensity score matching and probit

1.3. MOTIVATION - FILLING THE GAP

This dissertation investigates the connection between ESG scores and operational losses as well as between ESG scores and investor behavior in public companies. Through two research in the subsequent chapters, we attempt to uncover the underlying relationships and provide insights that can not only expand the boundaries of current knowledge but also shape future corporate and investment strategies. Studying both topics concurrently is important as it allows for a nuanced exploration of the broader impact of ESG considerations on businesses and financial markets. The interconnectedness of risk, returns, and investor behavior forms a complex web that merits simultaneous examination. By studying these topics together, the research aims to provide a comprehensive understanding of how sustainable practices not only influence risk and financial performance but also how investor sentiment and choices play a crucial role in shaping these relationships. Ultimately, these insights can guide businesses, investors, and policymakers towards more effective and sustainable decision-making.

Risk management practices have undergone significant evolution over the past few decades, especially in the wake of financial crises and growing global interconnectedness. Historically, much of the focus in both academic literature and industry best practices was around market and credit risks. These were often seen as the primary threats to financial stability and corporate integrity, which led to plenty of research and literature dedicated to understanding, measuring, and mitigating them.

Operational risk, defined as the risk of losses stemming from inadequate or failed internal processes, people, systems, or from external events, was recognized only after the 1990's in risk management paradigms. This delayed recognition means that there has been less time for academic investigation into operational risk as compared to the more traditional market and credit risks. Consequently, when it comes to the integration of ESG criteria into risk management, this skewness in academic attention persists.

Considering ESG's increasing prominence in corporate strategy and investment decision-making, many studies have dug into understanding how ESG factors influence or correlate with market and credit risks. This makes sense, given that market and credit risks were already well-established areas of study, and researchers sought to understand how new ESG considerations might impact these existing risk categories.

However, the nexus between ESG and operational risk remains comparatively underexplored in academic literature. This is somewhat surprising since many elements within the ESG framework, especially those related to governance and social responsibilities, have direct implications for operational risk. Issues like employee well-being, robust internal governance mechanisms, and adherence to environmental regulations can all significantly impact a firm's operational risk profile.

The limited body of literature in this field may also be indicative of the inherent challenges in measuring and quantifying operational risk compared to market and credit risks. While the latter can often be assessed using established financial metrics and models, operational risk can manifest in countless ways, from IT system failures to issues related to employee misconduct or external fraud (Csernobai, Rachev, and Fabozzi [2008]).

The large severity and frequency of corporate operational losses, stemming from such as frauds, legal battles, and systems failures, poses a significant threat to the stability of companies and the broader financial system. It's vital to understand whether adhering to ESG principles acts as a shield against these losses. A nuanced understanding can provide companies with strategies to mitigate these risks and offer investors a clearer view of potential vulnerabilities.

In the aforementioned literature review, we show that the relationship between ESG scores and stock returns is ambiguous, with various studies yielding mixed results. By examining this through the lens of behavioral finance, we aim to further nuance these findings, which might provide an explanation as to why different studies arrive at varying conclusions regarding the relationship between stock returns and ESG.

At the intersection of psychology and finance, behavioral finance has altered our understanding of market dynamics. As ESG becomes an integral part of the investment lexicon, there is a pressing need to decode the behavioral patterns associated with ESG investing. Are responsible investors' decisions purely rational, or do recent gains or losses cloud their judgment? Shedding light on this can help align investment strategies with cognitive realities.

The duo of research presented in this dissertation share a common thematic core: the various impacts of ESG scores in the financial domain. Understanding the collective impact of ESG factors on operational risk and stock returns, coupled with insights into investor behavior, empowers decision-makers with a more integrated perspective. This knowledge can assist businesses in aligning their operations with sustainability goals and guide investors in making informed and socially responsible investment choices.

1.4. RESEARCH QUESTIONS AND MAIN FINDINGS

Based on the literature review, higher corporate responsibility can mitigate risk. However, the specific channels through which this occurs are not yet clear. Operational risk can serve as the root cause for risks through the frequency and severity of operational risk events. Consequently, our first hypothesis is that the frequency of operational risks decreases with an increase in ESG scores. Our second hypothesis is that the severity of operational risks decreases with an increase in ESG scores. Moreover, we further investigate the likelihood and severity of different types of operational loss events based on companies’ ESG scores, hence we formulate two additional hypotheses in Chapter 2. The severity and the frequency of operational risks decreases with an increase in ESG scores in those operational risk categories, where the involvement of the company cannot be questioned. Chapter 2 explores using fixed effect panel regressions and Heckman selection, how ESG scores correlate with the severity and frequency of operational loss events. Here, we seek to understand if companies with better ESG scores are more resilient when faced with operational challenges.

Operational loss events have been identified as a key indicator or proxy for corporate misconduct. ESG scores have proven their mettle as a reliable tool for measuring downside risk, especially in light of such misconduct. An interesting observation is that while ESG performance may not significantly influence the frequency of losses, it certainly curtails their severity. This phenomenon becomes even more pronounced within the finance sector, emphasizing the relevance of ESG metrics in financial operations. Additionally, a company's reluctance or refusal to participate in a rating program can be construed as a strong negative signal, possibly hinting at deeper underlying issues. Given these findings, there is a compelling argument for regulatory bodies to consider the integration of ESG metrics into their frameworks. By doing so, they can better safeguard against potential operational losses, promote ethical corporate conduct, and ensure a more sustainable and responsible business environment for all stakeholders. With these findings, investors can make more informed decisions, choosing to support companies with strong ESG performances, and thereby potentially reducing the risk associated with their portfolios. By integrating these insights, investors not only safeguard their investments but also contribute to promoting sustainable and ethical corporate practices.

We also dig into the relationship between ESG scores and various operational risk events in detail. The examination is essential given the various types of operational risk events, which often occur independently, sometimes influenced by external factors. Thus, it may be beneficial to analyze these events individually. Based on the findings, only events leading to physical damages occur with a higher likelihood in companies with elevated ESG scores. However, the severity of damages can be significantly mitigated by companies with strong ESG performance, especially those damages arising from improper business practices (Márkus [2023]).

Table 4 summarizes the hypotheses of Chapter 2, the formulated research questions, the applied empirical models providing answers to these research questions, and the main findings.

Table 4. Hypothesis, research questions, empirical methods and main findings of Chapter 2.

Research question	**Hypothesis**	**Research method**	**Finding**
How ESG scores correlate with the frequency of operational loss events?	H1: The frequency of operational risks decreases with an increase in ESG scores	Yearly and risk category fix effect logit regression	No connection
How ESG scores correlate with the severity of operational loss events?	H2: The severity of operational risks decreases with an increase in ESG scores	Yearly and risk category fix effect regression, Heckman selection	Higher ESG curtails operational risk severity
How ESG scores correlate with the frequency of operational loss events in different risk event categories?	H3: The frequency of operational risks decreases with an increase in ESG scores in those categories where the company involvement cannot be questioned.	Yearly and risk category fix effect logit regression	Higher ESG score is paired with higher frequency in physical damage category
How ESG scores correlate with the severity of operational loss events in different risk event categories?	H4: The severity of operational risks decreases with an increase in ESG scores in those categories where the company involvement cannot be questioned.	Yearly and risk category fix effect regression, Heckman selection	Higher ESG score is paired with lower severity in the improper business practices category

Chapter 3 shifts the lens to the investors, exploring how their past financial experiences influence their decisions regarding ESG investments. Investor behavior is a key driver in financial markets. Analyzing how investor sentiments and preferences influence the relationship between ESG scores and stock returns contributes to a deeper understanding of market dynamics. This knowledge can be instrumental for investors, financial institutions, and policymakers in navigating the evolving landscape of sustainable finance. Studying the relationship between ESG scores, operational risk, stock returns, and investor behavior together goes beyond isolated analyses and provides a more nuanced and realistic portrayal of the complexities involved.

Sustainability and responsibility are getting more and more important in investment decisions generating a huge demand for stocks with high ESG scores. This demand is also driven by naive investors who are generally assumed to be more exposed to behavioral biases. Motivated by the literature of behavioral economics and finance, we study with a portfolio approach, whether investors are willing to sacrifice more return for sustainability and responsibility when they face prior gains rather than facing prior losses. We find that a higher ESG score has a lower expected return for stocks with prior gains and there is no statistically significant relation for stocks with prior losses. Furthermore, we also find that this pattern becomes much stronger for stocks in which naïve investors are more active. These results imply that the demand for sustainable and responsible investments varies a lot in a predictable way based on the past performance of the stock. This provides a view by placing the internal corporate implications of ESG scores next to the external investor behavior.

Table 5 summarizes the hypotheses of Chapter 3, the formulated research questions, the applied empirical models providing answers to these research questions, and the main findings.

Table 5. Hypothesis, research questions, empirical methods and main findings of Chapter 3.

Research question	Hypothesis	Research method	Finding
How investors past financial experiences influence their decisions regarding ESG investments?	H5: Investors might be more willing to sacrifice return for social benefits when they face prior gains in a stock	Portfolio approach	Higher ESG score has a lower expected return for stocks with prior gains
Do naïve investors drive the revealed relations?	H6: Naïve investor group drives the mispricing due to the limits of arbitrage	Sub-sample portfolio approach	Brown investors cannot immediately trade the mispricing due to the limits of arbitrage in the naïve investor group

In essence, these chapters collectively chart a comprehensive map of the ESG landscape, from the internal workings of companies to the external actions of investors, providing a panoramic view of the modern financial ecosystem.

1.5. RELEVANCE OF THE DISSERTATION

The current dissertation has relevance for numerous reasons, given the contemporary shifts in the economic, societal, and regulatory landscapes.

Firstly, due to the growing investor interest, more sophisticated and naiver investor are directing their capital towards sustainable investments. By 2024, ESG assets have been rapidly growing, and they're projected to represent a significant chunk of total global assets.

Secondly, governments and regulatory bodies in the U.S. and the EU are implementing guidelines and regulations around the disclosure of ESG risks and practices. Understanding ESG factors is becoming crucial for businesses to anticipate and adapt to these regulatory changes, which can impact business models and market dynamics.

In the European Union, the Non-Financial Reporting Directive (NFDR) was the first regulation dealing with the disclosure of the non-financial information of large companies. This includes aspects related to the environment, social and employee matters, human rights, anti-corruption, and bribery. Later, established in 2020, the EU Taxonomy Regulation set the framework to develop a taxonomy for sustainable activities, providing clarity on what is deemed sustainable in the EU. Effective from 2021, the Sustainable-Finance Disclosure Regulation (SFDR) states that financial market participants and advisers in the EU disclose relevant sustainability information to their clients, ensuring transparency in sustainable investment (EUR-Lex 2014/95/EU, 2020/852, 2019/2088).

As regulatory oversight on ESG matters becomes more stringent in the EU and U.K., featuring heightened disclosure standards and substantive requirements, the U.S. landscape is experiencing growing fragmentation. States are adopting conflicting stances, and ESG is now a political battleground at the federal level. This leaves companies and investment managers facing the complex task of navigating the intersections of business and politics while safeguarding their interests and investments. Several states and municipalities have enacted their own ESG regulations, addressing specific areas like climate change or sustainable investing practices. However, the state level regulations in certain states prohibits investing along ESG principles for public entities or state funds (e.g.: Idaho SB 1405, in effect 7/1/22, North Dakota SB 2291, in effect 3/24/21, Florida CFO Directive 1/23/23). On the other hand, there are states which highly promotes responsibility investing, such as Maine, where the retirement system cannot hold and has to divest fossil companies from their portfolios by a specific date (Maine HP 65 / LD 99, in effect 6/16/21). Moreover, pension plans in this state have to identifies the 200 largest carbon footprint companies in their portfolios (Malone et al. [2023]).

Although the unified, nationwide regulation is much more advanced in the European Union, the United States is catching up in this regard. This is because, on March 6, 2024, the SEC voted to require publicly traded companies to disclose certain climate-related risks in the future (Binnie and Kerber [2024]). In contrast, the part of the other inevitable regulatory player in the U.S. financial system stays narrow regarding climate regulations. In January 2023, Federal Reserve Chair Jerome Powell suggested a limited role for the Fed in addressing climate change risks in the financial system. Despite some recent steps, such as joining the Network for Greening the Financial System in 2020 and initiating climate committees, the Fed's actions appear less extensive compared to the European Central Bank's comprehensive approach. The ECB not only leads in requiring banks to address climate change but also integrates climate factors into various financial aspects, including corporate bond purchases and collateral frameworks (ING [2023]). Neszveda and Siket (2023) demonstrate that market participants are influenced by what the ECB says, and they also take into account their expectations and decisions based on how green the tone of the ECB's verbal communication is. According their results, the most eco-friendly firms are positively, while least eco-friendly ones are negatively affected by green speeches of the ECB.

Although there are undeniable steps from regulators and governances towards ESG reporting and regulation, this area still requires further research, as the long and short-term impacts remain questionable in many cases. For instance, Hevér and Csóka (2023) highlight that bad ESG divesting and funding liquidity regulations can result reduced market liquidity.

Last but not least, incorporating ESG metrics provides a more holistic understanding of a company's risk profile. The integration of ESG criteria enables a more forward-thinking risk assessment, as it considers evolving regulatory landscapes, societal expectations, and environmental constraints that can affect a company's future performance. Ultimately, ESG metrics enrich the traditional risk analysis by adding layers of non-financial information, ensuring a multi-dimensional understanding of a company's position in an increasingly complex and interconnected business environment.

1.6. DISSERTATION OUTLINE

Chapter 2 is based on an ongoing research, with the tentative title: 'More ESG, less misconduct?'. The plan is to submit the chapter to an international journal in 2024. The chapter contains elements from a sole-authored article by the author of this dissertation, Martin Márkus, titled "The relationship between social responsibility scores and operational risk categories" (original language title: A társadalmi felelősségi pontszámok és a működési kockázat kapcsolata kockázati kategóriaként). This article has already been published in Közgazdasági Szemle in 2023.

Chapter 3 is based on another research in preparation, tentatively titled: 'Are we responsible when it hurts? How investors evaluate ESG in recent gains and losses.' This chapter is also planned to be submitted to an international journal, ideally by 2024.

In Chapter 4, we summarize the conclusions, reflect on the research questions raised in Chapter 1, and present the limitations of the research uncovered in the dissertation, as well as future research opportunities.

2. MORE ESG, LESS MISCONDUCT?[2]

In recent years, Credit Suisse, a Swiss multinational investment bank, one of the 30 globally important financial institutions (G-SIBs), was involved in a string of scandals such as tax evasion, corruption, money laundering, breach of quarantine rules, and sanctions-busting. Regulatory fines, legal actions against the bank, and the corresponding reputational losses contributed to frequent removals of the top management, a continuous deprecation of the stock price (-27% in 2021 and -63% in 2022), a bank run in 2023 March, and finally, the collapse and the takeover of the bank by its main rival, UBS Group AG. During these hard times, Credit Suisse placed great emphasis on sustainability communication. In the Sustainability Reports of 2021 and 2022, the bank thanked their stakeholders for their patience and expressed a strong commitment to prudent operation: "We deeply regret that these incidents have caused significant concerns for our stakeholders and would like to thank them for their support during these times. (Credit Suisse [2021], page 3)… We build lasting value by serving our clients with care and entrepreneurial spirit (Credit Suisse [2022], page 38)… Our values of Inclusion, Meritocracy, Partnership, Accountability, Client focus and Trust form the word IMPACT and provide the framework by which we reinforce good behavior (Credit Suisse [2022], page 41)". Credit Suisse has been rated by several ESG providers like S&P Global, MSCI, CDP, Sustainalytics, ISS, and FTSE Russell with mixed results ranging from "high ESG risk" to the inclusion in the FTSE4Good Index of firms with "best ESG practices".

Similar cases have occurred in the United States as well. Wells Fargo, a major US bank, had a long-standing reputation for customer service and community involvement. They frequently emphasized their commitment to financial wellness and ethical practices. According to the vision of the company: "This is more than just doing the right thing. We also have to do it in the right way" (Tayan [2019], page 1). In addition, for several years, the Bank has consistently earned a spot on Gallup's "Great Places to Work" list, boasting employee engagement scores that rank in the top quintile among U.S. companies. Between 2009 and 2016, Wells Fargo employees opened millions of unauthorized bank accounts and credit cards to meet unrealistic sales quotas. This practice aimed to boost

[2] This chapter is partly based on Márkus (2023)

the bank's profits but resulted in significant harm to customers. Many customers were unaware of these accounts and incurred fees, impacting their credit scores. Wells Fargo's image as a responsible and trustworthy financial institution was severely tarnished. Regaining customer trust became a major challenge. The Bank faced significant financial penalties and had to refund customers for unauthorized fees. They also overhauled their sales practices and faced leadership changes (Tayan [2019]).

In this chapter, we investigate whether there is any link between ESG ratings and the frequency and severity of corporate misconduct. In addition, we also examine how this relationship holds in different operational risk categories. There is a great debate on the relevance of ESG in finance. Corporate social responsibility can create value for investors even if they have no preference for sustainability through different channels such as consumer preferences, other investors' preferences, regulation, and risk management (Albuquerque et al. [2019], Barko et al. [2022], Bofinger et al. [2022], Cornell [2021], Flammer [2021], Pástor et al. [2021]). In this chapter, we focus on the risk management channel and examine misconduct as one of the main sources of downside risk highly relevant for all types of investors. In the U.S., ESG investments are in the crossfire of political debates (demonization of asset managers, blacklists, law proposals against ESG, etc.), which makes our research highly topical (Economist [2023]).

Misconduct is difficult to define and measure (Alexander and Cummings [2022], Karpoff et al. [2017], Bertsch et al. [2020]). A novelty of our approach is that we proxy corporate misconduct by the operational loss events reported in the SAS Global Oprisk database (SAS [2021]) with a special emphasis on those, resulted from regulatory fines, restitution or other legal action, hence where the responsibility of the firm was established explicitly by official bodies. 76% of operational loss events can be considered explicit misconducts in this sense. We argue however that all operational loss events have some misconduct elements, hence during the preparation of the chapter and the application of empirical models, every event recorded in the SAS database was interpreted as a misconduct event, meaning as an operational risk event. However, in the robustness tests, we apply a different, more strict definition to identify misconduct events where the company's involvement is unquestionable. These are explicit misconduct events, which have attracted some form of legal, regulatory, or restitution fine, or they are coming from a specific operational risk category, where the company involvement in the misconduct is straight forward (internal fraud, improper business practices, or employment practices and workplace safety). In this sense, the base empirical results are built on 661 separate misconduct events, while the explicit misconduct models (in the robustness tests) are using 500 distinct events.

As most of the misconduct lasted several years (even decades in some cases), we divide the reported total loss amounts evenly between the first and the last year of misbehaving adjusting for the purchasing power parity. This measure of loss severity is particularly rich in information as official bodies can be assumed to carefully assess the conditions of a given misconduct event. Note that this severity measure focuses only on the original, monetary loss borne by the firm as a direct consequence of a misconduct, while further indirect effects such as financial markets' reactions, consumer boycotts, and reputational losses are not taken into account.

The market reaction on a corporate misconduct event has rich academic literature. A significant body of research suggests a negative market reaction to operational risk events. Murphy, Schrieves, and Tibbs (2009) show from a sample containing firms from all different sectors, that the announcement of corporate misconducts results a -1.4% cumulative average abnormal return (CAR) within two days after the publication of the misconduct. Furthermore, the authors also find that the negative stock price return is larger if the company is involved in the misconduct event compared to the setup, when a third-party caused the damage. Palmrose, Richardson, and Scholz (2004) analyze more than 400 restatement events in the U.S. and conclude an average -9% return after two days of the announcement. Cummins et al. (2006) with an event-study analysis focusing only on financial institutions due to their more regulated environment conclude on a more than 400 event sample from the U.S. between 1978 and 2003, that for banks, the mean cumulative abnormal return in the (-5, +5) window is -1.12%, while insurers show a stronger response, with a mean CAR of -3.27% in the (-1, +15) window. This suggests a greater surprise factor for insurers, possibly linked to the historical rarity of insurance-related events before the 1990s compared to the enduring impact of events like fraud on banks. Perry and De Fontnouvelle (2005) analyze the relationship between stock prices and operational risk events using event study methodology from a different angle, to quantify and understand reputational risk. They find that the decline in stock prices is three times greater when a loss event is caused by internal fraud compared to external events. They interpret this delta as the reputational effect. Authors arrive at similar results when examining the European markets (Gillet, Hübner, and Plunus [2010], Sturm

[2013]), the Chinese market (Bai, Gao, and Sarkis [2021]), and the Turkish market (Solakoglu and Kose [2009]).

Due to the well-established research findings and the fact that the current chapter is built upon yearly loss events and financial measures, we do not analyze the market reaction on the firms and misconduct events in the sample. Event studies typically focus on short-term market reactions immediately surrounding an event and can be influenced by market volatility and noise, making it challenging to distinguish the true impact of an operational risk event from short-term market fluctuations. The consequences of operational risk events may accumulate over time, affecting a company's operational efficiency, reputation, and long-term financial performance. Event studies often do not capture the full extent of cumulative effects. In our research, we analyze a more prolonged impact on a company's fundamentals, and their effects may not be fully captured in the short term (e.g., restitutions, legal and regulatory fines). While event studies can help understand market reactions to specific events, they may not provide sufficient information for comprehensive risk management. Buy and hold strategies require a more holistic assessment of a company's risk profile, including ongoing operational risks that may not be captured by isolated events.

As the database relies on the Basel classifications of operational loss events even of non-financial firms, data are comparable across different industries. Our data sample covers 661 loss events of 6,132 financial and nonfinancial firms traded on U.S. stock exchanges between 2013 and 2019, a prospering period without significant macro shocks when ESG communication became widespread.

We find by testing the full sample, that the frequency of misconducts is unrelated to previous ESG ratings, whereas the severity of the misconducts, measured by the loss value, is significantly lower if previous ESG ratings were higher. The results stayed consistent and unchanged after applying the same models on only the explicit misconduct events. Regarding severity, the significance of coefficients goes beyond statistical importance, it holds economic relevance as well. In other words, the values assigned to coefficients not only indicate their statistical reliability but also carry meaningful implications in the context of risk management. One-unit higher ESG is associated with 3.55-4.47% (log percentage) lower losses, hence one standard deviation (19.42) higher ESG rating (on a scale between 0 and 100, where a higher rating indicates better ESG performance) is associated with 50-58% lower losses. Examining the E, S, and G subcomponents separately, we find that coefficients for E and S are significant and approximately of the same size, but G tends to be not significant. The above findings hold also for the finance sector. After addressing endogeneity concerns by Heckman-adjustments for the selection bias, instrumental variable analyses, and several robustness checks, we can interpret our results as higher ESG ratings can lower loss severity. ESG ratings (especially components E and S) can capture important characteristics of firms' operation that are related to the downside risk driven by corporate misconduct. This suggests that ESG ratings can be a useful device to incentivize and monitor corporate (mis)behavior.

In addition, we also find, that the greater the ESG score, the higher the likelihood that a company will undergo (or at least publish) an operational risk incident that becomes publicly known and results in physical damage to its assets. Conversely, in accordance with the previous severity findings on the full sample, a higher responsibility score is associated with a reduced anticipated loss within the improper business practices category.

There is a large body of literature analyzing the relationship between ESG performance and downside risk. These papers examine extreme price movements on the stock or bond markets relying mostly on event study methodologies (Feng et al [2022], Hoepner et al. [2018], Kim et al. [2014], Yu et al. [2023]) or the effects of ESG performance on firm's fundamentals reflected in the balance sheet or the income statement (Albuquerque et al [2019], Barko et al. [2022], Flammer [2013], Godfrey et al. [2009]). Our research fills a gap in the literature as we investigate downside risk from a different angle focusing on corporate misconduct right at the origin and through the lens of regulators, judges, or other official bodies representing the interests of a wide range of stakeholders. Furthermore, our approach can provide additional insights on the source of downside risk.

While the association between Environmental, Social, and Governance (ESG) scores and market risk has been extensively documented in the academic literature, there is a notable scarcity of comprehensive articles addressing the relationship between ESG and operational risk. This gap is often filled by using proxy indicators (for example, extreme stock market returns or changes in specific balance sheet and income statement items) in lieu of adequate and high-quality operational risk data (Friede et al. [2015], Orlitzky et al. [2003]).

Contrary to the majority of publications exploring the relationship between ESG scores and various financial instruments or corporate metrics, this chapter does not rely on stock market trading or financial reporting data. By employing an empirical methodology based on raw fundamentals, specifically the direct data of damage events, it addresses questions of interest to the average investor. During portfolio allocation decisions, investors may wonder whether monitoring responsibility scores can help avoid events similar to the Volkswagen scandal or the British Petroleum oil disaster. Such events, beyond producing negative financial returns, pose a serious threat to sustainability.

Analyzing the relationship between operational risk and ESG indicators is essential from financial, regulatory, and ethical perspectives. From a financial standpoint, understanding the link between ESG performance and operational risk can assist investors and other stakeholders in making more informed decisions regarding their investments or collaborations with corporations. Regulatory authorities are attributing increasing importance to ESG factors during their oversight of firms, primarily in the EU (MNB [2022], EBA [2019]). Comprehending this relationship can help both financial and non-financial corporations in adhering to regulatory requirements, thus avoiding penalties stemming from non-compliance. From an ethical perspective, investors and stakeholders are progressively expecting corporate leadership to prioritize responsibility factors. Understanding the relationship between ESG performance and operational risk can also aid companies in making more informed decisions about resource allocation and risk management, aligning with their ethical obligations.

We find that high ESG scores do not decrease the number of public loss events but decrease their severity. Our results are consistent with the signaling theory of corporate social responsibility (CSR) implying that ESG communication is more beneficial for better firms, hence, firms with better ESG ratings are indeed better (Connelly et al. [2011], Flammer [2021]). Moreover, our findings support the risk management theory of CSR as well, thus, improving ESG performance can be a powerful risk management tool (Godfrey et al. [2009]).

2.1. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

ESG communication is closely related to CSR. ESG rating or its subcomponents are frequently used as CSR proxies (Gillan et al. [2021]). If a firm makes an effort to disclose ESG information regularly and is committed to improve its ESG rating, it is a signal indicating that the firm is moving from shareholder value maximization toward a stakeholder view (Lyon and Montgomery [2015]). Investors may have different ESG attitudes and strategies. *Value* investors care only about the pecuniary returns maximizing the future value of their investment, while *values* investors consider both pecuniary and nonpecuniary returns and have specific trade-offs between the two in line with their personal values (Starks [2023]). Pecuniary returns of an investment can be realized in the form of higher cash flows, lower risk, lower uncertainty, or a combination of these. Nonpecuniary returns can be realized in the form of external (spillover) effects realized in the dimensions of the environment (climate change, pollution, biodiversity, etc.) or the society (labor, social trends, politics, etc.). Values investors tend to sacrifice some returns in exchange for these positive externalities (Degryse at al. [2023]; Flammer [2021]).

Research and public discourse on corporate social responsibility, stakeholder theory, ESG rating, etc., face a number of difficulties and challenges. First, externalities are very difficult to define and measure, perhaps even more than misconducts. ESG ratings are supposed to reflect the effects of the firm on the environment and the society, but also vice versa, the effects of the environment and the society on the firm (double materiality). ESG ratings of different providers are much less correlated than credit ratings (ESG disagreement) which can be due to the obscurity and high-dimensionality of the latent variable(s) behind corporate social responsibility as well as the intentionally different strategies of the rating providers (Brandon et al. [2021]). Opinions are divided on whether ESG rating reduces or increases information asymmetry in corporate financing (Gillan et al. [2021]). Some authors regarded ESG communication as a greenwashing tool (de Freitas et al. [2020], Yu et al. [2020]), while others argued that greenwashing activity is not significant in the practice (Degryse at al. [2023]; Flammer [2013], [2015], [2021]). Greenwashing refers to the deceptive practice of companies or organizations exaggerating or falsely claiming their commitment to environmentally friendly practices in order to attract environmentally conscious consumers, investors and improve their public image.

Companies engaging in greenwashing often use misleading marketing tactics, labels, or advertising to create a false impression of their products or services being more responsible and sustainable than they actually are. These tactics may include highlighting a small environmentally friendly aspect of a product while ignoring more significant negative environmental impacts, using labels or certifications that may sound environmentally friendly but are not officially recognized or are irrelevant to the product's environmental impact (de Freitas et al. [2020]). The ESG score presents a valuable opportunity for companies to enhance their perception among investors and consumers concerning aspects of responsibility and environmental conservation. This is particularly relevant due to the potential for ESG fund inflow and the rise of environmentally conscious consumer behavior, as these factors can result in additional revenue and stock price growth. Companies that may engage in potential greenwashing seek to exploit the increased demand without delivering tangible added performance. They can do so by using misleading metrics or performance indicators, avoiding detailed disclosure of their efforts or performance, emphasizing areas where they perform well and hence creating a misleading impression of their overall commitment to sustainability, and highlighting minor improvements while neglecting significant areas of concern. Yu et al. (2020) assess greenwashing by comparing a firm's number of ESG-related publications with its ESG score. This approach allowed them to evaluate the extent to which the company promotes itself in relation to its actual ESG performance.

Second, it is not clear to what extent pecuniary and nonpecuniary returns are interrelated (Hassan and Romilly [2018]). Several authors argued that higher ESG performance has a positive impact on financial performance in the long run, even if short term effects are just the opposite in some cases (Barko et al. [2022], Eccles et al. [2014], Flammer [2015]). The separation of long- and short-term effects are challenging from both theoretical and empirical point of views. In any case, the stronger the correlation between pecuniary and nonpecuniary returns (bundling), the less difference there is between the value/values investors and between the shareholder/stakeholder approaches (Gillan et al. [2021], Tirole [2010]).

Finally, the time series of market returns, ESG ratings, firm characteristics, macro conditions, etc., are not stationary due to constant changes in preferences, regulation, and politics in this arena. Moreover, preferences, regulation, and politics interfere in a complicated way which can lead to unprecedented regime shifts that are hard to predict.

Policymakers and regulators intervene actively to promote sustainability (Yang et al. [2023]) to which different players may adapt at different rates. Not independent of the regulatory environment, investor and consumer preferences may drastically change over time, and these changes may have a feedback effect on politics and regulation as witnessed in the United States recently (Economist [2023]).

The relation between ESG ratings and financial performance has been thoroughly investigated in the literature. CSR proposals accepted with a slight majority of the shareholders were found to have positive announcement returns and superior financial performance, probably through the labor productivity, and the sales growth channels (Flammer [2015]). The sales growth channel can be effectuated through the increased efficiency of product differentiation (Albuquerque et al. [2019]). The value enhancement effect of CSR is supported by many authors (Bofinger et al. [2022], Eccles et al. [2014]; Friede et al. [2015], Guenster et al. [2011], Malik [2015]). This value enhancement effect might be due, at least partly, to reduced risks and uncertainties. In line with the risk management theory, higher ESG performance provides insurance-like protection (Albuquerque et al. [2019], Flammer [2013], Godfrey et al. [2009]). Several empirical papers conclude that engagement on ESG issues can reduce downside risk measured by value at risk and lower percentiles of stock market returns (Feng et al. [2022], Hoepner et al. [2018], Kim et al. [2014], Yu et al. [2023]).

Numerous studies have examined the application of ESG variables in market risk management. According to Hoepner et al. (2019), companies with high scores in the governance (G) and environmental (E) components have a lower Value at Risk (VaR) indicator and exhibit lower partial moments. Conversely, Sassen et al. (2016) reach similar conclusions regarding the environmental (E) factor but find an inverse relationship between risk metrics and the social (S) factor, and no significant correlation regarding the governance (G) variable. Hoje and Haejung (2012) find varying results across industries when examining the relationship between risk and ESG. Neszveda (2018) further nuances these findings using different risk modeling techniques.

Relatively few scientific articles address the relationship between ESG scores and operational risk, and the results among them vary. Most publications, however, do not account for raw operational risk losses but instead use proxy indicators to measure operational risks, such as the annual revenue variance or the variance of the return on assets (ROA). Buhr (2017) establishes a framework and categorized ESG-related risks into operational, climate, and capital-neutral risks.

Zhao et al. (2016), studying companies listed on the Chinese stock exchange, find that companies that improved their social responsibility faced lower operational risks. However, the mere disclosure of social responsibility (in their case, in the form of reports) had the opposite effect. The risk-reducing impact of social responsibility is particularly significant for companies with high-risk exposure. The article uses annual revenue variance and operational capital leverage as indicators of operational risk, explaining the operational risk using linear regression analysis with general market factors and the social responsibility index.

Chen et al. (2021), consistent with the work of Harjoto and Laksmana (2018), demonstrate that a higher ESG score inversely correlates with operational risk when operational risk is defined as the standard deviation of return on assets (SDROA). Mulia and Joni (2019) reach a similar conclusion, also using the standard deviation of return on assets, in the Indonesian capital market.

Upon analyzing 34 Islamic banks, Neifar and Jarboui (2017) deduct that professional, high-quality corporate governance enhances the disclosure and reporting of operational risk losses and events. This suggests that a higher ESG score, or merely the publication of the ESG score, indicates a higher frequency of operational risks since companies with high-quality corporate governance (and thus higher ESG scores) are more likely to report their operational risk events. An international analysis by Berlinger et al. (2022) indicates that firms have a strong interest in concealing damage events, meaning a significant portion of operational events remains hidden. Higher ESG scores likely correspond with greater transparency, potentially explaining the higher observed frequency of damages.

Other studies individually examine the relationship between CSR and ESG within various operational risk categories. Harjoto (2017) investigates the impact of corporate culture on the occurrence and severity of corporate fraud. He finds that companies that act responsibly towards their employees, environment, and products are less likely to face corporate fraud, and when they do, the severity of the fraud is diminished within such a responsible corporate culture.

He et al. (2022) determine, based on research on companies listed on the Chinese stock exchange between 2010 and 2020, that commitment to ESG principles significantly hinders executive misconduct. Insider trading frequency and the profits from such illicit trading are significantly less for companies with exemplary CSR performance, as highlighted by Gao et al. (2014). Yoon et al. (2021) identify a similar inverse relationship between tax evasion and CSR activities.

These findings suggest that responsible corporate leadership reduces both the number and severity of frauds. Furthermore, Hong et al. (2019) point out, after examining the enforcement data of the U.S. Foreign Corrupt Practices Act from 1990 to 2015, that companies with high ESG ratings received on average 65% or 2 million dollars less in fines. Firms that suffered from data phishing or theft in their stock prices and reputations were only able to restore their intangible assets by intensifying their CSR activities, as observed by Akey et al. (2021). Berlinger et al. (2021) associate country-level operational risk severity and frequency with real loss data and further explained it with sustainability and other megatrends like economic and technological advancements or globalization. Classical indicators post-2008, such as political stability and governmental efficiency, lost their explanatory power. Instead, variables like the number of impoverished individuals (sustainability), mobile subscriptions (modernization), and export volume (globalization) became significant. The number of impoverished positively correlated with the number of losses, whereas modernization and globalization negatively correlated.

Up until the 1990s, operational risk was not recognized as an independent category; the two main sources of financial risks were credit risk and market risk. The unregulated financial market treated operational risks as "other risk events," although events related to hedge funds, for instance, constituted approximately 50% of operational risk events (Chernobai et al. [2008]). According to de Fontnouvelle et al. (2003), internationally active banks experienced on average 50-80 operational risk events annually that caused damages exceeding 1 million dollars. For publicly traded companies, operational risk events often negatively affect stock prices beyond the direct damages and penalties (Goldstein et al. [2011], Fiordelisi et al. [2014]). However, without precise disclosure dates for these damaging events, it's not feasible to study stock market reactions based on annual data. Yet, as posited by Cummins et al. (2006), firms' market value losses significantly surpass the actual magnitude of operational risk damages, suggesting a general overreaction on the stock market side.

In the 1990s and 2000s, numerous scandals and events hit the headlines worldwide that couldn't be distinctly classified as market or credit risk incidents. For instance, in 1995, Barings Bank collapsed due to unauthorized trading, paralleled by the case of Japan's Daiwa Bank, where a trader accumulated a loss of $1.1 billion through unauthorized U.S. government bond trading. To cover up these losses, the trader created fictitious accounts, produced counterfeit documents, and manipulated internal accounting systems (Baxter [1997], Brown [2005]). In 1998, the hedge fund Long-Term Capital Management (LTCM) suffered significant losses from its overly leveraged investment strategy and modeling errors (Jorion [2000]). And in 2001, energy giant Enron imploded after it was revealed that the corporation was involved in accounting frauds and had inflated its profits and financial statements (Healy-Palepu [2003]).

These events, combined with globalization, accelerated information flow, and banking regulation reforms, led the Basel Committee to underscore the significance of recognizing operational risks in its Basel II regulatory package released in 2001. This also defined the capital requirements linked to this risk category (Bazzarello et al. [2006]). Concepts and methods of managing operational risks in banking have increasingly permeated the non-financial sector. In the non-financial sector, operational risks are evidently dominant as the importance of market and credit risks is lesser. The primary distinction lies in the frequency and magnitude of event types. For instance, in the non-financial sector, there are typically fewer but larger losses. The proportion of damages stemming from the malfunction of physical assets is higher, while external and internal frauds occur much less frequently (for a detailed breakdown, see Table 2 in Berlinger et al. [2021]).

Chernobai et al. (2008), in accordance with the Basel regulatory package (BCBS [2022]), define operational risk as the potential for loss stemming from inadequate or faulty systems, internal processes, human behavior, or external events.

There are numerous possible classifications for categories of operational risk. In this chapter, we adhere to a comprehensive classification used in the Basel II regulatory package. The database containing operational risks, SAS OpRisk Global Data (SAS [2021]), which we employed for risk event analysis, also employs this categorization. The categories and their brief descriptions are contained in Table 6. This table includes numerous risk mitigation techniques that can reduce either the frequency of occurrence or the potential magnitude of the loss for various operational risk categories. The presence and development of these internal processes, procedures, and techniques, thanks to the emergence of ESG scores, could pave new ways in managing operational risks.

Table 6. The seven operational risk categories based on the Basel regulations.

Operational Risk Categories	Examples	Risk Mitigation Techniques
Events resulting from system failures causing business interruptions	Utility outage IT-system malfunction	System development Business continuity management
Improper business practices	Trust-regulatory violation Compliance to customers Legal risk	Development of internal control processes Company culture embedded in employees
Events causing physical damage to assets	Natural disaster Business continuity errors Terrorist attack	Business continuity management Protective measures Employee trainings
Occupational harm or workplace-induced damages	Discrimination Workplace accident Epidemic	Development of internal control processes
Incorrect (faulty) execution procedures	Pricing-transaction-modeling errors Tax obligation breach	Clear regulations Up-to-date systems Development of internal control processes Employee trainings
External fraud	Cyberattack Theft of assets and information	Development of internal control processes and control systems Company culture embedded in employees
Internal fraud	Forgery, Unauthorized trading, improper use of confidential information	Development of internal control processes and control systems Company culture embedded in employees

Note: The table lists the names of the seven operational risk categories differentiated according to the Basel regulations, provides illustrative examples for each, and describes the risk mitigation techniques for the given category, without claiming completeness. Source: BCBS [2022], Open Risk Manual [2022].

Although several studies present the empirical relation between downside risk and ESG, the underlying mechanism is not yet established. Higher ESG may decrease the chance of being involved in a misconduct yielding a lower chance of suffering a huge loss, or higher ESG may also predict less severe misconducts or even both.

Thus, we formulate the following research hypotheses.

H1: Higher ESG performance decreases the frequency of corporate misconducts.

H2: Higher ESG performance decreases the severity of corporate misconducts.

Our empirical strategy is based on the analysis of operational loss events both in the financial and non-financial sectors (SAS [2021]). A more detailed industry analysis is hindered by the fact that there wouldn't be enough damage events within individual event categories to derive reliable statistical conclusions.

The main operational risk categories are internal frauds, external frauds, technological failures, process execution and management, labor relation and workforce safety, damage to tangible assets, consumers, and products and business practices. Operational losses can be endogenous or exogenous. In most of the cases, damage is not fully exogeneous. Although operational risk is considered mostly idiosyncratic, it may have systemic components as well (Berger et al. [2022]). Both managers and investors are motivated to reduce operational risk because of market failures such as asymmetric information and costs of financial difficulties. According to the risk management theory of CSR, ESG communication can be an effective tool to reduce operational risk (Albuquerque et al. [2019], Flammer [2013], Gillan et al. [2021]).

ESG scores encapsulate a myriad of corporate-level information, including, among others, the presence and quality of risk mitigation procedures within a given company, as previously illustrated. This leads us to our next research question: If ESG scores encompass corporate-level information that can aid in managing operational risks, can they be used to predict the frequency of occurrence or the severity of various types of operational risk events? Given that a higher ESG score indicates superior performance in responsible corporate governance practices, our expectation is that:

H3: Companies with higher ESG scores will be less exposed to the frequency of those types of operational risks, where the company's involvement cannot be questioned.

H4: Companies with higher ESG scores will be less exposed to the severity of those types of operational risks, where the company's involvement cannot be questioned.

For financial institutions, the Basel II and III frameworks recommend three different methods to calculate the capital requirement for managing operational risk. The simplest method, the Basic Indicator Approach (BIA), mandates that a company reserve 15% of its annual gross income. The slightly more advanced Standard Approach (SA) sets different revenue-based keys for capital reserves by business segment. The most sophisticated, the Advanced Measurement Approach (AMA), allows institutions to determine their required capital using supervised, internal models. These models must include both internal and external loss data and be complemented with scenario analyses and the presentation of internal control processes (BCBS [2023]).

It is a well-known fact among risk managers that modeling the severity of operational losses is a much more difficult task than modeling the frequency (De Fontnouvelle et al. [2007]). Our results show that the ESG rating contains substantial additional information on severity. This suggests that ESG ratings can reduce information asymmetry in this specific area. The existence of a connection between ESG scores and operational risk exposure also raises the possibility of further development in various risk management methods. The results of chapter can assist financial institutions, among others, in better accounting for the impacts of non-financial factors, potentially influencing the parameterization of AMA models. Although the use of the AMA method is only mandatorily selectable for the financial sector, our research findings can also be integrated into the internal risk management models of companies operating in other industries, independent of regulatory requirements. Integrating ESG factors necessitates continuous updates to corporate risk management policies, processes, and systems, as well as training and education for those involved in managing operational risks.

2.2. DATA

We match two databases, SAS Global OpRisk (SAS [2021]) of corporate operational loss events and Eikon Refinitiv (Refinitiv [2022]) of ESG ratings and other firm characteristics. First, we filter those firms having operational loss(es) overlapping with the period of 2013-2019. Using the firm names in the SAS database, we search manually for the corresponding Refinitiv tickers trying different versions of firm names. Although the SAS database contains worldwide data, we narrow down our sample to those firms that were traded on the stock exchanges of NASDAQ or NYSE at any time during this period. In this way, we can concentrate on large public companies operating in the developed world that have similar institutional environments. If a loss was realized by a subsidiary firm not traded on these exchanges, or firm-level data were not available, the loss was conferred to the parent company. In this way, 661 loss events and 266 firms remained in the basic sample.

Among the 661 different operational risk events, several news stories that circulated in the global media can be found. An example is the consumer deception scandal of Apple Inc. in October 2016, in which the company software-wise slowed down the computational performance of older devices and limited the battery life, prompting consumers to replace their old devices with newer models. This event falls under the category of improper business practices. Another example from the external fraud category is the case of Adobe Systems Inc., where the company reported a loss of $149.64 million due to an external cyber-attack in which the company's proprietary source codes and personal and credit card data of 2.9 million users were stolen by external fraudsters. Events causing physical damage to assets include events like the rampage on MGM Resorts International's property, where a gunman from a hotel room window shot down 58 people celebrating at the Route 91 Harvest music festival and injured an additional 422.

To investigate Hypothesis 1 and Hypothesis 3 (loss frequency), we need data on firms with no operational losses as well. Therefore, the basic sample is complemented with firms not included in the SAS database but traded on the NASDAQ or NYSE between 2013 and 2019. The complemented sample includes 6,132 different firms and 26,146 firm-year observations. Note that we have an unbalanced panel dataset as several firms were not traded on these exchanges during the whole period of 2013-2019, so a significant number of firm-year observations are not available.

2.2.1. DEPENDENT VARIABLE

The SAS Global OpRisk database contains all public operational loss events worldwide above the threshold of $100,000. We know the first year, the last year, and the settlement year of the incident, the loss severity in dollars calculated for the settlement date, the type of the event classified according to the Basel regulation, and a lot of other information including a short description of the loss events. Appendix A presents the descriptions of four representative cases selected from our basic sample.

In 500/661=76% of the cases, the misconduct is coming from a specific misconduct category (e.g., internal fraud) or there was a regulatory, restitution, or legal action against the firm, hence the responsibility of the firm has been established officially. This subset of the losses is called as explicit corporate misconduct examined in detail in the robustness tests. Note however, that corporate misconduct cannot be completely excluded even if there was no regulatory or legal action. For example, in cases A.2 (S&T Bank) and A.4 (Titanium Metals Corp), one can argue that firms were not prudent enough to avoid external fraud (by closer monitoring of business partners) and the damage to physical assets (by a more careful storage protocol), respectively. We can see in Table 7 that explicit misconducts are the least frequent in risk categories of damage to physical assets (66%), external fraud (24%), and business disruption and systems failure (56%), but even these types of events can be considered as misconducts by the investors or other stakeholders in most of the cases. For example, large and long-lasting external fraud events are a sign of poor control, monitoring and weak governance systems and are especially perceived as misconduct. Carol and Cummings (2020) discuss fraud and market manipulation as the two most prominent types of misconduct, which also shows that external and internal fraud events can be classified as misconducts even if no regulatory and legal actions are related to them. Therefore, in this chapter, we have two definitions for corporate misconducts, a broader one (all reported operational loss events) and a narrower one (explicit misconducts).

There is a noticeable consistency between the risk mitigation techniques for operational risk categories (see previously in Table 6) and the content of the ESG variables (see previously in Table 1). Industrial harm can be associated with the environmental (E) component. The external fraud category, which includes cyber-hacking or information theft, can typically be addressed by enhancing internal control processes. Notably, within the measurement criteria for the social (S) variable, data security receives special attention. Another example is the risk category for incorrect transaction processes, which can be managed through employee training, up-to-date systems, and internal control processes. This evidently aligns with information stored in the governance (G) variable intended to measure the quality of corporate management.

Table 7. Types of operational loss events.

Event type	Most related ESG component	Number of observations	Mean of loss amount (MUSD)	Standard deviation of loss amount (MUSD)	Explicit misconduct	
					Number of observations	% of all observation in the cat.
Business disruption and systems failures	E, S	16	17.06	28.98	9	56%
Clients, products and business practice	S	249	35.18	91.3	233	94%
Damage to physical assets	E	53	57.2	152.05	35	66%
Employment practices and workplace safety	S	39	20.36	51.96	38	97%
Execution, delivery and process management	S	80	6.06	12.32	71	89%
External fraud	G	143	37.19	92.71	34	24%
Internal fraud	G	81	5.58	17.34	80	99%
Total		661	28.92		500	76%

This table presents the distribution of 661 operational loss events according to the event type. Data are retrieved from the SAS Global OpRisk database. Events are classified in line with the Basel regulation of operational risk management. Explicit misconducts are operational loss events resulted from a regulatory action or a legal liability. Operational loss events are included in the sample only if occurred between 2013 and 2019 (in both financial and non-financial sectors).

We assume that the damage occurred evenly over time, therefore the loss amount calculated for the settlement year is distributed evenly between the first and the last year of the incident, indexed by purchasing power parity.

Firms can have several operational losses in progress in a year. When investigating frequency, the dependent variable of the model is binary, it takes 1 if there was at least one loss in progress at the given firm in the given year and 0 otherwise. When investigating severity, the dependent variable is the sum of all losses that occurred at the given firm in the given year related to the firm's revenue. We therefore do not differentiate between a company having 1 loss of 10 million or 10 losses of 1 million in a year.

2.2.2. EXPLANATORY VARIABLES

ESG is the main variable of interest. We used the Refinitiv database to retrieve ESG ratings and other firm characteristics. E, S, and G components are analyzed separately, and also as an aggregate score. ESG scores are on a scale of 0-100 where higher numbers indicate better ESG performance. In some specifications, we analyze a dummy ESG variable indicating whether the firm has an ESG rating (1) or not (0). Refinitiv's rating coverage depends mostly on Refinitiv's own strategy. However, in several cases, firms are required to participate in the ESG rating program but are reluctant to provide the necessary data. Therefore, missing data can be the result of the firm's strategy as well. Indicator scores in pillars S and E (G) are benchmarked against the industry (country) peers (Bofinger et al. [2022]). ESG ratings correspond to the end of the year.

Recent criticisms have arisen against the use of aggregated ESG scores due to subjective weighting and varying calculation methodologies across data providers (Berg et al., 2022). In our empirical research, apart from the overall ESG score, we included the individual E, S, and G scores as explanatory variables. The individual E, S, and G scores, according to Refinitiv's calculation methodology, consist of sub-scores such as carbon emissions, water usage, energy consumption for the environmental (E) sub-score, etc. However, not all variables apply to all industries; for instance, water usage or pollutant emissions aren't relevant for financial institutions. Additionally, the relatively small sample size, due to the low number of operational risk events, does not allow for detailed examination across various risk categories and industries. However, the individual E, S, and G categories are harmonized across industries and corrected for previously mentioned issues, making them the least subjective and most informative for empirical modeling.

The complemented dataset covers all stocks traded on NASDAQ or NYSE between 2013 and 2019. We have 26,142 firm-year observations, which means 7 firm-year observations if a company has data for every year between 2013 and 2019. Depending on ESG rating penetration, the same firm may not have an ESG score in a year but may have it in the next year. Firm-year observations according to years and industries are shown in Table 8.

Table 8. Firm-year observations according to years and industries.

Year	Firm-year obs.	%	With ESG (%)	Oprisk event if has ESG	Oprisk event if no ESG	Industry	Firm-year obs.	%	With ESG (%)	Oprisk event if has ESG	Oprisk event if no ESG
2012	2,766	10.6%	31.0%	-	-	Basic materials	996	3.8%	63.2%	0.3%	0.5%
2013	3,018	11.5%	31.3%	16.2%	1.6%	Consumer discretionary	3,705	14.2%	63.6%	3.6%	0.6%
2014	3,209	12.3%	33.6%	20.1%	1.9%	Consumer staples	1,078	4.1%	60.2%	2.9%	0.5%
2015	3,394	13.0%	50.6%	14.0%	1.8%	Energy	1,543	5.9%	45.4%	5.3%	0.8%
2016	3,478	13.3%	66.8%	11.0%	1.3%	Financial	5,273	20.2%	56.7%	27.8%	3.7%
2017	3,470	13.3%	77.2%	8.9%	1.1%	Healthcare	3,871	14.8%	51.8%	4.6%	0.2%
2018	3,427	13.1%	80.7%	5.7%	0.8%	Industrials	4,001	15.3%	59.7%	3.7%	0.5%
2019	3,380	12.9%	83.0%	2.5%	0.3%	Real estate	1,357	5.2%	69.5%	1.1%	1.2%
	26,142					Technology	2,721	10.4%	55.7%	5.2%	0.1%
						Telecommunications	783	3.0%	57.9%	11.5%	2.1%
						Utilities	746	2.9%	70.5%	7.2%	2.3%
						Other	68	0.3%	13.2%	0.0%	0.0%
							26,142				

This table presents the distribution of 26,142 firm-year observations according to years and industries. Data are retrieved from the SAS Global OpRisk and the Refinitiv databases. For industry classification, we use the main ICB (Industry Classification Benchmark) categories. The ratio of firms with ESG rating increased significantly in the period of investigation. Operational loss events are included in the sample only if occurred between 2013 and 2019 (in both financial and non-financial sectors). Firm characteristics are lagged relative to the operational loss event; therefore, we have observations also for 2012. Operational losses are more frequent in the finance sector and in ESG-rated firms.

The percentage of firms with ESG ratings has increased spectacularly from 31% to 83% over the investigated seven years. At the same time, we can observe a decreasing trend in the ratio of firms with operational losses. This can be explained by the attenuating effect of the great financial crisis, in a booming period, it can be easier or more beneficial for firms to operate in a prudent way. Another explanation is that a large part of the misconducts progressing between 2013 and 2019 will be detected, published, and included in the SAS database only in the upcoming years.

It is notable that most loss events occur in the financial sector (20.2%) and loss frequency is the highest here both for ESG (27.8%) and non-ESG (3.7%) firms, which can be due either to the larger number of misconducts or to the higher detection rate in this specific, highly regulated sector. ESG is more prevailing in industries like utilities (70.5%) and real estate (69.5%) whereas energy (45.4%) and healthcare (51.8%) sectors are lagging behind.

Both sections of Table 8 indicates that if a firm has an ESG rating, then the probability of operational loss events is higher. This can be explained by the higher transparency of ESG firms, or greenwashing (by promoting small responsibility achievements to hide more significant issues), or it can also be due to the feedback effect of operational losses: large scandals may induce ESG improvements.

2.2.3. CONTROL VARIABLES

We consider confounder variables that influence both ESG ratings and misconducts or represent unwanted mechanisms. In a usual corporate finance setting, all strategy-related variables are potential confounders (Bascle [2008]). However, in our case, most of these strategy-related variables are already included in the multidimensional ESG ratings.

Although the quality of the internal governance structure is included in the ESG ratings, variables capturing the attention of external monitors (A) should also be controlled for (Gillan et al. [2021]). Proxy variables can be the number of analysts (in the last month of the year) and indicators of market liquidity such as trading volume (last month's average), bid-ask spread (last month's average expressed in percentage), and Amihud illiquidity-measure (the ratio of the absolute value of the asset's return to its trading volume) (Amihud [2002]). We assume that more analysts and higher market liquidity represent a higher attention of external monitors (investors, short sellers, regulators, journalists, etc.) (Berlinger et al. [2022]).

Market reactions to good and bad corporate news can provide strong incentives for firms to (mis)behave (Cornell [2021], Cornell and Damodaran [2020], Feng et al. [2022], Gillan et al. [2021], Kim et al. [2014], Malik [2015], You et al. [2023]). The second group of the control variables is therefore related to market valuation (M). The book-to-market ratio and the P/E ratio are proxies for market over- or undervaluation; the yearly stock total return is related to the market sentiment at the end of the year, while equity volatility and equity beta (both calculated from daily returns over the year) capture market risk.

Finally, in line with the empirical literature on corporate finance (Bofinger et al. [2022], Feng et al. [2022], Kim et al. [2014], You et al. [2023]), we introduce proxy variables of firm fundamentals (F) such as size (log market capitalization), sector (financial sector dummy), credit rating (investment grade dummy), leverage (debt-to-equity ratio), funding liquidity (long term debt to current assets), profitability (operating profit margin and return on assets, ROA), and capital investments (log CAPEX). Non-performing loans are potentially highly correlated with other variables in the model (such as leverage or credit rating), hence their inclusion could introduce multicollinearity issues.

Table 9 summarizes the descriptive statistics of all model variables. To tackle the problem of extreme outliers that can lead to unreliable statistical modelling, we winsorize all variables at 1% and 99%.

Table 9. Descriptive statistics.

	Variable type	Firm-year obs.	Mean	Median	St. Deviation	Min.	Max.
Dependent variable							
Loss frequency	binary	26142	0.06	0.00	0.23	0.00	1.00
Current loss	ln(loss/revenue)	1466	11.67	1.08	44.43	0.02	767.03
Explanatory variables							
ESG score	0-100	15,170	39.88	36.05	19.42	0.44	93.45
E score	0-100	15,168	25.67	15.79	28.30	0.00	98.55
S score	0-100	15,168	42.30	38.72	21.09	0.26	98.94
G score	0-100	15,170	48.05	48.69	22.61	0.16	98.63
ESG dummy	binary	26,142	0.58	1.00	0.49	0.00	1.00
A - Attention of external monitors							
Number of analysts	integer	22,212	10.27	8.00	8.32	1.00	36.00
Trading volume	in log MUSD	21,609	14.30	14.56	2.54	8.49	19.47
Bid-ask spread	percentage	25,222	0.53%	0.09%	1.25%	0.01%	8.00%
Amihud illiquidity	logreturn/trading volume	21,534	-0.33	0.01	8.54	-55.50	34.60
M - Market valuation							
Book-to-market	ratio	25,319	3.34	1.95	7.45	-23.43	50.95
P/E	ratio	18,336	34.60	20.10	55.36	2.40	426.10
Logreturn	log%	25,961	3.13%	8.09%	43.81%	-162.42%	114.56%
Volatility	dollar	20,218	30.89	27.98	12.87	12.14	69.02
Beta		25,997	1.11	1.05	0.72	-0.72	3.40
F - Fundamentals							
Size	in log MUSD	26,009	6.93	6.96	2.20	2.04	12.36
Financial industry	binary	26,074	0.20	0.00	0.40	0.00	1.00
Leverage	ratio	25,777	90.53	50.36	234.51	-889.41	1,405.89
Funding liquidity	ratio	24,617	92.57	41.05	183.06	0.00	1,330.39
Operating profit margin	ratio	25,246	-63.43	9.94	445.30	-3,792.87	65.76
ROA	ratio	25,414	-3.01	3.09	26.31	-149.73	38.33
CAPEX	ln(Cap. Exp in MUSD)	24,476	9.92	10.13	2.77	2.57	15.73
Credit rating	Category	7,348	High yield	2,447	Investm. grade	4,901	

This table presents the descriptive statistics of the model variables after winsorization of 1% and 99%. Data are retrieved from the SAS Global OpRisk and the Refinitiv databases. Operational loss events are included in the sample only if occurred between 2013 and 2019 (in both financial and non-financial sectors).

To reduce multicollinearity, we excluded two market attention variables (the number of analysts and trading volume) and a fundamental variable (capital expenditure) from the analysis.

2.3. EMPIRICAL METHODOLOGY

To test the first hypothesis H1, we use the complemented database where the dependent variable is binary. We model loss frequency as

$$P(loss\ event_t) = f(ESG_{t-1}, A_{t-1}, M_{t-1}, F_{t-1}, YEAR_t) \quad (1)$$

where *t* is an index for years. A public loss event occurs if (i) there is a loss event and (ii) it becomes public. We assume that variables of ESG, attention of external monitors (*A*), market valuation (*M*), fundamentals (*F*), and the year of the incident are all relevant for modelling both the existence of a loss event and its likelihood of becoming public.

To test the second hypothesis H2, we use the basic database where the dependent variable is continuous. We model loss severity as

$$\ln\left(\frac{loss}{revenue}\right)_{i,t} = \alpha_0 + \beta \cdot ESG_{i,t-1} + \sum_j \gamma_j A_{j,i,t-1} + \sum_k \delta_k M_{k,i,t-1} + \sum_l \mu_l F_{l,i,t-1} + \sum_m \theta_m\, TYPE_m + \sum_n \tau_n\, YEAR_n + \varepsilon_{i,t} \quad (2)$$

where *i* is an index for firms and *t* is for years. As loss is divided by the yearly revenue of the firm, the size of the firm is taken into account; hence, we no longer include a size variable on the right side of (2).

In the panel regression models, first we introduce the aggregate ESG score, then its E, S, and G elements, and the ESG dummy separately. We use the whole sample (financial firms are also included but controlled for). To avoid reverse causality, explanatory and control variables are lagged by one year. The database has an annual frequency. Neither the exact date of damage events nor intra-year changes in ESG data are known on a daily basis. ESG scores can affect damage events, and vice versa, damage events have effect on ESG scores due to corrections involving ESG-controversary variables. Hence, ESG scores appear in the equation with a one-year lag, filtering out the feedback when damage events change the ESG score, for instance, due to tax fraud or illegal trading practices.

Risk events in the database were recorded in the first year of their occurrence, so ESG scores from the previous year could not yet include corrections applied due to the risk event. Analyzing both variables simultaneously could mix causal effects, but this is avoidable by lagging the ESG score. The loss/revenue ratio, trading volume, and size (market capitalization), variables are logarithmized. All continuous variables are winsorized at 1% and 99% (except for the ESG scores). Standard errors are clustered at a firm level in all specifications.

2.4. RESULTS

2.4.1. PANEL REGRESSION

First, we investigate the frequency of the losses. We estimate a logit model for (1) with year fixed effects. Results are shown in Table 10.

Table 10. Results of logit panel regressions for loss frequency.

	(1)	(2)	(3)	(4)	(5)
	LOGIT FREQUENCY FIXED EFFECT - YEAR				
lag Oprisk-flag	0.7167*** (0.0223)	0.7168*** (0.0224)	0.7168*** (0.0224)	0.7158*** (0.0222)	0.7210*** (0.0214)
lag ESG	0 (0.0003)				
lag E		0 (0.0002)			
lag S			0 (0.0003)		
lag G				0.0003 (0.0002)	
lag ESGdummy					0.0013 (0.0090)
A - ATTENTION OF EXTERNAL MONITORS					
Bid-ask spread	1.8712** (0.6970)	1.8906** (0.7045)	1.8880** (0.7000)	1.9293** (0.6773)	1.4868** (0.5323)
Amihud illiquidity	-0.0147 (0.0086)	-0.0147 (0.0086)	-0.0147 (0.0086)	-0.0146 (0.0086)	-0.0010 (0.0009)
M - MARKET VALUATION					
Book-to-market	-0.0023* (0.0010)	-0.0023* (0.0010)	-0.0023* (0.0010)	-0.0022* (0.0010)	-0.0019 (0.0010)
P/E	0 (0.0001)	0 (0.0001)	0 (0.0001)	0 (0.0001)	0 (0.0001)
Logreturn	0.0237 (0.0163)	0.0234 (0.0163)	0.0235 (0.0162)	0.0235 (0.0161)	0.0068 (0.0149)
Volatility	0.0030*** (0.0007)	0.0030*** (0.0007)	0.0030*** (0.0007)	0.0031*** (0.0007)	0.0030*** (0.0006)
Beta	-0.0073 (0.0089)	-0.0069 (0.0089)	-0.0069 (0.0088)	-0.0076 (0.0090)	-0.0074 (0.0080)
F - FUNDAMENTALS					
Size	0.0371*** (0.0050)	0.0377*** (0.0050)	0.0377*** (0.0049)	0.0365*** (0.0043)	0.0352*** (0.0039)
Financial industry	0.0727*** (0.0151)	0.0723*** (0.0153)	0.0723*** (0.0153)	0.0743*** (0.0152)	0.0703*** (0.0136)
Leverage	0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)	0.0002* (0.0001)
Funding liquidity	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0001)
Operating profit margin	-0.0001 (0.0004)	-0.0001 (0.0004)	-0.0001 (0.0004)	-0.0001 (0.0004)	-0.0001 (0.0003)
ROA	-0.0011 (0.0009)	-0.0012 (0.0009)	-0.0011 (0.0009)	-0.0011 (0.0009)	-0.0011 (0.0008)
Credit rating	0.0241* (0.0094)	0.0244* (0.0096)	0.0244** (0.0093)	0.0235* (0.0095)	0.0237** (0.0084)
Observations	3,684	3,684	3,684	3,684	4,196

* p<0.05; ** p<0.01; *** p<0.001

The table presents the logit panel regression estimations of the effects of a company's lagged ESG on the probability of misconduct. Misconducts are proxied by the ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database (broad definition). Loss amounts are divided evenly between the first and the last year of occurrence. If some variables were missing, observations are left out. ESG is not associated with frequency in any specifications.

None of the ESG variables is significant, thus we find no significant association between ESG and the probability of misconduct. The lagged operational loss indicator is however significant at 0.1% in all specifications. This is because most operational loss events last for several years, so if an event occurred in a year, the following year is likely to have an operational loss as well. The dependent variable changes only if a misconduct starts (the dependent variable switches from 0 to 1) or ends (the dependent variable switches from 1 to 0).

The financial dummy is also significant in all specifications at 0.1% with a positive sign. Overall, less liquid, overvalued, volatile, larger firms with good credit ratings in the finance sector tend to have more operational losses. We cannot disentangle, however, that more operational losses reported in the SAS database are due to more misconducts, or a higher detection rate, or both. Years are also significant with increasingly negative coefficients.

Table 11 shows the results of fixed effect panel regression models for the loss severity, measured by the logarithm of the operational loss/firm’s annual revenue.

Table 11. Results of panel regression models for loss severity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	SEVERITY FIXED EFFECT - YEAR, EVENT TYPE									
lag ESG	-0.0503***	-0.0315**								
	(0.0077)	(0.0115)								
lag E			-0.0323***	-0.0267***						
			(0.0049)	(0.0075)						
lag S					-0.0454***	-0.0336**				
					(0.0088)	(0.0114)				
lag G							-0.0295***	-0.0012		
							(0.0069)	(0.0092)		
lag ESGdummy									-2.8730***	-2.7699**
									(0.4705)	(0.9035)
A - ATTENTION OF EXTERNAL MONITORS										
Bid-ask spread		-36.1609		-64.6105		-125.9101		166.1526		155.1323
		(265.9548)		(258.6851)		(245.7970)		(303.6236)		(289.4261)
Amihud illiquidity		0.5219		0.9048		0.7420		0.0233		0.9673
		(1.3455)		(1.2920)		(1.2666)		(1.5451)		(1.2510)
M - MARKET VALUATION										
Book-to-market		-0.1533		-0.1556		-0.1665*		-0.1806*		-0.1756*
		(0.0838)		(0.0834)		(0.0813)		(0.0881)		(0.0847)
P/E		0.0199*		0.0217**		0.0210*		0.0262**		0.0262***
		(0.0081)		(0.0081)		(0.0082)		(0.0083)		(0.0076)
Logreturn		-0.8485		-0.8485		-0.8024		-1.3908		-1.4410
		(0.7903)		(0.7903)		(0.8307)		(0.7933)		(0.8174)
Volatility		-0.0209		-0.0229		-0.0237		-0.0144		-0.0255
		(0.0520)		(0.0460)		(0.0494)		(0.0564)		(0.0535)
Beta		0.1062		0.1301		0.1277		-0.3448		-0.3367
		(0.5028)		(0.4842)		(0.5040)		(0.4395)		(0.4564)
F - FUNDAMENTALS										
Financial industry		-0.6007		-0.3609		-0.4321		0.2473		0.3286
		(0.8928)		(0.8256)		(0.8729)		(0.7966)		(0.6898)
Leverage		-0.0059		-0.0029		-0.0058		-0.0093*		-0.0086*
		(0.0035)		(0.0039)		(0.0037)		(0.0036)		(0.0034)
Funding liquidity		0.0094		0.0071		0.0098		0.0136*		0.0126*
		(0.0049)		(0.0048)		(0.0051)		(0.0052)		(0.0049)
Operating profit margin		0.0530*		0.0412		0.0545		0.0493		0.0442
		(0.0240)		(0.0232)		(0.0240)		(0.0249)		(0.0229)
ROA		0.0767		0.0931		0.0879		0.1176		0.1216
		(0.0699)		(0.0676)		(0.0655)		(0.0728)		(0.0677)
Credit rating		0.4096		0.3489		0.4387		0.1790		0.1349
		(0.5154)		(0.4826)		(0.5282)		(0.4950)		(0.4929)
Observations	1,113	584	1,113	584	1,113	584	1,113	584	1,210	598
Adjusted R-Squared	0.227	0.2831	0.2333	0.3019	0.2015	0.2939	0.1456	0.2554	0.1559	0.2734

* p<0.05; ** p<0.01; *** p<0.001

The table presents the panel regression estimations of the effects of a company's lagged ESG on the severity of misconduct. Misconducts are proxied by the ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database (broad definition). Loss amounts are divided evenly between the first and the last year of occurrence. The dependent variable is the logarithm of the loss amount divided by the yearly revenue of the firm. If a firm has several losses in a year, loss amounts are added up. If some variables are missing, observations are left out. ESG is associated negatively with the severity of losses.

Table 11 presents the results of the univariate regression models, followed by the results after including the control variables. All ESG variables are significant at a significance level of 0.1% in the univariate models. After the inclusion of the control variables, the coefficients decrease slightly, but all ESG variables remain significant at a significance level of at least 1%, except for the governance (G) indicator. The signs of the coefficients are negative, one-unit higher ESG scores are associated with approximately 3% lower loss severity.

2.4.2. SAMPLE SELECTION BIAS

In the SAS Global Oprisk Database we can only observe loss events that became public. As firms have a strong interest in hiding loss events for reputational reasons, our sample of public losses can suffer from selection bias (Berlinger et al. [2022]). To tackle this problem, we use the two-stage Heckman method (Bascle [2008], Heckman [1976]).

From the severity model (2), we exclude all variables related to the attention of external monitors (A) which are the bid-ask spread and the Amihud illiquidity measure. We can assume that the attention of investors and other external monitors has an effect only on the probability of a public loss event, but not on the loss severity. Once a loss is revealed, loss severity cannot be manipulated due to the high transparency of exchange-traded firms we investigate. Furthermore, according to Becker's (1968) crime model, deterrence depends on the probability of detection and much less on the severity of the punishment. Becker's famous crime model has since got numerous practical and theoretical validations. Utilizing nearly thirty years of crime data from New York City between 1970 and 1996, Corman and Mocan (1999) demonstrate that the occurrences of murders, robberies, and thefts significantly decrease with an increase in police presence. Grogger (1991), also relying on empirical data, illustrates that while the severity of punishment essentially does not affect the incidence of criminal activities, the increased certainty of punishment does. Thus, the author questions the necessity of long and costly prison sentences for the purpose of prevention. Tealde (2021), building upon Becker's model, find a significant negative impact based on the relationship between public lighting, the strengthening of deterrence, and the reduction in the number of criminal incidents. Thus, the intense attention of external monitors discourages firms from committing a crime, but not from committing a larger crime. Therefore, it is reasonable to assume that the attention of external monitors affects the observed number of losses, but not their size. We remind that the bid-ask spread was significant for frequency in Table 10, while neither the bid-ask spread nor the Amihud illiquidity measure was significant for loss severity in Table 11. Therefore, the statistical analysis confirms the idea of addressing the selection bias with the help of the attention variables (A).

The first part of Table 12 shows the results of the first stage of the Heckman model (Bascle [2008], Heckman [1976]), a probit regression for the likelihood of operational loss. In the second stage, an OLS model is run for loss severity that is corrected for the selection bias.

Table 12. Results of the Heckman models.

	(1)	(2)	(3)	(4)	(5)
			HECKMAN/HECKIT ESTIMATION		
			Probit selection equation		
lag Oprisk-flag	2.4500 *** (0.0904)	2.4480*** (0.0901)	2.4540*** (0.0904)	2.4430*** (0.0903)	2.4600*** (0.0870)
lag ESG	-0.0006 (0.0026)				
lag E		0.0003 (0.0018)			
lag S			0.0023 (0.0024)		
lag G				0.0015 (0.0020)	
lag ESGdummy					-0.0237 (0.1564)
A - ATTENTION OF EXTERNAL MONITORS					
Bid-ask spread	-0.1471 (0.3886)	-0.1502 (0.3890)	-0.1500 (0.3936)	-0.1549 (0.3950)	-0.2895 (0.4256)
Amihud illiquidity	-0.2915 (0.1505)	-0.2906 (0.1506)	-0.2935 (0.1514)	-0.2887 (0.1510)	-0.0041 (0.0760)
M - MARKET VALUATION					
Book-to-market	-0.0221* (0.0103)	-0.0221* (0.0103)	-0.0225* (0.0104)	-0.0220* (0.0104)	-0.0160 (0.0099)
P/E	-0.0012 (0.0011)	-0.0011 (0.0011)	-0.0012 (0.0011)	-0.0011 (0.0011)	-0.0013 (0.0010)
Logreturn	0.5674** (0.1890)	0.5679** (0.1890)	0.5636** (0.1892)	0.5628** (0.1891)	0.3390* (0.1655)
Volatility	0.0386*** (0.0087)	0.0391*** (0.0086)	0.0378*** (0.0087)	0.0397*** (0.0086)	0.0418*** (0.0078)
Beta	-0.2181* (0.1093)	-0.2231* (0.1093)	-0.2073 (0.1098)	-0.2236* (0.1086)	-0.2334* (0.1023)

	(1)	(2)	(3)	(4)	(5)
F - FUNDAMENTALS					
Size	0.4007*** (0.0377)	0.3935*** (0.0391)	0.4134*** (0.0382)	0.3924*** (0.0341)	0.3769*** (0.0325)
Financial industry	0.6492*** (0.1292)	0.6590*** (0.1285)	0.6375*** (0.1278)	0.6708*** (0.1282)	0.6573*** (0.1201)
Leverage	0.0012 (0.0008)	0.0012 (0.0007)	0.0013 (0.0008)	0.0013 (0.0008)	0.0016* (0.0007)
Funding liquidity	-0.0007 (0.0009)	-0.0006 (0.0009)	-0.0007 (0.0009)	-0.0007 (0.0009)	-0.0012 (0.0008)
Operating profit margin	0 (0.0037)	0.0001 (0.0037)	-0.0001 (0.0037)	0.0001 (0.0037)	-0.0010 (0.0035)
ROA	-0.0144 (0.0037)	-0.0141 (0.0104)	-0.0143 (0.0104)	-0.0138 (0.0104)	-0.0148 (0.0100)
Credit rating	0.3662** (0.1186)	0.3628** (0.1185)	0.3736** (0.1188)	0.3595** (0.1183)	0.3418** (0.1102)
Intercept	-6.6120*** (0.4159)	-6.5970*** (0.4261)	-6.6450*** (0.4176)	-6.6730*** (0.4261)	-6.1590*** (0.3843)
			Outcome equation		
lag ESG	-0.0355*** (0.0059)				
lag E		-0.0285*** (0.0040)			
lag S			-0.0357*** (0.0053)		
lag G				-0.0082 (0.0053)	
lag ESGdummy					-2.4106*** (0.6069)
M - MARKET VALUATION					
Book-to-market	-0.0645* (0.0310)	-0.0572 (0.0308)	-0.0757* (0.0308)	-0.0718* (0.0317)	-0.0750* (0.0316)
P/E	0.0065 (0.0036)	0.0054 (0.0036)	0.0076* (0.0036)	0.0080* (0.0037)	0.0091* (0.0037)
Logreturn	-0.3731 (0.4815)	-0.5178 (0.4766)	-0.3650 (0.4784)	-0.4379 (0.4953)	-0.3577 (0.4578)
Volatility	-0.0441 (0.0244)	-0.0478* (0.0242)	-0.0476 (0.0243)	-0.0257 (0.0249)	-0.0383 (0.0233)
Beta	-0.1250 (0.2914)	-0.0125 (0.2902)	-0.1015 (0.2883)	-0.5278 (0.2930)	-0.5991* (0.2840)
F - FUNDAMENTALS					
Financial industry	-1.0194* (0.4072)	-0.8671* (0.3876)	-0.8368* (0.3887)	-0.2652 (0.4133)	0.0969 (0.3849)
Leverage	-0.0033 (0.0022)	-0.0001 (0.0023)	-0.0029 (0.0022)	-0.0069** (0.0022)	-0.0075*** (0.0021)
Funding liquidity	0.0052 (0.0028)	0.0022 (0.0029)	0.0052 (0.0028)	0.0091** (0.0028)	0.0099*** (0.0027)
Operating profit margin	0.0501*** (0.0117)	0.0367** (0.0116)	0.0514*** (0.0116)	0.0473*** (0.0121)	0.0393*** (0.0116)
ROA	0.0042 (0.0300)	0.0119 (0.0293)	0.0191 (0.0293)	0.0248 (0.0306)	0.0373 (0.0300)
Credit rating	0.6475* (0.2956)	0.6117* (0.2919)	0.6693* (0.2936)	0.4873 (0.3027)	0.4204 (0.2942)
Intercept	-7.7939*** (0.7137)	-8.2970*** (0.6469)	-7.9029*** (0.6800)	-9.6135*** (0.7079)	-7.3410*** (0.8678)

	(1)	(2)	(3)	(4)	(5)
Observations	3,684	3,684	3,684	3,684	4,196
Multiple R-Squared	0.2075	0.2221	0.2176	0.1681	0.1749
Adjusted R-Squared	0.192	0.2069	0.2024	0.1519	0.1595

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

The table presents the estimations of the two-stage Heckman model to tackle the selection bias in analyzing the effects of a company's lagged ESG on the severity of misconduct. Variables of the attention of external monitors are included only in stage one as these are assumed to have an effect only on the frequency but not the severity of losses. Misconducts are proxied by the ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database (broad definition). Loss amounts are divided evenly between the first and the last year of occurrence. The dependent variable is the logarithm of the loss amount divided by the yearly revenue of the firm. If a firm has several losses in a year, loss amounts are added up. If some variables are missing, observations are left out. ESG is associated negatively with the severity of losses.

Addressing the selection bias problem with two-stage Heckman regressions, the ESG coefficients (except for pillar G) remain significant both statistically and economically. Note that in the Heckman model, the financial industry dummy is significant both for the loss frequency and severity. In the strictly regulated finance sector, we can observe significantly more but less severe losses. In the finance sector, operational losses are of 57-64% lower in severity.

2.4.3. ROBUSTNESS CHECKS

To check the robustness of the models, further specifications are estimated. In the baseline setup, all variables are windsorized at 1% and 99% to avoid the problems deriving from the extreme outliers. To confirm the robustness of our results, we check the models without winsorization as well. As a second check, we use imputation since many missing variables decreased the number of observations. Missing data are imputed using a predictive mean matching technique, a special MICE (Multivariate Imputation by Chained Equations) method (Stata [2023]). The third analysis focuses on explicit misconducts, defined as when the loss resulted from regulatory action or legal liability (76% of all losses). Later we also analyze the relation between ESG scores and the frequency and severity of different misconduct categories. In this case, instead of scaling the losses between the first and settlement year of a misconduct, we model the loss for the year, when the loss first occurred.

Table 13. Robustness checks for frequency and severity.

		No winsorization	Imputation	Explicit misconducts
Logit frequency (year fixed-effect)	lag ESG	0.0001 (0.0003)	0.0003 (0.0002)	0.0001 (0.0003)
	lag E	0 (0.0002)	0.0001 (0.0001)	0 (0.0001)
	lag S	0 (0.0003)	0.0001 (0.0001)	0.0001 (0.0002)
	lag G	0.0003 (0.0002)	0.0002 (0.0001)	0.0002 (0.0002)
	lag ESGdummy	-0.0005 (0.0090)	-0.0091 (0.0067)	0.0006 (0.0079)
	Observations	3,684 / 4,196	6,630	3,623/4,135
Panel regression severity (year, event type fixed-effect)	lag ESG	-0.0315** (0.0115)	-0.0318*** (0.0084)	-0.0296* (0.0125)
	lag E	-0.0272*** (0.0079)	-0.0269*** (0.0051)	-0.0258** (0.0086)
	lag S	-0.0359** (0.0116)	-0.0264*** (0.0086)	-0.0361** (0.0131)
	lag G	-0.0065 (0.0088)	-0.0135 (0.0073)	0.0025 (0.0109)
	lag ESGdummy	-2.6503** (0.9274)	-1.9243** (0.6526)	-2.6076* (1.2171)
	Observations	584 / 598	1,034 /885	493 / 503
Heckman severity	lag ESG	-0.0363*** (0.0059)	-0.0398*** (0.0045)	-0.0306*** (0.0061)
	lag E	-0.0289*** (0.0040)	-0.0299*** (0.0028)	-0.0259*** (0.0042)
	lag S	-0.0358*** (0.0053)	-0.0389*** (0.0042)	-0.0296*** (0.0057)
	lag G	-0.0092 (0.0053)	-0.0167*** (0.0041)	-0.0087 (0.0054)
	lag ESGdummy	-2.2165*** (0.6035)	-1.8881*** (0.3845)	-2.2595** (0.6989)
	Observations	3,690 / 4,207	6,630	3,623 / 4,135

* p<0.05; ** p<0.01; *** p<0.001

The table presents the results of robustness checks to analyze the effects of a company's lagged ESG on the frequency and severity of misconducts. In particular, we examined the role of winsorization, the imputation of missing variables, and the definition of misconducts. Explicit misconducts are ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database that are resulted from regulatory action or legal liability (narrow definition). Loss amounts are divided evenly between the first and the last year of occurrence. Loss severity is measured by the logarithm of the yearly loss amount divided by the yearly revenue of the firm. If a firm has several losses in a year, loss amounts are added up.

Table 13 strengthens that ESG is not associated with the frequency of misconducts, but it is associated with loss severity. When focusing on the subsample of explicit misconducts, the two-stage Heckman method gives more stable results than simple panel regression. As usual, pillar G is not significant for severity either.

As an additional robustness check, we also consider an alternative measure of ESG performance, a dummy variable indicating whether the stock is included in the MSCI KLD 400 Social Index (Bofinger et al. [2022]). We find no operating losses recorded in the SAS Oprisk database for the firms included in this index during the investigated period. Therefore, this alternative ESG measure has a strong negative association with the frequency of misconducts.

2.4.4. FINANCIAL INDUSTRY

In this section we estimate the two-stage Heckman models only for the financial sector where losses are more frequent but less severe.

Table 14. Results of the Heckman models for the finance industry.

	(1)	(2)	(3)	(4)	(5)
	HECKMAN /HECKIT ESTIMATION				
	Probit selection equation				
lag Oprisk-flag	2.4495 *** (0.1503)	2.4280*** (0.1488)	2.4446*** (0.1501)	2.4425*** (0.1493)	2.5010*** (0.1423)
lag ESG	-0.0045 (0.0053)				
lag E		0.0034 (0.0036)			
lag S			-0.0030 (0.0051)		
lag G				-0.0031 (0.0037)	
lag ESGdummy					-0.3764 (0.2428)
A - ATTENTION OF EXTERNAL MONITORS					
Bid-ask spread	-9.2931 (42.6121)	-8.8454 (40.9873)	-9.8698 (42.8459)	-9.0534 (41.7092)	-0.3045 (0.4742)
Amihud illiquidity	-0.2696 (0.1937)	-0.2586 (0.1898)	-0.2678 (0.1940)	-0.2676 (0.1920)	-0.0441 (0.1362)
M - MARKET VALUATION					
Book-to-market	-0.0258 (0.0345)	-0.0292 (0.0350)	-0.0265 (0.0343)	-0.0262 (0.0350)	-0.0156 (0.0339)
P/E	-0.0037 (0.0056)	-0.0036 (0.0055)	-0.0034 (0.0055)	-0.0039 (0.0058)	-0.0034 (0.0053)
Logreturn	0.1695 (0.3444)	0.1791 (0.3462)	0.1697 (0.3443)	0.1837 (0.3447)	0.0287 (0.3256)
Volatility	0.0352* (0.0178)	0.0334 (0.0180)	0.0354* (0.0178)	0.0346 (0.0179)	0.0433** (0.0162)
Beta	0.1284 (0.2287)	0.0680 (0.2279)	0.1202 (0.2289)	0.1104 (0.2263)	0.0658 (0.2119)
F - FUNDAMENTALS					
Size	0.3946*** (0.0577)	0.3365*** (0.0630)	0.3925*** (0.0621)	0.3752*** (0.0509)	0.3499*** (0.0500)
Leverage	0.0016 (0.0008)	0.0015 (0.0009)	0.0016 (0.0008)	0.0016 (0.0008)	0.0020** (0.0007)

	(1)	(2)	(3)	(4)	(5)
Funding liquidity	-0.0016 (0.0013)	-0.0016 (0.0014)	-0.0016 (0.0013)	-0.0016 (0.0014)	-0.0025* (0.0012)
Operating profit margin	0.0034 (0.0058)	0.0051 (0.0059)	0.0037 (0.0058)	0.0039 (0.0058)	0.0027 (0.0054)
ROA	-0.0296 (0.0276)	-0.0179 (0.0273)	-0.0271 (0.0271)	-0.0279 (0.0273)	-0.0281 (0.0260)
Credit rating	0.4245* (0.2113)	0.3864 (0.2119)	0.4186** (0.2108)	0.4179* (0.2112)	0.3670 (0.1978)
Intercept	-6.0943*** (0.6414)	-5.7626*** (0.7057)	-6.1333*** (0.6589)	-5.9227*** (0.6525)	-5.5370*** (0.5886)
			Outcome equation		
lag ESG	-0.0413*** (0.0090)				
lag E		-0.0373*** (0.0059)			
lag S			-0.0529*** (0.0077)		
lag G				0.0104 (0.0083)	
lag ESGdummy					-2.4789*** (0.7428)
M - MARKET VALUATION					
Book-to-market	0.3224 (0.2566)	0.1782 (0.2529)	0.6118* (0.2552)	0.4048* (0.2605)	0.3437 (0.2545)
P/E	0.0135 (0.0254)	0.0364 (0.0245)	0.0134 (0.0245)	0.0435 (0.0264)	0.0355 (0.0245)
Logreturn	-1.0126 (0.6129)	-1.2412* (0.5989)	-1.2002* (0.5942)	-1.2676* (0.6376)	-1.0207 (0.6083)
Volatility	-0.0468 (0.0405)	-0.0393 (0.0396)	-0.0381 (0.0393)	-0.0487 (0.0416)	-0.0700 (0.0411)
Beta	-0.1293 (0.4348)	0.0456 (0.4238)	-0.0694 (0.4146)	-0.8464 (0.4457)	-0.6985 (0.4268)
F - FUNDAMENTALS					
Leverage	-0.0023 (0.0030)	0.0011 (0.0030)	-0.0006 (0.0029)	-0.0057 (0.0030)	-0.0064* (0.0029)
Funding liquidity	0.0050 (0.0047)	0.0035 (0.0046)	0.0042 (0.0046)	0.00994 (0.0048)	0.0099* (0.0047)
Operating profit margin	0.0219 (0.0200)	0.0206 (0.0196)	0.0211 (0.0195)	0.0129 (0.0202)	0.0094 (0.0189)
ROA	-0.1536 (0.0790)	-0.1139 (0.0759)	-0.1948* (0.0772)	-0.0593 (0.0798)	-0.0852 (0.0767)
Credit rating	0.3608 (0.4365)	0.3485 (0.4238)	0.5290 (0.4242)	-0.0589 (0.4437)	-0.1081 (0.4360)
Intercept	-8.0174*** (1.1768)	-9.2711*** (1.1141)	-7.9836*** (1.1250)	-10.0083*** (1.2573)	-6.0918*** (1.3392)
Observations	1,077	1,077	1,077	1,077	1,237
Multiple R-Squared	0.2387	0.2716	0.2814	0.2041	0.2173
Adjusted R-Squared	0.2158	0.2497	0.2597	0.1802	0.1945

* p<0.05; ** p<0.01; *** p<0.001

The table presents the results of the estimation of the effects of a financial institution’s lagged ESG on the frequency and severity of misconducts in the two-stage Heckman model. Misconducts are proxied by the ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database (broad definition). Loss amounts are divided evenly between the first and the last year of occurrence. Loss severity is measured by the logarithm of the yearly loss amount divided by the yearly revenue of the firm. If a firm has several losses in a year, loss amounts are added up.

Table 14 shows that the results hold for the finance sector as well, but the effect of ESG on the severity of misconducts can be even larger. One-unit difference in the ESG score is associated with more than 4% lower losses.

2.4.5. INSTRUMENTAL VARIABLE ANALYSIS

In corporate finance, the endogeneity of the explanatory variables is a major concern (Bascle [2008]). Endogeneity can be due to reverse causality, measurement errors, and omitted variables. In this chapter, the problem of reverse causality is excluded by using lagged ESG scores. However, omitted variables and measurement errors can lead to spurious correlations and incorrect conclusions.

To address the endogeneity problem, we perform a two-step least squares estimation using industry mean ESG scores as an instrumental variable (IV), following (Bofinger et al. [2022]). We can assume that the industry average ESG score has an effect on a firm's ESG strategy (relevance), but besides this channel, there is no direct relation between the industry mean ESG score and its operational losses (exogeneity).

Table 15. Results of the 2SLS model, the instrumental variable is the industrial mean ESG score.

	(1)	(2)	(3)	(4)
	2SLS - Industry average			
Predicted lag ESG	-0.0447***			
	(0.0058)			
Predicted lag E		-0.0492***		
		(0.0075)		
Predicted lag S			-0.0419***	
			(0.0053)	
Predicted lag G				-0.0176** (0.0054)
M - MARKET VALUATION				
Book-to-market			-0.0850**	
	-0.0695* (0.0298)	-0.0545 (0.0304)	(0.0296)	-0.0798** (0.0308)
P/E	0.0064 (0.0035)	0.0038 (0.0036)	0.0080* (0.0034)	0.0086* (0.0036)
Logreturn	-0.2257 (0.4741)	-0.3540 (0.4781)	-0.2435 (0.4716)	-0.2479 (0.4907)
Volatility	-0.0518* (0.0241)	-0.0647** (0.0248)	-0.0544* (0.0240)	-0.0344 (0.0248)
Beta	-0.0823 (0.2787)	0.2878 (0.3077)	-0.1026 (0.2759)	-0.4871 (0.2825)
F - FUNDAMENTALS				
Financial industry	-1.4890***	-1.4890***	-1.0030**	
	(0.4203)	(0.4203)	(0.3783)	-0.6490 (0.4058)
Leverage	-0.0040 (0.0022)	0.0038 (0.0029)	-0.0038 (0.0022)	-0.0091 (0.0021)
Funding liquidity	0.0062* (0.0027)	-0.0016 (0.0034)	0.0065 (0.0027)	0.0117*** (0.0027)
Operating profit margin	0.0525***		0.0536***	
	(0.0115)	0.0335** (0.0117)	(0.0114)	0.0521*** (0.0119)
ROA				0.0122
	-0.0045 (0.0296)	-0.0051 (0.0300)	0.0161 (0.0292)	(0.0307)
Credit rating				0.5069
	0.6893* (0.2946)	0.7335* (0.2993)	0.6955* (0.2931)	(0.3034)
Intercept	-6.7480***	-6.6404***	-8.3092***	
	(0.6698)	(0.7142)	(0.6784)	-7.0563*** (0.6424)
Observations	688	688	688	688
Weak instrument stat (p-value)	7,909.486***		8,020.943***	8,359.590***
	(0.0)	257.26*** (0.0)	(0.0)	(0.0)
Wu-Hausman stat (p-value)	7.483**	9.126**	4.471*	6.869**
	(0.00639)	(0.0026)	(0.0348)	(0.0090)

* p<0.05; ** p<0.01; *** p<0.001

The table presents the results of the estimation of the effects of a financial institution's lagged ESG on the frequency and severity of misconducts using the industrial mean ESG score as an instrumental variable. Misconducts are proxied by the ongoing operational loss events between 2013 and 2019 as reported in the SAS Global Database (broad definition). Loss amounts are divided evenly between the first and the last year of occurrence. Loss severity is measured by the logarithm of the yearly loss amount divided by the yearly revenue of the firm. If a firm has several losses in a year, loss amounts are added up.

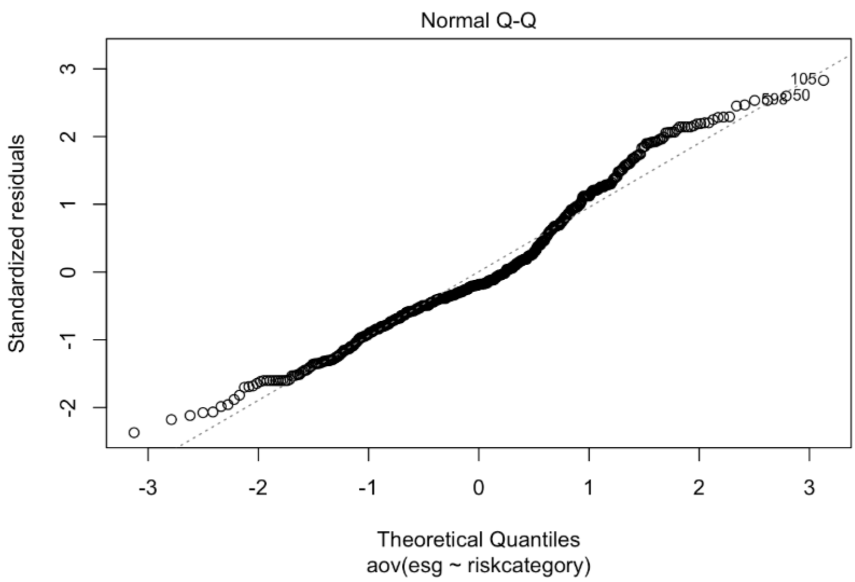
The instrumental variable proved to be relevant in all cases as the p-values of the weak instrument statistic are below 0. The results of the Wu-Hausman tests also confirm the consistency of the instrumental variable models at a significance level of at least 95%.

Overall, the analysis suggests that a one-unit improvement of the ESG, E, and S scores decreases the loss severity by 4-5%.

2.4.6. OPERATIONAL RISK CATEGORIES

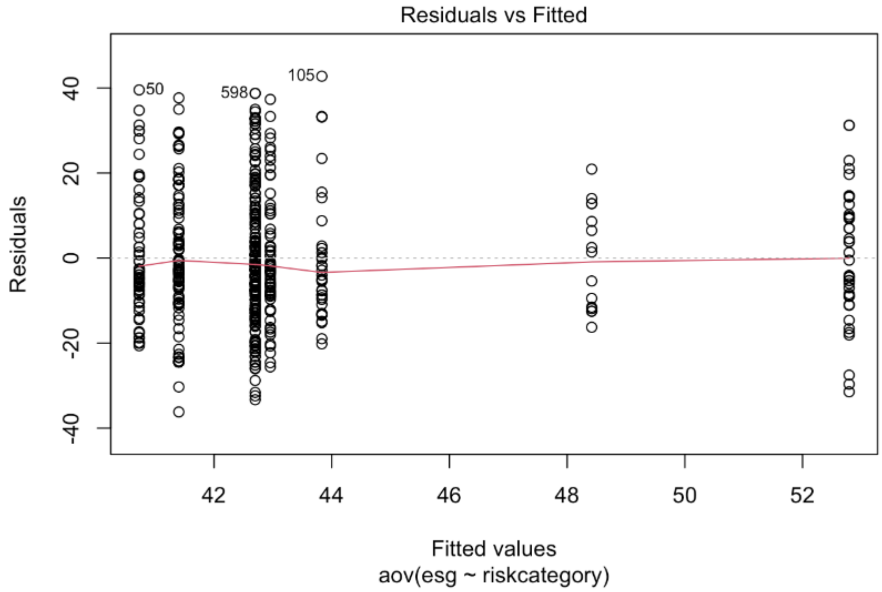
Using one-way analysis of variance (ANOVA), we examine the relationship between the different risk categories (categorical variable) and the ESG score as a continuous variable. This linear method shows whether the average ESG scores in the different risk categories differ significantly. The conformity of the model parameters to normality is illustrated in Figure 1, and the conformity to homogeneity of variances is illustrated in Figure 2. Based on these, we can infer that the ESG score variable is normally distributed in the sample, and the variance of the variable does not differ significantly among the individual risk categories.

Figure 1. Normality plot of the ESG score variable.



Note: The database contains the year-end financial, liability, and loss data of all companies listed on the NYSE and NASDAQ exchanges between 2013 and 2019 if the company suffered a public operational risk event causing a loss greater than $100,000, and if it has an ESG score. The chart shows the normality plot of the year-end ESG scores of the companies in the database.

Figure 2. The variance homogeneity of the ESG score across different operational risk categories.



Note: The database contains the year-end financial, liability, and loss data of all companies listed on the NYSE and NASDAQ exchanges between 2013 and 2019 if the company suffered a public operational risk event causing a loss greater than $100,000, and if it has an ESG score. The figure presents the variance homogeneity diagram of the ESG scores of the companies in the database across different operational risk categories.

The results of the ANOVA test are illustrated in Table 16, which indicates, with 99 percent confidence, that the means of different risk categories significantly differ. This is corroborated by the non-linear Kruskal–Wallis test, which suggests that the median ESG scores also significantly differ across the various categories, with a p-value of 0.0003 at the 1% significance level.

Table 16. Univariate Analysis of Variance (ANOVA) between the ESG scores and operational risk categories.

	df	Sum Sq	Mean Sq	*F* value	Pr(< *F*)
Risk-Cat	6	5260	876.7	3.729	0.0012**
Residuals	561	131893	235.1		

Note: The database contains the year-end financial, liability, and loss data of all companies listed on the NYSE and NASDAQ exchanges between 2013 and 2019 if the company suffered a public operational risk event causing a loss greater than $100,000, and if it has an ESG score. The table presents the year-end ESG scores of the companies in the database and the results of the univariate analysis of variance for the seven distinct operational risk categories. **The result is significant at the 99% level.

By employing the Tukey's post-hoc test, which is based on multiple comparisons, we can identify those risk categories where the difference in the average ESG scores significantly varies. According to this, the average ESG scores of observations falling under the category of events leading to physical damage of assets significantly differ from the scores in categories of external and internal fraud, improper business practices, and improper execution procedures.

Based on the findings, there exists a relationship between the disclosure of ESG scores, their level, and the various risk categories. In the category of events causing physical asset damage, ESG scores are generally higher, while they are lower in the categories of external or internal fraud, improper business practices, and incorrect execution procedures. One possible reason for this correlation is the firm-size bias in ESG scores, as evidenced by Drempetic et al. (2020). Their study suggests that on one hand, companies with a higher market capitalization usually have more resources and reserves, enabling them to allocate more resources towards complying with responsibility criteria and making the disclosure of ESG scores and reports more likely. On the other hand, these companies possess more assets and a larger income, which means potential losses can be higher than for smaller firms. Furthermore, larger companies, due to increased media and investor attention, are likely less able to hide losses resulting from operational risks compared to firms with a smaller market capitalization, as noted by Berlinger et al. (2022). Finally, the category involving physical asset damage also includes damages originating from climate risk, such as natural disasters. Kouloukoui et al. (2019) demonstrate that the disclosure of information related to climate risk positively correlates with firm size and performance.

From a risk management perspective, the third and fourth research questions are whether companies with higher ESG scores, operating more responsibly, can reduce losses from operational risks across various risk categories, thanks to better corporate governance practices, regulatory compliance, and responsible environmental and social operations.

To test the hypotheses H3 and H4, we conduct annual fixed-effects linear regression analyses on the panel database with firm-level clustered standard errors. To draw conclusions concerning the various risk categories, the population was initially segmented into seven parts based on the categories, followed by performing linear regression analysis according to equation (3).

The equation for the employed fixed-effects linear regression method is:

$$\mathrm{LOG}(\tfrac{L}{R})_{it} = \beta_0 + \beta_1 ESG_{it-1} + \beta_2 B_{it} + \beta_3 P_{it} + \beta_4 FL_{it} + \beta_5 ML_{it} + \beta_6 LE_{it} + \beta_7 dummyFI_{it} + \tau_n + \varepsilon_{it} \qquad (3)$$

By every misconduct category (events resulting from system failures causing business interruptions, improper business practices, events causing physical damage to assets, occupational harm or workplace-induced damages, incorrect (faulty) execution procedures, external fraud, internal fraud), the size-adjusted log-loss (L/R) was regressed by the lagged ESG score or the existence of the lagged ESG score (hasESG), controlling in each case for historical beta (B), profitability (P), market and funding liquidity (ML, FL), and leverage (LE). Given that operational risk management is primarily regulated for financial institutions, we also included the binary variable (FI) among the control variables.

Using the same control variables (supplemented with the company size (MC) variable, as the dependent variable was already adjusted for size in the linear regression procedure) and the explanatory variable, we conduct logistic regression tests on the entire sample to determine the relationship between the occurrence likelihood of each risk category and the magnitude of ESG scores, as well as their disclosure. The dependent variable is a binary variable derived from the occurrence of each risk category (taking a value of 0 if a particular risk category did not occur for a given observation and 1 if it did). We regress the binary variables for each risk category individually against the independent variables. For the logistic regression model, we also apply an annual fixed-effects panel regression, where we also cluster the standard error at the firm level. The equation for the fixed-effects logistic regression procedure is:

$$P\big(dummy\ Risk - Cat^{it} = 1\big) = \frac{1}{1+\exp\,[-(\beta_0+\beta_1 ESG_1^{it-1}+\beta_2 B_2^{it}+\beta_3 MC_3^{it}+\beta_4 P_4^{it}+ \beta_5 FL_5^{it}+\beta_6 ML_6^{it}+\beta_7 LE_7^{it}+ \beta_8 dummy\ FI_8^{it}+\tau_n+\varepsilon_{it})]} \quad (4)$$

Both linear and logistic regression analyses are executed across all operational risk categories using the lagged ESG scores, as well as the individual lagged E, S, and G scores, in conjunction with the binary variable (hasESG). This results conducting five linear and five logistic regression procedures for each of the seven risk categories, amounting to a total of 70 regression analyses.

Table 17 consolidates the outcomes of the aforementioned regression methodologies. In cases where no significant relationship is discerned, only the ESG coefficient is presented, rounded to three decimal places. For significant positive or negative associations, the coefficients are italicized and accompanied, in parentheses, by their respective t-values, rounded to the second decimal place. The significance of the varying responsibility scores is determined while incorporating the control variables.

Table 17. Summary of results from linear and logistic regression analyses with one-year lagged ESG variables.

Risk-Category	Logit regression					Linear regression				
	ESG	*E*	*S*	*G*	*hasESG*	*ESG*	*E*	*S*	*G*	*hasESG*
Events resulting from system failures causing business interruptions	0	–0.001	0	0	0.052	0.002	0.001	0.002	–0.005	0
Improper business practices	0	–0.001	0	–0.001	–0.191	*–0.012* *(–2.47)*	*–0.012* *(–1.95)*	*–0.016* *(–3.14)*	*–0.009* *(–2.29)*	*–1.173* *(–2.75)*
Events causing physical damage to assets	*0.003* *(2.47)*	*0.001* *(1.67)*	0.001	*0.002* *(1.93)*	0.041	–0.005	–0.009	–0.008	*–0.016* *(–2.61)*	0.809
Occupational harm or workplace-induced damages	0.003	0.001	0.001	0	0.050	*–0.018* *(–2.09)*	–0.016	*–0.025* *(–3.23)*	–0.009	0
Incorrect (faulty) execution procedures	–0.001	0	0.001	–0.001	0.072	–0.006	–0.007	–0.011	*–0.011* *(–2.26)*	–0.391
External fraud	–0.003	–0.001	–0.001	0	0.0394	–0.009	–0.002	–0.008	–0.008	*–1.736* *(–4.9)*
Internal fraud	0	0	–0.001	0	0.082	*–0.023* *(–2.65)*	–0.004	*–0.016* *(–2.11)*	*–0.021* *(–2.64)*	*–3.514* *(–5.55)*

Note: The database contains the year-end financial, liability, and loss data of all companies listed on the NYSE and NASDAQ exchanges between 2013 and 2019 if the company suffered a public operational risk event causing a loss greater than $100,000, and if it has an ESG score. The table presents the outcomes of both logistic and linear regression procedures per operational risk category and ESG variable (i.e., ESG, E, S, and G scores, and the binary 'hasESG' variable). Significant ESG variables display both the coefficients and t-values of the ESG variables, while non-significant relationships only present the ESG coefficients. For the annual fixed-effects logistic panel regressions, the binary dependent variable indicating the occurrence of the respective risk category was explained by the one-year lagged ESG variable and control variables (beta, market capitalization, profitability, financing and financial liquidity, leverage, and the financial institution). The standard error was clustered at the company level. In the annual fixed-effects linear panel regressions, the logarithm of losses adjusted for revenue for each risk category was explained using the one-year lagged ESG variable and control variables (beta, profitability, financing and financial liquidity, leverage, and the financial institution). The standard error was clustered at the company level.

Robust associations can be discerned in Table 17. The results of the logistic regressions reinforce conclusions drawn from the ANOVA, Tukey, and nonlinear Kruskal-Wallis tests. Specifically, the higher the responsibility score (E, S, G, or ESG score), the more probable the occurrence of events leading to the physical damage of assets across all risk categories. The ESG, E and G factors are significant within this risk category with an average of 0.003 coefficient value. This means that for a one-standard-deviation (one standard deviation of the ESG score is around 20 in the sample) increase in the ESG score, the probability of experiencing an operational risk event increases by approximately 5.1%. The other risk categories do not have significant connections with any of the ESG scores. This trend predominantly verifies that companies attentive to ESG factors tend to be more transparent regarding their operations and potential risks, meaning they are more likely to disclose information related to risk events. Furthermore, events resulting in the physical damage of assets predominantly occur due to external factors beyond a company's full control (e.g., natural disasters), making the disclosure of such damages less damaging to the firm's reputation (Perry-de Fontnouvelle, 2005). It is also plausible that such events are inherently more challenging to hide.

The results from linear regression analyses reveal distinct trends. Both the disclosure of ESG scores and the levels of responsibility scores have a significant negative linear relationship with the extent of damage in the categories of internal fraud and improper business practices. The average of the significant coefficients (ESG, E, S, and G factor) in the case of improper business practices is -0.012 and -0.02 in the case of internal fraud (where the significant ESG factors are ESG, S and G). It means that with a one unit increase in ESG scores companies can reduce their losses by 1.2% and by 2% resulting from improper business practices or internal fraud respectively. This suggests that as companies increasingly commit to responsible operations, the expected losses in these risk categories decrease when damages occur. A rise in ESG and S scores also leads to a reduction in expected losses in the category of workplace-caused damages.

To address the selection bias, we employ the two-step method proposed by Heckman et al. (1998), which allows for the estimation of the effects of ESG variables on the output variables of both logistic and linear models, even if the sample was not randomly compiled. Table 18 summarizes the model results after potential selection biases were eliminated. After correcting possible selection distortions, the previous findings regarding the relationship between asset physical damage events, improper business practices leading to damages, and ESG scores remain consistent.

Table 18. Summary of linear and logit regression results using the Heckman two-step method.

Risk-Category	Logit regression					Linear regression				
	ESG	*E*	*S*	*G*	*hasESG*	*ESG*	*E*	*S*	*G*	*hasESG*
Events resulting from system failures causing business interruptions	0.016	–0.021	–0.021	–0.011	15.047	0	–0.02	–0.361	–0.180	0
Improper business practices	–0.001	0.002	0.004	–0.004	–0.679	*–0.031 (–2.61)*	*–0.018 (–2.12)*	*–0.033 (–3.13)*	*–0.020 (–2.56)*	–1.480
Events causing physical damage to assets	*0.041 (3.25)*	*0.019 (2.13)*	0.020	*0.032 (2.94)*	0.134	–0.012	–0.043	–0.012	–0.028	–0.730
Occupational harm or workplace-induced damages	0.008	0.012	0.012	0.008	15.875	–0.027	–0.023	*–0.047 (–2.19)*	–0.013	–1.074
Incorrect (faulty) execution procedures	–0.011	0.008	0.007	–0.008	–0.190	–0.002	–0.006	–0.017	–0.020	–1.074
External fraud	*–0.019 (–2.43)*	–0.010	–0.009	–0.002	–0.440	0.001	–0.005	0.006	0.015	–1.128
Internal fraud	–0.001	–0.006	–0.011	–0.002	0.713	–0.047	–0.016	–0.017	–0.025	*–9.046 (–2.88)*

Note: The database includes year-end financial, responsibility, and loss data for all companies listed on the NYSE and NASDAQ between 2013 and 2019. This is in cases where the company suffered a public operational risk event that resulted in losses greater than $100,000 and if the company has an ESG score. The figure illustrates the results of a Heckman-style logit and a Heckman-style linear regression procedure for each operational risk category and ESG variable (ESG, E, S, and G scores, and the binary variable "hasESG"). For significant ESG variables, it displays the coefficient and t-values of these variables, while for non-significant relationships, only the coefficients of the ESG variables are shown. In the logit regressions, for each risk category, the binary dependent variable indicating the occurrence of that category was explained using the one-year lagged ESG variable and control variables (beta, market capitalization, profitability, financing and financial liquidity, leverage, and financial institution). In the linear regressions, for each risk category, we explained the logarithm of losses adjusted for revenue in that category with the one-year lagged ESG variable and control variables (beta, profitability, financing and financial liquidity, leverage, and financial institution).

While the fixed-effects logit regression shows an average significant ESG coefficient of 0.0018 in the physical damage category, the coefficients in the Heckman selection procedure are scattered around 0.032. Interpreted, with all other factors held constant, if the ESG score is one standard deviation higher (with the average standard deviation for ESG variables being roughly 22 points), it increases the likelihood by 2% according to the fixed effect, and by 66% according to the Heckman model, that a company will incur physical asset damage that becomes known. This relationship primarily reinforces the earlier conclusion that responsibly operating companies admit these damages.

There is a significant negative relationship between the ESG score and size-adjusted losses in the category of improper business practices, according to the results of both models. Coefficients for various ESG scores, both in fixed effect and Heckman selection procedures, ranged between -0.012 and -0.033 in this category. This means that a one-unit higher ESG score results in a 1.2% to 3.2% smaller loss within this category, holding all else constant. The average loss in this category was $35.18 million in the sample, and the average annual revenue of companies that incurred events within this category was about $49 billion. Therefore, a one-unit higher ESG score (on a scale between 0 and 100, where a higher rating indicates better ESG performance, the average ESG score in the sample is near 40 and the standard deviation is around 20), for a company with an annual revenue of one billion dollars per event, could reduce the expected loss by $9,000 to $23,000. For instance, taking Apple Inc.'s 2019 revenue of $260.1 billion as a base, for an improper business practice damage event, it could have reduced its losses by $2.34 million to $5.98 million, had its ESG score been one unit higher.

The fixed-effects linear model finds a similarly strong relationship between expected loss and ESG scores (with coefficients ranging between -0.011 and -0.228) in the category of internal fraud. However, after correcting for selection bias in the Heckman model, this significant relationship disappears, suggesting that its presence might be attributable to the non-representative sample.

In summary, from a risk management and corporate governance perspective, significant findings emerge in the delayed model correction and Heckman selection model results, indicating that ESG scores have a negative relationship with expected losses in the improper business practices category. From a corporate leadership perspective, better compliance with ESG guidelines can reduce the magnitude of expected losses in the aforementioned category. From a risk management viewpoint, a responsible investment strategy might correlate with lower operational risk exposure.

2.5. DISCUSSION

We find no evidence for the effects of ESG performance on the frequency of corporate misconducts, thus, Hypothesis H1 is rejected. The frequency of public loss events depends on at least two, potential offsetting effects. If higher ESG performance is associated with more prudent and transparent operations, then it is likely to reduce the number of corporate misconducts (deterrence) but increase the likelihood of misconducts becoming public (detection). It is possible that ESG actually has a strong effect on both damage occurrence and discovery, but the two effects roughly offset each other, and this is why we do not see statistically significant coefficients (Berlinger et al. [2022]). Of course, it is also possible that ESG does not have effects on the frequency of misconducts.

Hypothesis H2 is accepted as we conclude that a one-unit of improvement in the ESG, E, or S scores decreases the severity of corporate misconducts by 3.55%, 2.85%, and 3.57% (Heckman model, Table 12), or 4.47%, 4.49%, and 4.19% (instrumental variable model, Table 15), respectively (in log percentages). We estimate the aggregate ESG coefficient to be between 3.55% and 4.47%. Consequently, one standard deviation (19.42) higher ESG score decreases loss severity by 50-58%, which is a significant effect also in economic terms. The aggregate effect can be attributed to pillars E and S, because G scores are not significant in most of the specifications, which is consistent with findings in the empirical literature; pillar G is the most controversial and least consensually measured part of ESG (Gillan et al. [2021]).

In the finance sector, misconducts are more frequent but less severe. Interestingly, ESG (especially E and S) performance has an even stronger negative effect on the severity of misconducts in this highly regulated environment.

Note that the ESG dummy indicating whether a firm has an ESG rating in the given year proved to be significant for severity in most of the specifications. The coefficient is between -2.77 (fixed effect panel regression, Table 11) and -1.85 (Heckman model for explicit misconducts, Table 13), which means that firms without ESG rating have 84-94% larger losses. This suggests that firms that refuse the invitation to participate in ESG rating programs can be extremely risky in terms of corporate misconducts.

The results also suggest that the higher the responsibility score, the more likely a company is to experience or report an event causing physical damage to assets in the event of an operational risk incident that becomes public knowledge, hence we reject hypothesis H3.

This phenomenon is primarily explained by the fact that the damage is difficult to hide, and often the company lacks control over it, hence the market does not react negatively to these events (Perry and de Fontnouvelle [2005], Wang and Kutan [2013], Brounen and Derwall [2010]). Therefore, companies with higher ESG scores tend to admit environmental damages, as firms considering ESG factors are generally more transparent in their operations and in potential risks.

We accept Hypothesis H4, as with a higher responsibility score, the expected loss will be lower in the category of improper business practices. Therefore, if a company improves its internal control processes and adequately trains its employees, losses in this category can be mitigated, regardless of other corporate parameters. We identify improper business practices category as a misconduct type, where the company involvement cannot be questioned. For financial institutions, fine-tuning the Basel II and III frameworks' AMA calculation methodology with ESG scores would allow reducing the capital requirements for companies with higher ESG scores for this category. Furthermore, companies in other industries could also benefit from integrating responsibility aspects into their internal risk management models.

The conclusions of the chapter are consistent with previous literature results, which analyzed different markets, utilized different operational risk metrics, and different operational risk categories. In line with Harjoto and Laksmana (2018), Mulia and Joni (2019), and Zhao et al. (2016), it can be stated that more responsible corporate operations mitigate operational risk. Moreover, it is evident that this is particularly dominant in the category, where the misconduct is the company's responsibility (improper business practices).

Every risk category that has a significant association with any of the ESG variables possesses risk mitigation methods that the ESG scores also evaluate. For instance, losses originating from internal fraud and improper business practices can be mitigated through the enhancement of internal control processes and employee training. The presence and quality of these measures are reflected in ESG scores. These scores, among other things, contains data security, the company management's ability to implement or adjust best governance practices, and also account for issues concerning consumers or users.

Our research has several limitations. First, we match the latent variables of with measurable indicators, for example, ESG performance is proxied by Refinitiv ESG ratings, misconducts are defined as operational loss events reported in the SAS OpRisk Global, and firm controls are variables inspired by the previous literature to characterize the firms' fundamentals and financial markets. These measurable indicators, however, might only partially capture the essence of the latent variables. Second, the SAS OpRisk Global includes operational losses higher than US$100,000; thus, smaller losses are excluded from the analysis. Third, we investigate a 7-year period, from 2013 to 2019, a period of prospering economic conditions. In this period, we could witness large regime changes due to changes in investors' and consumers' preferences, regulations, and politics, which makes statistical inference more challenging. Fourth, we focus on firms traded on the NYSE and NASDAQ. Future research might aim to confirm our findings for other time periods and geographical areas.

2.6. CONCLUSION

Our research contributes to the literature by providing new evidence for the value enhancement theory of corporate social responsibility through the risk management channel (Albuquerque et al. [2019], Degryse at al. [2023], Flammer [2013], [2015], [2021], Godfrey et al. [2009], Malik [2015]). We use a specific definition for corporate misconducts based on operational losses and apply it to the finance and non-finance sectors. Our findings give new insights into the relationship between ESG and a specific downside risk: corporate misconduct. A higher ESG performance decreases the severity of misconducts, and this effect is even more pronounced in the finance sector. Corporate social responsibility exhibits therefore insurance-like features. Furthermore, ESG ratings can capture some important dimensions of corporate risk and, hence can effectively reduce asymmetric information in corporate finance (Gillan et al. [2021]). These findings are relevant not only for ESG investors, but all kinds of investors, regulators, policymakers, and other stakeholders as well Regulators should make an even greater effort to make the ESG rating methodologies more transparent, and the regulation of the most controversial pillar G requires special attention.

The results suggest that the magnitude of expected losses in various risk categories can be reduced with higher responsibility scores. This conclusion can prove valuable both in individual risk mitigation and in making portfolio diversification and risk management decisions, especially in a regulatory environment where the emphasis on operational risk management is intensifying. The findings also support the refinement of AMA (Advanced Measurement Approaches) through the incorporation of ESG scores.

3. ARE WE RESPONSIBLE WHEN IT HURTS?

3.1. INTRODUCTION AND LITERATURE REVIEW

According to the US SIF (The Forum for Sustainable and Responsible Investment) annual report already in 2021, every third dollar professionally invested in the US is somehow managed by taking into consideration sustainability or responsibility. The amount has continuously grown by 14% annually since 2013. Thanks to the pressure of society, investor trends, and the appearance of ESG measures that provide an easily accessible proxy for the responsibility and sustainability of firms, investors have started to maintain portfolios considering the responsibility aspect.

The effects of ESG ratings on corporate operational (COP) and corporate financial performance (CFP) is an already well-researched topic, however many dimensions of sustainability investing have not been explored and answered yet. Most of the related papers find negative ESG - CFP relation according to an aggregated summary containing 2000 studies by Friede, Busch, and Bassen (2015). Orlitzky, Schmidt, and Rynes (2003) conclude the same in their meta-analysis based on 52 studies regarding the relationship between corporate social responsibility (CSR) and CFP. On the other hand, Renneboog, Horst, and Zhang (2008), McWilliams and Siegel (2001), and Fain (2020) question the positive effects of CSR on value-adding, risk management, and financial performance. It is essential to highlight, that most of the above studies define performance as referring to accounting or fundamental value terms rather than performance in the capital market returns.

If we strictly interpret the financial performance of companies as stock returns, we find mixed results regarding the relationship between ESG and financial performance in the existing academic literature. Damodaran and Cornell's (2020) paper suggests that ESG investments are more beneficial for society than for shareholders in terms of profitability. Furthermore, Cornell (2021) finds that a high ESG score yields lower stock returns. Similarly to previous studies, regarding environmental and disruptive technology megatrends, Naffa and Fain (2020) find no significant excess returns attributed to ESG when controlling for the Fama French 5-factor. On the other hand, Verheyden, Eccles, and Feiner (2016) report a positive contribution of ESG to risk-adjusted return within the

ESG top 10% performers, while Feng, Long, Wang, and Chang (2022) conclude, that better CSR can contribute to the improvement of corporate stock returns, however, ESG cannot. Van der Beck's research (2021) suggests that the strong returns associated with sustainable investing are largely a result of price pressure generated by the inflow of funds into sustainable funds. This has led to high realized returns that may not necessarily correspond to high expected returns. Furthermore, his findings indicate that sustainable funds would have underperformed the market between 2016 and 2021 if it were not for this price pressure generated by fund flows. Pástor, Stambough, and Taylor (2022) appoint that the high realized return of green assets is unexpected and it is coming from the unexpected increase of climate concerns, not from the elevated expected return. This finding is in line with the results of Choi, Gao and Jiang (2020), who show that carbon-intensive stocks underperform if the temperature is warmer than expected due to the investors' climate charge, and in line with the results of Engle et al. (2020), who revealed that a climate hedging portfolio constructed on climate related news has superior performance. Revelli and Viviani (2013) show, that academic results are diverse, authors conclude differently due to the studies analyzing versatile markets, and using different time horizons and various research methods.

Motivated by behavioral economics, we test the hypothesis that the relation between ESG and stock returns depends on the stocks' prior performance. Intuitively, investors might be more willing to sacrifice return for social benefits when they face prior gains in a stock. Thaler and Johnson (1990) find that the participants of a gambling game make different decisions based on their prior changes in relative wealth. They stated that people are more willing to take risks and sacrifice return if they realize large or unexpected wealth gains. This phenomenon is known as the house money effect. Cárdenas, De Roux, Jaramillo, and Martinez (2014) further support the presence of the house money effect with an economic experiment. In addition, Ackert, Charupat, Church, and Deaves (2006) report the presence of the house money effect in a dynamic, financial setting and they found that market prices, traders' bids, and price predictions are predetermined by recent gains.

To model how much prior gains and losses investors face in a stock, we use the last year return, because Grinblatt and Han (2005) find that momentum as the last year return predictability comes from investors' tendency to engage in mental accounting, combined with the psychological biases of prospect theory regarding faces prior gains and losses. Similarly, Wang, Yan, and Yu (2017) in cross-sectional and time-series empirical models show that investors have reference-dependent preferences and evaluate the risk-return trade-off differently, depending on whether they sit in gain or loss. Consistent with our hypothesis, Yao (2015) finds that household income is in a significantly positive relationship with both donating and volunteering, considering all other factors constant. It is possible to draw a parallel between donating/volunteering and investing in ESG, meaning to give up a return in exchange for a noble purpose, like supporting responsible and/or sustainable company operations and management.

In the course of this research, investors are categorized into winners and losers every month based on their compounded returns from the last 12 months. In a given month, investors are considered winners if their calculated metric falls within the top 30% of the population, and losers if they are in the bottom tercile for that particular month. While Wang, Yan, and Yu (2017) use the capital gain overhang (CGO) measure to model whether investors are in winning or losing strake in a reference dependent research, we use the last 12 monthly returns because compounded returns in research provides a robust and comprehensive way to evaluate stock past performance, and also offering insights into objectives of many investors.

The seminal work by Jegadeesh and Titman (1993) establish momentum as a profitable strategy. They demonstrated that portfolios constructed based on past winners (stocks with high past returns) outperform portfolios of past losers. Subsequent research by Carhart (1997) and Moskowitz, Ooi, and Pedersen (2012) provide ample evidence for momentum across various asset classes, and Rouwenhorst (2009) documents its presence in geographical regions beyond the initial studies. Behavioral biases like overreaction to news and anchoring can lead investors to overprice recent winners and underprice recent losers, creating momentum. Moreover, investors may overweight recent information and herd towards momentum stocks, further amplifying the effect (Daniel et al. [1998], Hong and Stein [1999]).

Another layer of complexity emerges when considering momentum reversal, the tendency for past winners to eventually underperform and past losers to outperform. Despite the robustness of momentum, empirical evidence has unveiled instances where the opposite occurs, giving rise to momentum reversal anomalies. This observation challenges conventional momentum theories and has prompted scholars to explore the behavioral and institutional factors that contribute to such reversals. Investor overreaction, a prevalent behavioral bias, might be responsible for the unwarranted continuation of trends, leading to eventual reversals. Cognitive biases, such as anchoring and herding behavior, may contribute to the overshooting of stock prices, causing a subsequent correction. De Bondt and Thaler (1985) are among the first to document this, finding that past winners tend to underperform the market in the following period, while past losers tend to outperform. Subsequent research by Chan et al. (1996) and Lakonishok et al. (1994) confirms this reversal effect across various asset classes and investment horizons.

We find that ESG is not priced in the cross-section of expected stock return in our sample but there is a negative and significant relationship between ESG and expected stock returns among the last year's winner stocks. This is consistent with our following hypothesis.

H5: Investors are more willing to sacrifice returns if they face prior gains in a stock.

This result remains significant both economically and statistically after controlling for common factors such as the Fama-French 5 factors.

To explore the mechanism among prior gains-losses and ESG, we assume and test the statement of the upcoming hypothesis.

H6: The negative relation between ESG and expected stock returns among winner stocks is driven by naive investors.

To test this hypothesis, we create several subsamples of our sample using proxies to differentiate stocks that naive investors are more likely to hold. According to the literature by Shleifer and Vishny (1997), stocks with high limits to arbitrage (for instance, size, and illiquidity) and low professional attention (e.g., number of following analysts) are more likely to be held by naive investors than sophisticated investors. Similarly, during high sentiment time period, investors are more optimistic and naiver, they are more likely to become active on the stock market (e.g., Baker and Wurglar, 2006). Thus, we create sub-samples based on these dimensions to see the potential impact of naive investors on the negative relation between ESG and expected stock return among winner stocks.

We find that when investors face prior gains, they may prioritize ESG factors in their investment decisions, but if they have recently experienced losses, they are less likely to consider ESG. This behavior could be attributed to the house money effect, where decision-makers are more willing to risk after a gain than after a loss. This tendency to price responsibility seems to be driven by less sophisticated investors such as naive investors.

3.2. DATA AND METHODOLOGY

Firstly, we source daily stock time series and reference data for all stocks ever listed (listed and delisted) on NASDAQ and NYSE from 2015 to 2019. Delisted companies are also selected to avoid survivorship bias. To determine the investors past performance we source data earlier than 2015, but the analysis is performed only from 2015 onward. According to the US SIF annual report from 2020, ESG investing has been boosted since 2013 and the ESG score coverage of our data source seriously expanded from 2015, hence 2015 is appointed as the starting point of this chapter.

We use the Refinitiv database to collect the daily time series and reference data of the companies next to the responsibility scores (ESG). Then, monthly stock returns are calculated (on the last day of each month), and the dataset is filtered for completeness of the key variables (e.g. ESG score, Momentum, Size). Finally, 3228 individual stock time series are involved in the analysis from NASDAQ and NYSE through the time horizon. As the ESG scores coverage expanded over time, the number of series used increased, reaching nearly 900 for NASDAQ and 1200 for NYSE by the end of 2019.

The reference data of firms includes their size, number of analysts following, historical beta, leverage, bid-ask spread and book-to-market ratio. The size variable is calculated as the logarithm of the product of the closing price and common shares outstanding (CSO). The number of analysts following variable serves as a further proxy to measure the attention of sophisticated investors in a given company. We can assume that the higher the number of analysts following, the more the shareholders of the company are from the sophisticated / large investor segment. Monthly stock returns are calculated from the last trade day of the month adjusted daily closing market prices of the companies, and the investors' past performance is conducted based on the previous one year's monthly stock returns. Lastly, the Amihud illiquidity measure is also calculated by dividing the monthly returns by the volume of how many shares were traded (Amihud, 2002). The ESG variable is a continuous variable that ranges from 0 to 100, with higher values indicating better ESG performance.

To show that the expected return differences among various ESG and winner/loser categories are not driven by any of the underlying market factors except ESG, we source monthly the Fama-French three factors (excess return on the market, book-to-market values, size of firms) a Fama-French five factors (robust-minus-weak profitability and conservative-minus-aggressive investment in addition to the original three factors) next to the momentum factor from the data library of Kenneth R[3]. French. Similarly, the monthly market sentiment is also added to the database of Jeffrey Wurgler[4][5] to be able to investigate our research questions in different market sentiment regimes.

Based on Lakonishok, Shleifer and Vishny (1994) we double-sort the dataset first by past performance, then by ESG. We sort the firms, firstly into 3 past performance categories (top 30%, middle 40%, bottom 30%) based on their compounded last 12 months returns, where we identify the top 30% as the past winners, and the bottom 30% as the past losers. After that, within each investor performance category, we perform a univariate sort along ESG scores into 3 (top 30%, middle 40%, bottom 30%) categories. The portfolios are re-balanced hence the double sort is performed monthly. The portfolio-level analysis is applied to reveal, how investors price ESG depending on their recent performance. With long-short strategies, we long the best ESG category portfolios and short the bottom ones from the same past performance category each month. To test the expected return difference of the strategy, we use the Student t-test with an alternative hypothesis that the expected return difference is significantly different from zero. After that, we run linear regression in each past performance category, where the dependent variable is the return difference between the top and bottom ESG portfolios and the independent variables are the Fama-French 3 and 5 factors, and the momentum factor.

Lastly, variables expect the ESG score are winsorized after the 99th percentile to smooth the effect of the outliers. Hence, we swap the outlier values with the 99th percentile's observations in each of the selected variables.

[3] Kenneth R French Data Library

[4] Jeffrey Wurgler Data Library

[5] As the official database is only available until 2018, the analysis later using market sentiment is also performed between 2014 and 2018.

Table 19. Summary financial statistics about companies analyzed in the empirical models.

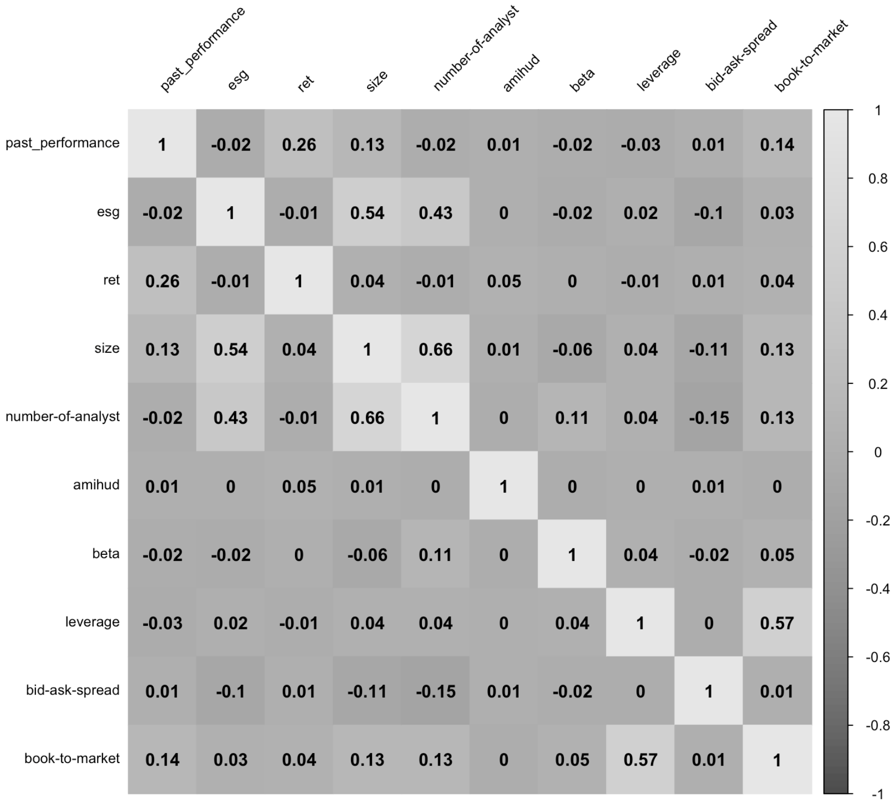
	Avg. No. of observations	Mean	Min	Max	St. Dev
ESG score	2190	36.33	1.34	90.74	16.95
Investor past performance	2190	0.12	-0.69	1.71	0.36
SIZE ($M)	2190	14.85	11.18	19.03	1.53
Number of Analysts Following	2190	10.45	0.0	48.38	8.37
Amihud	2190	0.0	-0.09	0.08	0.0
Beta	2190	1.07	-3.24	15.03	0.79
Book to Market	2190	3.18	-30.02	43.86	6.96
Expected monthly return (%)	2190	1.00	-28.0	34.0	9.0
Leverage (Debt/Equity)	2190	92.62	-1065.76	1529.22	253.1
Bid-Ask Spread	2190	0.05	0.0	1.29	0.15
Adjusted Close Price	2190	51.93	2.65	367.68	55.73

Descriptive statistics of the monthly frequency database. Statistics are calculated by averaging the monthly averages of the selected variables. The database contains more than 3200 individual stock prices and reference data time series between 2015 and 2019, traded on the NYSE and NASDAQ exchanges.

Based on Table 19 our empirical model is built up on more than 2000 observations monthly through five years. The average ESG score of firms in the sample is 36 (on a scale between 0 and 100, where a higher rating indicates better ESG performance) with a 17-point standard deviation. The average firm market capitalization is $15 million and the average beta of 1 suggests that, on average, the stocks in our research database have a similar level of volatility and risk as the overall market.

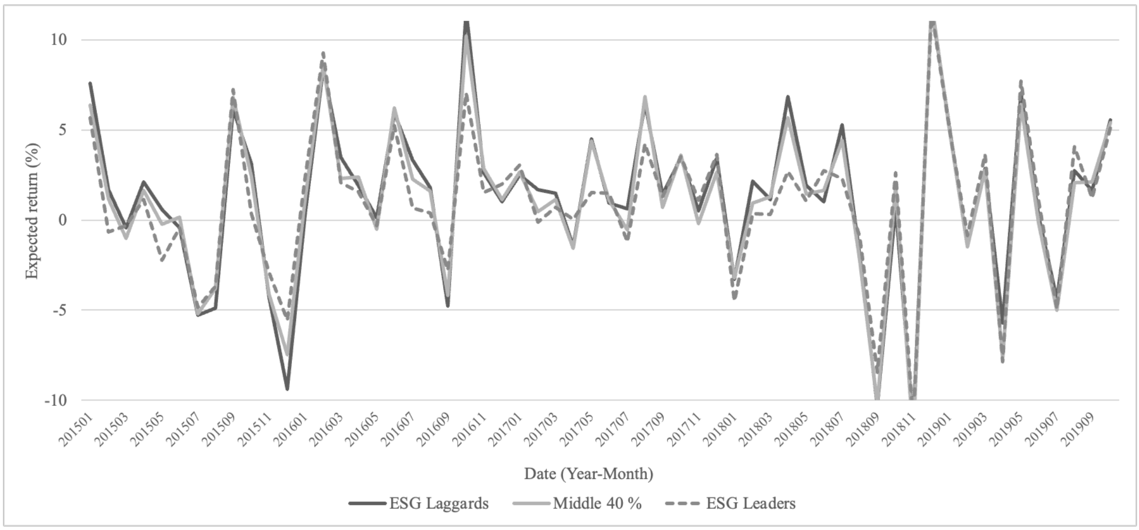
The Pearson correlation matrix examines the pairwise correlations between all key variables of the database. Each cell in the matrix represents the correlation coefficient, indicating the strength and direction of the linear relationship between the two variables.

Figure 3. Pairwise Pearson correlation matrix of variables of the research database.



The correlation matrix indicates that there is no linear relationship between past performance and the ESG variable, as the correlation coefficient is close to zero (-0.02). Most other pairwise relationships also do not exhibit linear dependencies. However, some trends are noticeable, aligning with generally accepted findings, such as the observation that larger-sized companies tend to have higher ESG scores (Drempetic et al. [2020]). There is a moderately strong positive correlation (0.54) between the two variables. Clear trends are also evident, such as the higher market capitalization companies attracting more attention (0.66), and higher book-to-market ratio is positively correlates with leverage due to the cheaper debt financing of value stocks (Chen and Zhao [2006]).

Figure 4. Average expected monthly return series of different ESG portfolios in the sample.



No clear trends can be identified in Figure 4 regarding the average monthly returns of different ESG portfolios. None of the portfolios consistently outperform or underperform the others. In certain periods, the ESG laggards (year-end and mid-year of 2016), and in other periods, the ESG leaders (year-end and mid-year of 2015) outperform the other portfolios.

Figure 5. Average monthly expected returns of the different winning-losing portfolios of our database and the data library of Kenneth R. French.

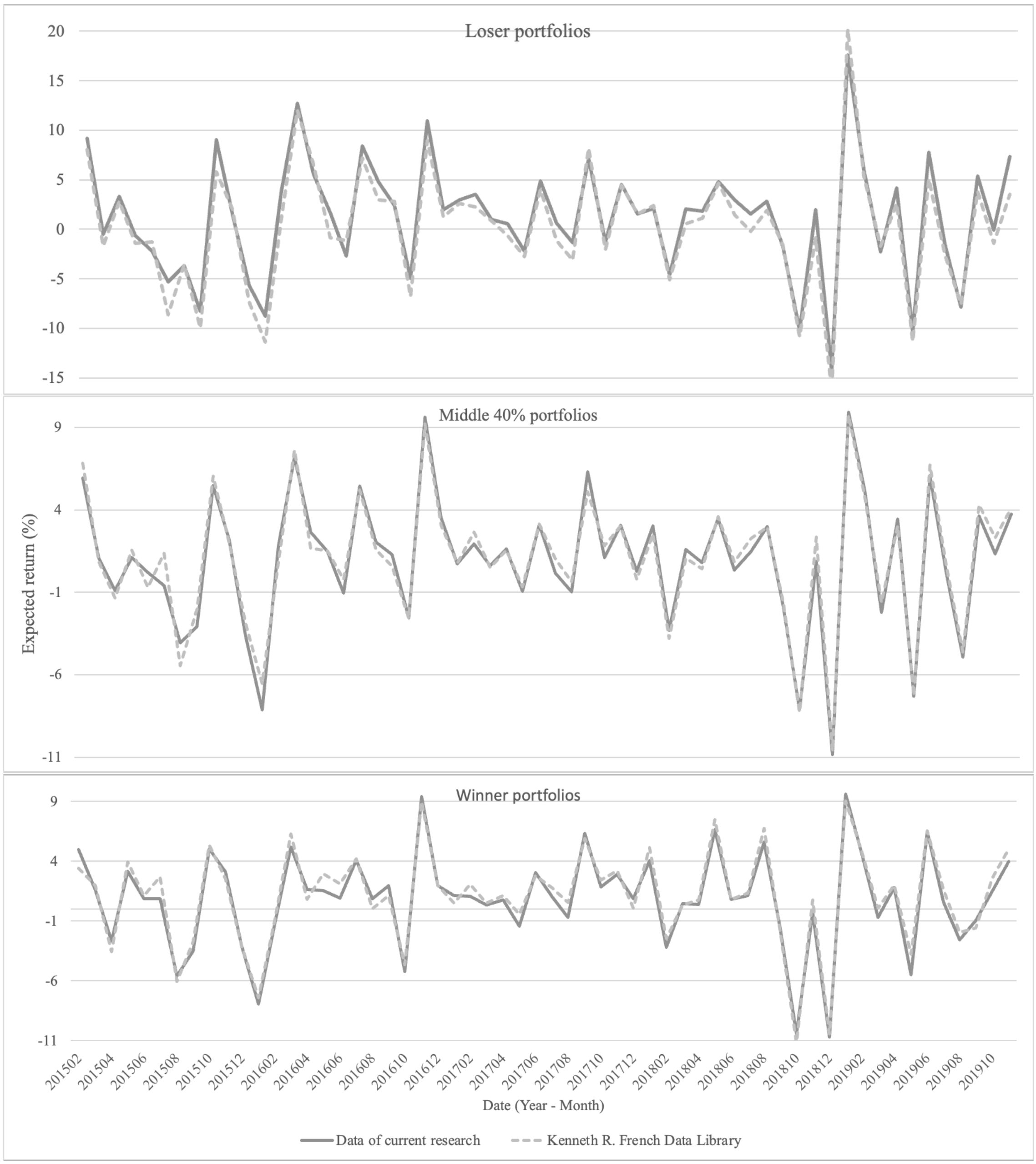


Figure 5 illustrates the validation of our sample and the metrics employed to identify the winner-loser portfolios. We compare the monthly calculated average expected returns of our winning-losing portfolios with the monthly expected returns of momentum portfolios available in the Kenneth French online data library (Kenneth R. French [2023]). It is visible that the expected returns of the portfolios used in our sample closely align with the returns of momentum portfolios identified by Kenneth French. The average monthly expected return for losers is 1.2%, with a standard deviation of 5.9% for the momentum portfolios listed on the Kenneth French website (average of the bottom three portfolios among the 10 momentum portfolios). In our database, these figures are 0.26% and 6.15%, respectively. For winners, the average expected return of the top 3 momentum portfolios by Kenneth French is 0.81%, with a 4.1% standard deviation, while in our dataset, it is 1.1% with a similar 4.1% standard deviation. The average expected return for the middle 40% portfolios are 0.92% and 1.0% respectively. The Pearson correlation coefficients between the three pairs of series suggest a very strong positive linear relationship with specific values for each pair as 0.979, 0.985 and 0.984 respectively.

Different reasons account for the occasionally divergent returns between the two databases. Firstly, a significant distinction arises from the stringent criteria in our sample due to the nature of the analysis. Only stocks with available ESG scores and market capitalization data from our data provider, Refinitiv, are included in our sample. The calculation methodology also varies between the two databases. In our research, we construct a metric from the last 12 months' returns to indicate investors' winning-losing streaks, whereas Kenneth French's database employs a different methodology for calculating momentum factors. We also use a filtering logic for liquidity to exclude stocks with flat price over a week. Furthermore, the applied portfolio approach is different among the two samples.

3.3. RESULTS

We assume that various sub-segments of investors are pricing ESG differently depending on their previous financial performance. Utilizing the results of Grinblatt and Han (2005), investors tend to be exposed to behavioral biases such as the house money effect and make divergent decisions contingent on their portfolio's previous performance.

To observe how investors price ESG depending on their recent unrealized capital gain or loss, firstly, we use the monthly rebalanced three winner/loser categories and then perform the univariate sort by ESG scores along each of the investor past performance categories. Lastly, we get the average expected returns of the sub-portfolios and test the average expected return differences between the top ESG portfolio and the bottom ESG portfolio in each of the investor performance categories. The former method allows us to explore, how much investors sacrifice return for better ESG scores depending whether they are sitting in gain or loss. The expected return differences are controlled by the common market risk factors to reveal the pricing of ESG with all other factors being constant.

Table 20. Expected monthly return differences of the portfolio-level analysis.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
Losers	1.4%	1.4%	1.1%	-0.3%	-1.1	-0.6	-0.6	-0.9	-0.9
Middle 40%	1.2%	1.0%	1.0%	-0.2%	-0.6	-0.2	-0.1	-0.3	-0.3
Winners	1.6%	1.1%	0.9%	-0.7%	-2.4**	-2.8**	-2.9**	-3.0**	-2.6**

Note: Double sorted database firstly by investor past performance and then by ESG score in each performance category. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West[6] t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to exclude company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables. **The result is significant at the 95% level.

Results of Table 20 show, that the profit of the long-short strategy is significantly negative (-0.7%) with 95% confidence among recent winners, meaning that those investors who are most probably facing gain tend to sacrifice return for responsibility (higher ESG score). The negative profit is significant in each of the setups where we control by CAPM, Fama-French and the Momentum factors as well (-2.8, -2.9, -3.0, and -2.6 alpha t-values respectively), meaning that the results are significant apart from the effects of the common market risk factors on this strategy. On the other hand, for investors in the other two categories (those who less probably realized gain, more likely sitting in loss or break-even) the long-short strategy is not significantly negative or positive. They are not pricing

[6] Newey and West (1968)

ESG but rather focusing on mitigating the losses and reaching break-even again with purely profitable decisions.

Table 21. Descriptive statistics of the sub-portfolios of the portfolio-level analysis.

	Average number of observations			Average ESG score			Average investor past performance (%)		
	ESG laggards	Middle 40%	ESG leaders	ESG laggards	Middle 40%	ESG leaders	ESG laggards	Middle 40%	ESG leaders
Losers	197	261	197	18	32	56	-0.27	-0.24	-0.21
Middle 40%	262	349	264	20	35	60	0.08	0.08	0.08
Winners	198	262	198	18	32	57	0.59	0.52	0.43

Note: Statistics are calculated by averaging the monthly averages of the selected variables.

According to the descriptive statistics, we have the same number of observations in each of the cross-sections of the winner/loser-ESG categories and the dispersion of the average ESG score and the average investor past performance is low within each of the corresponding categories (for example, average ESG score is nearly the same by ESG categories and average past performance score is roughly the same by winners, losers and by the central portion).

3.3.1. EMPIRICAL RESULTS OF SOPHISTICATED INVESTORS

To further explore the investor behavior behind responsibility investing we additionally perform the previous portfolio-level analysis by segmenting along firm size, the number of analysts following, and market price. The previous three variables turned out to be decent proxies to segment financial market participants along sophisticated (often institutional) and naive (often retail) investor groups. Sophisticated investors are more able to buy companies with high price magnitudes, more likely to invest in large-cap stocks, and higher number of analysts following them. In the case of naïve investors, the opposite is true. Due to the more professional trading of sophisticated investors and the particular attention to large-size stocks, the potential of mispricing is lower compared to naive investors. Therefore, after the double sorting, we divide the database into two sections along the monthly median and monthly top and bottom 30% of the observations regarding size, market price, and the number of analysts following. Table 22 contains the above-median and above 7th decile double sorts by firm size, market price, and the number of analysts following separately, describing the ESG pricing of sophisticated investors depending on their recent wins or loses.

Table 22. Expected monthly return differences of the portfolio-level analysis for sophisticated investors proxying with firm size, market price and number of analysts following.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
Above-median observations by firm size									
Losers	0.7%	0.7%	1.0%	0.3%	1.1	1.2	1.3	1.1	1.1
Middle 40%	0.9%	1.0%	1.0%	0.1%	1.5	2.1**	1.9	1.8	1.1
Winners	0.9%	0.9%	0.9%	-0.1%	-0.6	-0.2	-0.4	-0.4	-0.5
Top 30% of the observations by firm size									
Losers	0.7%	0.4%	1.1%	0.5%	1.1	1.2	1.4	1.4	1.5
Middle 40%	0.9%	1.0%	1.1%	0.2%	1.3	1.8	2.0**	1.9	1.1
Winners	0.9%	1.0%	0.9%	0.1%	-0.5	-0.2	-0.3	-0.3	-0.3
Above-median observations by market price									
Losers	-0.1%	0.8%	1.0%	1.0%	2.8**	3.1**	2.9**	3.0**	3.1**
Middle 40%	1.0%	1.0%	1.1%	0.1%	0.5	1.0	0.9	0.9	0.5
Winners	0.9%	0.8%	0.8%	-0.1%	-0.5	0.2	-0.5	-0.5	-0.5
Top 30% of the observations by market price									
Losers	-0.5%	0.7%	1.0%	1.5%	2.2**	2.7**	2.7**	2.4**	2.6**
Middle 40%	1.0%	1.0%	1.1%	0.1%	0.4	0.6	0.5	0.5	0.3
Winners	0.6%	0.7%	0.9%	0.3%	0.5	0.9	0.6	0.5	0.3

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
Above-median observations by number of analysts following									
Losers	0.8%	1.0%	1.1%	0.3%	1.0	1.4	1.5	1.4	1.5
Middle 40%	0.8%	0.9%	1.0%	0.2%	1.0	1.2	1.3	1.2	1.2
Winners	1.3%	0.9%	0.9%	-0.4%	-1.1	-1.1	-1.1	-1.1	-1.1
Top 30% of observations by number of analysts following									
Losers	0.8%	0.6%	1.1%	0.3%	0.6	1.0	1.1	1.0	1.0
Middle 40%	1.0%	1.0%	1.0%	0.0%	0.3	0.7	0.7	0.8	0.6
Winners	1.2%	1.1%	0.9%	-0.3%	-1.4	-1.2	-1.1	-0.9	-1.1

Note: Double sorted database firstly by investor past performance and then by ESG score in each performance category. The population was later sorted containing only above-median and only the top 30% of the observations by firm size, market price, and number of analysts following. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the Top (30%) ESG sub-portfolio and Shorting the Bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to lock company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables.

If we define sophisticated investors as those holding stocks of companies larger than the median firm size, we do not find significant evidence to suggest that these investors are willing to sacrifice return solely based on the ESG score. We expect significant alpha t-values in most of the CAPM and Fama-French settings in order to be sure, that the noise and the effect of other market factors can be excluded.

Those sophisticated investors, who are described by holding at least above-median market price stocks and most probably sitting in loss, do not give up return for responsibility. The opposite is true based on Table 22. The brown investor mindset is dominating contrary to the green one, and the long-short strategy in the loser category produces a profit of 1-1.5%.

Sophisticated investors do not price ESG, regardless if they are sitting in a gain or in loss because neither the t-values of the different setups, nor the one-sample t-test are significant. These results hold for the winners and for the losers as well. It means that the market is in equilibrium due to high liquidity and exceptional attention, hence sophisticated investors are not giving up returns for firms with higher ESG scores, regardless if they are facing gain or loss.

3.3.2. EMPIRICAL RESULTS OF NAIVE INVESTORS

In the following, we show the below-median and below-third decile segment of investors along with firm size, market price, and the number of analysts following, representing the naive investors.

Table 23. Expected monthly return differences of the portfolio-level analysis for naive investors proxying with firm size, market price and number of analysts following.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
Below-median observations by firm size									
Losers	1.6%	1.7%	1.4%	-0.2%	-0.7	-0.2	-0.3	-0.6	-0.5
Middle 40%	1.3%	1.1%	1.0%	-0.3%	-2.2**	-1.8	-1.9	-1.9	-1.3
Winners	1.8%	1.2%	0.9%	-1.0%	-2.3**	-2.1**	-2.0**	-1.8	-2.7
Bottom 30% of the observations by firm size									
Losers	2.1%	2.0%	1.7%	-0.4%	-0.9	-0.3	-0.5	-0.7	-0.7
Middle 40%	1.4%	1.4%	1.0%	-0.5%	-1.1	-1.7	-1.6	-1.6	-1.3
Winners	2.3%	1.5%	0.6%	-1.7%	-2.9**	-3.4**	-3.3**	-3.2**	-3.3**

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
Below-median observations by market price									
Losers	1.9%	1.6%	1.3%	-0.6%	-1.6	-1.2	-1.1	-1.5	-1.6
Middle 40%	1.3%	1.1%	0.8%	-0.5%	-1.4	-0.7	-0.5	-0.7	-0.8
Winners	2.1%	1.3%	1.0%	-1.1%	-2.7**	-3.0**	-3.0**	-2.8**	-3.1**
Bottom 30% of the observations by market price									
Losers	2.2%	1.8%	1.2%	-0.9%	-1.6	-1.2	-1.1	-1.9	-2.0
Middle 40%	1.5%	1.3%	0.9%	-0.6%	-1.4	-0.7	-0.5	-1.1	-1.3
Winners	2.6%	1.7%	1.3%	-1.1%	-2.7**	-3.0**	-3.0**	-2.7**	-3.6**
Below-median observations by number of analysts following									
Losers	1.7%	1.8%	1.4%	-0.3%	-1.0	-0.6	-0.7	-0.9	-0.9
Middle 40%	1.3%	1.2%	1.0%	-0.3%	-1.3	-0.9	-0.7	-0.9	-0.7
Winners	1.5%	1.2%	0.8%	-0.8%	-2.3	-2.7**	-2.8**	-2.5**	-2.4**
Bottom 30% of the observations by number of analysts following									
Losers	1.9%	1.9%	1.9%	0.1%	0.0	0.6	0.2	0.2	0.1
Middle 40%	1.3%	1.2%	0.8%	-0.5%	-2.3**	-2.1**	-2.1**	-2.0**	-1.3
Winners	1.7%	1.2%	0.5%	-1.2%	-2.7**	-3.9**	-3.7**	-2.8**	-2.0**

Note: Double sorted database firstly by investor past performance and then by ESG score in each performance category. The population was later sorted containing only below-median and bottom 30% of the observations by firm size, market price, and number of analysts following. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to lock out company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables. **The result is significant at the 95% level.

Among naive investors, whom we define as those purchasing stocks from companies with either a market capitalization below the median or falling within the lowest 30% of observations, there is a pronounced economic effect of the responsible mindset. Investors who have recently been on a winning streak are, on average, willing to forgo returns of 1 - 1.7% due to ESG considerations (given significant alpha t-values in the CAPM and Fama-French setups as well with around -2 and -3 alpha t-values). This is not true for those investor segment within naïve investors, who face loss. In that case, the losers are not pricing ESG.

In Table 23, a corresponding pattern is evident. Investors who are experiencing losses or are approximately at the point of break-even predominantly concentrate on accruing profits and materializing gains. Conversely, those who have recently reaped profits, on average, sacrifice a return of 1.1% in order to allocate funds to more ethically responsible firms.

The long-short strategy produces a significant negative profit for those investor groups, who most probably face gains in the previous 1 year. Those naïve investors (identified by purchasing those shares, which are followed by relatively few professional analysts), who recently won realized around -0.8% and -1.2% loss with high significance (alpha t-values between -2 and -4) due to having high ESG score stocks. It means, that naive investors are willing to sacrifice return for responsibility and sustainability only if they are sitting in gain. Other segments of investors are not pricing ESG during their investment decisions. The results can be originated from the increased potential of mispricing due to the limits of arbitrage among naive investors.

The above tables depict, that pricing the responsibility features of companies is more likely to happen among naive investors because the correction of the pricing of the green investors is harder due to the limits of arbitrage. Brown preferences are not able to adjust the mispricing of the greens. Short trades are one example of this limit. Sophisticated investors are more capable and tend to trade short rather than naive investors therefore this segment is not always able to move the prices to equilibrium.

ESG investing is not purely profit-oriented, deviation from equilibrium and mispricing should have been traded and eliminated due to arbitrage opportunities. The mispricing effect due to ESG exists for naive investors who are facing prior gains. It happens because it is too costly for the market to trade this arbitrage. According to Shleifer and Vishny

(1997), for small, illiquid companies having less attention from market participants, the correction is more expensive hence limits of arbitrage appear.

3.3.3. RESULTS TO FURTHER SUPPORT THE LIMITS OF ARBITRAGE

Table 24 further supports the limits of arbitrage. Dividing the portfolio-level analysis by above and below-median Amihud illiquidity measure makes it possible to see that high liquidity moves the mispricing of green investors back to equilibrium while when the liquidity is low, the brown investors are not able to trade the arbitrage opportunities of ESG mispricing. On average, recent winners willing to give up on average 0.8% return for firms with high ESG scores. The result remains significant even when controlling for the CAPM and the Fama-French market risk factors as well (with t-values around -2.5).

Table 24. Expected monthly return differences of the portfolio-level analysis in high and low liquidity proxying with Amihud illiquidity measure.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
In high liquidity (below-median Amihud illiquidity measure)									
Losers	1.9%	1.4%	1.1%	-0.8%	-1.1	-0.7	-0.6	-1.0	-1.1
Middle 40%	1.5%	1.2%	1.0%	-0.5%	0.1	0.6	0.7	0.7	0.5
Winners	1.8%	1.5%	1.2%	-0.6%	-1.1	-1.0	-1.5	-1.4	-1.2
In low liquidity (above-median Amihud illiquidity measure)									
Losers	0.8%	1.6%	1.2%	0.5%	-0.2	0.4	0.5	0.4	0.5
Middle 40%	1.0%	0.9%	1.1%	0.1%	-1.0	-0.5	-0.6	-0.7	-0.5
Winners	1.4%	0.8%	0.6%	-0.8%	-2.6**	-2.6**	-2.5**	-2.5**	-2.5**

Note: Double sorted database firstly by investor past performance and then by ESG score in each performance category. The population was later sorted containing only below-median and above-median observations separately by Amihud illiquidity measure. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the Top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to lock out company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables. **The result is significant at the 95% level.

Lastly, we divide our database based on the investor sentiment index constructed by Baker and Wurgler (2006), and then we execute the long-short strategy of the portfolio-level analysis for sophisticated and naive investors separately. Months with above-median investor sentiment and below-median investor sentiment are investigated separately. Table 25 presents the results about how different groups of investors price ESG in recent gains and losses in positive and negative investor sentiments.

Table 25. Expected monthly return differences of the portfolio-level analysis for sophisticated and naïve investors proxying with above and below-median firm size in positive and negative investor sentiment.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
SOPHISTICATED INVESTORS Positive investor sentiment (above-median Baker-Wurgler investor sentiment index)									
Losers	0.3%	0.5%	0.4%	0.1%	-0.1	0.3	0.3	-0.1	0.0
Middle 40%	0.4%	0.7%	0.8%	0.3%	1.4	1.7	1.5	1.5	2.2
Winners	0.9%	0.9%	0.6%	-0.3%	-0.9	-0.5	-0.5	-0.3	-0.8
SOPHISTICATED INVESTORS Negative investor sentiment (below-median Baker-Wurgler investor sentiment index)									
Losers	1.1%	1.1%	1.7%	0.6%	1.2	1.1	0.8	0.7	0.6
Middle 40%	1.0%	1.2%	1.1%	0.1%	1.2	2.6	2.1**	0.8	0.2
Winners	0.8%	0.6%	0.8%	0.0%	-0.4	-0.6	-0.1	-0.4	-0.1
NAÏVE INVESTORS Positive investor sentiment (above-median Baker-Wurgler investor sentiment index)									
Losers	1.2%	1.3%	0.7%	-0.5%	-1.0	-0.8	-1.2	-0.9	-0.9
Middle 40%	1.2%	0.8%	0.7%	-0.6%	-1.9	-2.0**	-2.0**	-3.0**	-1.7
Winners	1.8%	1.3%	0.7%	-1.1%	-2.2**	-2.8**	-2.6**	-2.3**	-1.9*
NAÏVE INVESTORS Negative investor sentiment (below-median Baker-Wurgler investor sentiment index)									
Losers	2.5%	2.5%	2.6%	0.1%	-0.3	-0.4	-0.1	-0.2	-0.1
Middle 40%	1.7%	1.7%	1.4%	-0.3%	-1.2	-1.7	-3.0**	-4.6**	-1.5
Winners	1.3%	1.5%	1.1%	-0.1%	0.4	1.0	1.5	1.3	0.8

Note: Double sorted database firstly by investor past performance and then by ESG score in each performance category. The population was later sorted containing only above-median or only below-median observations by firm size and above (positive investor sentiment) and below-median (negative investor sentiment) observations by the Baker-Wurgler investor sentiment index. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to lock out company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables. **The result is significant at the 95% level.

Based on Table 25, the possible arbitrage due to the green market participants among sophisticated investors is traded immediately back to equilibrium, regardless of the overall investor sentiment. Regardless of whether investors realized profits or losses recently, mispricing due to ESG factors were traded away. This is because this segment is less constrained by the limits of arbitrage, such as short selling. This is shown by that neither the winners nor the losers could realize a significant profit or loss with the long-short ESG strategy (none of the alpha t-values of the winners or losers are consistently significant).

According to Stambaugh, Yu, and Yuan (2012) in positive investor sentiment, the market anomalies are stronger. It connotes, that when the market mood is superior, naive investors trade increasingly and the behavior effect becomes stronger. The limits of arbitrage develop and turn out to be more expensive because, among other facts, naive investors are less prone to short. This is exactly shown in Table 25, as in positive investor sentiment the average profit of the long-short strategy is -1.1% and it is significant with around -2.5 alpha t-values. On the other hand, when the overall market sentiment is negative, it comes two possible explanations of the results of Table 25, as having no significant profit or losses in the different investor segments. Firstly, naïve investors are not pricing ESG, and secondly, the lower limits of arbitrage make it possible for the brown investors to trade back the price to equilibrium.

3.3.4. ROBUSTNESS CHECKS

We conduct the same analysis utilizing the returns of the past 11 months and computing the momentum indicator. In this scenario, we distinguish sophisticated and naive investors as follows: sophisticated investors are those who hold the top 30% of companies ranked by company size, while naive investors are those who hold the bottom 30% of companies.

Table 26. Expected monthly return differences of the portfolio-level analysis using 11-month momentum.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
SOPHISTICATED INVESTORS Top 30% of the observations by firm size									
Losers	1.1%	0.5%	1.0%	0.1%	1.0	1.0	1.1	1.0	1.1
Middle 40%	0.8%	0.9%	1.1%	0.3%	1.2	1.6	1.9	1.9	1.0
Winners	1.0%	1.1%	1.0%	0.1%	-0.7	-0.6	-0.6	-0.7	-0.4
NAÏVE INVESTORS Bottom 30% of the observations by firm size									
Losers	1.3%	1.4%	1.2%	-0.1%	-0.2	0.5	0.1	-0.1	-0.1
Middle 40%	1.4%	1.5%	1.3%	-0.1%	-0.7	-0.5	-0.5	-0.5	-0.4
Winners	1.8%	1.5%	0.6%	-1.2%	-1.7	-2.3**	-2.1**	-2.2**	-2.3**

Note: Double sorted database firstly by investor past performance and then by ESG score in each 11-month momentum category. The population was later sorted containing only top and bottom 30% of the observations by firm size. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each winner-loser category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to lock out company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables. **The result is significant at the 95% level.

Our results remained consistent even when we utilize the momentum indicator calculated from the 11-month return to identify the investor groups most likely to have gained or lost in the past year. As shown in Table 26, the arbitrage opportunity continues to be significant among naive investors.

In order to ensure that our results are not influenced by additional corporate financial factors such as leverage, liquidity, market risk, or book value, we employ a triple sort methodology. This allows us to examine our results while maintaining the independence of these financial factors.

Table 27. Expected monthly return differences of the portfolio-level analysis using triple sort by various fundamental variables.

	ESG laggards	Middle 40%	ESG leaders	ESG leaders – ESG laggards	Long-Short t-value	CAPM Alpha, t-value	FF-3 Alpha, t-value	FF-5 Alpha, t-value	FF-5 + MOM Alpha, t-value
				Book to market					
Losers	1.4%	1.4%	1.1%	-0.3%	-0.9	-0.5	-0.5	-0.7	-0.8
Middle 40%	1.3%	1.0%	1.0%	-0.2%	-1.0	-0.5	-0.5	-0.6	-0.6
Winners	1.5%	1.1%	0.8%	-0.7%	-2.6**	-2.9**	-2.9**	-2.8**	-2.4**
				Beta					
Losers	1.5%	1.4%	1.1%	-0.4%	-1.4	-1.1	-1.1	-1.5	-1.5
Middle 40%	1.1%	1.0%	1.0%	-0.2%	-0.6	-0.1	-0.1	-0.3	-0.4
Winners	1.6%	1.1%	1.0%	-0.6%	-2.2**	-2.5**	-2.5**	-2.5**	-2.6**
				Leverage					
Losers	1.5%	1.4%	1.1%	-0.3%	-1.1	-0.7	-0.6	-1.0	-1.0
Middle 40%	1.3%	1.0%	1.0%	-0.2%	-0.9	-0.4	-0.4	-0.5	-0.6
Winners	1.5%	1.0%	0.9%	-0.6%	-2.1**	-2.4**	-2.5**	-2.5**	-2.3**
				Bid-ask spread					
Losers	1.5%	1.4%	1.2%	-0.4%	-1.3	-1.0	-0.9	-1.3	-1.4
Middle 40%	1.2%	1.0%	1.0%	-0.2%	-0.9	-0.3	-0.3	-0.4	-0.5
Winners	1.5%	1.0%	0.9%	-0.6%	-2.2**	-2.3**	-2.6**	-2.6**	-2.9**

Note: Firstly, the population was sorted and categorized into three categories monthly by one of the fundamental variables. In each of the sub-samples the stocks were categorized into three categories based on their recent investment performance. Firms from the same winner-loser categories across all of the fundamental variable categories were merged and categorized into three ESG categories monthly. Equally weighted and monthly rebalanced portfolios from January 2015 to December 2019. Longing the top (30%) ESG sub-portfolio and shorting the bottom (30%) ESG sub-portfolio in each momentum category, each month. The return differences of the applied long-short strategies are calculated and Newey West t-tested with a lag of 12. Finally, the return differences are pooled OLS regressed against the monthly common market risk factors to exclude company-specific effects. The t-values of the regression intercepts (alphas) are showing those parts of the return differences, which are not explained by the control variables.

Regardless of corporate factors, our results remain consistent, as evidenced by Table 27. Investors in winning positions are willing to forego approximately 0.6-0.7% monthly return in favor of higher ESG-scored portfolios, regardless of the company's level of leverage, liquidity, or book value.

3.4. CONCLUSION

Summing up the results of the current chapter, we can make the following conclusions. Overall, investors tend to give away returns for higher ESG companies if they are sitting in gain. On the other hand, if they face a recent loss, they are not pricing ESG. This behavior can be originated from the house money effect, which details, that decision-makers are more risk seekers if they realized a gain in their wealth recently, and parallelly they are more conservative if they realized a loss.

Pricing the responsibility aspects of companies is more likely the case of the naive investors who are sitting in gain. The mispricing due to responsibility investing exists among them only, those who are not able to move back the prices to equilibrium due to the limits of arbitrage. There may be effects of the green investors on the sophisticated market, but the brown capital market participants immediately trade these arbitrage opportunities.

The behavior model of the house money effect accelerates when the investor sentiment is relatively positive. In these times, the market anomalies become stronger, and the limits of arbitrage get more expensive. In the case of sophisticated investors, ESG is not priced in any of the market moods.

In high liquidity, the potential mispricing of ESG disappears, however, the improvement of illiquidity makes the trades of this arbitrage opportunity more expensive.

All in all, investors tend to sacrifice return for responsible investment choices only if they are facing a gain, but this non-rational decision is immediately traded off among sophisticated investors, while creating mispricing among naïve investors, especially in relatively positive investor sentiment and illiquid markets.

4. CONCLUSIONS AND DISCUSSION POINTS

4.1. ANSWERING THE RESEARCH QUESTIONS

Our research profoundly examines the complex dynamics between ESG performance and corporate misconduct. At the forefront of our findings is the clear inverse relationship between ESG performance and the severity of corporate misconduct, a phenomenon most pronounced within the finance sector. ESG, beyond its ethical dimensions, showcases properties similar to insurance, guarding against misconducts in corporate behavior. These findings broaden the landscape of understanding for a range of stakeholders, emphasizing the pivotal role ESG metrics play in understanding and measuring corporate risk and the urgency with which regulators should pursue transparency.

From a nuanced risk management lens, an important discovery of our research is the diminished expected loss in improper business practices with a higher responsibility score. Such insights highlight the tangible benefits of robust internal controls and rigorous employee training in mitigating such losses. There is a distinct call for financial institutions to consider ESG scores when deliberating over frameworks like Basel II and III. This not only paves the way for potentially reduced capital requirements but also encourages other industries to integrate responsibility dimensions within their risk models.

Lastly, the behavioral aspects determining investment decisions, particularly in relation to ESG considerations, have been brought into sharp focus. The house money effect emerges as a key driver, influencing investors' attitudes toward ESG-centric investments based on their recent financial gains or losses. While naive investors seem more liable toward responsible investing, their influence on price equilibrium remains constrained by arbitrage limits. It's evident, however, that investor sentiment, market moods, and liquidity conditions play pivotal roles in shaping ESG's pricing dynamics.

Ultimately, we confirm four out of the six hypotheses set at the beginning of the dissertation through our empirical research, except for those two assumptions related to the impact of ESG scores and the frequency of operational risk events. In these cases, contrary to our expectations, the frequency of loss events does not decrease with the increase in ESG scores. In general, we do not find a correlation between the two factors, which may be because there is indeed no connection, or it could be due to fewer damage events in responsibly operated companies. However, the more frequent event disclosures resulting from higher ESG transparency offset each other. This is partly supported by the results obtained during the sub-chapter related to risk categories. In this context, we find a significant positive correlation only in the category of physical damage events between ESG and the frequency of operational risk events. This category is unique because not every event in this category can be attributed to the company (e.g., natural disasters), so the acknowledgment of such events does not lead to reputational loss, and it is difficult to conceal this type of damage event. The aforementioned is summarized in Table 28 more visually.

Table 28. Summary of the research questions, hypotheses, and the validation of the hypotheses of the dissertation.

Research question	**Hypothesis**	**The hypothesis has been validated**	**Reasonings/Findings**
How ESG scores correlate with the frequency of operational loss events?	H1: The frequency of operational risks decreases with an increase in ESG scores	No	No connection or two offsetting effects
How ESG scores correlate with the severity of operational loss events?	H2: The severity of operational risks decreases with an increase in ESG scores	Yes	Higher ESG curtails operational risk severity
How ESG scores correlate with the frequency of operational loss events in different risk event categories?	H3: The frequency of operational risks decreases with an increase in ESG scores in those categories where the company involvement cannot be questioned.	No	Higher ESG score is paired with higher frequency in physical damage category, where the company involvement can be questioned due to improved transparency through higher ESG score
How ESG scores correlate with the severity of operational loss events in different risk event categories?	H4: The severity of operational risks decreases with an increase in ESG scores in those categories where the company involvement cannot be questioned.	Yes	Higher ESG score is paired with lower severity in the improper business practices category
How investors past financial experiences influence their decisions regarding ESG investments?	H5: Investors might be more willing to sacrifice return for social benefits when they face prior gains in a stock	Yes	Higher ESG score has a lower expected return for stocks with prior gains
Do naïve investors drive the revealed relations?	H6: Naïve investor group drives the mispricing due to the limits of arbitrage	Yes	Brown investors cannot immediately trade the mispricing due to the limits of arbitrage in the naïve investor group

In summation, the multi-faceted conclusions drawn from this research provide a richer literature of understanding regarding ESG's role in corporate operations, risk management, and investment behaviors, urging stakeholders to adopt a more nuanced and informed approach in their investment and risk management decisions.

Reflecting upon the journey our research has undertaken, the title "Green Choices, Grey Areas" encapsulates the essence of our findings. While the ESG landscape has witnessed elevated interest and is often celebrated for its 'green' or sustainable tendency, our exploration has filled significant 'grey areas' - gaps in the academic literature that require more comprehensive scrutiny. The grey areas of the scientific literature, particularly the intricate relationship between ESG and operational risk, and the complexity of behavioral finance within ESG investing, have been colored, at least in part, by this dissertation.

4.2. LIMITATIONS AND FURTHER RESEARCH OPPORTUNITIES

The limitations of the research can be interpreted both temporally and geographically. The examined time frame encompasses the 2010s. However, extending the dissertation's timeframe prior to 2010 is not feasible, as the reporting of ESG information only became significant during the early 2010s, and therefore, due to a lack of data, the integration of years preceding 2010 is not possible using the Reuters Refinitiv database (Refinitiv [2022]).

Furthermore, during the research, we focus on stocks, which traded on the most liquid NASDAQ and NYSE exchanges to ensure our investigations are as insulated from illiquidity effects as possible. It would be valuable to replicate these two studies on other exchanges, such as the DAX or the Chinese stock exchange, rather than drawing conclusions solely from the information of American investors and corporations.

In addition, ESG scores can vary depending on the data provider due to differences in weighting and calculation methodologies employed by these vendors. Utilizing a standardized ESG score (which currently does not exist) or conducting research using various ESG metrics might provide further nuances or support to our findings.

It's important to be cautious when translating research findings into a trading strategy, especially in the light of the research in Chapter 3. During the chapter, we apply hypothetical portfolios without considering transaction costs, price impact, slippage costs, brokerage fees, commissions, and portfolio turnover. Transaction costs directly reduce the net returns of a trading strategy. Strategies that involve buying and selling stocks may lead to higher transaction costs, which can erode potential profits. Moreover, strategies with high portfolio turnover (due to monthly rebalancing at the portfolio sorts), meaning frequent buying and selling of securities, generally result in higher transaction costs. In addition, we do not consider slippage costs in our models. Less liquid stocks or assets with wider bid-ask spreads are more prone to slippage hence, in the case of illiquid stocks it may be more challenging to execute trades at the desired price, leading to greater slippage costs. It would require a separate study to determine whether the results of the research can be translated into a profitable trading strategy.

Statistical significance does not necessarily translate to economic significance in the case of a real-life trading strategy. Even if a relationship is statistically significant, the magnitude of the effect (e.g., 0.7% average monthly return in the winner portfolio, which is statistically significant arbitrage opportunity, visible on Table 20) may be small and impractical for building a profitable trading strategy. Especially, if we consider the results of Berkowitz, Logue, and Noser (1988), as the combined transaction costs, encompassing both commissions and market impact costs on the NYSE is an average of twenty-three basis points of principal value within their sample. Specifically, commission costs, averaging eighteen basis points, significantly exceed execution costs, which average five basis points. Due to the listed limitations and the factors omitted from the modeling mentioned earlier, it remains uncertain whether real profit can be gained for a fund with this strategy.

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7. APPENDIX

7.1. APPENDIX A.

A.1 Morgan Stanley, 2013-2015

Retail Brokerage, Execution, delivery, and process management, explicit misconduct (regulatory action)

In December 2016, Morgan Stanley & Co, a US financial institution and subsidiary of Morgan Stanley, reported that it was fined $7.5M by the US Securities and Exchange Commission (SEC) for violating the SEC's Customer Protection Rule (CPR). The law required broker-dealers to maintain an adequate customer reserve account to ensure customers' cash and securities were safe if the firms failed. The CPR specifically prohibited the use of affiliates to reduce customer account deposit requirements. Between 2013 and 2015, Morgan Stanley & Co (Morgan Stanley) instructed its affiliate Morgan Stanley Equity Financing Ltd (MSEF) to act as a customer of its US broker-dealer. This allowed MSEF to use margin loans from the broker-dealer to hedge swap trades with customers. The loans lowered MSEF's borrowing costs to finance its swap trade hedging operations. The transactions also reduced the amount of cash the broker-dealer was required to deposit into its customer reserve account. As a result, Morgan Stanley incorrectly calculated its customer reserve account requirements and reported the erroneous numbers to the SEC. The firm agreed to pay a $7.5M civil penalty and to review its compliance with the CPR. Morgan Stanley would then take remedial action to come into compliance with the law.

A.2 S&T Bank

Commercial Banking, External fraud, no explicit misconduct, 2015-2019

In August 2019, S&T Bank, a US financial institution and subsidiary of S&T Bancorp Inc, reported that it lost an estimated $5.2M due to fraud by Andrew Gabler and Chad Bednarski. Gabler owned Lakeside Chevrolet-Buick and Lakeside Auto Sales in Erie County, Pennsylvania while Bednarski served as the finance manager of the dealership. From January 2015 to January 2019, the two falsely indicated that customers made down payments for vehicles and falsified their income in order to qualify for automobile financing at local financial institutions. Gabler also sold extended warranties to customers who purchased vehicles from his dealerships, but failed to remit the paperwork and payment to the extended warranty company. Additionally, the two falsely reported vehicle sales to General Motors in order to obtain expiring incentive rebates. Finally, S&T Bank was not informed by either party when a vehicle was sold after it had been financed through S&T Bank's floor plan financing. The failure to notify delayed and attempted to avoid the dealerships' required payment to S&T Bank for the sold vehicles. Gabler and Bednarski were indicted on charges of conspiracy, bank fraud and wire fraud. Gabler's dealerships were liquidated in January 2019 after S&T Bank filed a lawsuit against the company to recover its losses.

A.3 Southern California Gas Co

Utilities, Damage to physical assets, explicit misconduct, 2015-2016

In June 2016, Southern California Gas Co, a US utility and subsidiary of Sempra Energy, reported that it Lost an estimated $717M due to a major gas leak at one of its natural gas wells. On October 23, 2015, a leak in the utility's storage facility in Aliso Canyon, California released .07M metric tons of methane into the air. Residents in the nearby Porter Ranch neighborhood complained of headaches, nosebleeds, and nausea from the fumes associated with the leak. Southern California Gas Co (SoCal Gas) agreed to relocate approximately 8,000 residents while it tried to stop the leak. It took four months to plug the leak because it was so far below ground. Even though nearby homes did not test positive for harmful levels of gas in, the utility agreed to clean the insides and exteriors of homes, schools, playgrounds, and parks before residents returned to their homes. As of June 2016, SoCal Gas estimated the leak would cost it $717M. Approximately 70 percent of the costs related to the temporary relocation program and associated costs. Another 15 percent went toward stopping the leak, controlling emissions, and analyzing the leak to determine the root cause. The remaining amount covered legal costs, value of lost gas, expenses related to mitigating the released gas, and other costs. SoCal Gas' estimation did not include damage awards, restitution, penalties, or other costs associated with civil or criminal proceedings. The utility expected to recover some of the loss from insurance.

A.4

Titanium Metals Corp

Manufacturing, Damage to physical assets, no explicit misconduct, 2013In June 2013, Titanium Metals Corp, a US metal products manufacturing company and subsidiary of Precision Castparts Corp, reported that it lost an estimated $3.5M due to a fire. On June 18, 2013, a fire started at the company's Caernarvon, Pennsylvania plant at about eight in the evening. The fire was located in a building where raw materials were stored. Due to the flammable nature of titanium, a special fire suppressant and salt were used to smother the flames. No one was injured in the blaze, but over 200 firefighters were needed to extinguish the fire. The company did not cease its operations, but it estimated the damage at $3.5M.