Essays in Empirical and Behavioral Finance

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Contents

Introduction

This cumulative dissertation brings together six papers that collectively address important issues in empirical and behavioral finance. These papers, while dealing with distinct topics, are interconnected through their focus on understanding decision-making processes in financial markets and institutions, with an emphasis on both individual and corporate behavior. The core theme that unites these works is the exploration of how behavioral factors, empirical evidence, and theoretical frameworks interact to influence financial outcomes, both at the micro-level of individual investors and the macro-level of firms and institutions. Together, they contribute to a better understanding of how financial decisions are made in the context of evolving technologies, regulatory environments, and market structures.

The first three papers are connected through their examination of robo-advisory services, a significant innovation in the field of personal finance in recent years. These papers explore how automated digital platforms, often marketed as low-cost alternatives to traditional financial advisors, provide investment advice to individual investors. Despite the promise of robo-advisors to democratize access to financial markets, these papers reveal critical insights into the limitations and benefits of such services. The first paper, *What Drives Robo-Advice?*, investigates the alignment between the portfolio recommendations of robo-advisors and the normative models of portfolio theory developed in academic finance. It uncovers that while robo-advisors offer simplified, pre-built portfolios based on easily understood factors like investment goals and time horizons, they often ignore more sophisticated hedging demands and personalized risk considerations that normative models would suggest. This finding is further expanded in the second paper, *Investor Experience and Portfolio Choice*, which analyzes the relationship between investor experience and portfolio recommendations, particularly in the context of regulatory frameworks like the MiFID II directive. The paper highlights the potential unintended consequences of regulations that constrain portfolio risk-taking based on investor experience, potentially worsen wealth inequality by limiting the risk exposure of less experienced investors. The third paper, *Trust me, I am a Robo-Advisor*, expands on these themes by exploring the critical role of trust in robo-advisory services. This paper emphasizes that while robo-advisors offer more objective, algorithm-driven advice compared to traditional advisors, they still face challenges in building and maintaining trust with users. The paper argues that the simplicity and familiarity of robo-advisor recommendations, though potentially suboptimal from a theoretical perspective, are deliberate choices made to build trust and meet client expectations.

The latter three papers of this dissertation focus on corporate decision-making, examining how firms manage ESG performance and how senior hiring and workforce geography impact corporate stock performance. The fourth paper, *On the Relationship between Financial Distress and ESG Scores*, analyzes how financially distressed firms may strategically improve their ESG scores to reduce financing costs and enhance their public image, questioning the reliability of ESG metrics as indicators of true sustainability. The fifth paper, *Senior Hiring Impacts: An Alternative Data Perspective*, uses LinkedIn data to assess how senior hiring affects corporate performance. It finds that while the market initially reacts negatively to senior hires, long-term benefits often emerge as the new leadership contributes positively to firm strategy, particularly in knowledge-intensive sectors. The final paper, *Balancing Dispersion and Agglomeration: How Workforce Geography Influences Corporate Performance*, explores how the geographic distribution of employees impacts financial performance. It shows that workforce dispersion can boost stock returns and operational flexibility in sectors like technology but poses challenges in others, such as utilities, where coordination costs and loss of cohesion can negatively affect profitability. Together, these papers highlight the importance of strategic decisions in corporate management.

Together, these six papers form a cohesive narrative that advances the understanding of decision-making in financial markets and institutions. They highlight the interconnectedness of behavioral factors, empirical evidence, and theoretical models in shaping both individual and corporate financial outcomes. At the individual level, the papers on robo-advice demonstrate how financial decisions are influenced not only by rational portfolio theory but also by practical considerations like simplicity, trust, and regulatory constraints. At the corporate level, the papers on ESG performance, senior hiring, and workforce geography emphasize the importance of strategic decisions in response to financial, human capital, and operational challenges. By integrating insights from both individual and corporate finance, this dissertation provides a comprehensive perspective on the evolving landscape of financial decision-making, offering valuable implications for investors, financial advisors, and corporate leaders alike.

1.1 Summary – What Drives Robo-Advice?

In this paper, the alignment between robo-advisory services and normative academic financial advice is investigated, with a focus on how these digital platforms recommend portfolios to investors. The central question addressed is whether robo-advisors, which are gaining popularity for providing investment advice, reflect the sophisticated portfolio theories developed in academic finance or adopt a more simplified, commercially driven approach that aligns with expectations of a broad audience.

This involves the web-scraping of portfolio recommendations from Charles Schwab, one of the largest U.S. robo-advisors. The analysis was performed on 151,200 unique investor profiles to understand how the robo-advisor tailors its recommendations based on responses to a predefined questionnaire. This questionnaire inquires about investors' investment goals, risk tolerance, time horizons, and a few other basic characteristics. Findings indicate that, rather than identifying and addressing individual hedging demands—such as those related to labor income risk or specific economic exposures—these responses are mapped by the robo-advisor to a set of eleven portfolios that broadly represent different points along a hypothetical efficient frontier.

The paper highlights that in a multi-factor world, the traditional efficient frontier might not be suitable for every investor because it does not account for the diverse and individualized risks investors might face. For example, some investors may not be comfortable holding certain types of risks—such as those associated with value stocks—that correlate with their human capital or other assets they own. However, the robo-advisor's approach does not consider such nuanced distinctions. Instead, investment goals and time horizons are focused on as the primary determinants of portfolio recommendations, a method that may be less aligned with the more complex, tailored advice typically suggested by academic financial theories.

A significant finding of the study is that while the robo-advisor's recommendations do not reflect the full complexity of academic portfolio theory, a mandatory allocation to equities is included in all portfolios, even the least risky ones. This approach is consistent with the participation theorem, which suggests that all investors should have some exposure to equities regardless of their risk aversion. By nudging even low-wealth and low-financial-literacy households into equity investments, market participation is potentially increased by the robo-advisor, which is seen as a positive outcome from a behavioral finance perspective.

To analyze the statistical relationship between the questionnaire responses and the recommended equity allocations, both linear regression models and regression trees were used. Results demonstrate that the most influential factors driving the robo-advisor's recommendations are the investor's stated investment goals and time horizons. These two factors dominate the advice given, while other variables, like financial literacy and risk tolerance, play a more secondary role. This finding underscores a key point: the robo-advisor's advice is heavily influenced by factors that are straightforward and easily understood by investors, rather than by a complex, multi-dimensional assessment of their financial situation.

Parallels are also drawn between the commercial strategies of robo-advisors and traditional financial advice. The paper argues that in their quest to build trust and attract clients, simpler, more familiar solutions may be deliberately chosen by robo-advisors rather than theoretically optimal but potentially more complex recommendations. This strategy is not necessarily viewed as a flaw but as a calculated decision to meet investor expectations and ensure client satisfaction in a competitive market. By aligning their advice more closely with what investors are expecting and are comfortable with, trust can be built by robo-advisors, reducing behavioral biases, and ultimately leading to better investment outcomes for their clients.

To complement the analysis of the web-scraped data, the National Financial Capability Study (NFCS) conducted by the Financial Industry Regulatory Authority (FINRA) was integrated. This survey provides a broad perspective on the financial behaviors and capabilities of U.S. adults, and it was used to examine how demographic factors might influence the usage of robo-advisors. Contrary to prior assumptions, the regression analysis shows that demographic factors like gender and age have a marginal influence, while trust in financial markets, verification of advisor credentials, and reaction to market downturns play more substantial roles. Ethnicity also emerged as a factor, with non-white individuals receiving more conservative recommendations, reflecting a cautious approach to risk-taking.

In conclusion, the findings indicate that while robo-advisors like Charles Schwab do not fully adhere to the principles of normative portfolio theory—where portfolios are tailored to reflect individual hedging demands and specific risks—a practical, commercial solution that resonates with a broad range of investors is provided. The emphasis on investment goals and time horizons, while potentially oversimplifying the complexity of optimal portfolio selection, makes the advice more accessible and understandable to the average investor. This approach can be particularly beneficial in increasing market participation among households with low wealth or financial literacy, potentially helping to reduce wealth inequality. The paper shows a significant divergence between academic theory and practical application in the field of financial advice. While the robo-advisory model does not fully meet the criteria set out by academic portfolio theory, it offers a pragmatic approach that aligns with investor expectations and builds trust, ultimately serving a broad audience effectively.

1.2 Summary – Investor Experience and Portfolio Choice

This paper investigates the regulatory framework of financial products, specifically wealth management for private clients under the European Union's Markets in Financial Instruments Directive II (MiFID II). The focus is on the requirement outlined in Article 25(2), which mandates that clients' knowledge and experience in the investment field be assessed by investment firms, with respect to the specific products or services being considered. This requirement, which is enforced by the European Securities and Markets Authority (ESMA), implies a presumed relationship between an investor's experience and the level of risk to which they should be exposed. The assumption underlying this relationship is critically examined, with questions raised about its theoretical and empirical validity, and the broader implications for financial institutions, investors, and economic welfare are explored.

Therefore, the theoretical foundations of the MiFID II regulation are questioned. The authors note that the directive assumes less experienced investors should naturally assume less risk, a conjecture not supported by traditional portfolio choice theory. Instead, they argue that the ESMA guidelines are based on an implied assumption that lower experience should correlate with lower risk-taking. This assumption is explicitly stated in the ESMA guidelines, which advise firms to be cautious of contradictions between an investor's expressed risk tolerance and their level of experience or knowledge. For example, a client with little knowledge or experience but an aggressive attitude towards risk is flagged as a potential inconsistency that must be addressed by the advising firm.

Significant legal risks for banks and asset managers are introduced by this regulatory stance. The ambiguity in the interpretation of the regulation leaves financial institutions vulnerable to lawsuits from clients who may suffer significant losses. An inexperienced investor, facing substantial financial losses, could claim that they were not properly advised and that their lack of experience should have led to more conservative investment strategies. As a result, banks might be deterred from recommending higher-risk portfolios to less experienced investors, not due to sound financial advice, but out of fear of potential legal repercussions.

Several key questions are analyzed in the paper: How do banks and wealth managers respond to this regulatory requirement? How much variability exists in their responses? Does this regulation significantly influence the portfolio choices made by these institutions? And what are the broader welfare implications for individual investors and society as a whole? Data from robo-advisory firms, which are subject to MiFID II regulations, is used to address these questions. These firms, often affiliated with traditional banks, provide a useful proxy for understanding how banks might respond to the regulation in practice.

Significant heterogeneity in the responses of different firms to the regulation is shown by the analysis. Some robo-advisors make only minimal adjustments to their portfolio recommendations based on the investor's experience, while others make substantial changes, significantly reducing the allocation to risky assets for less experienced investors. This variability suggests that different firms have different interpretations of the regulation or varying levels of risk tolerance concerning potential litigation. The authors note that there is no consistent relationship between the level of investor experience and the recommended portfolio risk across different firms, highlighting the lack of a clear theoretical foundation for the regulation.

A simple model is further developed to explore the implications of the regulation, approximating the banks' response function. In this model, a lack of investor experience is treated as analogous to an increase in perceived investment risk. This assumption leads to the conclusion that less experienced investors are likely to receive suboptimal portfolio recommendations, resulting in underinvestment in risky assets that could negatively impact their long-term financial outcomes. The welfare loss associated with this regulatory approach is suggested to be significant, particularly for investors with higher risk tolerance and those facing attractive investment opportunities. The welfare loss is quantified by comparing the utility of an unconstrained mean-variance investor with that of an investor constrained by the regulatory requirement to take on less risk due to their lack of experience.

Empirical data from the German robo-advisory market is used to validate the model. Considerable dispersion is found in the portfolio recommendations given to hypothetical investors with varying levels of experience. For instance, some robo-advisors reduce the allocation to risky assets by up to 50% for less experienced investors, while others make no change at all. This variability is reflected in the calculated utility losses, which can range from negligible to significant, depending on the firm's interpretation of the regulatory requirements.

The broader economic implications of this regulatory point are also examined. By discouraging risk-taking among less experienced investors, the regulation might inadvertently worsen wealth inequality. The paper points out that the top one percent of wealthiest households tend to take on more systematic risks, invest in more volatile portfolios, and thus earn higher long-term returns. By contrast, less experienced investors, who are often already at a disadvantage in terms of financial literacy and wealth accumulation, may be further discouraged from participating in higher-risk, higher-return investments. This could widen the wealth gap between experienced and inexperienced investors, counteracting the intended protective effects of the regulation.

To estimate the aggregate welfare loss for the economy, data from the Eurosystem Household Finance and Consumption Survey (HFCS) for German households is used. The potential utility loss across the economy is calculated by considering the proportion of inexperienced households and the wealth they control. The analysis reveals that a significant portion of the population (81%) falls into the inexperienced category, controlling about 42% of the liquid wealth in the economy. The regulatory-induced underinvestment in risky assets by this group could lead to an aggregate utility loss equivalent to several basis points of return on their wealth each year. While this might seem small on an individual level, the cumulative effect across the economy could be substantial, particularly given the long-term compounding of investment returns.

In conclusion, the paper argues that the MiFID II regulation, while well-intentioned in its aim to protect less experienced investors, might have the opposite effect of what is intended. By discouraging risk-taking, the regulation could lead to lower overall returns for less experienced investors, exacerbating wealth inequality and potentially leading to greater economic disparity. The paper suggests a reconsideration of the regulatory framework towards a more balanced approach—one that encourages appropriate risk-taking across all investor demographics, rather than disadvantaging less experienced investors. This could involve a shift away from a one-size-fits-all regulatory approach towards a more nuanced framework that takes into account the diverse needs and circumstances of different investors.

1.3 Summary – Trust me, I am a Robo-advisor

An in-depth analysis of the German robo-advisory market is provided in this paper, focusing on how portfolio recommendations are tailored by these platforms based on client inputs gathered through an online questionnaires. Robo-advisors are presented as innovative financial services that offer low-cost, diversified portfolios, theoretically aligned with academic principles of normative portfolio choice. Access to sophisticated investment strategies is promised to be democratized by these services, overcoming some of the limitations associated with traditional financial advisors, who often fail to adequately consider individual client characteristics such as risk aversion, wealth, and time horizon in their recommendations.

The key advantage of robo-advisors is their ability to provide customized investment solutions at a marginal cost, which is expected to be low due to the automated, web-based nature of their services. Unlike traditional advisors, who have faced criticism for being biased, costly, and may have conflicts of interest, robo-advisors are theoretically positioned to offer more objective, personalized advice. For instance, prior research has demonstrated that traditional advisors often ignore client preferences, steer clients away from passive investments, and provide advice reflecting more about the advisor's own incentives than the client's needs. These limitations have contributed to widespread household non-participation in financial markets, particularly among those with less wealth, who may find traditional advisory services too expensive or inaccessible.

Despite the theoretical advantages held by robo-advisors, a critical vulnerability is identified: the difficulty of establishing trust with users. Trust, a cornerstone of financial advisory relationships, is more challenging to build and maintain for robo-advisors, which lack the personal touch of human advisors. To address this, strategic design choices are made by robo-advisors, such as offering passive funds and ETFs, to avoid conflicts of interest and reduce costs. The paper argues that the low level of individualization observed in robo-advisor services is not merely a design flaw but a deliberate choice intended to create trust by aligning with familiar investment strategies and popular rules of thumb.

The empirical analysis in this paper is based on a dataset obtained through web-scraping the portfolio recommendations of 16 robo-advisors, collectively holding about a 78% market share in Germany. Comprising over 240,000 unique portfolio recommendations, this dataset represents one of the most data-intensive studies of robo-advisory services to date. It is found that the portfolios recommended by these robo-advisors show little evidence of true customization, particularly in terms of adapting to individual investor balance sheets or the characteristics of their human capital. This observation is significant because, according to normative portfolio theory—exemplified by the work of Merton—optimal portfolios should reflect not only market opportunities (speculative demand) but also hedging demands related to the investor's unique financial circumstances, such as their exposure to systematic economic risks.

Instead, it seems that these aspects are largely ignored by robo-advisors, which offer standardized portfolios that do not account for the diversity of their clients' financial situations. The portfolios tend to be generic, with a limited range of choices, and often fail to incorporate complex models that might deliver counterintuitive results, which could be difficult for financially untrained clients to understand and accept. The paper suggests that this is not due to a lack of awareness of academic literature on portfolio choice but rather a commercial decision. In a highly competitive market, simplicity and familiarity seem to be prioritized by robo-advisors over precision and sophistication, likely to avoid confusing or alienating potential clients.

In terms of the actual portfolio recommendations, little variation across different client types is observed. Most portfolios fall within a narrow range of equity exposure, with extreme allocations (such as 100% equities or 100% bonds) being rare. This lack of differentiation suggests that a "one-size-fits-all" mentality is being operated under by robo-advisors, offering pre-built portfolios rather than dynamically adjusting them based on individual client inputs. This approach may reduce the risk of litigation, as it avoids the perception of extreme or unsuitable recommendations, but it also limits the potential for truly personalized financial advice.

The paper also analyzes the relationship between the questions asked in the robo-advisors' questionnaires and the resulting portfolio recommendations. A statistical analysis is conducted to determine which client characteristics have the most influence on the portfolio advice given. The findings indicate that risk aversion is the most significant factor across all robo-advisors, with higher risk aversion consistently leading to lower equity allocations. Time horizon is also important, with longer horizons generally associated with higher equity allocations. However, other factors like wealth and personal experience, which theoretically should play a role in portfolio choice, have much less impact.

A potential reasons is that intentional simplification of their models is being carried out by robo-advisors to align with clients' expectations and avoid recommendations that might seem counterintuitive or overly complex. This approach, while potentially less optimal from a theoretical perspective, likely helps build trust and manage regulatory risks, as clients are more likely to feel comfortable with advice that matches their prior beliefs and understanding of investment strategies.

While previous studies have explored the economics of the robo-advisory industry or compared the performance of different platforms, little cross-sectional analysis of the actual portfolio structures recommended by these platforms has been conducted. This paper is positioned as filling this gap, offering a detailed examination of how different robo-advisors respond to client inputs and how these responses align with or diverge from normative portfolio theory.

1.4 Summary – On the Relationship between Financial Distress and ESG Scores

This paper provides an empirical analysis of the relationship between a company's financial distress and its Environmental, Social, and Governance (ESG) scores, focusing on publicly listed U.S. companies from 2003 to 2022. Financial distress is measured using a bankruptcy prediction model, while ESG scores are sourced from Refinitiv, MSCI, ESG Book, and Moody's ESG. The study employs nonparametric regression techniques to investigate whether a company's financial condition systematically influences its ESG performance metrics. A key finding is the presence of a statistically significant U-shaped relationship between financial distress and ESG scores. Specifically, companies that are in greater financial distress tend to exhibit higher ESG scores. This surprising result challenges the conventional view of ESG performance and highlights the potential for companies to strategically manage their ESG profiles in response to financial pressure.

The paper argues that financially distressed companies may increase their focus on ESG activities, particularly low-cost initiatives like ESG disclosures, as a way to improve their public image, reduce their cost of capital, and distract from poor financial performance. For instance, ESG disclosures are often perceived as a signal of responsible management and long-term sustainability, which can attract investment and lower financing costs, even if these disclosures do not reflect substantial changes in the company's actual operations. The observed increase in ESG scores among distressed firms calls into question the reliability of ESG metrics as accurate indicators of a company's true commitment to environmental, social, and governance principles, particularly for companies in the face of financial distress.

The study identifies several potential motivations for the upward management of ESG scores by distressed firms. First, the relationship between ESG performance and a company's cost of capital is well-documented in the literature, with firms that excel in ESG often benefiting from lower financing costs due to favorable perceptions among investors and creditors. Financially distressed companies, faced with the threat of bankruptcy, may prioritize ESG disclosures to enhance their reputations and secure more favorable financing terms. Second, management may use ESG initiatives to shift attention away from shareholder-oriented financial objectives, instead focusing on stakeholder-oriented goals, which are often less scrutinized. This shift can obscure poor financial performance, allowing management to maintain control or defer accountability.

To support these claims, the study conducts several robustness checks, controlling for variables such as industry effects, firm size, additional ESG data, and external shocks, like the introduction of U.S. tariffs in 2018 and the COVID-19 pandemic. Notably, the relationship between financial distress and ESG scores is robust to these shocks, suggesting that the U-shaped pattern is not driven by temporary or external factors but rather reflects a deliberate strategy by companies facing financial difficulties. The analysis also finds no significant relationship between unpredictable, exogenous shocks and ESG scores, supporting the idea that distressed companies proactively manage their ESG profiles to mitigate the impact of internal financial challenges.

The paper raises important questions about the validity of using ESG scores as a reliable measure of corporate sustainability, especially in the context of financially troubled firms. The potential systematic manipulation of ESG scores by distressed firms undermines the credibility of these scores as indicators of long-term value creation and responsible business practices. The findings imply that investors and stakeholders should exercise caution when interpreting ESG scores, particularly for companies with high financial distress. A more nuanced approach, incorporating measures of financial health, may be necessary to avoid overestimating the ESG performance of firms that are primarily motivated by the need to secure short-term financial relief rather than a genuine commitment to sustainability.

By examining the strategic behavior of distressed companies with regard to ESG scores, this paper contributes to the ongoing debate on the reliability and informational content of ESG metrics, offering a new perspective on how financial constraints shape corporate behavior in the realm of sustainability.

1.5 Summary – Senior Hiring Impacts: An Alternative Data Perspective

The paper explores the significant yet often challenging-to-measure impact of knowledge and experience on firm performance, particularly through the lens of hiring practices. In the fields of economics, finance, and human resources, these intangible assets are known to influence corporate outcomes, but quantifying their effects has been difficult due to data limitations. This study seeks to bridge that gap by leveraging a unique dataset scraped from LinkedIn, focusing on hiring patterns of firms within the S&P 500. The research particularly emphasizes the hiring of senior employees—those with titles of Vice President or higher—as proxies for the infusion of knowledge and strategic insight into the firm.

Previous studies have established that knowledge management is critical to enhancing firm performance, particularly in knowledge-intensive sectors. Hiring, especially at senior levels, is viewed as a strategic move aimed at acquiring high-level expertise and leadership capabilities. The paper examines the relative ratio of senior hires to other employees and how this ratio correlates with firm performance across various industries. This focus on the hiring of senior management allows the study to address an empirical gap in the literature, where the use of granular, firm-level hiring data has been sparse.

Using an event-study methodology, the paper analyzes the effect of hiring events on stock performance, analyzing the period leading up to and following such events. The findings reveal a nuanced market reaction to hiring, particularly senior hires. The study shows that the market generally reacts negatively to announcements of senior hires, with significant declines in cumulative average abnormal returns (CAARs) observed both before and immediately after these events. This negative reaction is more pronounced as the number of senior hires increases, indicating that the situation of the companies is challenging when integrating new, high-level talent into the company. However, the study also finds that, after an initial adjustment period, the negative impact of senior hires tends to stabilize, suggesting that these hires eventually contribute positively to firm performance.

The paper's regression analysis further supports these findings by showing a statistically significant negative relationship between the number of senior hires and stock returns. Interestingly, the study finds that hiring at non-senior levels does not significantly impact stock performance, reinforcing the notion that senior management hires are used from a strategically point for corporate development. Additionally, the paper explores the broader implications of these hiring practices by conducting a sector-specific analysis. It finds that the negative impact of senior hires on stock returns is particularly strong in sectors such as technology, industrials, utilities, finance, and energy. Conversely, in the consumer staples sector, the relationship between senior hires and stock returns is positive, highlighting a potential importance of industry context in evaluating the effects of hiring decisions.

The research contributes to the growing body of literature that uses alternative data sources to understand firm behavior and predict financial outcomes. By using LinkedIn data, the study provides a novel perspective on the role of hiring patterns in firm performance, offering insights that traditional financial data might not capture. This approach underscores the potential of social media and other non-traditional data sources to provide valuable information for investors, analysts, and academics.

1.6 Summary – Balancing Dispersion and Agglomeration: How Workforce Geography influences Corporate Performance

The paper analyzes the relevant topic of geographic workforce distribution and its impact on the financial performance of large corporations, particularly those listed in the S&P 500. As digital technologies and globalization continue to reshape how companies operate, the spatial distribution of employees has emerged as a crucial factor for corporate success. The COVID-19 pandemic, which accelerated the adoption of remote work, has only intensified the need to understand how the location of employees relative to corporate headquarters influences overall firm performance. This study specifically investigates this relationship by examining the average distance of employees from their corporate headquarters and how this geographic dispersion correlates with stock returns and gross profit margins.

The research shows the multifaceted effects of workforce distribution on company performance. Companies with geographically dispersed teams face unique challenges in managing knowledge effectively and maintaining employee engagement across different locations. Moreover, the potential possibilities that arises from such dispersion can enhance performance but also requires careful management to avoid conflicts. The study emphasizes that the way companies manage these challenges, particularly in terms of governance and administrative practices, can significantly influence the outcomes of geographic dispersion.

The analysis uses a unique dataset scraped from LinkedIn, focusing on the top 15 work locations for employees of S&P 500 companies. This dataset offers a detailed view of where employees are located relative to their company's headquarters, with data hierarchically structured to avoid overlap between larger regions and their subsets (e.g., the state of California versus the entire United States). The study calculates the weighted average distance of employees from headquarters and examines how this metric correlates with financial performance, controlling for various market factors such as the Fama-French five factors and momentum.

The regression analysis shows a positive and statistically significant relationship between the average weighted distance of employees from headquarters and stock returns. This suggests that companies with a more geographically dispersed workforce tend to achieve higher stock returns, potentially due to greater operational flexibility and broader market reach. Similarly, the analysis of gross profit margins indicates that a dispersed workforce is associated with higher profitability, although the effect is less pronounced than that on stock returns. These results imply that geographic dispersion may indeed confer competitive advantages, but these advantages are not uniform across all measures of performance.

However, the study's sector-specific analysis uncovers significant variations across different industries. For example, in the industrial and healthcare sectors, workforce dispersion positively impacts stock returns, suggesting that these industries can effectively leverage the flexibility and market access that comes with having employees spread across various locations. However, the same sectors experience a negative impact on gross profit margins, likely due to the increased operational costs associated with managing a dispersed workforce. In contrast, the technology sector shows both positive impacts on stock returns and gross profit margins, indicating that tech companies may have a better business model to leverage remote work. Conversely, sectors like utilities and consumer discretionary show either marginally significant or non-significant negative relationships between workforce dispersion and financial performance.

The findings of this paper underscore the complexity of managing a geographically dispersed workforce. While the benefits of such dispersion, including operational flexibility and access to diverse talent pools, are evident, these must be weighed against the potential drawbacks, such as increased coordination costs and the challenges of maintaining cohesion across diverse teams. The results suggest that the impact of geographic dispersion on financial performance is context-dependent, varying significantly across different sectors.

What Drives Robo-Advice?

Bernd Scherer [1], Sebastian Lehner [2]

Abstract

The promise of robo-advisory firms is to provide low-cost access to diversified portfolios built according to academic literature on normative portfolio choice. We investigate the extent to which robo-advice aligns with normative advice. Using web-scraped portfolio recommendations for 151,200 investor types from a major US robo-advisor, we find that investment goals and time horizons significantly influence recommended equity allocations, while Merton-type hedging demands are largely ignored. Our results suggest that commercial robo-advisors prioritize simplicity and client perceptions over complex, normative models. By integrating data from the NFCS survey, we further explore how demographic factors influence the likelihood of using robo-advisory services. This study provides empirical evidence on how closely robo-advisory services align with normative portfolio theory, highlighting the practical compromises made in the pursuit of broad market appeal and user-friendly solutions.

Keywords: robo-advice, portfolio theory, merton hedging demand, behavioral finance, demographic factors

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Investor Experience and Portfolio Choice – Regulatory Costs from MiFID II

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Abstract

MiFID II forces banks and wealth managers to ask clients for their investment knowledge and experience. The implied regulatory view is that less experience should result in less risk taking. While this is neither shared in theoretical nor in empirical finance, it becomes a source of legal risk for asset managers and banks. How do banks react? So far this question was impossible to answer. The relevant data have not been available as they are not shared by banks. We circumvent this problem by using publicly available portfolio recommendations from robo-advisory firms. These firms fall under the same regulations as banks and wealth managers with respect to MiFID II investor profiling and are often owned by traditional banks. It is therefore reasonable to assume that their treatment of investor experience is similar to traditional banks' approaches.

Keywords: financial market regulation, investor experience, MiFID II, regulatory costs, robo-advisory, household finance

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3.1 Introduction

Our paper deals with consumer product regulation, i.e., the microeconomic regulation of financial products. We focus on wealth management for private clients, particularly on a question raised by the European Securities and Markets Authority (ESMA). MiFID II, article 25(2), requires investment firms to ask investors for their "knowledge and experience in the investment field relevant to the specific product or service". This question is of interest as it finds no resemblance in the theory of portfolio choice. Instead, ESMA's request is based on an implied conjecture: less experience should result in less risk-taking. Their guideline on certain aspects of the MiFID II suitability requirements (51) explicitly states:

> *"Firms should be alert to any relevant contradictions between different pieces of information collected, and contact the client in order to resolve any material potential inconsistencies or inaccuracies. Examples of such contradictions are clients who have little knowledge or experience and an aggressive attitude to risk, or who have a prudent risk profile and ambitious investment objectives."*[1]

This is the only explicit interpretation in an otherwise vague document, but here the document is very clear in its intention. While the regulator seems to know cause and effect with a high degree of certainty (certain enough to enshrine it in regulation), any further interpretation of this regulation is deliberately left unclear. Technically, ESMA only requires banks and asset managers to document the answer to this question and act within the ESMA guidelines. Ambiguity leaves the precise interpretation to the court system. This confronts banks with the legal threat of an inexperienced investor with heavy losses turning to the court system and claiming he has not been well advised (cf. BGH, judgement as of 06/07/1993, XIZR 12/93). An inexperienced investor with large losses might then be inspired to claim that he “clearly should not have carried so much risk given his limited experience”. Legal ambiguity will act as a deterrent against advising large equity weights to investors with less experience or education. Bach et al. (2020) show that risk-taking is a major driver of cross-sectional differences in household wealth. The top one percent wealthiest households take more systematic risks, invest in more volatile portfolios, and hence earn much higher long-term average returns.[2]

In this paper, we want to address a series of questions. How do banks react to the regulatory desire to link portfolio choice with investor experience? How much dispersion is there in bank

[1] See ESMA (2023), Page 14-15.

[2] We focus on regulatory costs as we find it difficult to conjecture the benefits of this regulation. In addition, the MiFID documents do not contain a cost-benefit analysis.

responses? Is the impact of second-order importance, or does the answer to this question swamp all other inputs? What are the welfare implications for the individual and for society as a whole? So far, this question was impossible to answer. The relevant data have not been available as they are not shared by banks. We circumvent this problem by using publicly available portfolio recommendations from robo-advisory firms. These firms fall under the same regulations as banks and wealth managers with respect to MiFID II investor profiling and are often owned by traditional banks. It is therefore reasonable to assume that their treatment of investor experience is similar to traditional banks' approaches.

Our paper is not a paper on behavioral household finance as described in Beshears et al. (2018). We do not observe household decisions but rather robo-advice given to households. Hence, our paper focuses on the value of financial advice and on consumer finance regulation. Campbell (2016) argues that the complexity of modern financial products contributes meaningfully to the evolution of wealth inequality and therefore justifies paternalistic intervention. The literature treating the impact of financial literacy on financial risk-taking shows that investors with low financial literacy invest too reluctantly in risky assets and thus should be encouraged to increase their risk-taking.[3] The quoted MiFID view that low experience should translate into low risk-taking runs counter to this evidence. Robo-advisors that implement this view in fear of costly client litigation will fail to offer trusted advice in the sense of Gennaioli et al. (2015). Financial advice will not help to reduce behavioral biases, but rather ingrain behavioral biases. This offers a counter-example to the ending of Hoechle et al. (2017) that financial advice helps to overcome behavioral biases.

In Section 3.2, we review the portfolio choice literature with respect to investor experience. We find neither empirical nor theoretical support for a dependency of risk-taking on the amount (time spent) of investment experience. Instead, we develop a simple model to approximate banks' response function where we treat a lack of experience as equivalent to an increase in perceived investment risk. In Section 3.3, we look at the empirical data, i.e., how do banks actually react. For this purpose, we focus on German robo-advisory firms, rather than a European cross-section. First, maneuvering robo-advisory sites in 24 foreign languages is infeasible and error-prone. Second, all German robo-advisory firms are consistently regulated under BaFin interpretations of MiFID rules, which ensure that compliance functions at robo-advisory firms feel the same legal pressure. This and the competitive pressures within the same market for

[3]See Bannier and Neubert (2016), Van Rooij et al. (2011), Lusardi et al. (2017) for a variety of examples. However, Scherer (2017) finds limited evidence on the impact of education on the risk-taking of households using German panel data in a robo-advisory context.

automated investment advice create comparability of portfolio proposals. We find considerable dispersion, i.e., the marginal impact of investor experience leads to widely different (normative) advice. To illustrate our concerns about the unwarranted impact of experience on portfolio recommendations, we web crawl a representative robo-advisor (award winner Stiftung Warentest) in Section 3.4. Our results confirm our conjecture that investor experience plays a dominant part in portfolio recommendations. We acknowledge that this level of data granularity for a large cross-section of robo-advisors would be desirable. At the same time, we feel that empirical research on financial advice is typically centered around a single data provider (bank) as, for example, in Bhattacharya et al. (2012). Finally, we calculate the welfare loss for German households based on ECB household panel survey data in Section 3.5. Assuming a standard representative investor with CRRA utility, we find considerable welfare losses. Section 3.6 concludes.

3.2 Portfolio choice and investor experience

In order to evaluate what banks do, we need both data and theory. What choices do we observe and how can we evaluate them? How much welfare is lost by imposing a particular regulatory constraint?

3.2.1 Normative portfolio advice (theory)

Theoretical papers on portfolio choice do not offer normative models that link portfolio choice to the amount (length) of investor experience. Perhaps the Bayesian literature on the impact of parameter uncertainty on portfolio choice offers some guidance.[4] An inexperienced investor is uncertain about mean return and portfolio risk and has no prior information on their distribution. Typically, this situation is represented by Jeffreys' prior. In such a situation, the expected return would be unaffected by pure parameter uncertainty, i.e., it would still equal the sample mean ($\mu = \bar{\mu}$). However, with parameter uncertainty, an inexperienced investor would face both investment and estimation risk. In other words, the world just becomes riskier for inexperienced and less knowledgeable investors. Increased risk would translate, ceteris paribus, into less risk-taking. This sounds interesting, but how large would we expect this effect to be? In the case of a single risky portfolio, a Bayesian investor would simply leverage sample volatility ($\bar{\sigma}$) upwards, i.e., his volatility estimate (σ) becomes $\sigma^2 = \tau\bar{\sigma}^2$. The leverage parameter τ equals $(1+n^{-1})(n-1)(n-3)^{-1}$, where n denotes the number of return observations. The more data we have, the less important parameter uncertainty (inexperience) becomes. For ten years of monthly data,

[4] A concise review of the use of Bayesian methods in portfolio choice can be found in Rachev et al. (2008), chapters 6 - 8.

this yields $\tau = 1.0256$ and makes virtually no difference in determining the optimal share of risky assets. Most return series are available with higher frequency and for longer periods. Apart from these technicalities, it is very clear that risk aversion and experience are independent concepts. The trade-off suggested by ESMA (2023) does not exist.[5] Equally, the literature on learning from past data to build better forecasts, as in Berk and Green (2004), offers no link between experience and portfolio choice. Superficially, we can label learning from past returns via Bayesian updating as experience. However, in Berk and Green, investors simply learn about the ability of managers to generate positive or negative alpha from the most recent realized returns. Depending on the sign of their forecast, they decide to invest or not. Robo-advisors only ask for the time spent learning, irrespective of the learning outcome. Berk and Green emphasize the importance of the sign of realized short-term returns as investors need to chase promising funds before other investors do, as each additional inflow dilutes alphas down towards zero. Most importantly, it would be highly irrational to base long-term asset allocation decisions on personal investment biographies across different time horizons. Conditional forecasts should instead rely on economic state variables.

3.2.2 Empirical portfolio choice

A variety of studies document the positive empirical relation between investor education and portfolio risk (after controlling for wealth and other characteristics). Less cognitive ability might act as a psychological barrier to financial market participation. Unfamiliarity with a complex subject such as investing also increases costs (measured in time and money) for low-skill households and hence leads to lower levels of investment. Grinblatt et al. (2011) show that cognitive skills decrease information costs and therefore increase the likelihood of participating in financial markets. Campbell (2006) find evidence that stock market participation positively correlates with education. Finally, as argued by Hsu (2012), lower skills lead to lower wealth accumulation. If households also display decreasing relative risk aversion, optimal demand for risky assets will decrease with wealth levels as local risk aversion increases. However, this does not equate to normative advice. Rather to the contrary. Portfolio advice should be reversed, i.e., inexperienced households should invest more aggressively than they initially desire.

In this context, it is important to define how experience is measured. Is it simply the

[5]We should note that portfolio choice under ambiguity aversion can also lead to reduced risk-taking versus traditional portfolio theory. However, it is entirely unclear how experience/education would map into ambiguity aversion and whether ambiguity aversion is compatible with normative advice (based on rationality rather than on behavioral shortcomings). The literature (see Kleindorfer (2010)) offers no guidance on how to determine ambiguity aversion. In addition, Sims (2001) and Al-Najjar and Weinstein (2009) raise valid objections against the use of ambiguity aversion. They describe major violations of rationality axioms (violation of the sure-thing principle or Dutch Book outcomes).

passage of time (as used by robo-advisors) or is it living through particular times (recessionary or inflationary periods)? Ampudia and Ehrmann (2017) show that while experience has an impact on risk-taking, it is not experience per se, but the right type of experience. Investors with positive (negative) stock market experience are more likely to hold substantial (small) positions in risky assets. A recent study by Foltyn (2020) confirms this result. The empirical evidence for this effect carries over to inflation expectations (Blanchflower (2007)) or political preferences (Alesina and Giuliano (2011)). While individual experience might result in heterogeneity in belief formation as documented by Malmendier and Nagel (2011) or Malmendier et al. (2017), this is not relevant in our context. Advice is normative and should help to overcome behavioral biases as well as biased beliefs. In addition, robo-advisors measure experience as passage of time (cardinal input) and knowledge as levels of education (ordinal input), which makes mappings onto theoretical models difficult. According to Scherer and Lehner (2021) and Scherer and Lehner (2023), robo-advisors build constrained portfolios (with major input from legal and compliance) for various input combinations.

3.2.3 Inexperience as an increase in risk

So far, we have established that investor experience does not enter portfolio choice theory. In order to understand real allocations provided by banks, we propose a simple (heuristic) model that generically takes investor experience into account. Returning to our Bayesian example, we can think of missing investor experience as an example of parameter uncertainty. The world appears riskier for inexperienced investors. In the absence of an existing model, we assume without apology that missing experience leads to an upwards leverage of portfolio risk, i.e., mean-variance utility becomes $U = \omega\mu - \frac{\lambda}{2}\omega^2\tau\sigma^2$, where ω represents the weight in a risky asset with expected return (μ) and risk (σ). The client exhibits risk aversion λ. Upwards leverage on portfolio risk due to a lack of experience is introduced via $\tau > 1$. We think of this as $\tau = \tau$ (experience), i.e., τ is a function of investor experience. This allows us to compute portfolio solutions for inexperienced (risk leverage) and experienced (no leverage) investors. Comparing the optimal weight with leverage ($\omega = \frac{\mu}{\lambda\tau\sigma^2}$) and without leverage ($\omega^\star = \frac{\mu}{\lambda\sigma^2}$), we arrive at

$$\frac{\omega^\star - \omega}{\omega^\star} = (1 - \frac{1}{\tau}) > 0 \tag{3.1}$$

What are the empirical implications of Equation 3.1? Following regulatory pressure to account for investor experience leads to an underinvestment in risky assets as $(1 - \frac{1}{\tau}) > 0$ for $\tau > 1$. The percentage difference is independent of the product providers' risk and return expectations or clients' risk aversion and only depends on τ. We should therefore find similar percentage deviations across all banks (or in our context, robo-advisors) independent of their respective models.

From this, we can compute the utility loss for a particular investor. We compare the utility of an unconstrained mean-variance investor with the utility for the same investor when instead he is offered a less optimal portfolio due to a lack of experience.

$$\Delta U_i = U_i^\star - U_i = \frac{1}{2}\left(\frac{\mu^2}{\lambda_i \sigma^2}\right) - \left[\frac{\mu^2}{\lambda_i \tau \sigma^2} - \frac{\lambda_i}{2}\left(\frac{\mu}{\lambda_i \sigma^2 \tau_i}\right)^2 \sigma^2\right] \tag{3.2}$$

After some rearranging, we arrive at

$$\Delta U_i = \frac{1}{2}\left(\frac{\mu^2}{\lambda_i \sigma^2}\right)\left(\frac{\tau_i - 1}{\tau_i}\right)^2 \tag{3.3}$$

The individual loss in utility is higher for risk-tolerant investors (small λ) who face an attractive investment opportunity set (small σ and large μ) combined with a dogmatic regulator (large τ). Note that the utility difference can be seen as a security equivalent with a return dimension. We will use the above model in the following to compute the welfare implications of $\tau > 1$. For an individual investor with $\lambda = 5$, $\mu = 0.05$, and $\tau = 1.5$, we arrive at a utility loss of 0.0083 (i.e., 0.83%) per annum. For this parameterization, almost one percent of return on the investor's liquid wealth is lost every year.

3.3 Regulatory impact: Evidence from the robo-advisory market

What does the evidence look like? Do differences in client knowledge and experience lead (ceteris paribus) to different portfolios offered to clients? These data are not available as they are not shared by banks. Even if they were available, it would be difficult to isolate the marginal impact of changes in investor experience, as clients differ with respect to their characteristics. Clients who are identical in every aspect, apart from experience, are rare. We attempt to circumvent this problem by using publicly available portfolio recommendations from robo-advisory firms.[6] These firms fall under the same regulations as banks and wealth managers with respect to MiFID II investor profiling and are often owned by traditional banks. It is therefore reasonable to assume that the treatment of investor experience is similar to what traditional banks do. In addition, the availability of online questionnaires allows us to create otherwise identical clients who only differ with respect to investor experience. For this purpose, we assume a generic investor, who is 30

[6] See Bartram et al. (2020) for a review of robo-advisory with respect to their algorithmic tools.

years old, wants to invest 500,000 EUR in liquid assets, and has a net income of 9,000 EUR per month. Our hypothetical investor has no shadow assets (outside wealth) or debt. All questions are interpreted to input the lowest risk aversion and the longest time horizon. When answering the questionnaires, we simulate both a maximally experienced and a maximally inexperienced investor, with all other characteristics being equal.

We present the anonymized data for 16 German robo-advisors (Quirion, Zeedin, Growney, Investify, Ginmon, Navigator, Robin, Fidelity, Visualvest, Solidvest, Scalable, Targobank, Fintego, Whitebox, Cominvest, and Weltinvest) in Table 3.1. We find considerable variation in the baseline optimal allocation in risky assets, ranging from 58% to 100%, which is not surprising as firms use different models and risk-return inputs.[7] On average, our hypothetical dummy investor receives an allocation of 84% in risky assets (equities, commodities, alternatives), which coincides with our expectations. The isolated response to investor experience is markedly different across firms and ranges between reductions in risky assets of 50% and 0%. Consequently, our estimates of τ also vary. It can become as large as 1.66, i.e., it can lead to a percentage loss of utility of 15.8% for an individual investor. As seen in the previous section, this can become equivalent to a one percent loss in the investor's security equivalent year by year. This difference across firms is at odds with Equation 3.1 which would project that lower experience should result in the same percentage loss in the allocation to risky assets across all firms. This could be driven by firms using different heuristics to model the impact of experience on portfolio choice, different functional relations between τ and experience, or most likely by different appetites for taking on legal risks. However, we cannot find systematic differences between fintechs and traditional firms, i.e., the compliance departments within traditional firms are on average not more conservative than their fintech counterparts.

[7] A cynic might ask whether the robo-advisor is dominated by a robo-cop?

Table 3.1: Portfolio recommendation and investor experience.

	High	Low	$\omega^\star - \omega$	in %	τ	Ownership
Advisor 1	100	60	40	40.00%	1.67	Traditional
Advisor 2	81.65	81.65	0	0.00%	1.00	Traditional
Advisor 3	100	100	0	0.00%	1.00	Fintech
Advisor 4	87	55	32	36.78%	1.58	Fintech
Advisor 5	92	76	16	17.39%	1.21	Fintech
Advisor 6	58	35	23	39.66%	1.66	Traditional
Advisor 7	67	67	0	0.00%	1.00	Traditional
Advisor 8	90	90	0	0.00%	1.00	Traditional
Advisor 9	77.7	73.5	4.2	5.41%	1.06	Fintech
Advisor 10	100	100	0	0.00%	1.00	Fintech
Advisor 11	64	56	8	12.50%	1.14	Fintech
Advisor 12	75	75	0	0.00%	1.00	Traditional
Advisor 13	90	45	45	50.00%	2.00	Fintech
Advisor 14	95	95	0	0.00%	1.00	Fintech
Advisor 15	70	70	0	0.00%	1.00	Traditional
Advisor 16	100	100	0	0.00%	1.00	Fintech

We show the anonymized recommendations ($\omega^\star$ and ω) for investors with high or low experience across 16 German robo-advisors (Quirion, Zeedin, Growney, Investify, Ginmon, Navigator, Robin, Fidelity, Visualvest, Solidvest, Scalable, Targobank, Fintego, Whitebox, Cominvest, and Weltinvest) as well as their respective $\tau = \left(1 - \frac{\omega^\star - \omega}{\omega^\star}\right)^{-1}$ and whether these firms are fintechs or owned by a traditional financial intermediary. The share in risky assets (ω) is defined as the recommended fraction in equities, commodities (incl. gold), and alternatives (where applicable). The data have been gathered between the 14th and 18th of August 2020. Criteria for selection have been the availability of websites and the ability to model a standard investor.

Given the highly manual effort, it is infeasible to try all possible interactions of input variables for all robo-advisors. Experimental evidence shows us that when we lower the amount of endowed wealth for our dummy investor, we find that risk-taking (percentage allocations into risky assets) falls and that the difference in risky assets ($\omega^\star - \omega$) also falls with wealth. Both effects are moderate, but not consistent with mainstream CRRA utility.[8] We give a detailed example in the next section.

Table 3.2: Input choices in portfolio advice.

Input	Variations	Type	#
Time Horizon	Short (1-3 years), Medium (4-6 years), Long (+7 years)	Ordered Factor	3
Risk Tolerance	Low, Average, Above Average, High	Ordered Factor	4
Knowledge	None, Poor, Basic, Good, Very Good, Academic Degree	Ordered Factor	6
Add Risk	Less, Take Proposal, More	Ordered Factor	3
Acceptable Loss	Up to 5%, 10%, 25%, 50%, 100%	Ordered Factor	5

Average recommended equity allocations across the dimensions wealth and knowledge.

[8] CRRA utility is more plausible as it is compatible with the fact that risk premia over the last 200 years remained broadly constant even though individuals became many times wealthier.

3.4 Advisor specific evidence

At this point, we want to support our analysis by looking at one particular robo-advisor from the list in Table 3.1 (Advisor #1). As an award winner (by consumer safety group Stiftung Warentest in 2018), we view our choice as representative of best practices in the German robo-advisory market. For our purpose, we initially scrape 1,080 portfolio choices along five dimensions (leaving all other choices constant) from the robo-advisor's website. The dimensions are described in Table 3.2. They affect risk tolerance, time horizon, willingness to accept losses, investor knowledge, and additional risk-taking relative to a proposal. This amounts to $3 \cdot 4 \cdot 5 \cdot 3 \cdot 5 = 1{,}080$ portfolio recommendations, where each allocation reflects a different client situation. Portfolio recommendations range from 10% to 100% in equities.[9] We keep all other choices constant, i.e., we maintain the high net income (9,000 Euros per month) as well as the high level of wealth (500,000 Euros) for our previously defined "dummy" investor to exclude paternalistic motives.

First, we want to investigate how the two parameters in our model in section 2.3 (risk tolerance and knowledge) are used in the algorithmic portfolio choice of our sample robo-advisor. Which one is more influential? For this purpose, we take our dataset of 1,080 portfolio recommendations and apply a two-way sort with respect to knowledge and risk tolerance. For each possible combination, we calculate the average recommended portfolio weight. The results are given in Table 3.3. We see that higher risk tolerance maps into higher equity allocations, as we would expect from standard portfolio choice. However, we also see that knowledge is many times more influential for recommended equity allocation than risk aversion. For a given knowledge level, changes in risk aversion only account for 20 percentage points variations in recommended equities. The reverse is true for changes in knowledge. For the same risk aversion, changes in investor knowledge account for up to 40 percentage points changes in equity allocations. We observe: the most important parameter in portfolio choice (risk aversion) is dominated by a parameter without theoretical grounding. This is hard to reconcile with normative portfolio choice and is much more likely the response to anticipated legal risks rather than rational advice. In addition, we find that the increase in equity recommendation following an increase in knowledge by one category is almost linear (roughly in equidistant 10% steps). This again is unlikely the result of an endogenous model, but rather the consequence of constraints set by the compliance department.

[9] The minimum allocation to equities of 10% is desirable as it avoids household non-participation.

Table 3.3: Average equity recommendation for knowledge and risk tolerance.

	Knowledge Level					
Wealth	**None**	**Poor**	**Basic**	**Good**	**Very Good**	**Degree**
Low	22.39%	30.56%	39.94%	47.61%	52.39%	54.72%
Medium	22.00%	30.83%	40.50%	48.83%	55.72%	60.44%
High	22.11%	30.33%	39.94%	50.11%	59.17%	66.56%

Average recommended equity allocations across the dimensions of wealth and knowledge.

Second, we run a more formal parametric OLS regression with ordered factors as independent variables. Our results are shown in Table 3.4. The intercept of 44.45 represents the average allocation recommendation across all 1,080 choice sets. All other regression coefficients represent the marginal impact of answering questions on the robo-advisor homepage. As we need to deal with ordered factors, we cannot use one-hot encoding or Helmert contrasts but rather use orthogonal polynomial contrasts.[10] Therefore, the extensions .L, .Q, .C denote coefficients from linear, quadratic, and cubic regression terms. All higher-order terms in Table 3.4 are small in magnitude, and when we look at predictions from changing factor levels, we find all of them to be close to linear (unreported). All linear coefficients are highly significant and display the conjectured sign, i.e., an increase in time horizon, risk tolerance, experience, leads to higher recommended equity allocations.[11] The coefficient on knowledge has by far the highest value as well as t-value (indicating the highest influence). This supports our nonparametric analysis in Table 3.3 above. Given the missing theoretical underpinning, portfolio recommendations look highly influenced by legal considerations, rather than rational portfolio choice.

[10]See Venables et al. (2002), Page 146 for a description of our methodology.

[11]The academic literature on the impact of time horizon on risk-taking offers a variety of models that allow for increasing (term structures of risk from predictability), decreasing (parameter uncertainty), or constant risk-taking. While we do not believe that the analyzed data results from fitted term structures of risk as in Campbell and Viceira (2002), we do not follow up on this as it is not our main concern.

Table 3.4: Permutations in portfolio advice.

	β	$SE(\beta)$	t-val	p-val
(Intercept)	44.45	0.23	194.63	0.00
horizon.L	13.37	0.40	34.81	0.00
risk.L	21.51	0.46	47.08	0.00
risk.Q	-2.06	0.46	-4.50	0.00
knowledge.L	37.22	0.56	66.52	0.00
knowledge.Q	-1.52	0.56	-2.71	0.01
knowledge.C	-2.07	0.56	-3.70	0.00
addrisk.L	11.18	0.40	28.25	0.00
addrisk.Q	-0.94	0.40	-2.38	0.02
loss.L	1.10	0.51	2.15	0.03

OLS regression results of 1,080 equity allocation recommendations against input choices with respect to time horizon, risk tolerance, knowledge, additional risk-taking (relative to a current proposal), and maximum permissible loss. We only report significant variables (p-value smaller than 5%). The adjusted R^2 of the regression is 89%. The standard error of the regression (standard deviation of fitted versus actual portfolio recommendations) is 7.45%.

Third, we want to more formally interrogate our regression model to find out the most influential variable(s). For this purpose, we borrow from the literature on interpretable machine learning and employ the following model-agnostic algorithm suggested by Fisher et al. (2018). For each variable, we permute the values of that particular feature and recompute the chosen performance metric, in our case R^2_{perm}. We then record the difference between the baseline metric and the permuted metric $R^2_{base} - R^2_{perm}$ as our importance score.

Finally, we repeat this procedure 100 times and estimate the average importance score. The results are shown in Figure 3.1. Again, this confirms our earlier results. The investor's knowledge is the most important variable in our model. Creating noise in this variable leads to the most severe reduction in explanatory power across all variables.

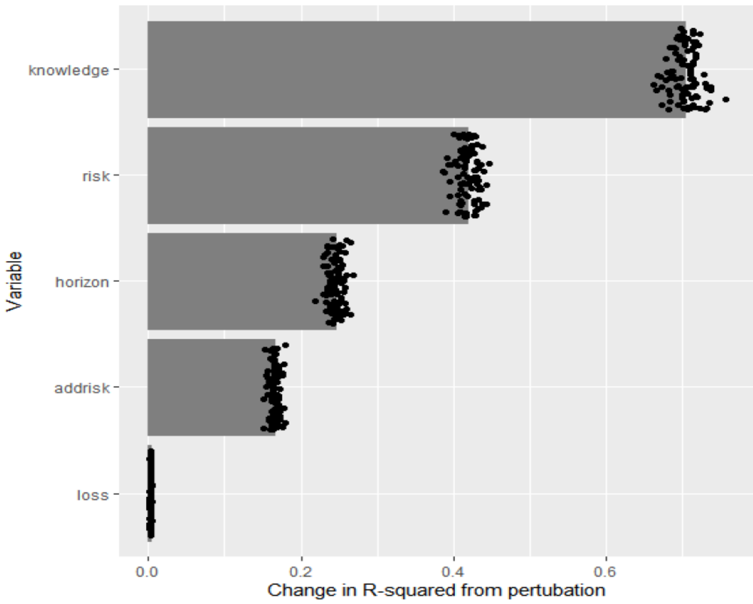
Table 3.5: Average equity recommendation for knowledge and wealth.

	Knowledge Level					
Wealth Level	**None**	**Poor**	**Basic**	**Good**	**Very Good**	**Degree**
Low	22.39%	30.56%	39.94%	47.61%	52.39%	54.72%
Medium	22.00%	30.83%	40.50%	48.83%	55.72%	60.44%
High	22.11%	30.33%	39.94%	50.11%	59.17%	66.56%

Average recommended equity allocations across the dimensions of wealth and knowledge.

So far, we deliberately excluded the impact of investor wealth on portfolio advice in order to exclude paternalistic motives, i.e., the idea that less wealthy individuals need higher protection. We therefore include two times 1,080 additional portfolios for low (5,000 Euros) and medium (50,000 Euros) levels of wealth and calculate average recommended allocations for all levels of investor knowledge for a total of 3,240 portfolios. The results are displayed in Table 3.5. We find that the suspected negative relation between financial literacy and recommended risk-taking remains confirmed at all levels of wealth. Wealth plays almost no role at low levels of financial literacy. Differences only start to rise for the two highest categories of financial education. However, the maximum difference remains a mere 10%. Knowledge dominates the influence of wealth, and wealth itself has a limited influence on recommended equity allocations.

Figure 3.1: Variable importance plot.



Importance plot of each decision variable in our OLS regression with ordered factors (given in Table 3.4) defined as change in R^2 after perturbation. We re-estimate the model five times, each time with one variable randomized. For each regression, we calculate the difference between the R^2 of the original data and the perturbed data for each regression. The more significant the difference, the more influential the variable. This calculation yields an importance score for each variable. Repeating this exercise 100 times results in the plot below for the five variables with the highest importance score.

3.5 Approximate regulatory costs using panel survey data

How do we get from individual portfolio choice data to an aggregate number for the whole economy? Clearly, we need a theoretical framework as well as some assumptions. Generically, we take the utility loss for a particular investor as in Equation 3.3 and aggregate it over all inexperienced households (that will not receive the economically optimal allocation under the

ESMA regulatory framework), where $\omega_i = \frac{asset_i}{\sum asset_i}$ represents the normalized wealth for an inexperienced household (i is an element in the set of inexperienced households). The total loss in utility will amount to:

$$\Delta U_i = \sum \omega_i \Delta U_i = \frac{1}{2}\left(\frac{\mu^2}{\sigma^2}\right)\left(\frac{\tau_i - 1}{\tau_i}\right)^2\left(\sum \omega_i \frac{1}{\lambda_i}\right) \tag{3.4}$$

Given that the inverse of risk aversion is risk tolerance, we can interpret $\sum \omega_i \frac{1}{\lambda_i}$ as risk tolerance for inexperienced investors. The larger this risk tolerance, the higher the aggregate utility loss. To calibrate our model to available data, we need to make some further assumptions. All households face the same haircut implied by $\tau_i = \bar{\tau}$, and all households display the same risk aversion $\lambda_i = \bar{\lambda} = \frac{\mu}{\sigma^2}$, which is derived from the investment opportunity set.[12] Let θ denote the fraction of inexperienced households and ϕ the fraction of liquid wealth they command. Using the simplifications above, Equation 3.4 becomes:

$$\Delta U = \frac{\mu}{2}\left(\frac{\tau_i - 1}{\tau_i}\right)^2 \theta \text{ and } \Delta U = \frac{\mu}{2}\left(\frac{\tau_i - 1}{\tau_i}\right)^2 \phi \tag{3.5}$$

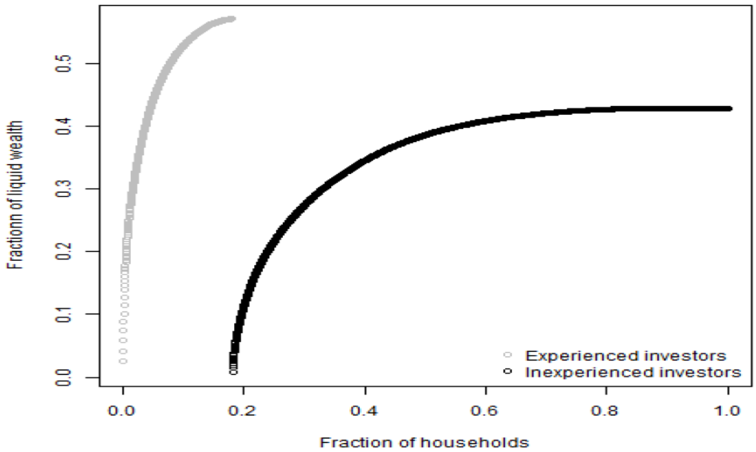
To calibrate our model from here, we need to find the percentage of inexperienced households in an economy and the wealth they command. For this purpose, we use the Eurosystem Household Finance and Consumption Survey (HFCS) for 3,565 German households. The data are described in European Central Bank (2012). For each household, we obtain liquid financial wealth consisting of cash ("HD1110"), savings accounts ("HD1210"), mutual funds ("HD1320g"), bonds ("HD1420"), and shares ("HD1510"). Experienced households are those that already hold equity funds or shares directly. We summarize the data in Figure 3.2. It appears that $\theta = 81\%$ is the fraction of inexperienced households (across x-axis) and $\phi = 42\%$ is the fraction of wealth from these households. In contrast, 19% of households are classified as experienced and own in sum 58% of liquid wealth. The high fraction of inexperienced households could be the reason why so many robo-advisors (nine out of 16) take regulatory risk. After all, 81% of potential clients would be told that they cannot invest as desired.

Finally, we need to assume that the investment opportunity set is given by the global market portfolio consisting of 55% global equities (MSCI World All Country in Euro) and 45% in global bonds (Barclays Bloomberg Multiverse hedged in Euro).[13] For the last 10 years (from 2010 to 2019), such a portfolio earned an average annual risk premium over cash (EONIA) of 7.4%. The

[12] For $\bar{\lambda} = \frac{\mu}{\sigma^2}$, the optimal weight becomes $\omega^\star = \bar{\lambda}^{-1}\frac{\mu}{\sigma^2}$, i.e., every investor would optimally invest 100% in the "market portfolio", which will not be true individually, but still is expected to hold on average.

[13] This allocation resembles the average capitalization-weighted portfolio of MSCI World AC and Barclays Bloomberg Multiverse for 2000 to 2020.

Figure 3.2: Fraction of liquid wealth across investor experience.



We plot the fraction of liquid wealth versus fraction of households (Which fraction of households own what percentage of economy-wide liquid wealth?) for experienced and inexperienced investors. Wealth is cumulative and sorted from largest to smallest wealth share. Data are from the first wave of the Eurosystem Household Finance and Consumption Survey (HFCS) for 3,565 German households.

average leverage across all firms in Table 3.1 is $\bar{\tau} = 1.17$.[14]

$$\Delta U = \frac{7.4\%}{2}\left(\frac{1.17-1}{1.17}\right)^2 0.81 = 0.06\% \text{ and } \Delta U = \frac{7.4\%}{2}\left(\frac{1.17-1}{1.17}\right)^2 0.42 = 0.03\% \tag{3.6}$$

The expected utility loss ranges between six and three basis points, depending on how we weight individual utility loss. The authors would prefer equal weighting of individual utilities as this coincides more with democratic decision-making and ultimately, regulation is a political decision. In any case, the size of the utility loss is of the same order of magnitude as an institutional custody fee. This looks excessive for a regulation outside normative portfolio advice.

3.6 Conclusion

MiFID II mandates that banks and wealth managers assess their clients' investment knowledge and experience. The implied regulatory stance, that less experience should lead to less risk-taking, is explicitly outlined in ESMA's guidelines. However, this regulatory conjecture finds no support in theoretical or empirical finance. Instead, it introduces significant legal risks for asset managers and banks. To thoroughly investigate the degree of compliance and the associated costs of this regulation, account-level data would be ideal. Unfortunately, such data are not

[14]The robo-advisory market is infamous for its intransparency. As we do not have assets under management for the above robo-advisors, we cannot offer a volume-weighted average. In any case, the direction of this calculation is clear. Should the regulator aggressively pursue the idea that investors with less experience and/or lower education need to be shielded from risk-taking, welfare losses will accumulate.

publicly available as banks do not share them.

To overcome this limitation, we utilize publicly available portfolio recommendations from robo-advisory firms, which are subject to the same MiFID II investor profiling regulations as traditional banks and wealth managers. Our analysis reveals that the responses of banks and wealth managers to the regulatory framework are highly heterogeneous. These responses range from negligible changes (0% change in recommended portfolio allocations) to extremely compliant adjustments (up to a 50% reduction in the share of risky assets).

The individual welfare implications of these regulatory responses are predominantly negative. These negative impacts increase with the Sharpe ratio of the investment opportunity set, the investor's risk tolerance, and the aggressiveness with which the regulation is implemented. On an aggregate level, the welfare implications are also negative and become more pronounced as the proportion of inexperienced investors in the economy increases.

The regulator's concern appears to be heavily skewed towards preventing households from taking on too much risk, without considering the adverse effects of households taking on too little risk. This regulatory stance seems to neglect the well-documented participation puzzle in household finance, where a significant number of households refrain from holding risky assets and thus lack relevant investment experience. This oversight suggests that the regulatory framework might be counterproductive, potentially exacerbating distributional inequality.

In summary, while the intention behind MiFID II and ESMA's guidelines is to protect less experienced investors, the actual impact of the regulation might be the opposite of what is intended. By discouraging risk-taking among less experienced investors, the regulation could inadvertently widen the gap between experienced and inexperienced investors, thereby increasing wealth inequality. Policymakers should consider these findings and strive for a more balanced approach that encourages appropriate risk-taking across all investor demographics, ultimately fostering a more inclusive and equitable financial environment.

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Trust me, I am a Robo-advisor.

Bernd Scherer [1], Sebastian Lehner [2]

Abstract

This paper offers cross-sectional and data-intensive insights into Robo-advisory portfolio structures. For this purpose, we scrape portfolio recommendations for 16 German Robo-advisors. Our sample accounts for about 78% of assets in the German Robo-advisory market. We analyze about 243.000 pairs of recommended portfolios and their corresponding client characteristics. Our results show that current Robo-advice offers limited individualization. Variables that matter in modern portfolio choice like the amount and nature (beta) of human capital or shadow assets are largely ignored. Instead, portfolio recommendations are designed to meet investor preconceptions or the regulator's understanding of portfolio choice. While ensuring consumer trust and regulatory approval makes business sense, it also limits the economic benefits of Robo-advisors.

Keywords: robo-advice, trust, household finance, portfolio choice, behavioural finance

JEL classification: G11, G18

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On the Relationship between Financial Distress and ESG Scores

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This Version

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Abstract

This empirical study analyzes the relationship between a company's financial distress obtained from a bankruptcy prediction model and ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. Applying nonparametric regression technique on panel data of listed US companies for 2003–2022 reveals a pronounced and statistically significant U-shaped relationship between financial distress and ESG scores. Financially distressed companies exhibit high ESG scores. Empirical evidence shows that the high ESG scores of financially distressed companies cannot be explained by past capital expenditures and R&D expenditures or by the actual energy intensity of a company's revenue, but that it is significantly related to a company's stakeholder orientation in its 10-K filings. Furthermore, the high ESG scores of financially distressed companies are related to predictable company-related causes rather than unpredictable exogenous causes of financial distress. The most plausible interpretation is that companies anticipate their upcoming financial distress and intensify ESG-supporting disclosures to manage their ESG scores upward. The empirically observable, systematic management of ESG scores by the group of financially distressed companies reduces the validity and credibility of ESG scores and makes it imperative to consider the degree of a company's financial distress when interpreting ESG scores

Keywords: ESG, ESG score, Financial distress, Nonparametric regression, Measure of bankruptcy risk, Stakeholder orientation

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5.1 Introduction

There is an ongoing debate on the informativeness of ESG scores that measure the ESG activities of a company. This debate also includes the effective relationship between a company's financial performance and ESG scores. Thereby, the latter constructed by various ESG rating agencies are used in business to inform operational corporate and long-term investment decisions (e.g., investment decisions by ESG funds; Raghunandan and Rajgopal (2022)) and in science for empirical research. The present study contributes to this research line by introducing the measure of bankruptcy risk as a new variable related to ESG scores. The measure of bankruptcy risk is the result of a bankruptcy prediction model and indicates the level of a company's financial distress. The present study analyzes the effective relationship between the measure of bankruptcy risk and ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG by applying a nonparametric regression technique on panel data of listed US companies from 2003 to 2022.

The analysis reveals a pronounced and statistically significant U-shaped relationship between the level of financial distress and ESG scores at the company level. An increase in the measure of bankruptcy risk above a certain threshold is associated with increasing ESG scores. As a result, financially distressed companies exhibit ESG scores comparable to ESG scores from financially healthy companies. This empirical finding is robust as it is observable across the four different ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG.

However, one challenge of the analysis is to identify sufficiently strong evidence for the causality between financial distress and ESG scores. We address concerns related to reverse causality by applying a set of alternative variables and natural experiments. Based on our analysis, the most plausible explanation for the observed U-shaped relationship between financial distress and ESG scores is that companies anticipate financial distress and focus on cost-effective ESG activities, such as ESG-supporting disclosures, to increase their ESG scores. This may help them reduce their cost of capital, improve their financial conditions, and distract from their financial failure. We add to the existing literature by showing that managing ESG scores by the group of financially distressed companies reduces the validity and credibility of ESG scores and makes them less reliable. Therefore, it is imperative to consider a company's financial situation when interpreting ESG scores.

The empirical findings to date document a negative linear relationship between the level of financial distress and ESG scores (e.g., Aslan et al. (2021); Badayi et al. (2021); Zheng et al. (2019)). These empirical findings support two lines of argument that postulate a negative linear relationship between the level of financial distress and ESG scores. The first line of argument is that financially unconstrained companies have more financial resources than financially constrained companies to pursue ESG objectives and invest in projects demonstrating corporate goodness. The second line of argument relates to the predominantly positive relationship between financial performance and the ESG activities of a company. If increasing financial distress of a company is generally associated with lower financial performance, there should be a negative relationship between the level of financial distress and ESG scores.

However, the previous results that show a consistently negative relationship between the level of financial distress and ESG scores are only reliable to a limited extent as these studies (e.g., Aslan et al. (2021); Badayi et al. (2021); Zheng et al. (2019)) exclusively use linear regression technique and thus exclude a possible non-linear relationship in the data from the outset although there are three good reasons for an at least partially positive relationship in the case of financially distressed companies. First, financially distressed companies have a solid interest in achieving high ESG scores to obtain equity and debt capital at relatively low cost as they rely on the low cost of capital to avoid or at least delay bankruptcy. Second, financially distressed companies may conceal information about the company's failures and opportunistically pursue ESG objectives to distract from their financial distress. Third, the intra-company incentive system may set incentives to achieve ESG objectives rather than financial ones that are particularly difficult to achieve in the case of financially distressed companies. To identify the effective and unrestricted relationship between the level of financial distress and ESG scores, a comprehensive empirical study has to apply a nonparametric regression technique to the available panel data.

The interpretation of the revealed U-shaped relationship between the level of financial distress and ESG scores has to address the problem of reverse causality (Gow et al., 2016). On the one hand, financial distress could be the cause, and a high ESG score could be the effect. In this case, one interpretation could be that financially distressed companies intensify ESG-supporting disclosures and manage their ESG scores upward, very likely to decrease the cost of capital, improve the financial conditions, and distract from their financial failure. Another reason for that observation could be the incentive system and the desire of management to increase personal benefits by achieving stakeholder-oriented ESG objectives rather than shareholder-oriented financial objectives. On the other hand, measures that lead to a high ESG score could be the cause, and financial distress could be the financial consequence of these measures. Such a relationship would be more likely to be observed with ESG investments, which have a greater impact on cash flows and corporate finances, than operational measures or ESG-supporting disclosures.

We narrowed down the problem of reverse causality by extending our empirical analysis.

First, we take into account multi-year capital expenditures and multi-year R&D expenditures as additional independent variables. The U-shaped relationship between the level of financial distress and ESG scores cannot be attributed to multi-year capital expenditures and multi-year R&D expenditures, meaning that a large investment volume, which also includes ESG investments, is likely not the cause of this U-shaped relationship. Second, we introduce a variable that captures the actual energy intensity of a company's revenue. The empirical analysis shows that there is neither a statistically significant linear nor a statistically significant U-shaped relationship between the level of financial distress and the actual energy intensity of a company's revenue. The data show that financially distressed companies are not associated with a low energy intensity that may be reflected in a high ESG score. This result suggests that ESG investments and operational measures designed to reduce a company's environmental footprint are unlikely to be the cause of this U-shaped relationship. Third, we construct and apply an additional variable that captures the shareholder-stakeholder orientation in corporate reporting by counting the words "shareholder" and "stakeholder" in the 10-K filings. The shareholder-stakeholder orientation in corporate reporting is a proxy variable for ESG-supporting disclosures primarily aimed at stakeholders. The regression analysis reveals a comparable and statistically significant U-shaped relationship between the level of financial distress and the shareholder-stakeholder orientation in corporate reporting. Financially distressed companies exhibit a particularly pronounced stakeholder-oriented reporting behavior, and there is a positive and statistically significant relationship between stakeholder-oriented reporting and ESG scores. This is a very strong sign that financially distressed companies are intensifying their stakeholder orientation in their corporate reporting and providing ESG-supporting disclosures to a greater extent. Fourth, we take into account President Trump's tariff policy in 2018 and the COVID-19 pandemic in 2020 as two unpredictable exogenous shocks that increased the financial distress of companies in specific industries. That enables the distinction between unexpected causes of financial distress and more predictable company-related causes of financial distress. If an increasingly financial distressed company tries to manage its ESG scores upward, we should not be able to observe a positive relationship in the presence of unforeseeable events. Using the two natural experiments, we document that there is no statistically significant relationship between an increase in financial distress that results from an unpredictable exogenous shock and ESG scores.

Based on the results of the empirical analysis, the most plausible interpretation of the revealed U-shaped relationship between the level of financial distress and ESG scores is that companies anticipate their upcoming financial distress and intensify cost-effective ESG activities such as

ESG-supporting disclosures to manage their ESG scores upward, very likely to decrease the cost of capital, improve the financial conditions, and distract from their financial distress. This interpretation is also consistent with empirical findings that emphasize the importance of the quantity of ESG disclosures and consider the content of these ESG disclosures to be of secondary importance (Lyon and Maxwell 2011; Marquis et al. 2016). ESG scores are presumably influenced to a greater extent by the existence of ESG disclosures and less by their content (Drempetic et al., 2020; Lopez-de Silanes et al., 2020). ESG scores are also enhanced by excessive and over-expectant disclosures on diversity, equity, and inclusion (Baker et al., 2022), and ESG funds pay more attention to the existence and less to the content of ESG disclosures (Raghunandan and Rajgopal, 2022). The empirically observable, systematic management of ESG scores by the group of financially distressed companies makes it imperative to consider the degree of a company's financial distress when interpreting ESG scores.

The paper is structured as follows: In the next section, we provide an overview of the literature and clarify the arguments in favor of a negative and positive relationship between financial distress and ESG scores. In Section 5.3, we provide details on the applied data, describe the variables used for the main analysis, and explain the applied nonparametric regression technique. Section 5.4 presents the empirical results on the estimated non-linear relationship between the level of financial distress and ESG scores. This section also includes insights into the three ESG sub-factors and applied control variables. In Section 5.5, we extend the empirical analysis to address the problem of reverse causality and discuss the robustness of the results. Section 5.6 concludes the paper with an overview of our findings and discusses the practical significance of the results.

5.2 Literature review

The analysis of the relationship between financial distress and ESG scores refers to two strands of literature. The first strand of literature relates to the construction and significance of the measure of bankruptcy risk. Powerful, empirical bankruptcy prediction models (e.g., (Balcaen and Ooghe, 2006; Beaver et al., 2005; Bellovary et al., 2007; Campbell et al., 2008; Jones, 2017; Lohmann and Möllenhoff, 2023c) can validly estimate the measure of bankruptcy risk. In contrast to periodic accounting indicators, such as return on equity and return on assets, and value-based indicators, such as market value of equity, the measure of bankruptcy risk, which includes a large set of accounting-based, market-based, company-specific, and macroeconomic variables, enables a valid and robust estimation of a company's financial situation. The measure of bankruptcy risk is a forward-looking indicator as it predicts an impending bankruptcy within the forecast horizon of the bankruptcy prediction model. Empirical findings show that professional investors likely apply bankruptcy prediction models to optimize their risk position as professional investors sell the shares of financially distressed companies that file for bankruptcy at an early stage and retain the shares of financially distressed peer companies that remain solvent (Lohmann and Möllenhoff, 2023c). As a result, the measure of bankruptcy risk is very well suited to measuring the sustainable financial situation of a company and, thus, making a valid statement about its continued existence.

The second strand of literature relates to the relationship between financial distress and ESG scores and the arguments in favor of a negative or positive relationship. The empirical findings document a negative linear relationship between financial distress and ESG scores. Particularly, Aslan et al. (2021) show a negative relationship between the S&P Credit Rating and the ESG score from Refinitiv, Badayi et al. (2021) show a negative relationship between Altman's Z-score and the ESG score from Refinitiv, and Zheng et al. (2019) show a negative relationship between Altman's Z-score and the ESG score from MSCI. Lisin et al. (2022) and Cohen et al. (2023) provide further empirical evidence on negative and mixed correlations between a company's financial distress and ESG scores. However, the informativeness of the cited empirical studies is limited, as they only use one ESG score and less developed bankruptcy risk measures such as Altman's Z-score and apply linear regression technique to analyze older datasets that are smaller in size and do not include firm-year observations from more recent years. Nevertheless, the empirical findings on a negative linear relationship between financial distress and ESG scores can be justified by two lines of argument.

The first line of argument refers to the financial constraints of a company. A negative relationship between financial distress and ESG scores is expected for financially constrained companies. Hong et al. (2012) and Xu and Kim (2022) find that financially unconstrained companies have more resources than financially constrained ones to pursue social and environmental objectives and invest in projects showing corporate status. A company in financial distress should have severe financial constraints and will have less freely available financial resources to invest in ESG-related projects. In addition, there is empirical evidence that financially distressed companies prefer operational and investment decisions that place less strain on the current cash flow and have a positive impact on short-term financial performance indicators (e.g., Eisfeldt and Rampini (2007); Ma et al. (2022); Thomas et al. (2022)). Such short-sighted decisions address the financial constraints of a financially distressed company. ESG investments are likely to be associated with uncertainties regarding their impact on future cash flows and should therefore not be suitable for easing financial constraints in the short term. As a result, short-sighted decisions in the context of financial distress are expected to be associated with an effective reduction in ESG performance.

The second line of argument refers to the financial performance of a company. Lower financial performance is generally associated with the increasing financial distress of a company. The relationship between a company's financial performance and ESG scores has been extensively studied by applying predominantly linear regression techniques. A significant four-digit number of individual studies and over a dozen meta-studies (e.g., Friede et al. (2015); del Mar Miras-Rodríguez et al. (2015); Hou et al. (2016); Lu and Taylor (2016); Wang et al. (2016); Jeong and Harrison (2017); Plewnia and Guenther (2017); Rost and Ehrmann (2017); Busch and Friede (2018); Hoobler et al. (2018); López-Arceiz et al. (2018); Gallardo-Vázquez et al. (2019); Hang et al. (2019); Vishwanathan et al. (2020)) found a predominantly positive relationship between the financial performance figures, mainly including variables such as return on equity, return on assets, and market value of equity, and the ESG activities of a company, which were very often considered in ESG scores' quantified form. The positive relationship between a company's financial performance and these scores shows that there should also be a negative relationship between the level of financial distress and ESG scores.

The empirical evidence on the relationship between a company's financial performance and ESG ratings is ambiguous and does not allow for a clear interpretation. Previous studies on this relationship apply linear regression models to a large extent; however, the estimated coefficients fluctuate considerably (e.g., the meta-study of del Mar Miras-Rodríguez et al. (2015)) and sometimes even show a negative correlation (e.g., the meta-study of Rost and Ehrmann (2017)). In addition to using different samples that differ in country, time, and company characteristics, an explanation for these only partially consistent results could be an effective non-linear relationship between a company's financial performance and ESG scores. However, the latter are also inconclusive as there is empirical evidence for a U-shaped relationship (e.g., Nollet et al. (2016); Nuber et al. (2020); Naimy et al. (2021); Agarwala et al. (2024)) and an inverted U-shaped relationship (e.g., Buallay et al. (2022); Teng et al. (2022); El Khoury et al. (2023); Pu (2023)). As a result, an effective non-positive or non-linear relationship between a company's financial performance and ESG scores may indicate an effective non-negative or non-linear relationship between financial distress and ESG scores.

Besides the empirical arguments for a negative relationship between the level of financial distress and ESG scores, there are also three lines of argument that can justify a positive relationship. The first line of argument is based on the empirical observation that higher ESG scores are associated with lower cost of capital. Companies that implement the ESG principles and, in particular, are considered to be highly environmentally friendly can reduce their cost of capital relative to environmentally harmful companies that do not comply with ESG principles (e.g., Chava (2014); Van der Beck (2021); Kacperczyk and Peydró (2022); Pástor et al. (2022); Aron-Dine et al. (2024); Green and Vallee (2024). The difference in the cost of capital between compliant and non-compliant ESG companies is difficult to estimate; however, an analysis of quarterly earnings conference calls of US companies for the period 2016 to 2021 revealed that the difference in the cost of capital could be in the range of 2% to 3% (Gormsen et al., 2024). As financially distressed companies aim to keep the cost of capital as low as possible to ease financial constraints or to avoid or delay bankruptcy, they have a solid interest in achieving high ESG scores to obtain equity and debt capital at relatively low costs. The negative relationship between ESG scores and the cost of capital incentivizes financially distressed companies to strive for high ESG scores. As a result, there could be a positive relationship between the level of financial distress and ESG scores, at least for financially distressed companies that have to lower their cost of capital to increase the probability of survival.

In a second line of argument, the "management obfuscation hypothesis" supports a positive relationship between the level of financial distress and ESG scores. Bloomfield (2002) introduced the management obfuscation hypothesis and argued that managers have incentives to provide clear information about the company's successes and to obfuscate information about the company's failures. Several studies provide empirical evidence that the management obfuscation hypothesis is valid concerning information on a company's performance and earnings (e.g., Lang and Lundholm (1993); DeFond and Jiambalvo (1994); Schrand and Walther (2000); Jaggi and Lee (2002); Li (2010)). The empirical evidence on the management obfuscation hypothesis is less conclusive about bankruptcy risk information in annual reports. Holder-Webb and Cohen (2007) doubt that the annual reports of financially distressed companies are informative, as self-interested managers are incentivized to delay the disclosure of severe risks to the continued existence of their company as a going concern. Mayew et al. (2015) analyzed a large sample of listed US companies and found that the management obfuscation hypothesis is largely invalid. On the contrary, Lohmann and Ohliger (2020) provided empirical evidence that supports it as the annual reports of companies that eventually went bankrupt contain, on average, longer and relatively more complex risk reports and generally exhibit a less negative linguistic tone than the reports of financially distressed companies that remained solvent. As imminent bankruptcy risks are complex and challenging to communicate (Bloomfield, 2008), the high linguistic complexity may result from both obfuscation and complex information (Bushee et al., 2018).

Another option to obfuscate a company's financial distress is to focus on disclosed information about non-financial ESG objectives. If the company management pursues ESG objectives, financial objectives become less critical. Corporate governance and monitoring target achievement are complex, as ESG objectives are often qualitative and can only be measured subjectively. The increased complexity of such a multidimensional objective system could be useful to distract from financial objectives or conceal poor financial performance (Bebchuk and Tallarita, 2020; Karpoff, 2021). As financial distress mounts, the need to explain complex financial information increases, unless the focus can be placed on ESG objectives and their achievement. The required explanation of financial information can be interpreted as transaction costs that the company management aims to minimize. This argument is reinforced by empirical evidence on the positive relationship between CSR and ESG activities and earnings management (e.g., Patten and Trompeter (2003); Gargouri et al. (2010); Yip et al. (2011); Muttakin et al. (2015); Martínez-Ferrero et al. (2016); Jordaan et al. (2018); Buertey et al. (2020); Yu et al. (2020); Pasko et al. (2021); Zhang et al. (2021)) that is in line with the stakeholder agency theory (Jensen and Meckling, 2019; Hill and Jones, 1992). Thereby, the positive relationship between ESG activities and earnings management is enhanced by a company's financial distress (Almubarak et al., 2023). Another empirical finding that supports the validity of the management obfuscation hypothesis is the fact that the existence and scope of ESG disclosures are particularly relevant rather than the real circumstances reflected in the ESG disclosures (Lyon and Maxwell, 2011; Marquis et al., 2016; Drempetic et al., 2020; Lopez-de Silanes et al., 2020; Raghunandan and Rajgopal, 2022)).

Recently, Flugum and Souther (2023) analyzed the company communication after quarterly earnings reports and provided empirical evidence that the management distracts from missing earning expectations by highlighting non-financial ESG objectives. One conclusion might be that companies that report particularly extensively on their ESG activities and prioritize ESG objectives in a publicity-effective manner are financially underperforming (Bhagat, 2022). It is conceivable that financially distressed companies will also show an affinity with ESG objectives to distract from their financial distress. As the financial resources of a financially distressed company are likely to be very scarce regularly (Myers, 1977), an improvement in ESG scores is more likely to result from cost-effective extensions of ESG-supporting disclosure rather than ESG investments, which require upfront capital expenditures and will only lead to positive cash flows in the long term. Thereby, extensions of ESG-supporting disclosure should be effective as ESG scores are presumably influenced to a greater extent by the existence of ESG disclosures and less by their content (Drempetic et al., 2020; Lopez-de Silanes et al., 2020) and investors such as ESG funds focus on the existence and less to the content of ESG disclosures (Raghunandan and Rajgopal, 2022). Suppose the management obfuscation hypothesis about stakeholder-oriented ESG objectives and associated ESG disclosures is valid. In that case, there should be a positive relationship between the level of financial distress and ESG scores, at least for financially distressed companies incentivized to obfuscate their financial failure.

The third line of argument relates to the intra-company incentive system. In addition to financial objectives, ESG objectives are also pursued and implemented within the intra-company incentive system, whereby the design options are still very heterogeneous (Reda, 2022). Recent analyses show a growing share of listed US companies that incorporate ESG measures in annual incentive plans (e.g., Salzbank et al. (2023); Kuk et al. (2023)). A company's management likely allocates the available resources to maximize the remuneration based on financial and ESG objectives. Cohen et al. (2023) provide empirical evidence that ESG-based incentives increase ESG performance and the associated ESG scores, while ESG-based incentives tend to lead to poorer financial performance. Chang et al. (2016) analyzed the relationship between financial distress risk and the incentive-based compensation of new CEOs. They found new CEOs receive more equity-based incentives to ensure that the company's financial position is improved. As a result, the choice and design of incentive-based remuneration significantly influence management decisions and the achievement of both financial and ESG objectives.

Furthermore, the difficulty of achieving the target must be taken into account. It may be possible that ESG objectives can be achieved more easily than financial objectives; this is the case for companies that do not have enough resources to recover from their financial distress and regularly fall short of financial objectives. If resources are scarce, it would be rational to pursue the more easily achievable ESG objectives first and maximize the associated remuneration components. In addition to increasing variable remuneration, management could follow alternative career paths (Song and Thakor, 2006; Zhang, 2021) or reputational objectives (Jiang et al., 2016) that are promoted by achieving the highest possible ESG scores. The priority allocation of scarce resources to achieve ESG objectives is a further argument for a positive relationship between the level of financial distress and ESG scores that could be observed for financially distressed companies.

Both the negative and positive relationship between financial distress and ESG scores can be valid simultaneously but for different companies. A negative relationship might be proper for financially healthy companies, and a positive one might be valid for financially distressed companies. As a result, the existing literature provides solid arguments for a U-shaped relationship between financial distress and ESG scores. While a high ESG score for financially healthy companies underpins the positive relationship between a company's ESG activities and financial performance, a high ESG score for financially distressed companies would call into question the meaningfulness of ESG scores for this group of companies. Therefore, nonparametric regression models must be used to reveal the actual relationship between the level of financial distress and ESG scores (Hastie and Tibshirani, 1990, 1995; Wood, 2017) and interpreted accordingly. However, a U-shaped relationship between financial distress and ESG scores has not yet been empirically documented, as the findings to date exclusively use linear regression techniques and thus exclude a possible non-linear relationship in the data from the outset. Suppose there is a U-shaped relationship between financial distress and ESG scores. In that case, we need to clarify the existing cause-effect relationship between the level of financial distress and ESG scores. A useful follow-up study needs to analyze the reasons underlying this cause-effect relationship. Presumably, however, a mixture of arguments will be responsible for a U-shaped relationship between the level of financial distress and ESG scores.

5.3 Data, variables, and methodology

5.3.1 Raw data, final dataset, and final samples

The starting point of our empirical analysis is a merged database of listed US companies. This database includes accounting and market data from the CRSP/Compustat database, ownership data derived from Form 13F and Form 13D(/A) filings, and data on financial distress from BRAINKRUPTCY. Overall, the database of listed US companies includes 71,451 firm-year observations for the period 2003–2022.

The bankruptcy prediction model of BRAINKRUPTCY was recently described by Lohmann and Möllenhoff (2023a), and the bankruptcy predictions were applied by Lohmann et al. (2023). The bankruptcy prediction model uses numerous variables proven informative for financial distress and prospective corporate bankruptcy (e.g., the explanatory variables introduced by Campbell et al. 2008) and is available for all listed US companies. BRAINKRUPTCY estimates the measure of bankruptcy risk by using a logistic bankruptcy prediction model and a gradient-boosting model. The out-of-time validations of the annually updated bankruptcy prediction models provide empirical evidence that the classifications based on the measure of bankruptcy risk are accurate. The AUC values for the annual out-of-time validations fluctuate within a small range of around 0.9. In comparison, the out-of-time validity of a re-estimated bankruptcy prediction model that includes the variables of Altman's Z-score (Altman, 1968, 2013) achieves only an AUC value of 0.716 (Lohmann and Möllenhoff, 2023b). Our main analysis applies the measure of bankruptcy risk based on a logistic bankruptcy prediction model; the measure of bankruptcy risk based on a gradient-boosting model is used for a robustness check.

In the next step, databases on ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG were matched to the merged database of listed US companies. An empirical analysis of ESG has to consider that the content of ESG and the associated ESG scores are heterogeneous. Many definitions describe the content of ESG (Meuer et al., 2020), which leads to a considerable need for more clarity in the empirical observation of ESG activities (Douglas et al. 2017). Empirical studies often use one or more ESG scores provided by ESG rating agencies to quantify a company's ESG activities. ESG scores vary due to the evaluation of differently weighted ESG criteria using different methodical approaches. ESG scores measure the ESG activities of a company by focusing on ESG disclosure and reporting, ESG performance, and/or ESG risks. A manual evaluation of the weighted ESG criteria, an algorithm-based evaluation, or a mixture of both methodical approaches can quantify ESG scores. Although ESG rating agencies claim their scores are a reliable indicator of a company's ESG activities, research on ESG rating disagreement shows that the ESG scores of different ESG rating agencies can differ considerably (Chatterji et al., 2016; Dimson et al., 2020; Billio et al., 2021; Berg et al., 2022). In addition, there are indications of a deliberate distortion of ESG scores by ESG rating agencies if the ESG rating agencies are subject to a conflict of interest and generate significant revenue from ESG score-based indices (Agrawal et al., 2023). Given these significant differences between the available ESG scores, it is plausible that ESG scores can only quantify a company's effective ESG activities approximately. Thereby, the discrepancy between ESG scores and a company's effective ESG activities can be pronounced differently for different company characteristics, such as company size (Drempetic et al., 2020) and industry (Du and Sun, 2023). Nevertheless, the ESG scores are positively correlated with each other, and therefore, corporate activities such as new ESG investments, additional ESG-related operations, and the provision of ESG information will likely increase all ESG scores. Valid empirical findings must, therefore, be reproducible for all material ESG scores, or the empirical results must not contradict each other, at least for different ESG scores.

Overall, after matching the databases on ESG scores from Refinitiv, MSCI, ESG Book, and

Moody's ESG to our merged database of listed US companies, we ended up with 34,011 firm-year observations with at least one ESG score. One hundred thirty-six firm-year observations (or 0.40% of the 34,011 firm-year observations, respectively) were eliminated due to missing control variables; 132 firm-year observations did not include the dividend yield, and the stock return volatility was missing in four firm-year observations. As a result, the final dataset includes 33,875 firm-year observations with at least one ESG score and all other applied control variables. We further processed the final dataset by winsorizing variables that we consider in the empirical analysis at the 1st and 99th percentiles if a variable has no natural limit and exhibits recognizable outliers.

Four samples of four different ESG scores applied as dependent variables were extracted from the final dataset. Table 5.1 provides information on the sample sizes, the number of firm-year observations for which a pair of ESG scores are available, and the correlations between the ESG scores. The ESG scores from Refinitiv and MSCI form the basis for the larger samples, whereas the ESG scores from ESG Book and Moody's ESG form the basis for the smaller samples. The larger samples include a large share of firm-year observations from the smaller samples. The pairwise correlations of the ESG scores range between 0.269 and 0.673. That empirical finding is consistent with Chatterji et al. (2016), who showed that the pairwise correlations between CSR ratings of different rating agencies are generally low and mostly below 0.5, and Berg et al. (2022), who showed that the average pairwise correlation between prominent ESG scores ranges between 0.38 and 0.71.

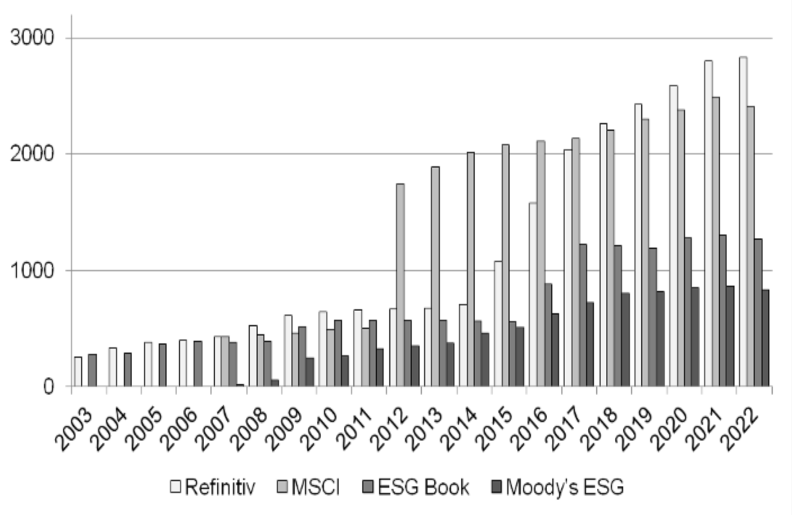
Table 5.1: Summary statistics on the four samples of four different ESG scores.

Sample	**Firm-year Observations**	**Refinitiv**	**MSCI**	**ESG Book**	**Moody's ESG**
Refinitiv	23,890		0.383	0.482	0.673
MSCI	26,563	17,579		0.269	0.418
ESG Book	14,390	11,558	11,477		0.419
Moody's ESG	8,139	7,201	7,623	4,807	

The table reports the final sample sizes (column 2), overlapping firm-year observations with at least two specific ESG scores (lower section in columns 3–5), and the respective pairwise correlations between the ESG scores (upper section in columns 4–6).

Figure 5.1 shows the number of companies for which the ESG scores were available over time. The ESG databases are distinguished from each other in terms of the history of data availability and the number of companies covered. The ESG scores from Refinitiv and MSCI cover a more significant number of companies. Hence, the ESG scores from Refinitiv and MSCI also provide data on smaller companies that receive less attention from investors and stakeholders. Nevertheless, Refinitiv, MSCI, ESG Book, and Moody's ESG provide large ESG databases that include long-term ESG information.

Figure 5.1: Panel data structure of the final samples of four different ESG scores.



This figure shows the number of companies for which ESG scores were available over time after cross-checking against our merged database of listed US companies. Our empirical analysis considers ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. While Refinitiv and ESG Book cover companies for the entire history up to 2003, MSCI and Moody's ESG data are available since 2007.

5.3.2 Applied variables and descriptive statistics

The relationship between financial distress and ESG scores is analyzed using linear and nonparametric regression techniques. Four ESG rating agencies provide the dependent variables for the regressions, while a comprehensive set of company-related independent variables is used. The ESG data were obtained from Refinitiv, MSCI, ESG Book, and Moody's ESG, and each includes a company's overall ESG score and the respective E-S-G sub-factors. As a result, we apply four overall ESG scores as dependent variables in the principal analysis and 12 E-S-G sub-factors as dependent variables in additional regressions.

The independent variable of interest is the measure of bankruptcy risk that BRAINKRUPTCY provides. A company's level of financial distress is indicated by the measure of bankruptcy risk. The measure of bankruptcy risk is the outcome of a logistic bankruptcy prediction model calibrated for listed US companies and can be interpreted as the probability of bankruptcy. The measure of bankruptcy risk ranges in the interval [0, 1]. BRAINKRUPTCY also estimates an alternative measure of bankruptcy risk by applying a gradient-boosting model. We use the alternative measure of bankruptcy risk to check the robustness of the results.

Table 5.2 provides the definitions of the applied dependent and independent variables. Besides the dependent variables on ESG scores and the measure of bankruptcy risk, the regression analysis considers 14 control variables on company fundamentals and ownership. Additionally, the regression analysis controls for year-fixed, industry-fixed, and company-fixed effects in the panel data.

Table 5.3 reports the descriptive statistics on the four final samples. The mean and the standard deviation of the ESG scores from Moody's ESG are lower as the value range is [0, 10] instead of [0, 100] for all other applied ESG scores. The larger samples based on ESG scores from Refinitiv and MSCI include a more significant number of firm-year observations from smaller companies. This difference between the four final samples becomes apparent in the mean of the independent variables. The larger samples are associated with lower mean values of total assets, market value of equity, return on equity, and return on assets. Regarding the other independent variables, the final samples have comparable characteristics and do not differ significantly.

Table 5.2: Definitions of the applied dependent and independent variables.

Variable	Definition
ESG variables	
ESG score Refinitiv(j,a)	Company j's ESG score from Refinitiv at the end of the fiscal year a.
E sub-factor Refinitiv(j,a)	Company j's E sub-factor from Refinitiv at the end of the fiscal year a.
S sub-factor Refinitiv(j,a)	Company j's S sub-factor from Refinitiv at the end of the fiscal year a.
G sub-factor Refinitiv(j,a)	Company j's G sub-factor from Refinitiv at the end of the fiscal year a.
ESG score MSCI(j,a)	Company j's ESG score from MSCI at the end of the fiscal year a.
E sub-factor MSCI(j,a)	Company j's E sub-factor from MSCI at the end of the fiscal year a.
S sub-factor MSCI(j,a)	Company j's S sub-factor from MSCI at the end of the fiscal year a.
G sub-factor MSCI(j,a)	Company j's G sub-factor from MSCI at the end of the fiscal year a.
ESG score ESG Book(j,a)	Company j's ESG score from ESG Book at the end of the fiscal year a.
E sub-factor ESG Book(j,a)	Company j's E sub-factor from ESG Book at the end of the fiscal year a.
S sub-factor ESG Book(j,a)	Company j's S sub-factor from ESG Book at the end of the fiscal year a.
G sub-factor ESG Book(j,a)	Company j's G sub-factor from ESG Book at the end of the fiscal year a.
ESG score Moody's ESG(j,a)	Company j's ESG score from Moody's ESG at the end of the fiscal year a.
E sub-factor Moody's ESG(j,a)	Company j's E sub-factor from Moody's ESG at the end of the fiscal year a.
S sub-factor Moody's ESG(j,a)	Company j's S sub-factor from Moody's ESG at the end of the fiscal year a.
G sub-factor Moody's ESG(j,a)	Company j's G sub-factor from Moody's ESG at the end of the fiscal year a.
Company variables	
Measure of bankruptcy risk(j,a)	Company j's measure of bankruptcy risk from BRAINKRUPTCY based on a logistic bankruptcy prediction model at the end of the fiscal year a.
Total assets(j,a)	Company j's total assets in fiscal year a, winsorized at the 99th percentile.
B&h stock return(j,a)	Company j's buy-and-hold stock return in fiscal year a, winsorized at the 99th percentile.
Stock return volatility(j,a)	Company j's annualized stock return volatility in fiscal year a, winsorized at the 99th percentile.
Tobin's Q(j,a)	Company j's market value of equity plus its book value of total assets, minus its book value of equity, divided by its book value of total assets in fiscal year a, winsorized at the 99th percentile.
Market value of equity(j,a)	Company j's market value of equity in fiscal year a, winsorized at the 99th percentile.
Market value to book value(j,a)	Company j's market value of equity divided by its book value of equity in fiscal year a, winsorized at the 99th percentile.
Leverage(j,a)	Company j's total debt divided by its total assets in fiscal year a, winsorized at the 99th percentile.
Return on equity(j,a)	Company j's earnings before tax divided by its book value of equity in fiscal year a, winsorized at the 1st and 99th percentiles.
Return on assets(j,a)	Company j's earnings before interest, tax, depreciation and amortization (EBITDA) divided by its total assets in fiscal year a, winsorized at the 1st and 99th percentiles.
CapEx(j,a)	Company j's capital expenditures (CapEx) divided by its total assets in fiscal year a, winsorized at the 99th percentile.
R&D(j,a)	Company j's research and development expenditures (R&D) divided by its total assets in fiscal year a, winsorized at the 99th percentile.
Dividend yield(j,a)	Company j's total annual dividend divided by its market value of equity in fiscal year a, winsorized at the 1st and 99th percentiles.
Active ownership(j,a)	The total active ownership of company j, based on Form 13D(/A) filings at the end of the fiscal year a.
Institutional ownership(j,a)	The share of institutional ownership of company j, based on Form 13F filings at the end of the fiscal year a.
Industryj	Company j's standard industrial classification: SIC1–SIC9.

This table presents and defines the variables we used. We include ESG scores and E-S-G sub-factors from Refinitiv, MSCI, ESG Book, and Moody's ESG as dependent variables. Furthermore, we derived the measure of bankruptcy risk from BRAINKRUPTCY, further company variables from the CRSP and Compustat databases, active ownership from 13D(/A) filings, and institutional ownership from 13F filings.

Table 5.3: Descriptive statistics of the four final samples.

Sample		Refinitiv	MSCI	ESG Book	Moody's ESG
Firm-year observations		23,890	26,563	14,390	8,138
ESG Score	Mean	39.577	4.291	51.124	31.218
	SD	19.203	1.989	8.125	8.164
E sub-factor	Mean	25.290	4.611	47.654	24.370
	SD	27.087	2.136	13.072	15.818
S sub-factor	Mean	41.901	4.304	51.782	26.163
	SD	20.969	1.533	8.624	8.376
G sub-factor	Mean	48.146	5.442	52.070	44.869
	SD	22.498	1.834	13.261	7.870
Measure of bankruptcy risk	Mean	0.050	0.047	0.048	0.046
	SD	0.095	0.093	0.082	0.081
Total assets	Mean	17,157.56	14,439.88	18,677.25	37,882.43
	SD	42,768.11	38,973.82	44,154.51	61,963.87
B&H stock return	Mean	0.121	0.117	0.124	0.126
	SD	0.482	0.457	0.406	0.374
Stock return volatility	Mean	0.433	0.415	0.379	0.347
	SD	0.256	0.232	0.216	0.193
Tobin's Q	Mean	2.158	2.122	2.046	2.184
	SD	1.748	1.680	1.476	1.678
Market value of equity	Mean	12,764.19	10,713.32	14,221.46	29,136.68
	SD	28,730.55	26,131.50	29,340.54	40,885.50
Market value to book value	Mean	3.985	3.948	3.882	4.673
	SD	5.969	5.959	5.636	6.993
Leverage	Mean	0.604	0.597	0.614	0.660
	SD	0.259	0.259	0.238	0.225
Return on equity	Mean	0.019	0.026	0.087	0.126
	SD	0.449	0.423	0.365	0.349
Return on assets	Mean	0.057	0.068	0.098	0.113
	SD	0.192	0.168	0.140	0.103
CapEx	Mean	0.033	0.035	0.036	0.036
	SD	0.041	0.043	0.040	0.040
R&D	Mean	0.044	0.042	0.030	0.024
	SD	0.104	0.096	0.076	0.056
Dividend yield	Mean	0.011	0.011	0.012	0.014
	SD	0.015	0.015	0.014	0.014
Active ownership	Mean	0.183	0.180	0.158	0.136
	SD	0.278	0.270	0.257	0.238
Institutional ownership	Mean	0.343	0.401	0.360	0.358
	SD	0.229	0.223	0.223	0.218
Industry	% SIC1	0.056	0.056	0.049	0.069
	% SIC2	0.181	0.171	0.175	0.143
	% SIC3	0.204	0.212	0.245	0.209
	% SIC4	0.092	0.087	0.090	0.136
	% SIC5	0.087	0.094	0.101	0.082
	% SIC6	0.237	0.221	0.210	0.218
	% SIC7	0.110	0.126	0.102	0.119
	% SIC8	0.031	0.033	0.023	0.020
	% SIC9	0.003	0.002	0.003	0.004

This table shows the descriptive statistics of the four final samples. The samples based on the available ESG scores from Refinitiv and MSCI include a larger number of firm-year observations from smaller companies. Thus, the larger samples are associated with lower mean values of total assets, market value of equity, return on equity, and return on assets. As far as the other variables are concerned, the final samples have comparable characteristics.

Table 5.4 shows the correlations between the independent variables when considering the final dataset of 33,875 firm-year observations. The measure of bankruptcy risk shows no significant correlation with any other independent variable. There are meaningful correlations between two independent variables if the variables are comparable in content. This applies to the pairing total assets and market value of equity, Tobin's Q and market value to book value, and return on equity and return on assets. In unreported results, we find similar correlations in the four final samples. We address these correlations by varying the independent variables when we check the robustness of the results. However, we apply all independent variables in the regressions presented in the results section.

Table 5.4: Correlations between the independent variables based on the final dataset.

	Measure of Bankruptcy Risk	**Total Assets**	**B&H Stock Return**	**Stock Return Volatility**	**Tobin's Q**
Total Assets	0.062				
B&H Stock Return	-0.353	-0.009			
Stock Return Volatility	0.340	-0.149	-0.090		
Tobin's Q	-0.224	-0.123	0.295	0.090	
Market Value of Equity	-0.039	0.659	0.050	-0.205	0.124
Market Value to Book Value	-0.125	-0.058	0.186	0.030	0.602
Leverage	0.242	0.203	-0.035	-0.053	-0.162
Return on Equity	-0.253	0.091	0.160	-0.443	-0.063
Return on Assets	-0.195	0.042	0.156	-0.475	-0.071
CapEx	0.110	-0.061	-0.024	0.009	0.038
R&D	0.059	-0.118	-0.075	0.396	0.373
Dividend Yield	0.015	0.117	-0.079	-0.223	-0.176
Active Ownership	0.092	-0.110	-0.001	0.194	-0.004
Institutional Ownership	-0.138	-0.058	0.038	-0.066	-0.004
	Market Value of Equity	**Market Value to Book Value**	**Leverage**	**Return on Equity**	**Return on Assets**
Market Value to Book Value	0.140				
Leverage	0.063	0.071			
Return on Equity	0.164	-0.068	0.041		
Return on Assets	0.161	-0.017	0.021	0.664	
CapEx	0.021	0.026	-0.081	0.053	0.204
R&D	-0.061	0.199	-0.177	-0.506	-0.708
Dividend Yield	0.093	-0.078	0.199	0.168	0.159
Active Ownership	-0.134	-0.011	0.021	-0.103	-0.109
Institutional Ownership	-0.106	-0.001	-0.031	0.035	0.068
	CapEx	**R&D**	**Dividend Yield**	**Active Ownership**	
R&D	-0.102				
Dividend Yield	-0.085	-0.240			
Active Ownership	0.040	0.033	-0.033		
Institutional Ownership	0.007	-0.031	-0.118	-0.111	

This table reports the correlations between the applied independent variables. There are meaningful correlations between two independent variables if the variables are comparable in content.

5.3.3 Applied methodology

The relations between the independent and dependent variables are analyzed using multivariate regression models. The independent variables include the measure of bankruptcy risk and a set of control variables, and the dependent variables consist of several ESG scores and their E-S-G subfactors. Besides linear regression models, we apply nonparametric regression technique by using additive regression models with polynomial splines (see for an application in business research, e.g., Lohmann and Ohliger (2017); Lohmann and Möllenhoff (2023a). Polynomial splines can be applied to model an unspecified function $f(\cdot)$. An unspecified function $f(\cdot)$ can show a non-linear relationship between any metric independent variable and the dependent variable without restrictions (Stone and Koo, 1985; Hastie and Tibshirani, 1990). On the contrary, a linear model requires compliance with the linearity constraint. Only by applying an additive regression model is it possible to estimate and analyze the non-linear relationship.

Equation 5.1 gives the additive regression model and consists of the unspecified functions $f_1(x_1), f_2(x_2), ..., f_p(x_p)$. The additive regression model includes the linear regression model as a particular case that exists if every unspecified function is linear.

$$y = \beta_0 + f_1(x_1) + f_2(x_2) + ... + f_p(x_p) + \zeta \tag{5.1}$$

Each unspecified function $f(\cdot)$ is modeled using a polynomial spline. The range of each independent variable, whose lower and upper limits are x_{min} and x_{max}, respectively, is divided into intervals. The boundaries of those intervals are denoted as knots K_j with $j = 1, ..., m$. A separate polynomial of rank $g > 0$ is estimated for each interval $[K_j, K_{j+1})$ to ensure a sufficient data fit. Thereby, the unspecified function $f(\cdot)$ has to be $(g-1)$-times continuously differentiable, ensuring that the polynomials build a spline without discontinuities at the interval boundaries. As a result of this requirement, the unspecified function $f(\cdot)$ is smooth (Kneib, 2006).

An unspecified function modeled by a polynomial spline must balance fitting the data and smoothing. The balancing takes place by establishing an additional penalty term for every spline function in the maximum likelihood estimation of the additive regression model. This term refers to the fit to the interval-specific data and penalizes very different interval-specific polynomials. In likelihood maximization, the penalty term is weighted with a smoothing parameter λ that controls the variability of a penalized spline (Eilers and Marx, 1996). While the fit to the data deteriorates as the smoothing parameter λ increases, the smoothness of the function $f(\cdot)$ increases with an increase in the smoothing parameter λ. Since it is not possible to increase the smoothing and the fit to the data simultaneously, the smoothing parameter λ must be objectified. One way to determine an objectified smoothing parameter is to apply and minimize the generalized cross-validation criterion (Eilers and Marx, 1996; Green and Silverman, 1993).

We apply penalized splines to model the non-linear relationships between independent variables, including the measure of bankruptcy risk (MBR) and a set of control variables, and dependent variables consisting of several ESG scores and their E-S-G sub-factors. We put each unspecified function $f(\cdot)$ in concrete terms by using seven equidistant intervals and polynomials of rank $g = 3$ for each penalized spline. The minimum of the generalized cross-validation criterion determines the smoothing parameter λ. Equation 5.2 shows the additive regression model for the dependent variable *ESG Score*. We contrast our result with a linear regression model given by Equation 5.3.

$$\begin{aligned} ESGScore = \beta_0 + f_1(MBR) + f_2(Control_1) + \cdots + f_{16}(Control_{15}) + \beta_{17} \cdot Industry \\ + \beta_{18} \cdot Year + \zeta \end{aligned} \tag{5.2}$$

$$\begin{aligned} ESGScore = \beta_0 + \beta_1 MBR + \beta_2 Control_1 + \cdots + \beta_{16} Control_{15} + \beta_{17} \cdot Industry \\ + \beta_{18} \cdot Year + \zeta \end{aligned} \tag{5.3}$$

Both regression models control for year-fixed, industry-fixed, and company-fixed effects in the panel data. Thereby, year-fixed and industry-fixed effects are taken into account by dummy variables, and company-fixed effects are taken into account by applying the within transformation.

5.4 Empirical results

5.4.1 Linear regression results

The linear regression models estimate a linear relationship between the independent and dependent variables. Table 5.5 shows the results of the linear regression models LRM1–LRM4 in terms of the estimated regression coefficients of the metric independent variables. The linear regression models apply different ESG scores as dependent variables. Based on the applied ESG scores, there are also differences in the applied samples. However, all four linear regression models use the same independent variables, and we estimated all regressions with standard errors clustered at the company level. The linear regression models estimate a negative and statistically significant relationship between the measure of bankruptcy risk and the ESG scores; there is always a negative coefficient. The coefficient of the linear regression model LRM2 is much smaller as the ESG score from MSCI is in the value range [0, 10] instead of [0, 100] for all other applied ESG scores. Based on the linear regression models, we can conclude that, ceteris paribus, the ESG score decreases if a company's financial distress increases.

Overall, the linear regression models show mixed results concerning the metric control variables. The sign of the estimated coefficient or its statistical significance often changes when the results of a specific control variable are compared for the linear regression models LRM1–LRM4. The heterogeneity of the results is to be expected and can be explained by the low correlation between the various ESG scores. As expected, the estimated coefficients differ significantly in magnitude, as the control variables have a different range of values (see the descriptive statistics in Table 5.3). Numerically large control variables have very small coefficients, and numerically small control variables have very large coefficients.

Table 5.5: Results of the linear regression models LRM1–LRM4.

Regression Model	LRM1	LRM2	LRM3	LRM4
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Measure of bankruptcy risk	–9.189***	–0.798***	–3.786**	–3.070*
Total assets	0.000***	0.000	–0.000	–0.000*
Buy-and-hold stock return	–1.715***	–0.162***	–0.957***	–0.356*
Stock return volatility	0.946	0.239**	–0.677	1.908**
Tobin's Q	0.252	0.039*	0.989***	–0.098
Market value of equity	0.000***	0.000**	–0.000	0.000***
Market value to book value	–0.002	0.001	–0.026	–0.002
Leverage	6.060***	0.184	–8.351***	1.593
Return on equity	0.143	0.067*	0.404	–0.029
Return on assets	–0.606	0.040	2.528*	–1.085
CapEx	–29.09***	–0.101	–15.69***	–16.51***
R&D	–5.749*	–0.166	10.37**	–5.966
Dividend yield	47.65***	0.885	43.98***	19.13*
Active ownership	3.553*	–0.303	1.718	0.865
Institutional ownership	6.620***	–0.056	1.385	0.636
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	23,890	26,563	14,390	8,139
Adjusted R^2	0.367	0.090	0.112	0.296

This table shows the results (i.e., estimated coefficients) of the linear regression models LRM1–LRM4, where different ESG scores are applied as the dependent variable. The independent variables include the company variables that are defined in Table 2. All linear regression models take into account year-fixed, industry-fixed, and firm-fixed effects. All standard errors are clustered at the company level. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

5.4.2 Additive regression results

The basic assumption of a linear regression model is that there are linear relationships whose slopes (i.e., coefficients) are estimated by the model. As we need to know whether there are linear relationships, a linear regression model will produce misleading results if non-linear relationships exist between the independent and dependent variables. To overcome this shortcoming of a linear regression model, we have to apply additive regression models that estimate the effective relationship in terms of an unspecified function, which could be linear or non-linear.

Table 5.6 shows the results of the additive regression models ARM1–ARM4. The output value for the metric independent variables is the equivalent degree of freedom. The equivalent degree of freedom indicates the nonlinearity in the estimated spline function. An equivalent degree of freedom $df_f = 1.000$ represents a linear function, and an increasing equivalent degree of freedom ($df_f > 1.000$) indicates increasing nonlinearity in the estimated spline function. All four estimated spline functions (ARM1–ARM4) of the independent variable Measure of bankruptcy risk show a meaningful nonlinearity ($2.848 \leq \ df_f \leq \ 2.966$), which is statistically significant in all cases. Except for the independent variable Market value of equity, the other independent variables do not exhibit meaningful and statistically significant nonlinearities ($df_f > 2.000$) in all additive regression models ARM1–ARM4.

The spline function estimates the relationship between the independent and dependent variable. However, we must analyze the spline patterns in detail to describe the relationship's direction. The equivalent degrees of freedom of the additive regression models ARM1–ARM4, and thus the estimated non-linear relationships, do not meaningfully differ with regard to the independent variable *Measure of bankruptcy risk*.

Figure 5.2 depicts the spline patterns of the independent variable Measure of bankruptcy risk for the additive regression models ARM1–ARM4, which include the four ESG scores from various data providers as dependent variables. To compare the estimated spline patterns with the estimated linear functions, we inserted the estimations of the linear regression models LRM1–LRM4 as dashed line. We centered the estimated linear functions with the estimated spline patterns at the function value 0.

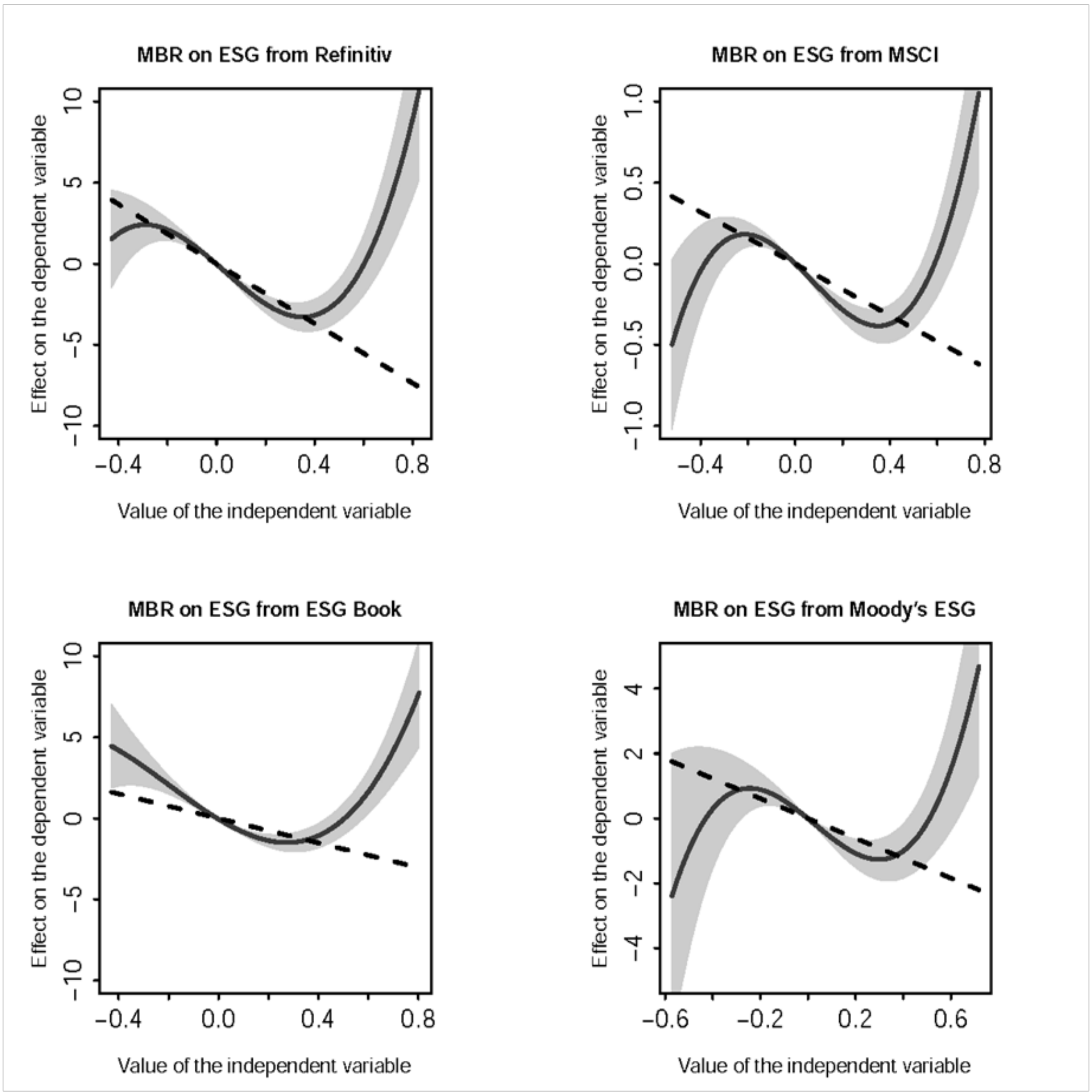
Table 5.6: Results of the additive regression models ARM1–ARM4.

Regression model	ARM1	ARM2	ARM3	ARM4
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Measure of bankruptcy risk	2.952***	2.966***	2.848***	2.959***
Total assets	2.982***	2.892**	1.728**	1.000***
Buy-and-hold stock return	2.956***	1.000***	1.000***	2.769**
Stock return volatility	2.919***	1.664***	2.632***	2.305***
Tobin's Q	1.000	1.000**	2.962***	2.748*
Market value of equity	2.991***	2.989***	2.884***	2.987***
Market value to book value	1.582	1.968*	1.000**	1.766
Leverage	1.000***	1.000**	1.089***	1.793**
Return on equity	1.000	1.000*	1.859*	1.585
Return on assets	1.000	1.000	2.966***	2.803
CapEx	1.000***	2.693	2.655***	1.742***
R&D	2.055***	1.000	2.959***	1.000*
Dividend yield	2.972***	2.719	1.570***	2.589***
Active ownership	2.879***	1.000*	2.776**	1.000
Institutional ownership	1.000***	1.000	1.105**	2.882*
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	23,890	26,563	14,390	8,139
Adjusted R^2	0.380	0.097	0.127	0.305

This table shows the results (i.e., equivalent degrees of freedom) of the additive regression models ARM1–ARM4 where different ESG scores are applied as the dependent variable. The independent variables include the company variables that are defined in Table 2. All additive regression models take into account year-fixed, industry-fixed, and firm-fixed effects. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

Figure 5.2 displays pronounced and almost identical U-shaped relationships between the measure of bankruptcy risk and all four ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The turning point of the U-shaped relationships is about 0.25, meaning that a company's measure of bankruptcy risk exceeds the mean of the measure of bankruptcy risk by 0.25. If a company is financially healthy, there is a negative relationship between the measure of bankruptcy risk and the ESG score. Since an OLS estimator fits the linear function based on the firm-year observations of mostly financially healthy companies, the estimated linear function of the linear regression models LRM1–LRM4 largely corresponds to the negative slope of the estimated spline function. The estimated spline function exhibits a positive slope if a company is sufficiently financially distressed. As a result, the additive regression analysis reveals a positive relationship between the measure of bankruptcy risk and the ESG score in the case of financially distressed companies. Thus, financially distressed companies are associated with high ESG scores. That empirical finding is valid and holds for all applied ESG scores.

Figure 5.2: The U-shaped relationship between the measure of bankruptcy risk (MBR) and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG.



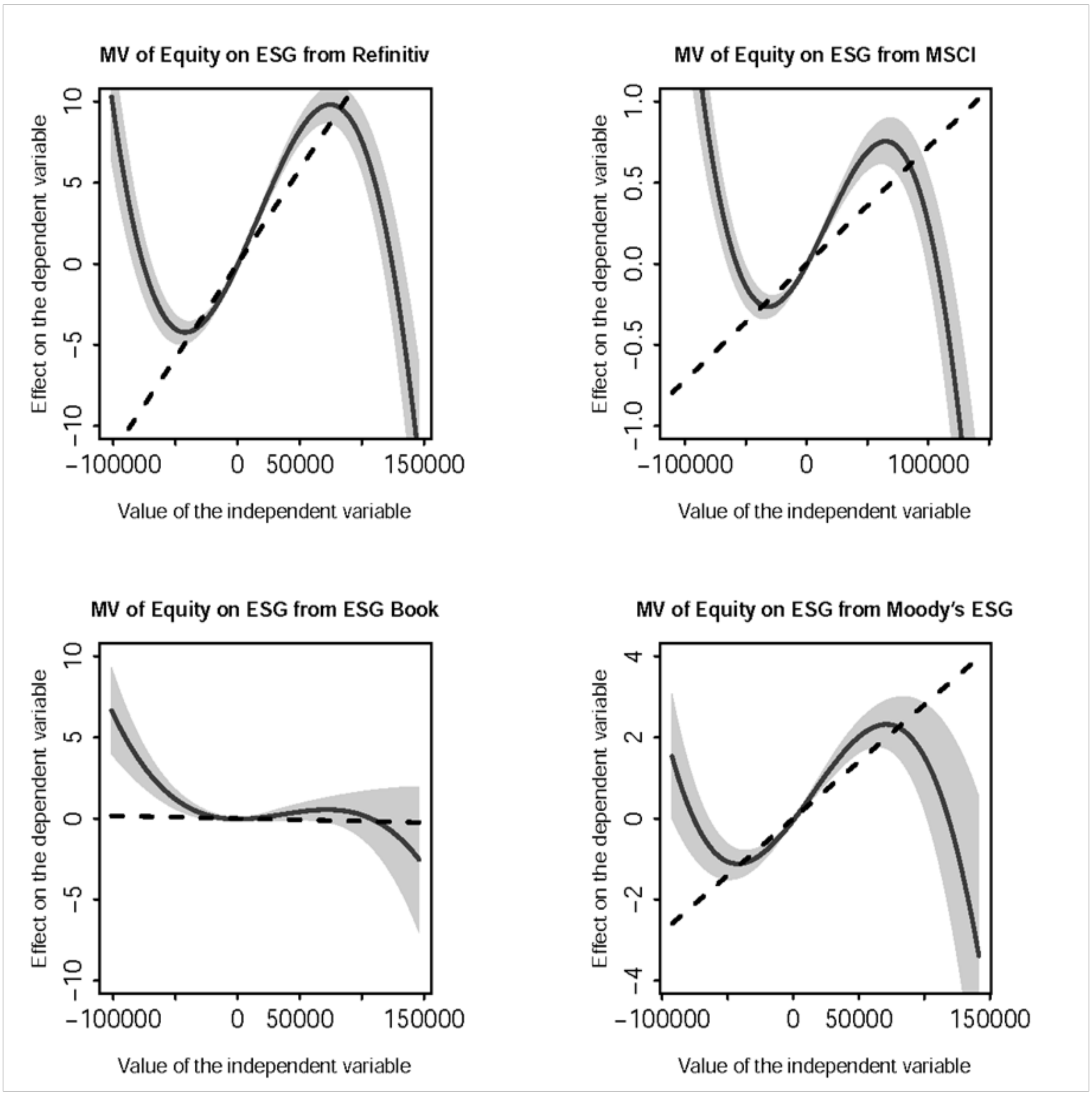
This figure shows the statistically significant spline patterns for the relationship between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The measure of bankruptcy risk is plotted on the x-axis, and the ESG score on the y-axis. Due to the within transformation, the values on the axes represent deviations from the company mean value. The bold black line represents the estimated spline function, and the dashed line represents the estimated linear function. The 95% confidence band is shaded gray.

Figure 3.2 also shows that the 95% confidence bands are very narrow when the estimated spline functions exhibit a positive slope. That observation provides an initial insight into causality. We expect narrow confidence bands if most financially distressed companies manage their ESG scores upward. ESG investments or operational ESG measures may also cause financial deterioration as a side effect. In that case, narrow 95% confidence bands would only appear if ESG activities were the only significant cause of financial distress. However, this is the much less likely case as the failure of the business model, management failure, frictions on the sales and procurement markets, and difficulties in corporate financing can be seen as further important causes of financial distress. As a result, the narrow 95% confidence bands in Figure 5.2 indicate that financially distressed companies likely manage their ESG scores upward.

The spline patterns for the relationship between the market value of equity and the ESG scores are shown in Figure 5.3 and reveal further meaningful insights. The x-axis plots the difference between a company's market value of equity and the company's mean market value of equity. As a result, negative values indicate a shrunken market value of equity, and positive values indicate an increased market value of equity. The relationships between the market value of equity and the ESG scores are comparable for all four ESG scores and can be split into three parts. First, when the market value of equity is below the company's mean value, a negative relationship exists between the market value of equity and the ESG score, indicating that companies with a shrunken market value of equity are associated with higher ESG scores. Second, when the market value of equity fluctuates around the company's mean value, the relationship between the market value of equity and the ESG score is comparable to the estimated positive linear relationship. Third, when the market value of equity exceeds the company mean value, there is a negative relationship between the market value of equity and the ESG score. An increasing market value of equity could be particularly common in growth companies. If the focus is on economic growth, ESG activities intended to reduce environmental impacts will likely not be a priority. Overall, the peripheral areas deviate from the estimated positive linear relationship to a large extent. That empirical finding is valid and holds for all applied ESG scores.

A negative ESG divergence could occur in a financially healthy company with a high market value of equity and high current and future growth, while a positive ESG divergence could occur in a financially distressed company with a declining market value of equity. These interpretations, while plausible, should be approached with caution. The relationships between the market value of equity and the ESG scores and the associated interpretation complete the results presented in Figure 5.2. If the companies with a shrunken market value of equity were not associated with higher ESG scores, this would refute our empirical finding regarding the relationship between the measure of bankruptcy risk and ESG scores. Instead, the empirical observation that companies with a shrunken market value of equity are associated with high ESG scores completes the overall picture. It is an additional sign that financially distressed companies are indeed associated with high ESG scores.

Figure 5.3: The non-linear relationship between the market value (MV) of equity and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG.



This figure shows the statistically significant spline patterns for the relationship between the market value of equity and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The market value of equity is plotted on the x-axis, and the ESG score is plotted on the y-axis. Due to the within transformation, the values on the axes represent deviations from the company mean value. The bold black line represents the estimated spline function and the dashed line represents the estimated linear function. The 95% confidence band is shaded gray.

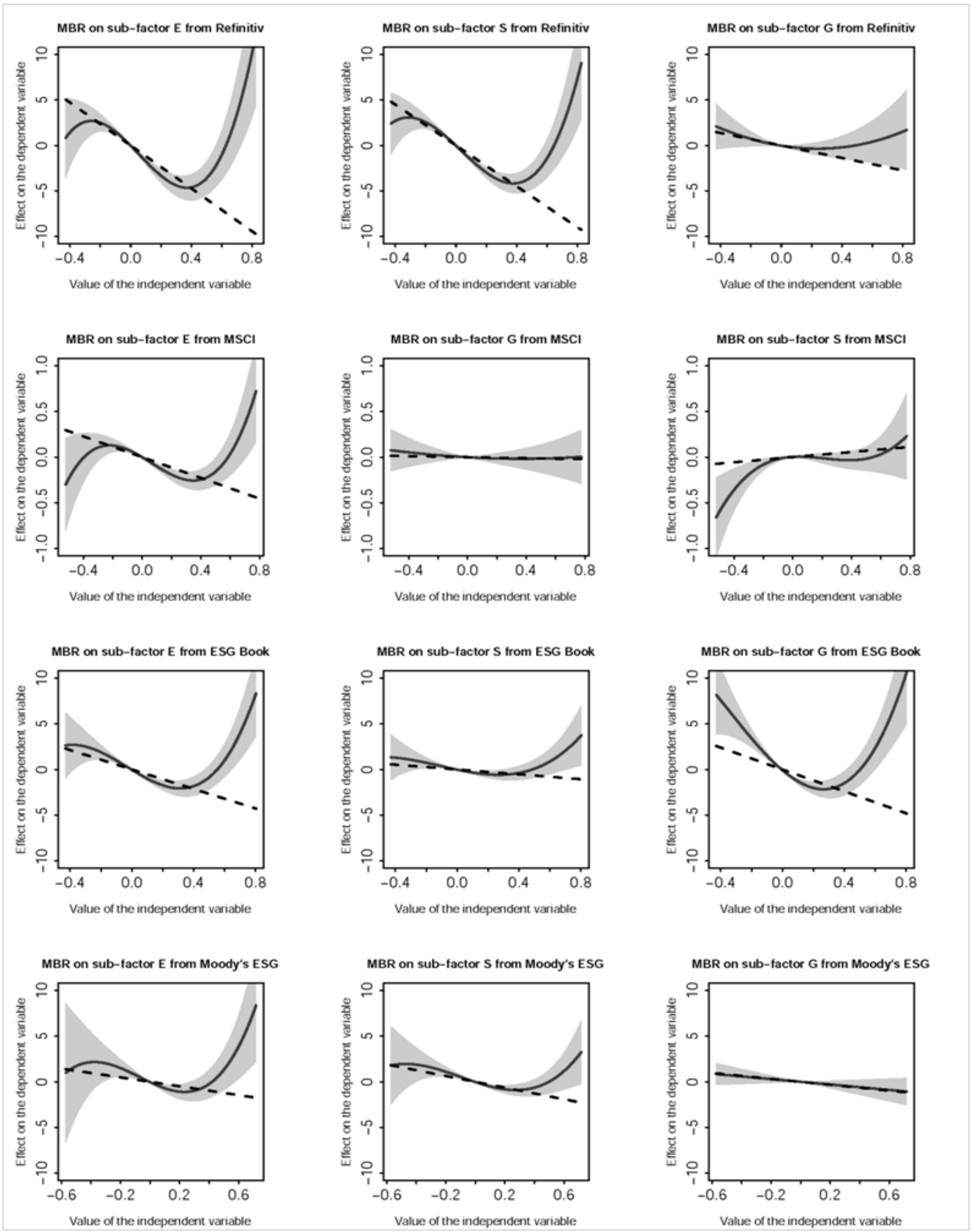
5.4.3 Additive regression results for the ESG sub-factor

Each ESG score analyzed consists of three E-S-G sub-factors: the environmental (E) sub-factor, the social (S) sub-factor, and the governance (G) sub-factor. We repeated the linear and additive regression analyses for the three sub-factors from each ESG score to reveal the relationships between the measure of bankruptcy risk and the E-S-G sub-factors in more detail. We estimated 12 linear and 12 additive regression models that apply the E-S-G sub-factors as dependent variables. The results of these 24 regressions are condensed in Figure 5.4, which depicts the estimated linear and non-linear relationships between the measure of bankruptcy risk and the E-S-G sub-factors from each ESG score. A pronounced U-shaped relationship between the measure of bankruptcy risk and the environmental sub-factor can be observed in all additive regression models. Figure 5.4 also shows U-shaped relationships between the measure of bankruptcy risk and the social and governance sub-factors. However, the U-shaped relationships between the measure of bankruptcy risk and the social and governance sub-factors do not occur in every additive regression model and are less pronounced.

The most crucial sub-factor in all ESG scores is the environmental sub-factor, followed by the social and governance sub-factor. The environmental sub-factor and its components have the greatest weighting within the ESG score. A high correlation between the environmental and ESG scores, along with high inter-correlations with the social and governance sub-factor, demonstrates the significance of the environmental sub-factor for the ESG score (Billio et al., 2024). The individual components of an ESG score are often qualitative, and the evaluation made by ESG rating agencies can only be objectively verified to a limited extent. The subjective selection and evaluation of very often qualitative components of an ESG score explains a very large part of ESG disagreements among ESG rating agencies. Berg et al. (2022) found that the inconsistencies in ESG ratings are mainly due to the scope of the ESG definition applied and the criteria selected to measure a company's ESG activities rather than the weighting of these criteria. Companies have extensive opportunities to influence the ESG score through real facts and ESG-supporting disclosures. ESG-supporting disclosures are crucial in shaping ESG scores, as they offer a cost-effective way for companies to impact their ESG standing, often outweighing their content (Drempetic et al., 2020; Lopez-de Silanes et al., 2020). Since the phenomenon of "greenwashing" has been studied more extensively than "social washing" or "governance washing" and can be regarded as empirically confirmed (e.g., Kirk and Vincent (2014); Marquis et al. (2016); Yu et al. (2020)), it can be assumed that ESG-supporting disclosures primarily relate to the components of the environmental sub-factor.

If ESG-supporting disclosures are used to manage the ESG score upward, we can expect a pronounced U-shaped relationship between the measure of bankruptcy risk and the environmental sub-factor. This expectation is met as the U-shaped relationships between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG are primarily based on the environmental sub-factor. Additionally, constructing the E-S-G sub-factors can lead to the social and governance sub-factors reinforcing the U-shaped relationship between the measure of bankruptcy risk and the ESG scores. That is especially true for the ESG scores from Refinitiv and ESG Book.

Figure 5.4: Relationships between the measure of bankruptcy risk (MBR) and the E-S-G sub-factors from Refinitiv, MSCI, ESG Book, and Moody's ESG.



This figure shows the spline patterns for the relationship between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The measure of bankruptcy risk is plotted on the x-axis, and the E-S-G sub-factors are plotted on the y-axis. Due to the within transformation, the values on the axes represent deviations from the company mean value. The bold black line represents the estimated spline function, and the dashed line represents the estimated linear function. The 95% confidence band is shaded gray.

The non-linear relationships between the market value of equity and the environmental sub-factors are very similar to those between the market value of equity and ESG scores. There is a positive divergence in all four environmental sub-factors from Refinitiv, MSCI, ESG Book, and Moody's ESG for companies with an already declining market value of equity. The empirical observation that companies with a shrunken market value of equity are associated with high values of the environmental sub-factor provides a further sign that financially distressed companies are indeed associated with high values of the environmental sub-factor.

5.5 Extensions and robustness of the regression analysis

5.5.1 Regression results with multi-year capital expenditures and R&D expenditures

Company-related measures that lead to a high ESG score could induce financial consequences that increase the measure of bankruptcy risk. Such a relationship should be particularly evident in ESG investments, as these impact a company's financial position more than operational measures or ESG-supporting disclosures. It is a plausible argument that past cash flow-effective ESG investments can increase a company's current ESG score while worsening its current financial position. A previous increase in capital and R&D expenditures with a subsequent increase in the ESG score would indicate this cause-effect relationship.

We tested this hypothesis by taking into account the capital expenditures of the previous two and three years when we calculated the independent variable $CapEx_{(j,a)}$ and the R&D expenditures of the previous two and three years when we calculated the independent variable $R\&D_{(j,a)}$. Tables 5.7 and 5.8 report the results of the regression analyses when the extended independent variables $CapEx_{(j,a)}$ and $R\&D_{(j,a)}$ are applied. The results of the regression analyses are comparable to Table 5.6 and remain almost unchanged, demonstrating the robustness of our research. The hypothesis that past ESG investments worsen a company's current financial situation and, at the same time, increase the current ESG scores cannot be confirmed as the estimated spline function for the measure of bankruptcy risk remains almost unchanged.

One-year and multi-year capital expenditures and R&D expenditures do not have any effect on the U-shaped relationship between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. Notwithstanding this, the type of investments made could differ between financially distressed companies and financially healthy companies. Financially distressed companies could make ESG investments to a greater extent. This could have a positive impact on ESG scores and at the same time worsen the financial situation as a side effect, as ESG investments tend to pay off in the longer term. Specific information on ESG investments is required to verify this hypothesis.

Table 5.7: Results of the additive regression models ARM1–ARM4 with $CapEx_{(j,a)}$ and $R\&D_{(j,a)}$ of the previous two years.

Regression model	ARM1	ARM2	ARM3	ARM4
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Measure of bankruptcy risk	2.954***	2.969***	2.844***	2.948***
Total assets	2.982***	2.892**	1.714**	1.000***
Buy-and-hold stock return	2.955***	1.000***	1.000***	1.000***
Stock return volatility	2.915***	1.656***	2.476***	2.282***
Tobin's Q	1.000	1.000**	2.967***	2.866**
Market value of equity	2.991***	2.989***	2.871***	2.986***
Market value to book value	1.600	1.976*	1.000**	1.766
Leverage	1.000***	1.000**	1.423***	1.771**
Return on equity	1.000	1.000*	1.892*	1.342
Return on assets	1.000	1.000	2.962***	2.881*
CapEx (2 years)	1.000***	1.018	1.000***	1.668***
R&D (2 years)	2.053***	1.000	2.975***	2.878**
Dividend yield	2.972***	2.721	1.515***	2.857***
Active ownership	2.875***	1.029*	2.808**	1.000
Institutional ownership	1.000***	1.000	1.295**	1.000
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	23,890	26,563	14,390	8,139
Adjusted R^2	0.380	0.097	0.131	0.306

This table shows the results (i.e., equivalent degrees of freedom) of the additive regression models ARM1–ARM4 where different ESG scores are applied as the dependent variable. The independent variables include the company variables defined in Table 5.2; the independent variables $CapEx_{(j,a)}$ and $R\&D_{(j,a)}$ are calculated for the previous two years. All additive regression models take into account year-fixed, industry-fixed, and firm-fixed effects. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

CDP (formerly the Carbon Disclosure Project) surveys companies annually about their projects started in the current year to reduce greenhouse gas emissions (GGE). Participation in the survey is voluntary and the information companies provide to CDP is self-reported. Currently, the CDP database is the largest dataset on company projects to reduce their greenhouse gas emissions. One data point of the survey is the investment expenditure of the project. We aggregated the reported investment expenditures on project level to the investment expenditure at the company level (*GGE investment*). Overall, there are 4,396 firm-year observations of 784 listed US companies in the period 2011–2022 that are also included in the final data set of 33,875 firm-year observations. In addition, we excluded the firm-year observations with an annual investment expenditure of 0, as the investment expenditures were presumably not reported. As a result, there are 2,822 firm-year observations of 529 listed US companies in the period 2011–2022 that are also included in the final data set of 33,875 firm-year observations.

Table 5.8: Results of the additive regression models ARM1–ARM4 with $CapEx_{(j,a)}$ and $R\&D_{(j,a)}$ of the previous three years.

Regression model	ARM1	ARM2	ARM3	ARM4
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Measure of bankruptcy risk	2.956***	2.969***	2.873***	2.942***
Total assets	2.983***	2.892**	1.719**	1.000***
Buy-and-hold stock return	2.955***	1.000***	1.000***	2.746**
Stock return volatility	2.921***	1.644***	2.399***	2.382***
Tobin's Q	1.000	1.000**	2.969***	2.758*
Market value of equity	2.991***	2.989***	2.869***	2.987***
Market value to book value	1.665	1.980*	1.000**	1.825
Leverage	1.000***	1.000**	1.421***	1.781**
Return on equity	1.000	1.000*	1.824*	1.498
Return on assets	1.000	1.000	2.950***	2.887*
CapEx (3 years)	1.000***	1.000*	2.637***	2.776***
R&D (3 years)	2.804***	1.000	2.950***	2.766*
Dividend yield	2.973***	2.723	1.472***	2.909***
Active ownership	2.873***	1.008*	2.829**	1.000
Institutional ownership	1.000***	1.000	1.403**	1.000
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	23,890	26,563	14,390	8,139
Adjusted R^2	0.380	0.097	0.130	0.307

This table shows the results (i.e., equivalent degrees of freedom) of the additive regression models ARM1–ARM4 where different ESG scores are applied as the dependent variable. The independent variables include the company variables defined in Table 5.2; the independent variables $CapEx_{(j,a)}$ and $R\&D_{(j,a)}$ are calculated for the previous three years. All additive regression models take into account year-fixed, industry-fixed, and firm-fixed effects. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

Based on the relatively small sample of 2,822 firm-year observations, we examined whether financial distress is associated with high investment expenditures to reduce greenhouse gas emissions. We analyzed the relationship between the dependent variables *GGE investment* and *GGE investment to total assets* and the independent variable *Measure of bankruptcy risk* and all other control variables that are defined in Table 5.2. In addition, year-fixed, industry-fixed, and firm-fixed effects were taken into account. All regression results show that there is no statistically significant relationship ($p - value < 0.1$) between the dependent variables *GGE investment* and *GGE investment to total assets* and the independent variable *Measure of bankruptcy risk*. Although the number of firm-year observations in the CDP database is relatively low and the statistical evidence must therefore be regarded as limited, there is no indication that financially distressed companies implement a different investment mix in relation to GGE investments than financially healthy companies. Consequently, the hypothesis that ESG investments are the cause of high ESG scores of financially distressed companies must be rejected with a probability bordering on certainty.

5.5.2 Regression results with energy intensity as dependent variable

Company-related measures that lead to high ESG scores and an increase in financial distress do not necessarily require ESG investments. However, these measures should mainly affect the environmental sub-factor, as the revealed U-shaped relationship is primarily based on this sub-factor. An important indicator of a company's environmental footprint is the energy intensity of its value-added process. If company-related measures lead to a high ESG score and an increase in the measure of bankruptcy risk, we would expect a reversed U-shaped or at least negative relationship between a company's energy intensity and the measure of bankruptcy risk. Financially distressed companies should have a smaller environmental footprint regarding their energy intensity.

We selected *Energy intensity* as the new dependent variable to test this hypothesis. The dependent variable *Energy intensity* was sourced from the Refinitiv database and is defined as a score that is based on the total direct and indirect energy consumption in gigajoules divided by net sales or revenue in US dollars. This dependent variable *Energy intensity* was matched to the final dataset of 33,875 firm-year observations. Overall, there are 6,057 firm-year observations with the dependent variable *Energy intensity* and all other applied control variables. Despite the lower observation density compared to ESG scores, the firm-year observations are sufficient to perform a linear and additive regression analysis.

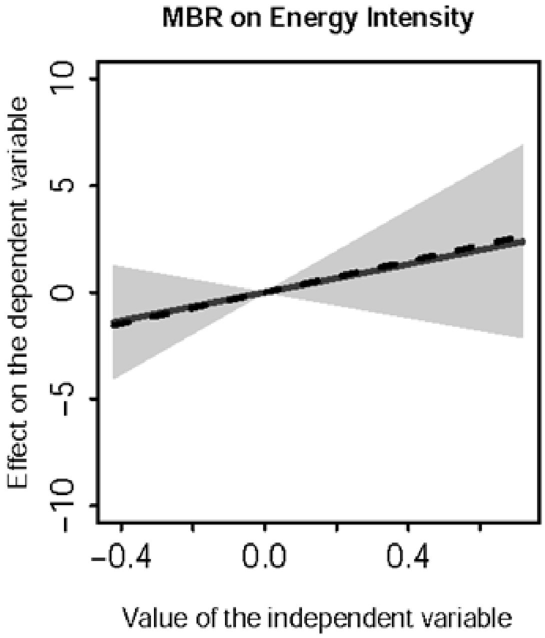
Table 5.9 shows the results of the linear regression model LRM-EI and the additive regression model ARM-EI when Energy intensity is applied as the dependent variable. Neither the estimated linear nor the non-linear relationship between the measure of bankruptcy risk and a company's energy intensity is statistically significant. Figure 5.5 depicts the estimated relationship between the measure of bankruptcy risk and Energy intensity. The shaded gray 95% confidence band is wide and illustrates the statistically non-significant relationship between the measure of bankruptcy risk and a company's energy intensity. As a result, it can be ruled out with sufficient certainty that financially distressed companies reduce their environmental footprint through real effective measures to an extent that plausibly explains the observed increase in the environmental sub-factor. This result is consistent with existing empirical findings, which show that financially constrained companies take measures that improve their financial situation in the short term but regularly lead to an effective reduction in ESG performance (e.g., Eisfeldt and Rampini (2007); Ma et al. (2022); Thomas et al. (2022).

Table 5.9: Results of the linear regression model LRM-EI and the additive regression model ARM-EI with the dependent variable *Energy intensity*.

Regression model	**LRM-EI**	**ARM-EI**
Dependent variable	Energy intensity	Energy intensity
Measure of bankruptcy risk	3.665	1.000
Total assets	–0.000***	1.707***
B&H stock return	–0.379	1.000
Stock return volatility	–4.413**	1.000
Tobin's Q	0.017	1.000
Market value of equity	0.000***	2.748***
Market value to book value	–0.071	1.097
Leverage	–4.575*	1.000**
Return on equity	–0.159	1.464
Return on assets	19.77***	2.678***
CapEx	–8.637	1.000
R&D	14.310	1.621
Dividend yield	6.741	1.350
Active ownership	–0.014	1.000
Institutional ownership	–7.243***	1.244
Year-fixed effects	Yes	Yes
Industry-fixed effects	Yes	Yes
Firm-fixed effects	Yes	Yes
N	6057	6057
Adjusted R^2	0.020	0.030

This table shows the results of the linear regression model LRM-EI (i.e., estimated coefficients) and the additive regression model ARM-EI (i.e., equivalent degrees of freedom) where *Energy intensity* is applied as the dependent variable. The independent variables include the company variables that are defined in Table 5.2. Both regression models take into account year-fixed, industry-fixed, and firm-fixed effects. All standard errors of the linear regression model LRM-EI are clustered at the company level. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

Figure 5.5: Estimated relationship between the measure of bankruptcy risk (MBR) and *Energy intensity.*



This figure shows the estimated relationship between the measure of bankruptcy risk and *Energy intensity.* The measure of bankruptcy risk is plotted on the x-axis, and *Energy intensity* is plotted on the y-axis. Due to the within transformation, the values on the axes represent deviations from the company mean value. The bold black line represents the estimated spline function of the additive regression model ARM-EI, and the dashed line represents the estimated linear function of the linear regression model LRM-EI. The 95% confidence band is shaded gray.

5.5.3 Regression results with shareholder-stakeholder orientation as dependent and independent variable

A plausible explanation of the revealed U-shaped relationship between the measure of bankruptcy risk and ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG is that financially distressed companies manage their ESG scores upward by intensifying cost-effective ESG activities such as ESG-supporting disclosures. The narrow 95% confidence bands in Figure 5.2 strongly indicate this causality. In order to validate this interpretation even more robustly, we introduce the *Shareholder-stakeholder* orientation as a further dependent variable. The variable *Shareholder-stakeholder* orientation is based on the number of words "shareholder" and "stakeholder" that were counted in the 10-K filings and is calculated according to Equation 5.4.

$$Shareholder - stakeholder orientation = \frac{Count"stakeholder" - Count"shareholder"}{Count"stakeholder" - Count"shareholder" + 1} \tag{5.4}$$

The variable *Shareholder-stakeholder orientation* assumes a value in the interval [–1, 1]. Lower values show a stronger shareholder orientation in corporate reporting, and higher values show a stronger stakeholder orientation. The variable *Shareholder-stakeholder orientation* can be interpreted as a proxy variable for ESG-supporting disclosure. We eliminated all firm-year observations when the variable *Shareholder-stakeholder* orientation takes the value of 0 due to word counts of 0. The variable *Shareholder-stakeholder orientation* was matched to the final dataset of 33,875 firm-year observations. Overall, there are 29,054 firm-year observations with the variable *Shareholder-stakeholder orientation* and all other applied control variables

To provide additional empirical evidence for the hypothesis that financially distressed companies manage their ESG score upward by intensifying ESG-supportive disclosures, we need to show how financially distressed companies influence their ESG score. If there is a cause-effect relationship between the measure of bankruptcy risk and ESG scores and ESG-supportive disclosures are an important instrument for achieving high ESG scores, we would expect three empirical observations: First, there should be a U-shaped relationship between the measure of bankruptcy risk and the variable *Shareholder-stakeholder orientation* that is comparable to the U-shaped relationship between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. Second, there should be no correlation between the variable *Shareholder-stakeholder orientation* and the residuals of the additive regression models ARM1–ARM4 presented in Table 5.6. Third, the variable *Shareholder-stakeholder orientation* should be able to explain the variance of the ESG scores to a similar extent as the variable Measure of bankruptcy risk and should show a positive, statistically significant, and almost linear relationship with the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG.

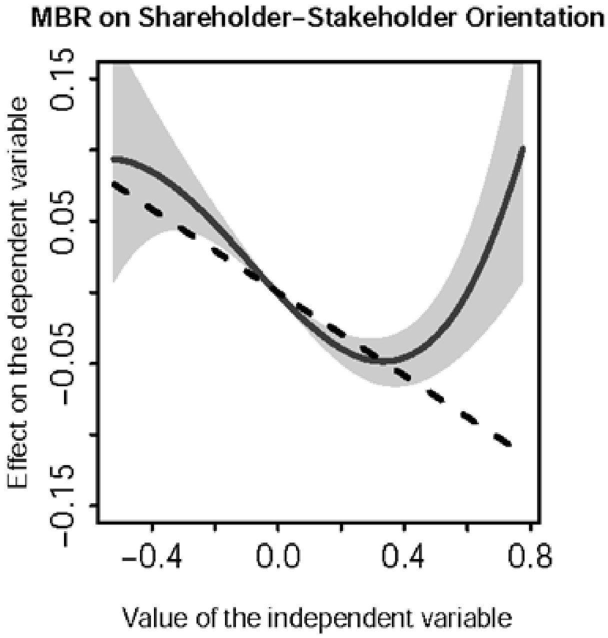
Table 5.10 shows the results of the linear regression model LRM-SSO and the additive regression model ARM-SSO when the variable *Shareholder-stakeholder orientation* is applied as the dependent variable. The linear regression model indicates a negative and statistically significant linear relationship between the measure of bankruptcy risk and a company's stakeholder orientation. On the contrary, the additive regression model reveals a statistically significant non-linear relationship between the measure of bankruptcy risk and a company's stakeholder orientation, depicted in Figure 5.6. The non-linear relationship between the measure of bankruptcy risk and the *Shareholder-stakeholder orientation* can be described by a U-shaped relationship comparable to the relationships between the measure of bankruptcy risk and ESG scores in Figure 5.2. Financially distressed companies generally exhibit a high stakeholder orientation, although all management efforts should be directed toward preserving the company and protecting the shareholders' equity. The comprehensive stakeholder orientation is consistent with the financially distressed companies' high ESG scores.

Table 5.10: Results of the linear regression model LRM-SSO and the additive regression model ARM-SSO with the dependent variable *Shareholder-stakeholder orientation* (SSO).

Regression model	LRM-SSO	ARM-SSO
Dependent variable	Shareholder-stakeholder orientation	Shareholder-stakeholder orientation
Measure of bankruptcy risk	–0.146***	2.853***
Total assets	0.000	2.982***
B&H stock return	–0.028***	1.812***
Stock return volatility	0.086***	2.631***
Tobin's Q	0.002	2.930**
Market value of equity	0.000***	1.000***
Market value to book value	0.001	1.833**
Leverage	0.135***	1.465***
Return on equity	0.018**	2.941***
Return on assets	–0.010	1.000
CapEx	–0.358***	2.642***
R&D	–0.167*	1.000***
Dividend yield	–0.300	2.817**
Active ownership	0.102***	1.000***
Institutional ownership	–0.006	1.000
Year-fixed effects	Yes	Yes
Industry-fixed effects	Yes	Yes
Firm-fixed effects	Yes	Yes
N	29,054	29,054
Adjusted R^2	0.05	0.06

This table shows the results of the linear regression model LRM-SSO (i.e., estimated coefficients) and the additive regression model ARM-SSO (i.e., equivalent degrees of freedom) where *Shareholder-stakeholder orientation* is applied as the dependent variable. The independent variables include the company variables that are defined in Table 5.2. Both regression models take into account year-fixed, industry-fixed, and firm-fixed effects. All standard errors of the linear regression model LRM-SSO are clustered at the company level. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

Figure 5.6: Estimated relationship between the measure of bankruptcy risk (MBR) and *Shareholder-stakeholder orientation.*



This figure shows the estimated relationship between the measure of bankruptcy risk and *Shareholder-stakeholder orientation.* The measure of bankruptcy risk is plotted on the x-axis and *Shareholder-stakeholder orientation* is plotted on the y-axis. Due to the within transformation, the values on the axes represent deviations from the company mean value. The bold black line represents the estimated spline function of the additive regression model ARM-SSO, and the dashed line represents the estimated linear function of the linear regression model LRM-SSO. The 95% confidence band is shaded gray.

Table 5.11 shows the correlations between the variable *Shareholder-stakeholder orientation* and the residuals of the additive regression models ARM1–ARM4 presented in Table 5.6. No anomalies were found in the review of the correlations. The residuals of the additive regression models ARM1–ARM4 are not correlated with the variable *Shareholder-stakeholder orientation.* The variable *Shareholder-stakeholder orientation* does not explain any variance in the ESG scores that is not explained by the additive regression models ARM1–ARM4. When the variable *Shareholder-stakeholder orientation* replaces the variable Measure of bankruptcy risk, and there is a statistically significant positive relationship between the variable *Shareholder-stakeholder orientation* and the ESG scores, we provide empirical evidence that financially distressed companies mimic the stakeholder-oriented behavior of financially healthy companies by emphasizing stakeholder-oriented ESG objectives and intensifying ESG-supporting disclosures.

Table 5.11: Results of the linear regression model LRM-SSO and the additive regression model ARM-SSO with the dependent variable *Shareholder-stakeholder orientation* (SSO).

Correlation between	with Shareholder-Stakeholder Orientation	Number of Observations
Residuals from ARM1	0.013	20,709
Residuals from ARM2	0.003	22,842
Residuals from ARM3	0.011	12,585
Residuals from ARM4	0.029	7,224

Correlations between the variable *Shareholder-stakeholder orientation* and the residuals from the additive regression models ARM1–ARM4. This table shows the correlations between the variable *Shareholder-stakeholder orientation* and the residuals from the additive regression models ARM1–ARM4.

Table 5.12 shows the results of the additive regression models ARM1-SSO–ARM4-SSO, where the variable *Shareholder-stakeholder orientation* replaces the variable Measure of bankruptcy risk. There is a statistically significant relationship between the variable *Shareholder-stakeholder orientation* and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. Furthermore, the adjusted R^2 of the additive regression models ARM1-SSO–ARM4-SSO are comparable to the adjusted R^2 of the additive regression models ARM1–ARM4 presented in Table 5.6. The independent variable *Shareholder-stakeholder orientation* explains the variance of the ESG scores to a similar extent as the independent variable *Measure of bankruptcy risk.*

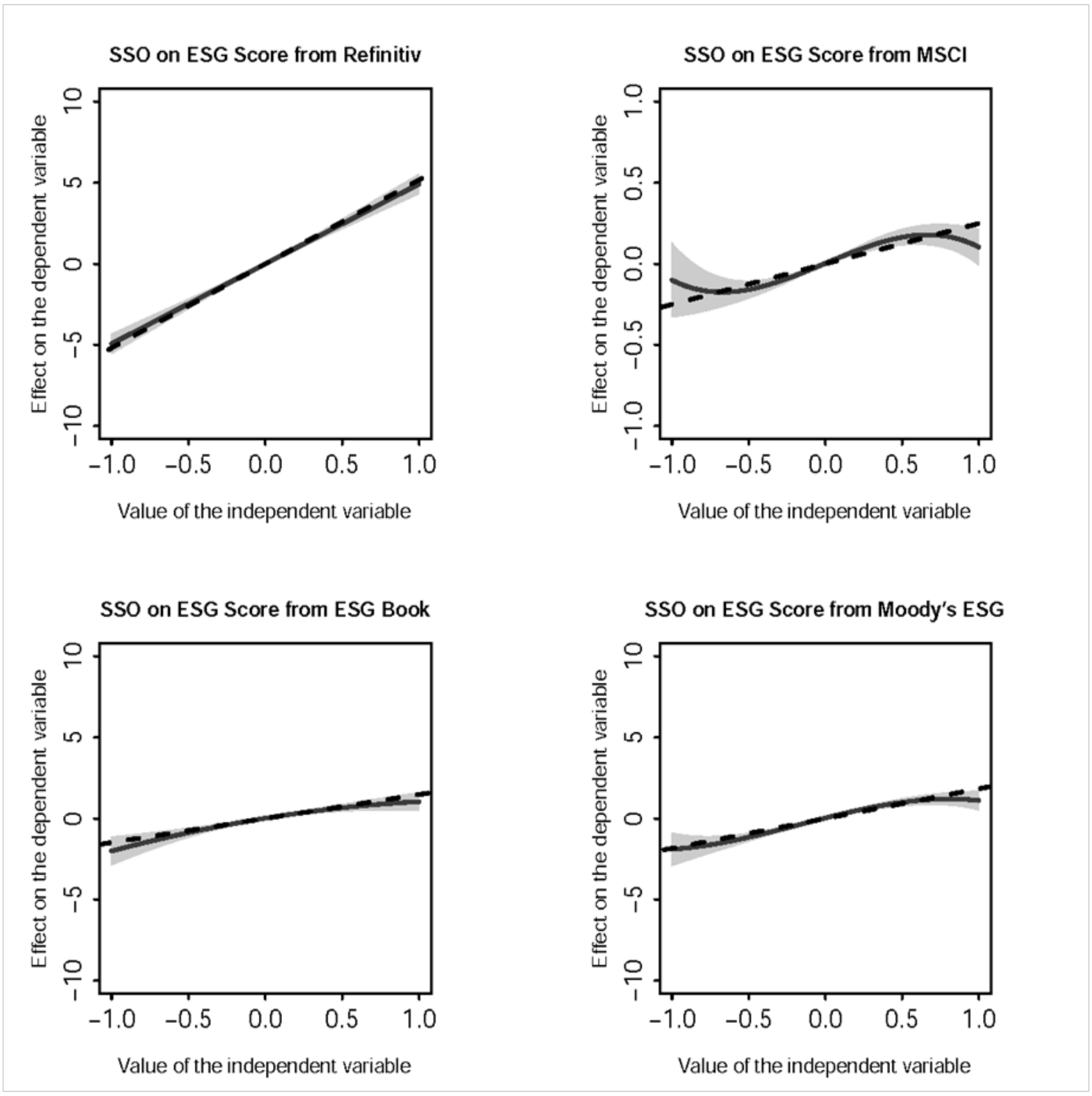
Figure 5.7 depicts the spline patterns of the independent variable *Shareholder-stakeholder orientation* for the additive regression models ARM1-SSO–ARM4-SSO that consider four different ESG scores as dependent variables. Figure 5.7 reveals a positive and almost linear relationship between the independent variable *Shareholder-stakeholder orientation* and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The 95% confidence bands are very narrow and do not allow any other conclusion. As a result, the most plausible interpretation of the revealed U-shaped relationship between the measure of bankruptcy risk and ESG scores is that companies anticipate their upcoming financial distress and mimic the stakeholder-oriented behavior of financially healthy companies by emphasizing ESG objectives and intensifying ESG-supporting disclosures. The empirical finding suggests that financially distressed companies manage their ESG scores upward by increasing their stakeholder-oriented reporting, expressed by the groups addressed in the 10-K filings.

Table 5.12: Results of the additive regression models ARM1-SSO–ARM4-SSO.

Regression model	ARM1-SSO	ARM2-SSO	ARM3-SSO	ARM4-SSO
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Shareholder-stakeholder orientation	1.000***	2.923***	1.814***	2.821***
Total assets	2.978***	2.847**	2.721**	1.000***
Buy-and-hold stock return	2.947***	1.000***	1.091***	1.000
Stock return volatility	2.859*	1.000**	1.800**	2.203***
Tobin's Q	1.000	1.000	2.976***	2.866***
Market value of equity	2.989***	2.990***	2.818***	2.988***
Market value to book value	1.000	1.876	1.286**	2.881**
Leverage	1.000***	1.000	1.074***	1.785*
Return on equity	1.000	1.000*	1.956*	1.624
Return on assets	1.111	1.000*	2.978***	2.837*
CapEx (3 years)	1.000***	1.000	2.594***	1.637***
R&D (3 years)	2.074***	1.000	2.927***	1.188
Dividend yield	2.958***	2.826*	1.250***	1.000***
Active ownership	1.000***	1.000*	2.802*	1.000
Institutional ownership	1.000***	1.000	1.000***	1.000
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	20,709	22,842	12,585	7,224
Adjusted R^2	0.376	0.100	0.120	0.311

This table shows the results (i.e., equivalent degrees of freedom) of the additive regression models ARM1-SSO–ARM4-SSO, where different ESG scores are applied as the dependent variable. The independent variables include the company variables that are defined in Table 5.2; the variable *Shareholder-stakeholder orientation* replaces the variable *Measure of bankruptcy risk*. All additive regression models take into account year-fixed, industry-fixed, and firm-fixed effects. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

Figure 5.7: Relationship between the *Shareholder-stakeholder orientation* (SSO) and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG.



This figure shows the estimated relationship between the *Shareholder-stakeholder orientation* and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. *Shareholder-stakeholder orientation* is plotted on the x-axis, and the ESG score is plotted on the y-axis. The values on the axes are deviations from the company mean value due to the within transformation. For better comparability, the value range of the x-axis was limited to [–1, 1]. The bold black line represents the estimated spline function, and the dashed line represents the estimated linear function. The 95% confidence band is shaded gray.

5.5.4 Regression results with exogenous shocks

The regression analysis is extended by two exogenous shocks that increased the financial distress of selected industries to distinguish between unexpected causes of financial distress and more predictable company-related causes. The first exogenous shock is the change in the US tariff policy in 2018. President Trump introduced new tariff policies in April and June 2018, particularly hurting manufacturing (SIC 2 and SIC 3) and wholesale and retail trade (SIC 5). The second exogenous shock is the COVID-19 pandemic in 2020 and the associated governmental measures to get the pandemic under control. The COVID-19 pandemic hit the world in the first quarter of 2020 and particularly negatively impacted transportation and public utilities (SIC 4), wholesale and retail trade (SIC 5), and services (SIC 7 and 8).

We extend the regression analysis and include a dummy variable that indicates the existence of an exogenous shock and an interaction effect between the dummy variable and the measure of bankruptcy risk. The dummy variable $d(Tariff\_2018)$ equals one if a firm-year observation is from 2018 and the company belongs to SIC 2, SIC 3, or SIC 5. The dummy variable $d(Covid19\_2020)$ equals one if a firm-year observation is from 2020 and the company belongs to SIC 4, SIC 5, SIC 7, or SIC 8.

This extended regression analysis shows that an exogenous shock increases companies' financial distress levels in an affected industry. The exogenous shocks happen quickly and are not foreseeable. Suppose such an unpredictable increase in financial distress is associated with a statistically significant increase in the ESG score. In that case, we cannot get any additional insight into the causality of how the level of financial distress influences the ESG scores. However, suppose such an unpredictable increase in financial distress is not associated with a statistically significant increase in the ESG score. In that case, we can add empirical evidence that only a predictable increase in financial distress resulting from poor corporate performance is very likely associated with an increase in the ESG score. The absence of a relationship between an unpredictable increase in financial distress and an increase in the ESG score can be demonstrated if the interaction effect between the dummy variable and the measure of bankruptcy risk is not statistically significant in the regression analysis. The conclusion would be that financially distressed companies with high stakeholder orientation will likely manage their ESG scores upward.

Table 5.13 shows the results of the extended additive regression models ARM1e–ARM4e. All extended additive regression models include the dummy variables $d(Tariff_2018)$ and $d(Covid19_2020)$ and the interaction effects between the dummy variables and the measure of bankruptcy risk $d(Tariff_2018)xMBR$ and $d(Covid19_2020)xMBR$. Comparable to the additive regression models ARM1–ARM4 in Table 5.6, the extended additive regression models ARM1e–ARM4e estimate the spline functions for the metric independent variables. As a result, Table 5.13 reports the equivalent degree of freedom for each metric independent variable, which indicates the nonlinearity in the estimated spline function. The interaction effects are metric variables and are modeled as spline functions. On the contrary, the dummy variables $d(Tariff_2018)$ and $d(Covid19_2020)$ are categorical variables for which Table 5.13 reports the estimated coefficients.

Table 5.13: Results of the extended additive regression models ARM1e–ARM4e with variables on exogenous shocks.

Regression model	ARM1e	ARM2e	ARM3e	ARM4e
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Measure of bankruptcy risk	2.946***	2.966***	2.785***	2.931***
Total assets	2.982***	2.891**	2.310**	1.000***
Buy-and-hold stock return	2.955***	1.000***	1.000***	2.886**
Stock return volatility	2.921***	1.595***	2.667***	2.197***
Tobin's Q	1.000	1.000**	2.962***	2.846*
Market value of equity	2.991***	2.989***	2.883***	2.984***
Market value to book value	1.598	1.968*	1.000**	1.734
Leverage	1.000***	1.000**	1.089***	1.781**
Return on equity	1.000	1.000*	1.869*	1.595
Return on assets	1.000	1.000	2.962***	2.808
CapEx (3 years)	1.000***	2.694	2.708***	1.661***
R&D (3 years)	2.063***	1.000	2.958***	1.000
Dividend yield	2.972***	2.719	2.609***	2.684***
Active ownership	2.874***	1.000*	2.781**	1.000
Institutional ownership	1.000***	1.000	1.122**	2.929*
d(Tariff_2018)	–0.934*	–0.017	–0.381	–0.853**
d(Tariff_2018) x MBR	1.817	1.000	1.145	1.000
d(Covid19_2020)	–0.789	–0.101*	–1.107***	–0.130
d(Covid19_2020) x MBR	1.000	1.000	1.619	1.000
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
N	23,890	26,563	14,390	8,139
Adjusted R^2	0.380	0.097	0.128	0.306

This table shows the results (i.e., equivalent degrees of freedom) of the extended additive regression models ARM1e–ARM4e, where different ESG scores are applied as the dependent variable. The independent variables include the company variables that are defined in Table 5.2. The variables $d(Tariff_2018)$ and $d(Covid19_2020)$ are dummy variables for which the estimated coefficients are reported. All additive regression models take into account year-fixed, industry-fixed, and firm-fixed effects. *, **, and *** represent significance levels of 0.05 [or 5%], 0.01 [or 1%], and 0.001 [or 0.1%], respectively.

The results of the extended additive regression models ARM1e–ARM4e in Table 5.13 are comparable to the additive regression models ARM1–ARM4 in Table 5.6. As a result, the introduction of the dummy variables and the associated interaction effects do not have any meaningful impact on the results. The estimated spline functions of the measure of bankruptcy risk do not change and are comparable to the spline functions displayed in Figure 3.2. The interaction effects exhibit equivalent degrees of freedom that are equal or close to 1 and not statistically significant. The linear regression model LRM-SSO and the additive regression model ARM-SSO, whose results are presented in Table 5.10, were also extended by the dummy variables that indicate the existence of an exogenous shock and the interaction effects between the dummy variable and the measure of bankruptcy risk. Again, the introduction of the dummy variables and the associated interaction effects do not have any meaningful impact on the results. Therefore, we conclude that the revealed U-shaped relationship between the measure of bankruptcy risk and ESG scores is based on financial distress due to failed corporate business rather than unforeseeable exogenous shocks that negatively affect selected industries or the entire economy. The empirical evidence suggests that the group of financially distressed companies tries to manage its ESG scores upward. The most likely cause is a company's self-inflicted financial distress, and one observable effect is increasing ESG scores induced by stakeholder-oriented ESG-supporting disclosures.

5.5.5 Robustness

The regression analysis revealed comparable U-shaped relationships between the measure of bankruptcy risk and four different ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. The empirical analysis consistently documents that financially distressed companies are associated with higher ESG scores and that this finding is mainly based on the environmental sub-factor. We substantiated the robustness of the empirical results in great detail by varying the applied data and the number of intervals for which each spline function was estimated.

The U-shaped relationships between the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG were revealed by applying additive regression models. A critical design element of additive regression models is the number of intervals for which each spline function was estimated. First, we checked the appropriateness of the applied number of intervals by performing the test recommended by (Wood (2017), section 5.9). The test is based on randomly sampled data and produces a test statistic that may widely vary if the test is replicated. Therefore, we repeated the test 100 times for the additive regression models ARM1–ARM4 to make a valid statement about the robustness of the additive regression models. The test statistic includes the k-index and the p-value. The further the k-index is below 1, the more likely it is that there is a missed pattern left in the data. Furthermore, low p-values with low k-index values may indicate that the applied number of intervals has been set too low. Table 14 shows the robustness check results regarding the number of intervals for the independent variable *Measure of bankruptcy risk*. The k-index is always close to 1, and most p-values are above 0.05, with a very high standard deviation at the same time. As a result, the applied number of intervals is appropriate to model the relationship between the measure of bankruptcy risk and the ESG scores. Nevertheless, we estimated the additive regression models using a larger number of intervals for all metric-independent variables. The U-shaped relationship between the measure of bankruptcy risk and the ESG scores is always recognizable and robust against any reasonable change in the number of intervals.

Table 5.14: Results on the robustness check regarding the number of intervals for the independent variable *Measure of bankruptcy risk.*

Regression model	ARM1	ARM2	ARM3	ARM4
Dependent variable	ESG score Refinitiv	ESG score MSCI	ESG score ESG Book	ESG score Moody's ESG
Number of random samples	100	100	100	100
k-index				
Minimum	0.94	0.95	0.95	0.96
Mean	0.98	0.99	0.99	0.99
Median	0.99	0.99	0.99	0.99
Maximum	1.02	1.03	1.03	1.02
Standard deviation	0.01	0.02	0.02	0.01
p-value				
Minimum	0.000	0.000	0.000	0.000
Mean	0.209	0.343	0.301	0.308
Median	0.138	0.258	0.198	0.245
Maximum	0.920	0.985	0.99	0.915
Standard deviation	0.224	0.289	0.282	0.251

This table shows the descriptive statistics on the test recommended by Wood (2017, section 5.9). The test was repeated 100 times. The test statistic includes the k-index and the *p*-value.

The applied final dataset and the derived final samples include firm-year observations from 2003 to 2022. We excluded from the dataset the last three years in which the COVID-19 pandemic occurred. The COVID-19 pandemic and the associated governmental measures to get the pandemic under control possibly led to distortions in the applied data. Another advantage of the shorter observation period 2003–2019 is that we do not consider ESG scores from Refinitiv, which are still changing. If there is new ESG-relevant information from an earlier year, the ESG scores from Refinitiv are adjusted. This applies, in particular, to ESG scores of the last few years. We repeated all linear and additive regressions with the ESG scores and the E-S-G sub-factors as independent variables and found similar relationships.

We examined the robustness of the regression models by varying the independent variable *Measure of bankruptcy risk*, and highly correlated independent variables. Thereby, the independent variable *Measure of bankruptcy risk* is varied by applying an alternative measure of bankruptcy risk that results from a gradient-boosting model rather than a logistic bankruptcy prediction model. The results of the regression models are robust against this variation of the measure of bankruptcy risk. Furthermore, we observed that the U-shaped relationships between the measure of bankruptcy risk and the ESG scores and their sub-factors (mainly, the environmental sub-factor) are more pronounced if the number of control variables is reduced or if industry-fixed effects are not taken into account.

We varied the procedure several times to refine the final dataset and analyze whether the applied procedure influenced the empirical results. We replaced missing values using the k-nearest neighbors algorithm, winsorized outliers at the 2nd and 98th percentiles, and eliminated outliers. The review showed that the empirical results are robust and not affected by the applied procedure to refine the final dataset.

We also reviewed whether the results of the independent variables *Energy intensity* and *Shareholder-stakeholder orientation* are robust. The applied data was varied in terms of the samples based on the available ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG, as well as the number of intervals for estimating each spline function. We also analyzed the variable *Shareholder-stakeholder orientation* by replacing the ESG score with the environmental sub-factor. The review showed that the extensions of the regression analysis about the independent variables *Energy intensity* and *Shareholder-stakeholder orientation* are robust against any reasonable change in the applied data and the number of intervals for which each spline function was estimated.

5.6 Conclusion

The empirical analysis provides evidence of a U-shaped relationship between the level of financial distress measured by the measure of bankruptcy risk and the ESG scores from Refinitiv, MSCI, ESG Book, and Moody's ESG. Above a certain threshold, financially distressed companies are associated with high ESG scores. The study not only provides a concrete answer to the empirical relationship between financial distress and ESG scores, but also works out a concrete cause-effect relationship between financial distress and ESG scores. Severe financial distress is the cause, and a high ESG score is the effect. Financially distressed companies intensify their cost-effective ESG activities, such as ESG-supporting disclosures and manage their ESG scores upward. The motivation for such behavior could be based on the need for a lower cost of capital and improved financing conditions that can be achieved through higher ESG scores, the management's desire to divert attention from financial failure, or the managerial incentive system which rewards ESG objectives that may be easier to achieve than financial objectives. In a follow-up study, the motivations behind the ESG disclosure policies of financially distressed companies need to be analyzed in more detail.

The cause-effect relationship between financial distress and ESG scores has been elaborated by first invalidating the reverse cause-effect relationship, stating that measures leading to a high ESG score are the cause and financial distress is the financial consequence of these measures based on empirical evidence. The interpretation of the narrow confidence bands of the additive regression models ARM1–ARM4, the unchanged regression analyses with multi-year capital expenditures and R&D expenditures, and the empirically unverifiable relationship between the measure of bankruptcy risk and *Energy intensity* are significant arguments against a reverse cause-effect relationship. Subsequently, empirical evidence was presented to support the actual cause-effect relationship between financial distress and ESG scores. This empirical evidence consists of the interpretation of the narrow confidence bands of the additive regression models ARM1–ARM4 and the regression analyses with the variable *Shareholder-stakeholder orientation*. Overall, there is empirical evidence of a pronounced stakeholder orientation for the group of financially distressed companies.

In addition, further insights were gained, which are fundamentally neutral in terms of a cause-effect relationship. Particularly, the U-shaped relationship can be observed regarding the environmental sub-factor of the analyzed ESG scores. The empirical analysis indicates that the U-shaped relationship is not affected by unforeseeable exogenous shocks such as President Trump's tariff policy in 2018 and the COVID-19 pandemic in 2020, as there is no statistically significant relationship between an increase in the measure of bankruptcy risk that results from an unpredictable exogenous shock and ESG scores. Furthermore, there is a consistent finding that a negative relationship exists between the market value of equity and the ESG score when the market value of equity is below the company's mean value, indicating that companies with a shrunken market value of equity are associated with higher ESG scores.

An overall picture can be put together from the individual empirical results. Financially distressed companies systematically manage their ESG scores upward by reinforcing the perception of their ESG activities and intensifying ESG-supporting disclosures. The motivation for such behavior is multifaceted and could be based on the need for lower cost of capital and improved financing conditions that can be achieved through higher ESG scores, the management's desire to divert attention from financial distress, or the managerial incentive system that rewards ESG objectives that may be easier to achieve than financial objectives. We can rule out with a probability bordering on certainty that ESG investments or other ESG-related operational measures increase ESG scores and cause financial distress as a side effect. The intensification of ESG-supporting disclosures relates primarily to the environmental sub-factor, meaning that the group of financially distressed companies can speak of systematic greenwashing. This systematic and planned influence on ESG scores is further supported empirically by the fact that only an unforeseeable increase in financial distress due to poor corporate performance is likely associated with an increase in ESG scores.

The management of ESG scores by the group of financially distressed companies reduces the validity and credibility of ESG scores and makes them less reliable. Due to the observed management of ESG scores by the group of financially distressed companies, it is imperative to consider a company's financial situation when interpreting ESG scores. If ESG scores are viewed in isolation, they may lead to an incorrect evaluation of financially distressed companies. As a result, the methodology for determining ESG scores in particular and ESG performance in general must be scrutinized. A methodology must be designed so that extensive distortions, such as those practiced by the group of financially distressed companies, are not possible or are at least shown transparently. On the other hand, the incentives that lead to such opportunistic behavior by the group of financially distressed companies must be examined more closely. These problem areas are urgent, as an increasing proportion of listed US companies are in financial distress (Lohmann and Möllenhoff 2023b). Notwithstanding this, the present study shows that stakeholders and ESG rating agencies should not be blinded by extensive ESG disclosure and that shareholders of financially distressed companies must insist that boards address financial matters first.

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Senior Hiring Impacts: An Alternative Data Perspective

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This Version

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Abstract

This study examines how the ratio of senior to other hires affects firm performance across industries using five years of LinkedIn hiring data for S&P 500 firms. It finds that large numbers of senior hires are initially associated with negative market reactions, but their impact stabilizes over time, suggesting a long-term positive effect on firm performance. Non-senior hires have no significant effect on stock returns, viewed as routine by the market. The study underscores the need to consider industry-specific factors in evaluating hiring practices and contributes to the literature on using alternative data to predict firm behavior.

Keywords: Hiring, Human Capital, Corporate Strategy, Workforce Composition, Labor Market Dynamics, Alternative Data

JEL classification: J24, L25, M51

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Declaration of Interest: None.

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6.1 Introduction

The impact of knowledge and experience on firm performance is crucial in economics, finance, and human resources research. While these intangible assets are known to influence corporate outcomes (Elsaid et al., 2011), quantifying their impact has been difficult due to limited data. This study fills that gap by using alternative data on firms' hiring patterns to measure the impact of knowledge and experience on firm performance.

Previous research shows that knowledge management improves firm performance (Darroch, 2005; Moustaghfir, 2008; Olavarrieta and Friedmann, 2008), making hiring a strategic goal, especially in knowledge-intensive sectors (Pulakos et al., 2003). Senior employees, associated with high-level expertise and strategic insights, are proxies for the impact of knowledge and experience. Non-senior hires generally support business growth or efficiency, controlling for operational workforce demand. By analyzing a unique dataset of monthly LinkedIn hiring data, collected over a five-year period for firms in the S&P 500, this study investigates the relative ratio of senior hires to other hires and explores how this ratio correlates with firm performance across various industries.

Despite the importance of hiring patterns, empirical research on these patterns using granular data across a broad sample of firms and industries is limited. This study addresses this by leveraging an extensive dataset to analyze hiring trends within firms and sectors.

The findings offer valuable insights for scholars and practitioners in economics, finance, and human resources. Understanding how hiring employees with knowledge and experience impacts firm performance can enhance human capital theories. For investors and analysts, these trends may indicate a firm's financial performance.

This study also contributes to the growing literature on alternative data, including data from social media used for stock performance prediction. While Twitter and Glassdoor data have been used in previous studies (Rao and Srivastava, 2012; Ranco et al., 2015; Bartov et al., 2018; Dube and Zhu, 2021; Chen et al., 2023), LinkedIn data has not, making this research a novel contribution.

The paper is structured as follows: First, the dataset and methodology are described, including ratio calculations and regression models. The findings are then presented, focusing on industry-level insights. Finally, implications are discussed, limitations acknowledged, and future research directions suggested.

6.2 Data

The dataset utilized in this study is sourced from company pages on LinkedIn, capturing detailed hiring data for firms listed in the S&P 500 index through an automated script. This unique dataset provides monthly updates since 2019 and includes the following key metrics:

- Total number of employees
- Number of senior management and other hires[15]

Additionally, several calculated metrics are included, such as:

- Changes in total headcount
- Percentage of senior and other hires relative to total headcount
- Ratio of senior to other hires
- Dummy variables on senior and other hires

Hiring trends are visually represented in Figures 6.4 to 6.8 in the Appendix. The ratio of senior hires to other hires is calculated to assess the balance between strategic leadership acquisition and operational staffing.

To enrich the analysis, this dataset is merged with financial data from Refinitiv and Bloomberg, allowing for an examination of stock returns and other financial metrics, including the Fama-French 5 factors plus momentum. Given the monthly frequency of data collection, all subsequent analyses are conducted on a monthly basis. In total, the dataset comprises 17,352 observations. Table 6.6 provides a summary of the key variables used in the analysis.

6.3 Methodology

This study employs an event-study approach using a constant mean model to assess the impact of hiring on firm performance. The event window spans from three months before the hiring event to six months after, allowing time for the effects of the hire to manifest (see Figure 6.3 in the appendix).

Following the methodology of MacKinlay (1997), expected returns (μ_i) are modeled as constant over time:

$$R_{it} = \mu_i + \epsilon_{it} \tag{6.1}$$

[15]Senior hires are defined as employees with current or previous titles of "Vice President" or higher.

where R_{it} represents the actual return for firm i on day t, μ_i is the expected (mean) return for firm i, and ϵ_{it} is the error term, with $E(\epsilon_{it}) = 0$ and $Var(\epsilon_{it}) = \sigma^2$.

The abnormal return (AR_{it}) for firm i on day t is calculated as the difference between the actual return (R_{it}) and the expected return (μ_i):

$$AR_{it} = R_{it} - \mu_i \tag{6.2}$$

To aggregate the abnormal returns across multiple firms, the average abnormal return (AAR_t) is calculated as the mean of the abnormal returns (AR_{it}) across all N firms for each time period t:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{6.3}$$

Finally, the cumulative abnormal return ($CAR_i(t_1, t_2)$) and cumulative average abnormal return ($CAAR(t_1, t_2)$) are obtained by summing the abnormal returns over the desired period:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \quad \text{and} \quad CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t \tag{6.4}$$

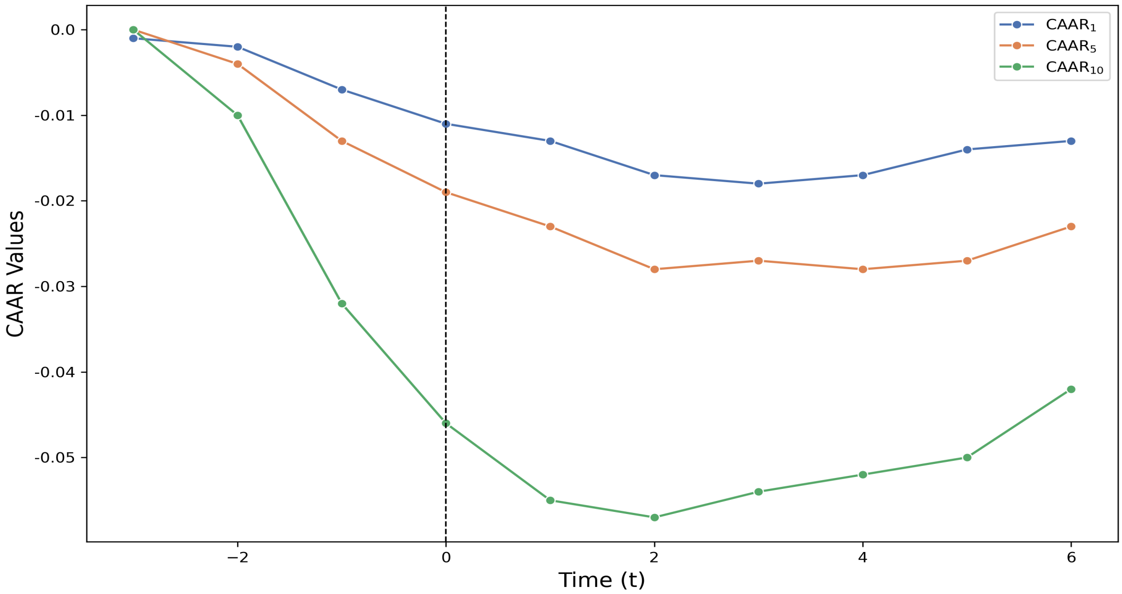
The CAARs will be tested for statistical significance. Additionally, a regression analysis will be conducted to estimate the impact of various variables. In this analysis, returns will serve as the dependent variable. The independent variables will be derived from the dataset, with Fama and French's five factors and momentum included as control variables.

6.4 Results

6.4.1 Event-study

To examine the impact of knowledge and experience on firm performance, proxied by senior hires while controlling for operational workforce demand, an event study was conducted. It uses dummy variables representing senior and other hires to estimate the event dates. The dummy variables were constructed with three different thresholds, where the dummy equals 1 if there were at least 1, 5, or 10 senior hires or 10, 50, or 100 regular hires within a given month. The results are presented in Figures 6.1 and 6.2.

Figure 6.1: Comparison of CAARs of senior hires for different thresholds.



The analysis shows that CAARs for senior hires, which serve as a proxy for the impact of knowledge and experience, decline across all thresholds leading up to the hiring event, with a more pronounced drop as the threshold of the number of hires increases. This suggests that the company's stock is bearish and the market might anticipate potential short-term disruption associated with the integration of new knowledge and experience. Post-event, the CAARs continue to decrease initially, particularly for the threshold of 10 senior hires, indicating a continued negative market reaction. While all scenarios show some recovery after the event, this recovery is limited for higher thresholds compared to the start of the pre-event window.

In contrast, the CAARs for other hires, which control for the actual operational demand for workforce, show a less pronounced decline leading up to the hiring event and a quicker recovery post-event across all thresholds. This indicates that the market perceives the hiring of operational workforce as a less disruptive event and a signal of potential growth or increased efficiency.

The event study for other hires exhibits a similar initial decline in CAARs across different thresholds, followed by varying degrees of recovery. The results suggest that while the market reacts negatively to substantial hiring activity in general, the recovery is more uniform and modest compared to the steeper drops observed in the senior hiring scenarios.

Overall, these results indicate that both senior and other hires trigger negative market reactions, with the severity and recovery patterns varying depending on the number of hires. The initial decline in CAARs, particularly for senior hires, with the eventual stabilization suggests that hiring could impact firm performance, especially when the number of hires is lower.

Figure 6.2: Comparison of CAARs of other hires for different thresholds.

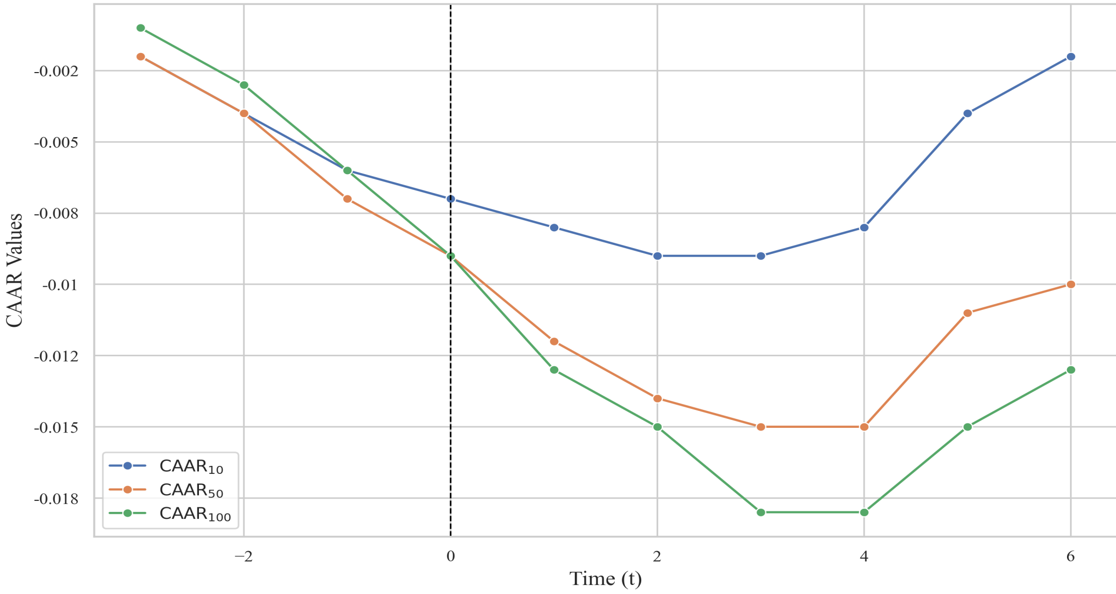


Table 6.1: CAARs and t-statistics for senior and other hires in event windows [-3,0] and [0,0].

Event Windows	**[-3,0]**		**[0,0]**	
Threshold	**CAAR**	**T-stat.**	**CAAR**	**T-stat.**
Senior hires				
1	-0.01***	-3.96	-0.004***	-2.86
5	-0.018***	-3.49	-0.005*	-1.87
10	-0.037***	-3.74	-0.009*	-1.75
Other hires				
10	-0.007***	-4.79	-0.001	-0.88
50	-0.009***	-5.69	-0.002***	-2.81
100	-0.009***	-5.29	-0.003***	-3.68

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

The analysis of CAARs and t-statistics across various event windows highlights distinct market reactions to senior versus other hires (see Tables 6.1 and 6.2). In the event windows [-3,0] and [0,0], the market reacts more negatively to senior hires, with significant declines in CAARs, particularly at higher thresholds of hires. This is in line with the observations in the charts above and suggests that during the hiring, the stock shows negative momentum, though the immediate impact post-event is slightly less severe.

In contrast, while other hires also trigger negative CAARs, the declines are smaller, and the market appears less concerned. However, a recovery is observed in the [3,6] window for both senior and other hires, particularly at higher thresholds. This recovery is more pronounced for senior hires, indicating that the market may have initially overreacted and later adjusts its expectations as the benefits of the hires become clearer. Overall, the market's response to hiring events is more sensitive and initially negative for senior hires but shows signs of recovery as the integration process progresses.

Overall, these results indicate that both senior and other hires trigger negative market reactions, with the severity and recovery patterns varying depending on the number of hires. The initial decline in CAARs, particularly for senior hires, with the eventual stabilization suggests that hiring could impact firm performance, especially when the number of hires is lower.

Table 6.2: CAARs and t-statistics for senior and other hires in event windows [0,3] and [3,6].

Event Windows	**[0,3]**		**[3,6]**	
Threshold	**CAAR**	**T-stat.**	**CAAR**	**T-stat.**
Senior hires				
1	-0.01***	-3.93	0.011***	4.25
5	-0.008	-1.63	0.017***	3.29
10	-0.002	-0.16	0.045***	4.45
Other hires				
10	-0.002	-1.56	0.01***	6.87
50	-0.007***	-4.57	0.008***	5.04
100	-0.011***	-6.01	0.007***	4.1

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

6.4.2 Regression analysis

Overall analysis

The event study suggested a potential link between stock returns and hiring activity, but with some delay. To further investigate this relationship, a regression analysis was conducted using various versions of hiring-related variables to assess their impact on stock returns. The results, presented in Table 6.3, show that senior hires have a statistically significant negative effect on all return measures, with significance at the 1% or 5% level. This finding indicates that an increase in senior hires is consistently associated with a decrease in returns, supporting the notion that at the time of hiring, the impact seems to be negative.

In contrast, the coefficients for variables representing other hires are not statistically significant across the models, suggesting that these hires do not have a measurable impact on stock returns. This outcome aligns with the idea that senior hiring is more strategically significant compared to other types of hires.

A change in employee count is also positively associated with stock returns, even though the impact is very low. The number of senior hires divided by other hires is highly significant and has a negative coefficient, indicating that a higher ratio of senior hires relative to other hires is associated with lower returns. This suggests that firms heavily investing in senior positions, relative to operational roles, may not see immediate positive returns. This variable seems to be crucial for understanding the balance between strategic and operational hiring and its impact on firm performance and is used in the future analysis.

Table 6.3: Detailed regression results.

Dep. Variable	Returns					
No. Observations	17352	17352	17352	17352	17352	17352
R-squared	0.3600	0.3603	0.3603	0.3605	0.3600	0.3607
F-statistic	1626.1	1220.9	1085.3	1396.5	1393.9	1223.2
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Const.	-0.0001	0.0006	-0.0011	0.0006	-0.0001	-0.0002
	(-0.0433)	(0.3297)	(-0.6527)	(0.3551)	(-0.0524)	(-0.1330)
Mkt-RF	0.9607***	0.9605***	0.9614***	0.9612***	0.9606***	0.9613***
	(35.1010)	(35.0000)	(34.8600)	(35.0140)	(35.0870)	(34.5280)
SMB	0.0991	0.0978	0.1007	0.0980	0.0994	0.0997
	(1.2751)	(1.2618)	(1.3011)	(1.2602)	(1.2794)	(1.2720)
HML	0.1821***	0.1820***	0.1799***	0.1818***	0.1821***	0.1795***
	(3.6943)	(3.7093)	(3.6714)	(3.6915)	(3.6955)	(3.6235)
RMW	0.1237	0.1225	0.1240	0.1221	0.1242	0.1246
	(1.4246)	(1.4082)	(1.4314)	(1.4046)	(1.4301)	(1.4258)
CMA	0.0557	0.0562	0.0591	0.0572	0.0557	0.0602
	(0.7141)	(0.7238)	(0.7603)	(0.7357)	(0.7137)	(0.7723)
MOM	-0.0893**	-0.0904**	-0.0900**	-0.0895**	-0.0892**	-0.0909**
	(-2.3872)	(-2.4079)	(-2.3934)	(-2.3890)	(-2.3815)	(-2.3932)
Number Senior Hires		-0.0005**				
		(-2.2916)				
Number Other Hires		0.0000				
		(0.4305)				
Percentage of Senior Hires			-2.0118			
			(-0.0000)			
Percentage of Other Hires			1.0568			
			(0.0000)			
Percentage of Total Hires			-0.9551			
			(-0.0000)			
Senior Hires to Other Hires				-0.0681***		
				(-3.0825)		
Employee Count Change					0.0001***	
					(4.8201)	
Dummy Senior Hires						-0.0075***
						(-3.8943)
Dummy Other Hires						0.0075
						(1.3380)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

The regression analysis also confirms the influence for HML and MOM, while other control variables, such as SMB, RMW, and CMA, show no sign of significance. The later stock reaction to hires, with a first continuation of a decline in stock prices as seen in the event study charts above, could explain the negative reaction of momentum, while the stocks seem to benefit from the value premium. Notably, size isn't significant, so the explanation that larger companies tend to hire more than smaller companies cannot be agreed upon.

Notably, the introduction of hiring variables into the models does not substantially alter the coefficients of the control variables, indicating that hiring activity does not significantly influence the relationship between these control variables and stock returns.

Lead and lag analysis

To examine the impact on both past and future returns, cumulative returns were calculated for leading and lagging periods of 3, 6, and 12 months. The results are presented in Table 6.4.

The variable representing the hiring of senior employees compared to other employees shows significant negative coefficients across all three time horizons for past cumulative returns. Notably, a strong negative impact is observed for the 3-month, 6-month, and even 12-month past cumulative returns, indicating a potential association between comparably higher senior hiring and lower past returns. In contrast, the mixed coefficients for future cumulative returns are insignificant, suggesting that senior hiring does not significantly predict future returns. For 3- and 12-month periods, positive coefficients are visible. The results for senior hiring in the event study are mirrored in the regression outcomes.

Table 6.4: Cumulative returns regression results.

Dep. Variable	3 Months		6 Months		12 Months	
	Lagging	Leading	Lagging	Leading	Lagging	Leading
No.Observations	17352	17352	17352	17352	17352	17352
R-squared	0.0700	0.0290	0.0431	0.0618	0.0476	0.0622
F-statistic	186.46	74.092	111.57	163.08	123.82	164.26
P-value(F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Const.	0.0267***	0.0219	0.0636***	0.0673***	0.1452***	0.1394***
	(2.6852)	(1.5313)	(3.1624)	(3.8252)	(4.8402)	(4.9696)
Mkt-RF	0.6595**	-0.2720	0.6834*	-0.3007	0.9976*	-0.1914
	(2.3112)	(-0.9082)	(1.8141)	(-0.7485)	(1.7865)	(-0.2828)
SMB	0.2851	1.2068**	-0.6693	2.1137***	-2.2505*	2.2536**
	(0.5116)	(2.2454)	(-0.7391)	(3.0688)	(-1.9410)	(1.9696)
HML	0.2809	-0.5850	0.7759	-0.7709	2.3043**	-2.6595**
	(0.6708)	(-1.2811)	(1.2620)	(-1.2024)	(2.2990)	(-2.3097)
RMW	-0.3205	0.5126	-0.4563	0.2226	-0.0746	0.4733
	(-0.7740)	(0.8976)	(-0.6986)	(0.2959)	(-0.0640)	(0.3853)
CMA	0.1708	0.3708	-0.3120	-0.3324	-1.6139	1.0880
	(0.2924)	(0.5621)	(-0.3285)	(-0.3591)	(-1.2023)	(0.7871)
MOM	0.0345	0.2116	-0.3999	0.4429	0.0407	0.1153
	(0.1291)	(0.7865)	(-0.7979)	(1.0095)	(0.0502)	(0.1471)
Senior Hires to Other Hires	-0.1134***	0.0126	-0.1574**	-0.0038	-0.3115**	0.0010
	(-3.0787)	(0.2495)	(-2.4321)	(-0.0473)	(-2.5263)	(0.0087)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

The control variables also exhibit some interesting patterns. The size factor (SMB) has a significant positive impact on leading returns for the 3-month and 6-month periods, and a significant negative impact on lagging returns for the 12-month period. The value factor (HML) has a significant positive impact on lagging returns and a significant negative impact on leading returns for the 12-month period. The other control variables (RMW, CMA, and MOM) do not show consistent significant effects across the different time horizons.

These findings suggest that the hiring of senior employees relative to other employees has a negative association with past stock returns, but does not significantly predict future returns. The size and value factor, also play a role in explaining the variation in cumulative returns over different time horizons.

6.4.3 Sector-specific impacts of hiring

As sectors might have different demands for knowledge among their hiring (Pulakos et al., 2003), a sector-wise analysis was conducted, reflecting the unique dynamics within each sector. The results are shown in Table 6.5.

The hiring variable shows significant negative coefficients in most sectors, including technology, industrials, utilities, finance, and energy, suggesting that a higher proportion of senior hires is associated with lower returns in these industries. This finding aligns with the results from the previous subsection. Conversely, the consumer staples sector exhibits a positive significant relationship.

Interestingly, the size factor (SMB) becomes significant in the consumer discretionary and utilities sectors, indicating that smaller firms in these industries may experience different returns relative to larger firms. Momentum loses significance in those sectors. Along with others, the tech sector, dominated by growth stocks, shows a negative coefficient for HML.

In summary, this sectoral analysis highlights the importance of considering industry-specific factors when evaluating the impact of hiring practices on returns. The varied results across sectors suggest that while some general trends exist, the unique operational environment within each sector plays a critical role in shaping the outcomes of hiring decisions on financial performance.

Table 6.5: Regression results for different sectors.

	Cons. Discr.	**Tech.**	**Indus.**	**Materials**	**Health Care**	**Utilities**	**Finance**	**Telecom.**	**Energy**	**Real Estate**	**Cons. Stap.**
No. Observations	2866	2007	3267	641	2139	1111	2146	270	709	1125	1071
R-squared	0.3922	0.4357	0.4845	0.4367	0.2528	0.3540	0.5201	0.3282	0.5138	0.4612	0.2806
F-statistic	263.42	220.52	437.49	70.094	102.98	86.341	331.08	18.289	105.81	136.59	59.232
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Const.	0.0001	0.0062**	-0.0002	-0.0013	-0.0013	-0.0034	0.0020	-0.0053	0.0167**	-0.0083**	-0.0040
	(0.0377)	(2.1294)	(-0.0644)	(-0.2413)	(-0.3277)	(-0.6340)	(0.7043)	(-1.4517)	(2.0771)	(-2.0094)	(-1.2270)
Mkt-RF	1.1252***	1.0204***	0.9748***	1.0324***	0.8692***	0.6830***	0.9664***	0.8460***	1.5472***	0.9017***	0.4925***
	(13.340)	(16.327)	(21.513)	(9.5572)	(10.122)	(6.2134)	(16.649)	(5.7676)	(6.7961)	(9.4247)	(6.1844)
SMB	0.3620***	0.0921	0.1375	0.1837	0.1194	-0.6075***	0.0171	-0.0705	0.1132	0.0914	0.0992
	(2.9463)	(0.6949)	(1.1224)	(0.8059)	(0.7049)	(-2.8114)	(0.0979)	(-0.4906)	(0.2858)	(0.4368)	(0.7120)
HML	0.2236**	-0.1478*	0.2263***	0.2414	-0.2569**	0.2137	0.6828***	-0.2590*	1.1531***	0.1462	-0.1439
	(2.1496)	(-1.8516)	(3.3602)	(1.4018)	(-2.0836)	(1.2894)	(6.2959)	(-1.8230)	(4.5425)	(0.9424)	(-1.4964)
RMW	0.2321	0.0915	0.3449**	0.1655	0.2012	0.0944	-0.2113*	0.2189***	-1.1399***	0.2777	0.3415*
	(1.3497)	(0.5683)	(2.5344)	(0.7547)	(0.8554)	(0.3661)	(-1.7415)	(2.6978)	(-2.9924)	(1.4796)	(1.7116)
CMA	-0.1485	-0.0989	-0.1498	0.4104*	0.4119**	0.1910	-0.2984**	0.4903***	0.5724*	0.0499	0.7538***
	(-0.9679)	(-0.7672)	(-1.2408)	(1.7130)	(2.3997)	(0.7831)	(-2.0348)	(3.5645)	(1.7889)	(0.2436)	(4.9585)
MOM	-0.1372	-0.2008***	-0.0938	-0.2589**	0.0917	0.0309	-0.0202	-0.0316	-0.1860	-0.2007*	-0.1010
	(-1.3818)	(-3.6015)	(-1.5414)	(-2.0242)	(1.2697)	(0.2412)	(-0.2452)	(-0.3973)	(-0.6206)	(-1.6616)	(-1.3040)
Senior Hires to Other Hires	-0.0618	-0.0679**	-0.0784**	0.0326	0.1754	-0.1858***	-0.1078***	0.3648	-0.6882***	-0.0419	0.2057**
	(-1.3977)	(-2.4627)	(-2.4302)	(0.0987)	(0.5554)	(-4.3790)	(-2.6870)		(-3.3544)	(-1.3622)	(2.0051)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

6.5 Conclusion

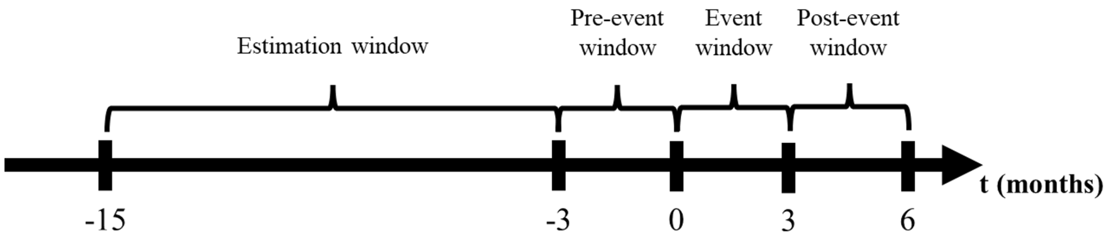
This study explores the impact of senior hires on firm performance, finding that these hires often occur during periods of negative stock returns, especially to large numbers of senior hires. However, the analysis indicates that after an initial adjustment period, the negative impact stabilizes, suggesting senior hires eventually contribute positively to firm performance. A sector-specific analysis reveals that industry factors significantly influence how hiring affects returns, with varied outcomes across sectors.

Moreover, this study contributes to the growing literature on the use of alternative data sources in understanding and predicting firm behavior. The data used in this research, derived from LinkedIn, provides a novel perspective on the impact of hiring patterns on firm performance, highlighting the potential of such data to offer insights that traditional financial data may not capture.

Future research could investigate the conditions under which senior hires have the most stabilizing effects and how these effects vary by industry or economic cycle.

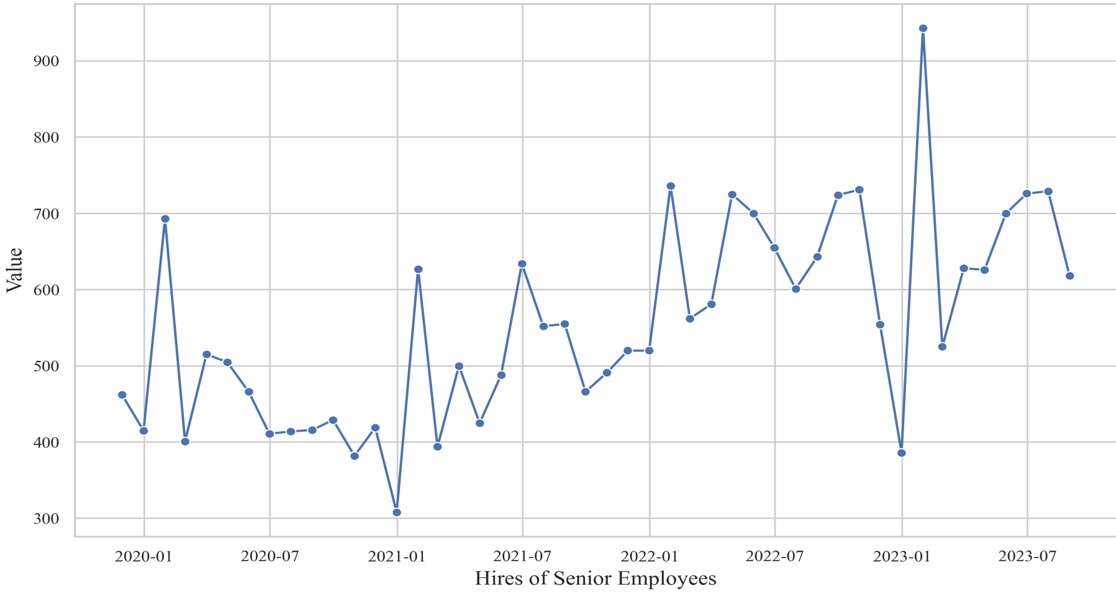
Appendix: Figures and Tables

Figure 6.3: Timeline of an event study.



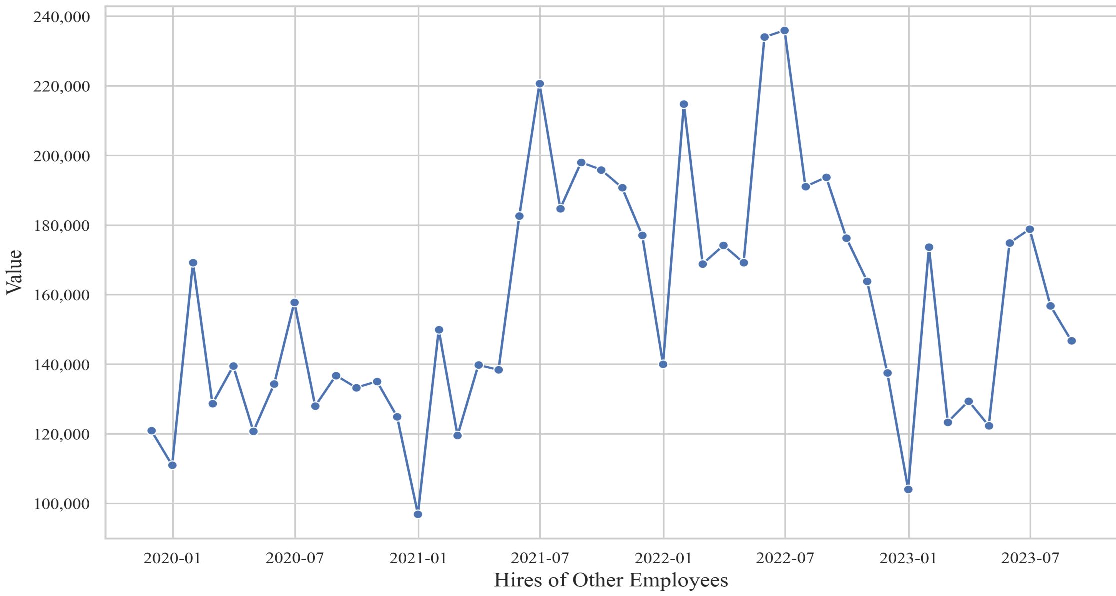
The figure illustrates the typical timeline of an event study, outlining key periods such as the estimation window, the event window, and the post-event window.

Figure 6.4: Senior management hiring over time.



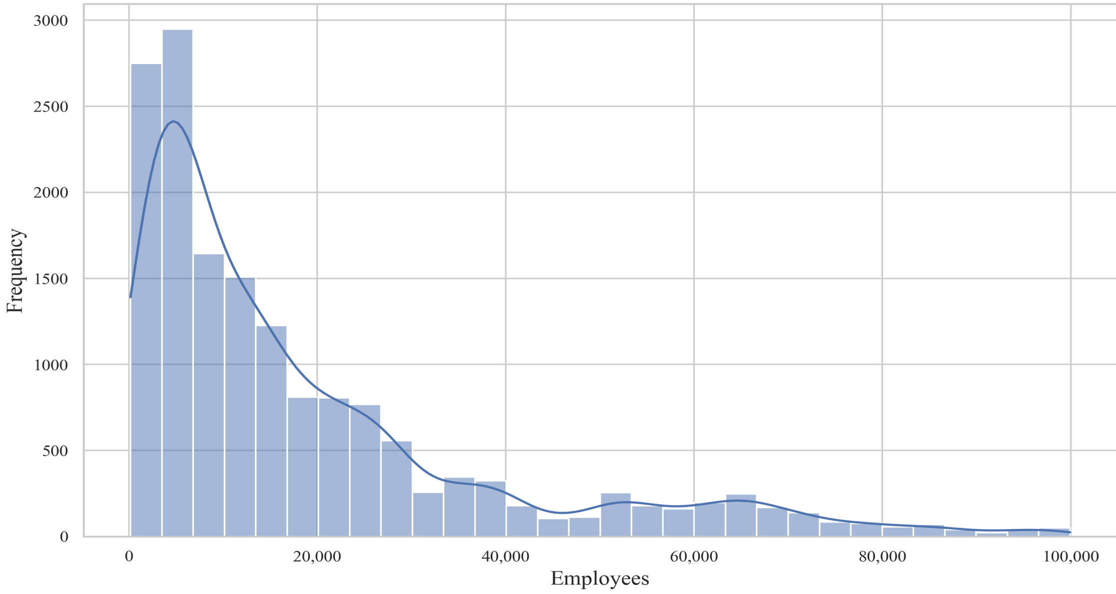
The chart shows the aggregated number of hiring of senior employees over time.

Figure 6.5: Other hiring over time.



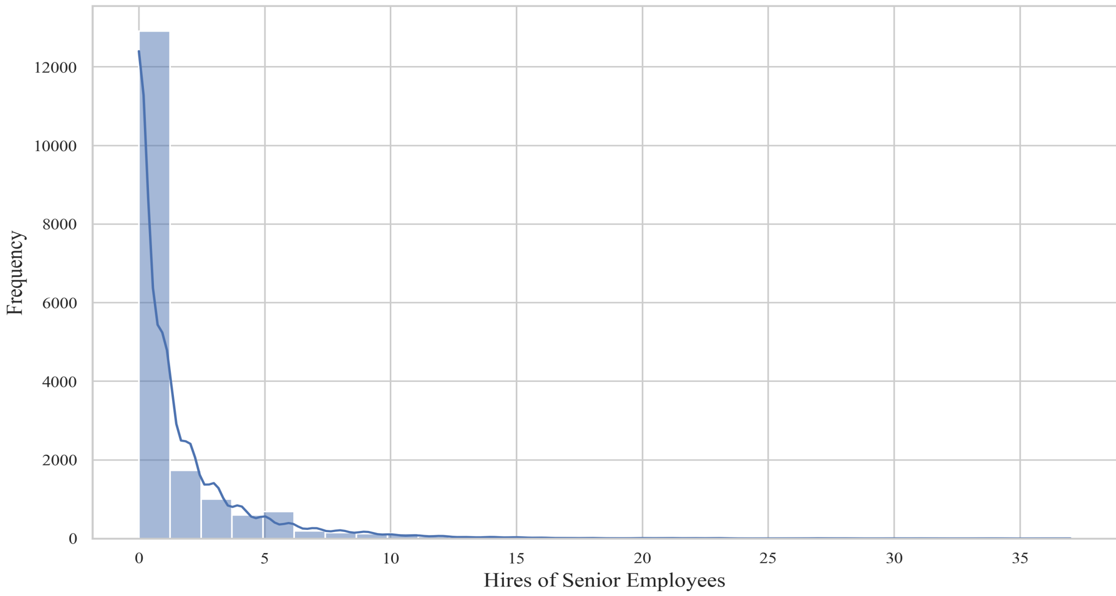
The chart shows the aggregated number of hiring of non-senior employees over time.

Figure 6.6: Total headcount distribution.



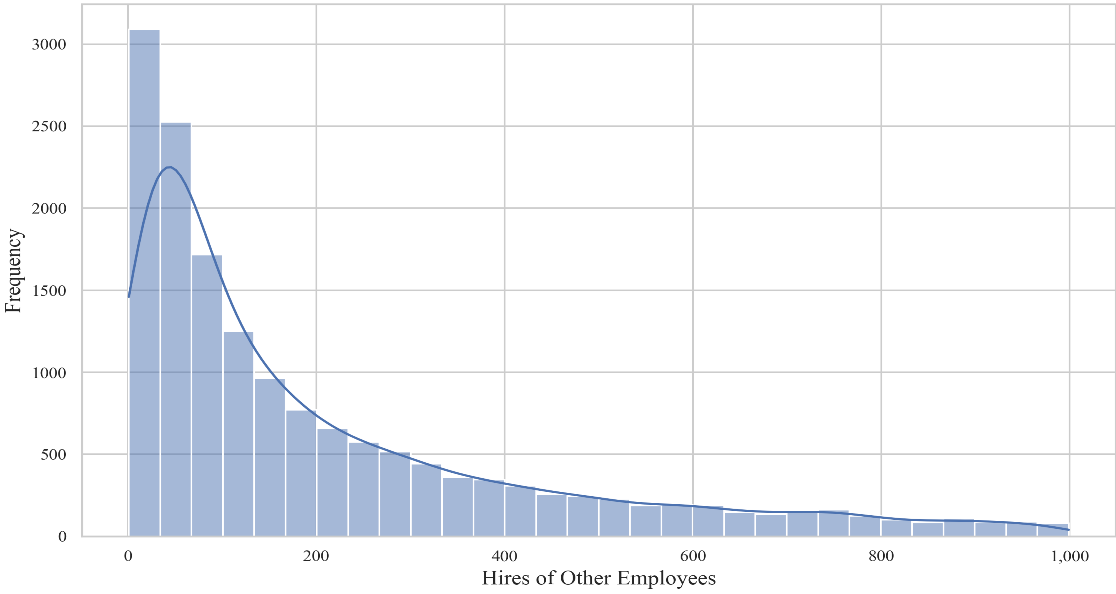
The chart shows the distribution of total employees per company (capped at 100,000 visual reasons).

Figure 6.7: Senior management hiring distribution.



The chart shows the distribution of number of hiring of senior employees (capped at 40 for visual reasons).

Figure 6.8: Other hiring distribution.



The chart shows the distribution of number of hiring of non-senior employees (capped at 1,000 visual reasons).

Appendix: Variable definitions

Table 6.6: Variable definitions

Variable Name	Definition	Calculation	Source
Total Employees	Number of employees of a company.	N/A	LinkedIn company website
Change in Employee Count	Monthly change in employees.	Percentage change of Total Employees.	LinkedIn company website
Number Senior Hires	People that joined the company with previous or current titles as Vice President or higher as reported by LinkedIn members at this company.	N/A	LinkedIn company website
Number Other Hires	People that joined the company as reported by LinkedIn members at this company.	N/A	LinkedIn company website
Percentage of Senior Hires	Percentage of Senior Hires compared to total headcount.	Number Senior Hires divided by Total Employees	LinkedIn company website
Percentage of Other Hires	Percentage of Other Hires compared to total headcount.	Number Other Hires divided by Total Employees	LinkedIn company website
Percentage of Total Hires	Percentage of Senior and Other Hires compared to total headcount.	Number Senior and Other Hires divided by Total Employees	LinkedIn company website
Ratio of Senior Hires to Other Hires	Senior Hires divided by Other Hires.	Number Senior Hires divided by Other Hires	LinkedIn company website
Dummy Senior Hires	Dummy variable for senior hires.	Equals 1 if there are at least 5 senior hires within a given month.	LinkedIn company website
Dummy Other Hires	Dummy variable for other hires.	Equals 1 if there are at least 2.5% other hires within a given month.	LinkedIn company website
Return	Return of the corresponding stock in USD.	$\text{Return} = \frac{\text{Price}_t - \text{Price}_{t-1}}{\text{Price}_{t-1}}$	Refinitiv/Bloomberg
Const	Intercept term for the regression model.	Constant value (= 1)	N/A
Mkt-RF	Excess return on the market portfolio over the risk-free rate.	Market Return − Risk-Free Rate	Fama-French Database
SMB	Size factor (Small Minus Big).	Difference in returns between small-cap and large-cap portfolios	Fama-French Database
HML	Value factor (High Minus Low).	Difference in returns between high book-to-market and low book-to-market portfolios	Fama-French Database
RMW	Profitability factor (Robust Minus Weak).	Difference in returns between firms with robust and weak profitability	Fama-French Database
CMA	Investment factor (Conservative Minus Aggressive).	Difference in returns between firms with conservative and aggressive investment policies	Fama-French Database
MOM	Momentum factor.	Difference in returns between portfolios of stocks with high past returns and those with low past returns	Fama-French Database

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Balancing Dispersion and Agglomeration: How Workforce Geography influences Corporate Performance

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This Version

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Abstract

This paper examines the impact of workforce geographic distribution on the financial performance of S&P 500 companies, focusing on stock returns and gross profit margins across sectors. Using LinkedIn data as an alternative data set on employee locations, the analysis finds that increased workforce dispersion can positively influence stock returns in sectors like technology, while posing challenges for profit margins, particularly in utilities. These findings highlight the importance of considering sector-specific factors when making strategic decisions about employee location, as the benefits of geographic dispersion are not uniform across industries.

Keywords: Geographic Workforce Distribution, Human Capital, Remote Work, Employee Location, Alternative Data

JEL classification: J24, O15, R23

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7.1 Introduction

In a world that is increasingly interconnected through digital technologies and globalization, the geographic distribution of a company's workforce has gained significant attention from both academics and business leaders. The shift towards remote work, particularly accelerated by the COVID-19 pandemic, has underscored the need to understand how the location of employees impacts corporate performance. This study seeks to explore the relationship between the geographic dispersion of employees and the financial performance of S&P 500 companies, focusing specifically on the effects observed since the pandemic began.

The geographical distribution of the workforce significantly impacts company performance, particularly through its effects on knowledge management, employee engagement, and workforce diversity. In organizations with distributed teams, efficient knowledge management is critical (Schneider et al., 2018; Slavković et al., 2021). Moreover, the diversity arising from geographical distribution can enhance organizational performance (Kundu and Mor, 2017; Tariq and Rehman, 2020; Guerrero, 2022). However, managing this diversity effectively is essential to prevent conflicts that may emerge from differing perspectives and backgrounds. Thus, robust governance and administrative systems are vital for addressing geographical disparities within the workforce (Roome et al., 2014). Companies often manage knowledge differently across locations and may prioritize certain divisions based on their proximity to headquarters, likely due to improved information flow and stronger social connections (Landier et al., 2009). The impact of these factors can vary across different industry sectors (Lucas et al., 2023).

This study analyzes the geographic distribution of the workforce in S&P 500 companies, investigating how this distribution influences company performance, particularly in terms of stock returns and gross profit margins. The analysis utilizes data from LinkedIn, focusing on the top 15 work locations for each company over a defined period. The study examines the relationship between the average distance of employees from corporate headquarters and stock performance, assessing whether a more dispersed workforce correlates with better or worse financial outcomes.

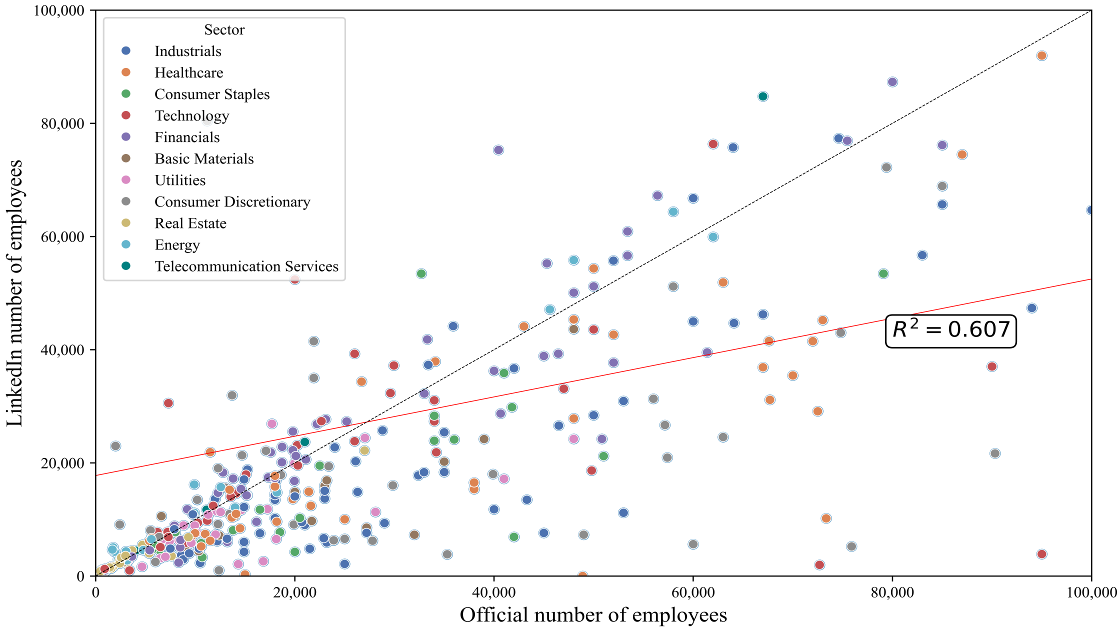
This research makes several contributions to the existing literature. It provides updated empirical evidence on how the geographic distribution of employees in large U.S. corporations impacts firm performance. Furthermore, the study contributes to the broader literature on the use of alternative data, including social media data, in assessing financial performance (Dessaint et al., 2024; Lehner, 2024).

The paper is structured as follows: Section 7.2 details the dataset and methodology, Section 7.3 presents the empirical results, and Section 7.4 discusses the implications of the findings and concludes the study.

7.2 Data

The dataset utilized in this study is derived from LinkedIn company pages and contains monthly data on the top 15 locations where employees are concentrated, ranked by the number of employees. The data has been filtered to include only locations within the United States. Given that some locations might be subsets of others (e.g., California being a subset of the entire United States), the data was hierarchically structured to create disjoint subsets. For instance, the number of employees in California was subtracted from the total number of employees in the U.S. to ensure that the remaining U.S. figure accurately represents only those employees not working in California.

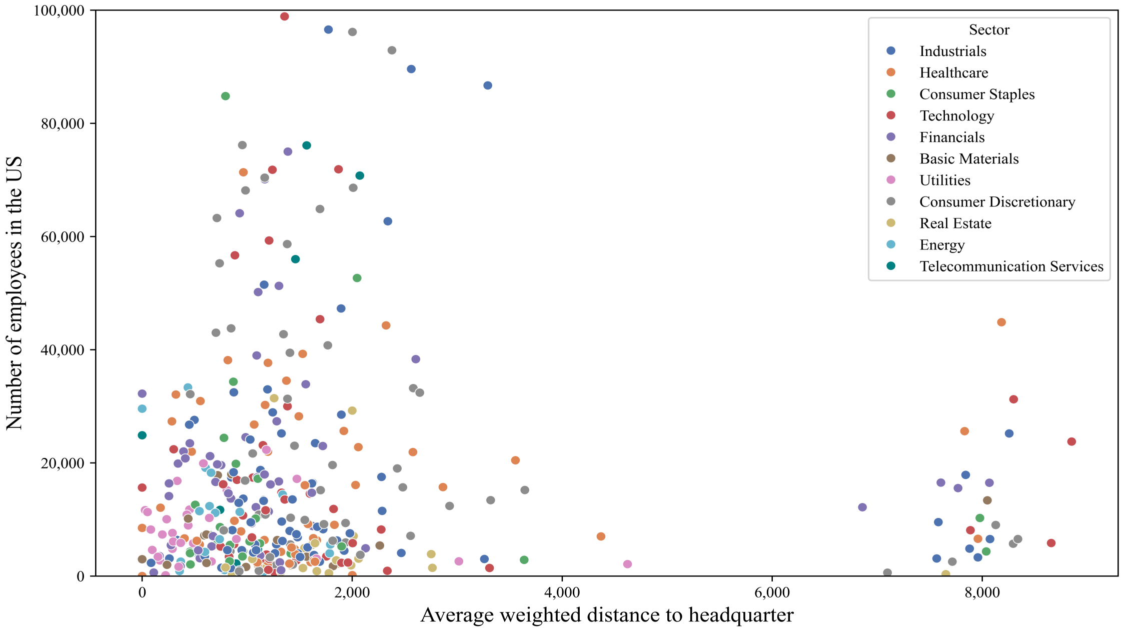
Figure 7.1: Biased number of employees on LinkedIn.



The addresses of company headquarters were extracted from the 10-Q filings to ensure the most up-to-date information corresponding to each month in the study period. For each location and month, the distance to the headquarters was calculated and weighted by the number of employees, resulting in a weighted average distance from the headquarters for each company and month.

Company-specific information, including stock data, was collected for subsequent analysis. It is important to note that from November 2022 to June 2023, LinkedIn temporarily reduced the number of listed locations from 15 to 10, which led to the omission of certain U.S. cities from the dataset. This limitation resulted in the exclusion of this period from the analysis, as calculations involving the ratio of employees in specific cities during this time would be unreliable compared to other periods. The final dataset encompasses 470 companies.

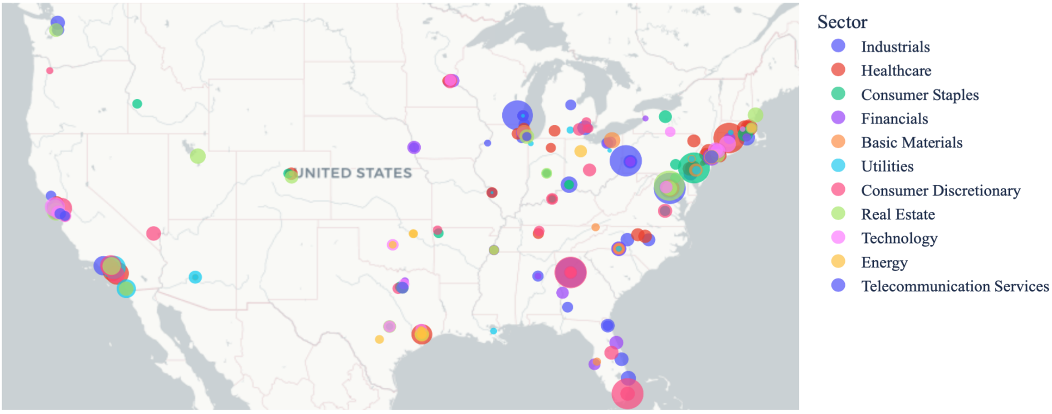
Figure 7.2: Average weighted distance to headquarter and number of employees on LinkedIn.



The dataset has some limitations compared to traditional data sets, as usual for alternative data. A notable bias exists towards industries that are overrepresented on LinkedIn, such as technology and finance, which could potentially skew the results. This bias is visually depicted in Figure 7.1. Additionally, inaccuracies might arise due to outdated or incomplete LinkedIn profiles, particularly for remote or hybrid workers who may list locations that do not reflect their actual work locations. The reliance on self-reported data introduces the possibility of an incomplete representation of workforce distribution. Despite efforts to cross-reference with other data sources, these biases may affect the generalizability and precision of the findings.

When comparing the average distance to the headquarter with the employees in the US, the data reveals an interesting pattern, as shown in Figure 7.2. Distances tend to cluster within two primary ranges: between 0 to 2,000 kilometers (1,240 mi) and around 8,000 kilometers (4,970 mi). This distribution likely reflects the broader geographical spread of companies across the United States. The map in Figure 7.3 visually represents the locations of these companies, with bubble sizes indicating the average distance of employees from the headquarters.

Figure 7.3: Geographic distribution and average weighted distance.



7.3 Results

The empirical analysis in this study employs a series of multivariate regression models to explore the relationship between the geographic distribution of a company's workforce and its stock performance, specifically within the S&P 500. The primary dependent variable in these regressions is the company's stock return and the gross profit margin, while the independent variables focus on a measure of employee distribution: the weighted average distance of employees from the corporate headquarters. To ensure robustness and account for broader market influences, the models incorporate the Fama-French five factors as well as the momentum factor and the natural logarithm of the market capitalization as control variables.

7.3.1 Overall regression analysis

The combined regression analysis reveals several important insights regarding the relationship between geographic distribution of employees and company performance, measured by stock returns and gross profit margins.

One of the most notable findings is the positive and significant relationship between the average weighted distance of employees from the company headquarters and stock returns. This relationship, significant at the 1% level, indicates that companies with a more geographically distributed workforce tend to experience higher stock returns. This suggests that geographic dispersion, possibly reflecting broader market reach or operational flexibility, could be an advantage in enhancing market performance.

The regression model for gross profit also show statistically significant results. Within this model, the natural logarithm of market capitalization shows a strong positive relationship with gross profit margins, suggesting that larger companies tend to achieve higher profitability. Furthermore, the average weighted distance to headquarters also has a significant positive impact on gross profit margins, indicating that a more dispersed workforce may contribute to higher profitability, potentially through operational efficiencies or enhanced market reach.

Given the observed relationships between geographic distribution of employees and overall company performance, it is important to consider that these effects may not be uniform across all industries. Different sectors might exhibit varying sensitivities to workforce dispersion due to distinct operational characteristics, market demands, and business models. To gain a deeper understanding of how these dynamics play out across different industries, it is essential to conduct a sector-specific analysis in the next subsection.

Table 7.1: Combined regression results for returns and profitability.

Dep. Variable	**Stock Returns**		**Gross Profit Margin**	
No. Observations	3,202	3,202	3,202	3,202
R-squared	0.3813	0.3813	0.0283	0.0284
F-statistic	281.20	246.03	13.288	11.686
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
Const.	-0.0193	-0.0199	11.162*	10.940
	(-0.7303)	(-0.0177)	(3.0679)	(0.1062)
Log market cap	0.0018	0.0017	3.2869*	3.2586
	(0.7679)	(0.0165)	(9.6213)	(0.3356)
Mkt-RF	0.9891*	0.9890	0.0677	0.0365
	(23.242)	(0.1227)	(0.0089)	(0.0002)
SMB	0.1922*	0.1917	-1.8312	-2.0107
	(1.7519)	(0.0079)	(-0.0796)	(-0.0031)
HML	-0.0590	-0.0594	-1.8148	-1.9508
	(-0.5841)	(-0.0034)	(-0.1089)	(-0.0041)
RMW	0.1640	0.1641	2.4174	2.4423
	(1.5123)	(0.0118)	(0.1841)	(0.0066)
CMA	0.3423	0.3432	1.7775	2.0637
	(2.3139)	(0.0144)	(0.0783)	(0.0032)
MOM	-0.0466	-0.0464	3.2581	3.2977
	(-0.3733)	(-0.0025)	(0.1833)	(0.0066)
Avg. weighted distance		0.0013*		0.4597*
(in 1,000 km, 620 mi)		(3.1612)		(24.651)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

7.3.2 Subgroup analysis by industry

The sector-specific analysis reveals how the geographic distribution of a company's workforce affects its financial performance, particularly stock returns and gross profit margins, with significant variation across sectors. The results of the regressions are shown in Tables 7.2 and 7.3.

In the Industrial and Healthcare sectors, workforce dispersion positively impacts stock returns. In these sectors, a geographically dispersed workforce provides operational flexibility and market access, leading to better market performance. However, both sectors also exhibit a negative impact on gross profit margins, suggesting increased operational costs associated with managing a dispersed workforce.

The Technology sector shows a marginally significant positive relationship with stock returns and a positive impact on gross profit margins, indicating that tech companies may effectively manage workforce dispersion, turning it into a profitability advantage.

Conversely, the Utilities sector experiences a marginally significant negative impact on both stock returns and gross profit margins. This reflects the operational challenges of managing a dispersed workforce in a sector that relies heavily on centralized operations.

In the Consumer Discretionary and Telecommunications sectors, workforce dispersion has a negative but not statistically significant relationship with stock returns, indicating that other factors may play a more significant role in determining financial performance.

Overall, the sector-specific analysis reveals that the benefits and challenges of workforce dispersion are not uniform across industries. While some sectors, such as technology and industrials, can leverage dispersion to enhance both market performance and profitability, others, like healthcare and utilities, may struggle with the operational complexities that a dispersed workforce entails.

7.4 Conclusion

This study underscores the complex relationship between the geographic distribution of a company's workforce and its financial performance. The analysis reveals that while a dispersed workforce can enhance stock returns in sectors like technology and industrials, it may present challenges for maintaining profit margins, particularly in healthcare and utilities. These findings suggest that the advantages of workforce dispersion are not universally applicable across all industries. Companies need to consider their specific operational contexts and sectoral characteristics when making strategic decisions about employee location. The results highlight that geographic dispersion can offer significant benefits, such as operational flexibility and access to a diverse talent pool, but these must be balanced against potential drawbacks, including increased coordination costs and operational inefficiencies. Effective management of these factors is crucial for optimizing the financial performance of companies with a dispersed workforce.

Table 7.2: Sector-specific regression results for returns.

Dep. Variable						**Returns**					
Sector	**Industr.**	**Healthc.**	**Basic Mat.**	**Utilit.**	**Cons. Discr.**	**Real Estate**	**Cons. Staples**	**Tech**	**Telecom. Services**	**Energy**	**Financ.**
No. Observations	572	457	178	223	477	226	220	403	84	134	228
R-squared	0.5359	0.3124	0.4633	0.5319	0.4007	0.5643	0.3875	0.5165	0.3918	0.5906	0.5478
F-statistic	81.269	25.439	18.238	30.401	39.109	35.133	16.685	52.606	6.0401	22.539	33.167
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Const.	-0.0137	-0.1062	-0.0207	0.0330	0.0095	0.0406	-0.0269	-0.0142	0.0603	-0.0365	0.0240
	(-0.0005)	(-0.0054)	(-0.0003)	(0.0064)	(0.0004)	(0.0005)	(-0.0042)	(-0.0078)	(0.0005)	(-0.0006)	(0.0018)
Log market cap	0.0003	0.0080	0.0005	-0.0027	-0.0006	-0.0062	0.0018	0.0017	-0.0076	0.0058	-0.0029
	(0.0001)	(0.0043)	(6.952e-05)	(-0.0052)	(-0.0003)	(-0.0008)	(0.0028)	(0.0105)	(-0.0007)	(0.0011)	(-0.0022)
Mkt-RF	1.1118	0.8458	0.9396	0.7385	1.1291	0.8050	0.2879	1.2349	1.0097	1.6340	1.0048
	(0.0158)	(0.0147)	(0.0125)	(0.1324)	(0.0164)	(0.0070)	(0.0447)	(0.1695)	(0.0094)	(0.0290)	(0.0451)
SMB	0.2449	0.4779	0.7636	-0.2697	0.3336	0.1558	0.8026	-0.3866	0.3945	-0.7804	0.3078
	(0.0012)	(0.0027)	(0.0037)	(-0.0163)	(0.0016)	(0.0004)	(0.0408)	(-0.0181)	(0.0011)	(-0.0048)	(0.0046)
HML	0.1419	-0.1769	-0.8462	-0.5932	0.3321	-0.9656	-0.3819	0.1695	-0.5042	1.6669	0.0240
	(0.0009)	(-0.0014)	(-0.0052)	(-0.0479)	(0.0022)	(-0.0038)	(-0.0268)	(0.0107)	(-0.0021)	(0.0133)	(0.0005)
RMW	0.3473	0.4034	-0.2288	-0.0938	0.1567	0.2685	0.6672	0.2803	0.2925	-1.3536	-0.1010
	(0.0029)	(0.0041)	(-0.0018)	(-0.0095)	(0.0013)	(0.0013)	(0.0588)	(0.0226)	(0.0016)	(-0.0138)	(-0.0026)
CMA	0.0076	0.3506	2.0519	1.2507	-0.1377	1.4013	1.0123	-0.6374	0.8657	-0.2326	0.0728
	(3.628e-05)	(0.0021)	(0.0095)	(0.0741)	(-0.0007)	(0.0040)	(0.0524)	(-0.0298)	(0.0027)	(-0.0014)	(0.0011)
MOM	0.0306	0.2010	-0.6598	-0.5489	0.0619	-0.7863	-0.4478	0.2819	0.2586	0.8315	-0.0901
	(0.0002)	(0.0015)	(-0.0040)	(-0.0410)	(0.0004)	(-0.0029)	(-0.0298)	(0.0170)	(0.0010)	(0.0063)	(-0.0018)
Avg. weighted distance	0.0110	0.0091	0.0166	-0.0018*	-0.0099	0.0156	0.0010	0.0011*	0.0187	0.0118	0.0039
	(1.9761)	(2.0213)	(1.4281)	(-1.7566)	(-1.5034)	(1.2020)	(1.3208)	(1.8181)	(1.2216)	(0.8500)	(1.0868)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7.3: Sector-specific regression results for gross profit margin.

Dep. Variable	**Gross Profit Margin**										
Sector	**Industr.**	**Healthc.**	**Basic Mat.**	**Utilit.**	**Cons. Discr.**	**Real Estate**	**Cons. Staples**	**Tech**	**Telecom. Services**	**Energy**	**Financ.**
No. Observations	572	457	178	223	477	226	220	403	84	134	228
R-squared	0.1669	0.0722	0.1799	0.0230	0.0832	0.1482	0.1779	0.0222	0.6023	0.1182	0.0646
F-statistic	14.0970	4.3572	4.6335	0.6301	5.3119	4.7211	5.7074	1.1163	14.1960	2.0941	1.8906
P-value (F-stat)	0.0000	0.0000	0.0000	0.7520	0.0000	0.0000	0.0000	0.3510	0.0000	0.0411	0.0627
Const.	-41.2160	13.0590	-4.3292	28.8880	82.4770	-25.2350	-14.0330	35.5350	119.0700	23.7110	6.0474
	(-0.0054)	(0.0011)	(-0.0001)	(0.0022)	(0.0319)	(-0.0020)	(-0.0003)	(0.0066)	(0.0020)	(0.0004)	(0.0031)
Log market value	8.2768	4.6231	2.7340	1.9402	-4.4367	5.9371	3.5273	1.6107	-7.5786	0.0768	6.1453
	(0.0111)	(0.0041)	(0.0009)	(0.0015)	(-0.0190)	(0.0046)	(0.0007)	(0.0034)	(-0.0014)	(0.0000)	(0.0318)
Mkt-RF	1.5178	-2.9115	1.4529	4.8401	-4.3995	4.1995	-1.6423	-2.0196	-3.5180	2.5550	0.8480
	(0.0001)	(-0.0001)	(0.0000)	(0.0003)	(-0.0006)	(0.0002)	(-0.0000)	(-0.0001)	(-0.0001)	(0.0000)	(0.0003)
SMB	4.5006	10.6600	-0.7615	-12.5510	-23.6280	7.4528	-6.4316	16.5930	-0.7573	-0.8514	8.0211
	(0.0001)	(0.0001)	(-0.0000)	(-0.0003)	(-0.0010)	(0.0001)	(-0.0000)	(0.0003)	(-0.0000)	(-0.0000)	(0.0008)
HML	3.5239	0.9816	0.3137	-12.5550	-41.1550	15.3010	-15.2360	-3.6881	-13.3400	35.2090	13.8500
	(0.0001)	(0.0000)	(0.0000)	(-0.0004)	(-0.0025)	(0.0004)	(-0.0001)	(-0.0001)	(-0.0001)	(0.0003)	(0.0020)
RMW	-9.1038	5.0560	4.2918	28.5370	12.8320	-4.8740	4.3293	1.6317	-2.5444	-32.1590	7.3523
	(-0.0003)	(0.0001)	(0.0001)	(0.0011)	(0.0010)	(-0.0002)	(0.0000)	(0.0000)	(-0.0000)	(-0.0003)	(0.0013)
CMA	-13.8220	-6.7858	0.5775	7.8987	66.3760	-31.1500	21.2880	3.1396	17.4630	-42.1350	-19.5830
	(-0.0002)	(-0.0001)	(0.0000)	(0.0002)	(0.0029)	(-0.0006)	(0.0001)	(0.0000)	(0.0001)	(-0.0002)	(-0.0020)
MOM	2.0458	-10.9230	11.1160	19.8150	-10.4920	5.0551	-11.8010	-34.5800	-28.9830	32.0390	19.5190
	(0.0000)	(-0.0001)	(0.0001)	(0.0006)	(-0.0006)	(0.0001)	(-0.0001)	(-0.0007)	(-0.0002)	(0.0002)	(0.0026)
Avg. weighted distance	-3.2722	-5.5079	7.9513	-4.6200*	1.0962	2.5138	8.2401	3.3978*	9.3140	12.2160	-0.5547
	(-1.9777)	(-2.0216)	(1.4284)	(-1.7605)	(1.5009)	(1.2015)	(1.3218)	(1.8109)	(1.2214)	(0.8503)	(-1.0902)

* indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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