Sustainable Finance
Essays on Methods and Impact

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Abstract

This dissertation advances the discourse on sustainable finance by critically examining its methods and impact in promoting a low-carbon, climate-resilient, and socially sustainable future. Recognizing that environmental, social, and governance (ESG) factors significantly influence both society and the economy, the research underscores the crucial role of integrating these factors into financial decision-making to improve sustainability efforts and financial system resilience.

The cumulative dissertation consists of four papers. They cover the areas: (1) applying machine learning to bridge company-level sustainability data gaps, thus improving the accuracy of corporate sustainability assessments; (2) evaluating the role of responsible institutional investors in driving real-world decarbonization, revealing limitations in their current impact; (3) exploring sustainable small business lending by analyzing how banks incorporate sustainability into lending practices for small and medium-sized enterprises (SMEs); and (4) assessing the coherence between ESG ratings and the EU Taxonomy, identifying slight alignment but significant potential for increased transparency and reduced rating divergence. The findings suggest that while sustainable finance holds significant promise, its mechanisms have yet to fully realize their potential in promoting sustainability and resilience, highlighting the need for more research to enhance its effectiveness.

Contents

Dedicated to Carina, Sabine, and Wolfgang.

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This thesis is as much yours as it is mine. Thank you all.

0
Introduction

Today, many are of the view that finance and the financial system will facilitate the global transition towards a sustainable and resilient economy (United Nations, 2015; Starks, 2023; GFANZ, 2024). Article 2.1c of the Paris Agreement states that the world should "mak[e] finance flows consistent with a pathway towards low greenhouse gas (GHG) emissions and climate-resilient development" (United Nations, 2015). "Redirecting financial flows" towards the sustainability policy targets is also a key pillar of the EU Green Deal (European Commission, 2019). These efforts are subsumed under the term *sustainable finance*.

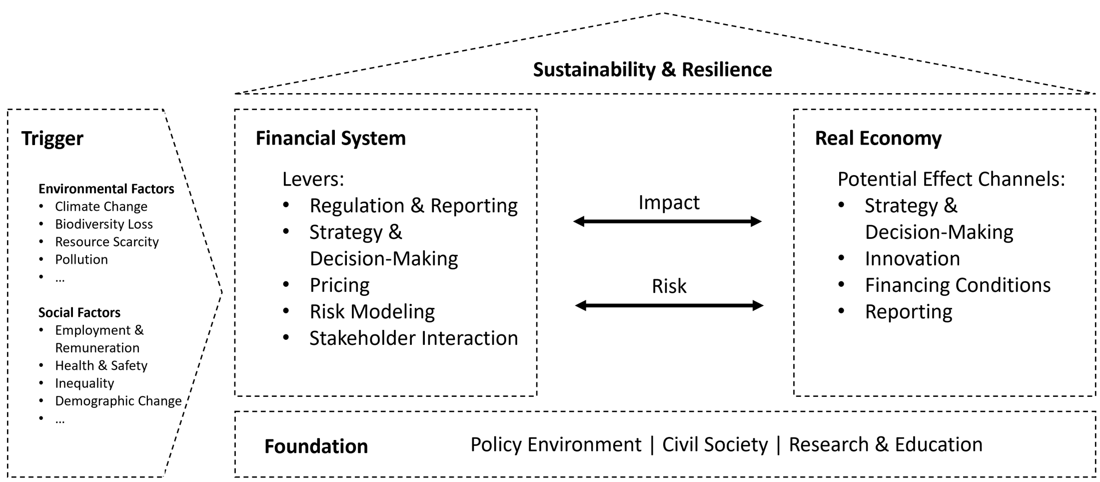
At its core, sustainable finance seeks to integrate environmental, social, and governance (ESG) factors into financial decision-making processes, influencing both the financial system and the real economy (Edmans and Kacperczyk, 2022; Starks, 2023; Schoenmaker and Schramade, 2023). The goals of this integration are two-fold. First, sustainable finance should promote sustainability efforts in the economy through the financial system (European Commission, 2021). Second, it should help improve the resilience of the financial system to the risks posed by environmental degradation and social shocks (NGFS, 2019; ECB, 2022; Acharya et al., 2023). In this dissertation, I contribute to the field by advancing the discourse on the methods and impact of sustainable finance.

0.1 The Role of Sustainable Finance

The premise of sustainable finance is grounded in the recognition that environmental and social factors, such as climate change, loss of biodiversity, resource scarcity, and inequality, have significant implications for society and the economy (Rockström et al., 2009; United Nations, 2015; Kunming Declaration, 2021; Intergovernmental Panel on Climate Change (IPCC), 2021). Financial markets and financial institutions are increasingly considered central actors in addressing these challenges by driving capital allocation to sustainable economic activities, influencing corporate behavior, and managing the risks associated with the transition to a sustainable economy, as well as related physical hazards (United Nations, 2015; European Commission, 2019; Starks, 2023; Schoenmaker and Schramade, 2023).

The core idea of sustainable finance is to use existing standard tools and mechanisms of finance, such as financial instruments (Zerbib, 2019; Flammer, 2021; Auzepy et al., 2023) and decision-making criteria and processes (Berg et al., 2022; Edmans, 2023b; Schoenmaker and Schramade, 2023), to promote sustainable practices throughout the economy and to ensure that the financial system remains resilient in the face of environmental and social risks. To illustrate these objectives and relevant interactions, I introduce the *House of Sustainable Finance* in Figure 1. It presents the interaction between environmental and social triggers, the financial system, and the real economy under the overarching goals of sustainability and resilience. The *House of Sustainable Finance* takes a system-level view of sustainable finance.

Figure 1: House of Sustainable Finance



The *House of Sustainable Finance* is based on a foundation of policy environments, civil society, and research and education. The policy environment deals with societal and economic questions related to sustainability such as internalization of environmental and social externalities (Stern, 2007; Nordhaus, 2013; Dasgupta, 2021; Wiesmeth, 2023) and support for innovation (Acemoglu et al., 2018). Civil society can play an important role in this process, as individuals have direct effects on sustainability through change in behavior (IEA, 2021) and through the creation of societal movements with the aim of moving stakeholders (Smith, 2012). Research and education enable people to act by providing the knowledge and capacities for a sustainable and resilient society and as such affect all parts of the system. The financial system and the real economy are based on this foundation.

The financial system consists, among others, of banks, asset managers, insurers, institutional and retail investors, and service providers. These actors must deal with or adapt to new circumstances due to sustainability. This is independent of whether they aim to support a more sustainable economy or take an agnostic position toward sustainability, as the risks associated with sustainability are very likely to materialize for all actors in the financial system (Bolton et al., 2020). The levers for integrating sustainable finance into the financial system include regulation and reporting, strategy and decision-making, pricing mechanisms, risk modeling, and stakeholder interaction.

Regulation sets standards for sustainable finance and influences how financial institutions integrate ESG factors into their operations (European Commission, 2021). Sustainable finance regulation has taken many forms. One key pillar of regulation is reporting by financial institutions, with the aim of creating transparency on sustainable impacts and risks in financial institutions' portfolios, as well as their processes and governance (European Banking Authority, 2022; ECB, 2022). Usually, regulators aim for accurate and comprehensive sustainability reporting, which should allow market participants to make informed decisions and align financing activities with larger sustainability goals (Ilhan et al., 2023; Krueger et al., 2024). However, many aspects of recent regulation are underexplored. For example, the interlinkages of reporting regulation with existing practices in data use are not well understood. In addition, financial institutions often do not have the sustainability data readily available to disclose with a high degree of granularity or to perform bottom-up analyses, raising questions about the efficacy of existing regulation and methods.

Similarly to policy making, strategy and strategic decision-making within financial institutions increasingly incorporate sustainability considerations from a risk and impact perspective (Krueger et al., 2020; Bolton and Kacperczyk, 2021; De Haas, 2023). Financial markets are also increasingly incorporating sustainability risks into pricing mechanisms (Ilhan et al., 2021; Heeb et al., 2023). To achieve adequate pricing, risk modeling is evolving to include sustainability risks and opportunities, allowing financial institutions to better assess the potential impacts of ESG risks on their portfolios (NGFS, 2019; Jung et al., 2021; ECB, 2022; Baer et al., 2023; Rebonato, 2023).

In addition, financial institutions are interacting with stakeholder on sustainability, including regulators, non-governmental organizations, and market participants. This is usually accompanied by public communication and marketing campaigns. In recent years, financial institutions have, for example, pledged to support international climate targets (GFANZ, 2021). An open question to this date is how effective such a public communication of being a ”responsible” financial institution is in supporting the decarbonization of the real economy.

The *House of Sustainable Finance* highlights the dynamic interaction between the financial system and the real economy. The levers of the financial system are likely to influence the real economy through several impact channels, including strategy and decision-making, innovation, financing conditions, and reporting. Companies in the real economy often adjust their strategies in response to signals from the financial system, such as changes in pricing or investor pressure (Dimson et al., 2018; Flammer et al., 2021). The first evidence suggests that some price signals are observable indicating that greener financial products enjoy cheaper access to finance while transition risks in (dark) brown firms are reflected (Flammer, 2021; Ilhan et al., 2021; Altavilla et al., 2024). For example, companies can benefit from lower interest rates for green projects or other favorable financing terms that are aligned with sustainability goals (Altavilla et al., 2024). Finally, improved corporate reporting on sustainability factors ensures that financial institutions have access to the necessary data to make informed investment decisions (Krueger et al., 2024).

The dynamic interactions between the financial system and the real economy can differ substantially for large and capital market-oriented corporations and small and medium-sized enterprises (SMEs) (Boot, 2000). The literature on sustainable finance has so far mainly focused on the former. This overlooks an important part of the economy that is a significant lever for the sustainability transformation and a potential source of sustainability risk.

0.2 Research Objectives and Contributions

The *House of Sustainable Finance* shows the scope of sustainable finance. However, many of the levers and interactions within the *House of Sustainable Finance* are not yet fully understood with respect to their effectiveness in driving sustainability and resilience. The often non-linear, complex, or even chaotic relationships between the earth system (the triggers), society, the economy, and the financial system create a challenging environment for economists and finance scholars for study.

This dissertation addresses four key research questions in this area in four papers: (i) how to close sustainability data gaps using machine learning reliably, (ii) what role responsible investors have in real economy climate action, (iii) how sustainable small business lending could be designed and banks' current view at it, and (iv) how ESG ratings and the EU Taxonomy are linked. By extending the sustainable finance debate to include small business lending and applying machine learning to close data gaps, this work offers novel insights into underexplored areas of the field. By adding to the growing debates on measuring sustainability (Berg et al., 2022; Edmans, 2023a) and the impact of financial institutions on climate action in the real economy (Atta-Darkua et al., 2023; Heath et al., 2023), the work helps to further refine sustainable finance. Through both strands, this dissertation contributes to a deeper understanding of how finance can promote sustainability and resilience, as well as how methods in sustainable finance can be further developed. As such, it also offers practical guidance for financial institutions and regulators.

The first paper focuses on overcoming company-level sustainability data gaps using machine learning. We propose a versatile approach for predicting sustainability metrics from only company-level financial and fundamental data. This research demonstrates how machine learning can help bridge the data gap in sustainability reporting and provide more accurate evaluations of corporate sustainability performance. However, we caution that estimated sustainability data in the form of point estimates are insufficient to make decisions in many situations. To overcome this issue, first, we show the relevance of prediction variations among dimensions such as time and space. Second, we introduce an uncertainty measure based on recent developments in the machine learning literature (Tibshirani et al., 2019; Barber et al., 2023), which helps to move machine learning in the business and finance literature beyond point estimates. This opens up new use cases for the technology due to increased reliability and knowledge of distributional properties. We conclude that policy makers should motivate market actors to apply these considerations to make machine learning an additional tool when implementing sustainable finance.

The second paper examines the role of responsible investors in climate action, investigating whether responsible institutional investors are driving decarbonization efforts in the real economy. The analysis reveals that responsible investors rarely contribute to real-world decarbonization. In addition, they shun high-polluting companies, which reduces their lever in climate-related engagement strategies. In contrast, they focus on improving companies' ESG ratings, which exhibit weak links to physical change at the company level (Elmalt et al., 2021). This raises questions about the transformative potential of impact-oriented sustainable finance and highlights the need for a more nuanced understanding of the role of institutional investors in climate policy making. Specifically, in a follow-up climate agreement to the Paris climate agreement, policy makers should consider reviewing the current language of "mak[ing] financial flows consistent" (United Nations, 2015) to increase its specificity.

The third paper explores the role of small business lending in promoting sustainability and resilience among small and medium-sized enterprises (SMEs). Using a survey among a representative sample of German banks, I analyze how banks perceive and implement sustainable small business lending. The findings suggest that while banks are incorporating sustainability considerations into their small business lending practices, they tend to emphasize risk management over the transformation of business models. This finding contrasts with statements from banks that claim to position themselves as partners or even enablers in the sustainability transformation. In addition, the survey reveals a role for relationship banking in sustainable small business lending, although with a focus on generating hard sustainability information about SMEs. As a consequence of these findings, regulators and banks should review public communication on the role of banks as sustainability partners of SMEs and should discuss how to improve conditions for sustainable small business lending so that it becomes more transformative.

Finally, the fourth paper evaluates ESG rating coherence with the EU Taxonomy. The paper posits that the European Commission sent a signal to market actors about what it considers sustainable by publishing a standardized framework for classifying green economic activities, i.e., the EU Taxonomy. This signal would also affect the definition of sustainability among ESG rating providers. As the first ever published empirical paper on the EU Taxonomy, the paper thus examines how ESG ratings across different data providers align with the EU Taxonomy. The research suggests that the EU Taxonomy and ESG ratings are slightly coherent, and in particular for green pure players. However, the full potential to reduce divergence among ESG ratings is not used. The paper concludes that policy makers could use the EU Taxonomy in the field of ESG ratings more effectively to increase transparency and, potentially, reduce divergence.

The remainder of the dissertation is organized along the four research papers. Each of the following chapters presents one research paper. All appendices to the papers are available in the appendix of the dissertation along with additional information on the papers. Chapter 1 presents "Corporate Sustainability Data, Machine Learning, and Prediction Uncertainty" co-authored with Christian Haas and Ulf Moslener. Chapter 2 presents "Consistency or Transformation? Finance in Climate Agreements" co-authored with Maurice Dumrose and Youri Matheis. Chapter 3 shows "Sustainable Small Business Lending". Finally, Chapter 4 contains "Disaggregating Confusion? The EU Taxonomy and ESG Rating" co-authored with Maurice Dumrose and Julia Eckert.

All models are wrong, but some are useful.

George Box

1 Corporate Sustainability Data, Machine Learning, and Prediction Uncertainty

Sustainability commitments such as the Paris Climate Agreement (United Nations, 2015) and the Kunming Biodiversity Declaration (Kunming Declaration, 2021) underscore the ambition to transform economies worldwide. As a result, multinational enterprises (MNEs), financial institutions, and researchers increasingly require sustainability information. Availability and quality of sustainability data throughout the dimensions environment (E), social (S), and governance (G) are more important than ever. However, these data are incomplete, often of inadequate granularity and unknown quality, or (artificially) scarce. In this paper, we present a novel approach that leverages machine learning to address these issues and fill sustainability data gaps using readily available company data.

The growing importance of sustainability for MNEs, financial institutions, and regulators underscores the critical need for granular and reliable company-level sustainability data. MNEs face regulatory and investor pressures (Slager et al., 2023), customer and employee expectations (Whelan and Kronthal-Sacco, 2019; Jing et al., 2023), and the need to optimize financial performance (Adams and Ferreira, 2009; Kim and Starks, 2016), directing their focus on sustainability across operations and global value chains (Marano et al., 2024). Similarly, financial institutions require these data to align portfolios with sustainability goals (Bolton et al., 2022), cater to retail investor preferences for green products (Bauer et al., 2021), and manage financial risks associated with climate and biodiversity impacts (Ilhan et al., 2021, 2023; Giglio et al., 2023; Garel et al., 2023), all within the context of strengthening regulatory frameworks (ECB, 2022). Empirical research on sustainability and business practices also relies heavily on high-quality data (Marano et al., 2024; Starks, 2023), yet the gradual and incomplete availability of reported and audited metrics forces stakeholders to rely on alternative sources.

Currently, sustainability at the company level is typically measured by ESG ratings. However, these ratings diverge in terms of measuring specific aspects of ESG (Berg et al., 2022), putting into question the usability of these ratings. Given the difficulty of measuring company sustainability (Edmans, 2023a), granular physical indicators would enable different actors to assess corporate sustainability more independently, allowing greater diversity of views and, as a result, potentially more efficient functioning of markets, for example, through capital allocation and global value chain (GVC) engagement. These granular physical indicators include corporate carbon emissions, the corporate biodiversity footprint, corporate resource usage (water, primary materials, etc.), health and safety as well as diversity measures. In order to serve these data needs, corporate ESG disclosure around the world is currently evolving but far from being established (Krueger et al., 2024). It is unlikely that full sustainability information on GVCs will be available soon. Corporate carbon reporting seems to be the most evolved, but it remains incomplete (Busch et al., 2022). This lack of comprehensive data can result in incomplete or biased assessments, which can lead to misinformed decision-making. Therefore, methods are needed to address these data issues.

Data providers and researchers have realized this need and have provided different modeling approaches to estimate ESG data. To date, this work has typically been limited to corporate carbon emissions. Methods include simple estimations, which use a direct proportional relationship between a company's size (e.g., revenue, number of employees) and the corporate carbon footprint, and regression setups, where emissions are regressed against a variety of operational and financial predictors to encapsulate a company's business model, scale, and technological practices (e.g., Goldhammer et al. (2017) and Griffin et al. (2017)). However, due to incomplete knowledge of the statistical association of accounting data and corporate emissions, these approaches suffer from inadequate complexity and thus bias or over-fitting and hence poor out-of-sample predictions. This reduces the reliability of such data in practical and research contexts.

Machine learning can help overcome these shortcomings, even beyond corporate carbon footprints. Companies are complex systems (Loughran and McDonald, 2023). They have different ages, sizes, product lines, geographic presences, financing structures, financial performance, and company cultures. These aspects may all play a role for companies' sustainability metrics, and it is very likely that relationships between and within company-level metrics are non-linear. Machine learning with its ability to search large non-parametric algorithmic spaces (Jordan and Mitchell, 2015) seems well positioned for this environment.

Previous work employing machine learning to predict sustainability data already shows promising results, but is limited in metrical and methodological scope. Nguyen et al. (2021) and Nguyen et al. (2022) estimate corporate Scope 1-3 emissions using a set of regression-based supervised learning algorithms and achieve up to 30% improvement compared to parametric approaches. Other estimates of environmental data at the company level remain rare. Tian (2023) estimates the water efficiency of the companies. The literature is largely silent on the estimation of social aspects at the company level. Governance aspects are discussed, especially diversity aspects, with Ranta and Ylinen (2023) using text-based machine learning to generate diversity indicators from social media posts and Khan et al. (2023) predicting board diversity from company characteristics. The variety of approaches to applying machine learning requires the user to tailor new data sets, code environments, and machine learning algorithms for each sustainability metric. This is time-consuming, costly, and challenging in environments where a variety of sustainability data points are necessary, such as in disclosures by MNEs' global value chains, in risk management by banks, or research on company-level sustainability.

In addition, even if such estimations are available, regulators normally do not accept their use by financial institutions or MNEs. The main reason is that only point estimates are provided and no additional information is available as to how reliable that estimation is at the firm or portfolio level. Point estimates as they are generated by machine learning models typically represent the conditional expected value of the predicted variable. Information about confidence or prediction intervals is typically not provided. This is also a challenge when making causal inferences from these data in research.

We propose an approach that solves these challenges. Essentially, this is achieved through three characteristics of our approach: First, we restrict the independent variables (features) to a large, multidimensional but readily available set of reported company-level financial data supplemented by fundamental data such as industry, country, and company age. Those data represent company level activity, which should also have prediction power for sustainability data. Second, the code architecture systematically integrates the search for the best-performing regression algorithms with the search for the most appropriate data preprocessing steps before those combinations are intensively optimized and then fed into a final meta model training. Third, our approach incorporates considerations about prediction uncertainty. Based on recent developments in the machine learning literature in the area of conformalization (e.g. Tibshirani et al. (2019) and Barber et al. (2023)), we add two prediction intervals to our framework. The first refers to the probability that *on average* in all predictions the true value lies within the interval (*marginal coverage*). The second refers to the probability that the true value lies within the interval *for a specific set* of input values (*conditional coverage*).

In this paper, first, we test whether information on sustainability metrics is actually captured in reported company-level financial and fundamental data. We apply our approach to the sustainability metrics Scope 1 and Scope 2 greenhouse gas emissions, air pollution (NOx emissions), water discharge, and female board share. We show that the models perform well and produce unbiased results.

Second, we show that the performance of the models varies between time, region, and sector dimensions. For the earlier years in the dataset (2005 until about 2015), the predictions tend to be better than in the following years. When looking at different world regions, we also observe variations with the predictions for Europe being better than those in other parts of the world. With respect to the different sectors, the approach performs differently and is dependent on the sustainability indicator predicted. In agriculture, for example, the prediction of water discharge is comparatively good, while that of air pollution is relatively bad. This is vice versa for transportation.

Third, we introduce prediction uncertainty measures by adapting recent developments in the technical literature on machine learning. We find that the *conditional coverage* provides relatively precise information on the confidence intervals for the predictions. As such, this metric should be reported. The intervals are dependent on the coverage needed, that is, the desired confidence a user would like to have in her predictions. Using 68% versus 95% coverage as examples, we find that intervals for a higher risk tolerance (68% coverage) are relatively narrow, whereas intervals for a lower risk tolerance (95% coverage) are considerably wide.

We conclude by making the case for the use of machine learning to fill data gaps, as it is a cost-efficient way to generate company-specific sustainability data while maintaining high standards for data integrity. Our suggested approach should help regulators to accept the use of estimations as they are more qualified. Additionally, our approach will help MNEs and financial institutions meet the disclosure requirements on their GVCs and portfolios, as well as enable them to run more granular analyses including the consideration of risk tolerances in sustainability data predictions.

As such, this paper contributes to the growing literature on sustainability data by introducing a novel machine learning approach that addresses significant gaps in the availability, quality, and granularity of sustainability metrics. Our approach is distinguished by its systematic integration of financial and fundamental company-level data with advanced algorithmic optimization, enabling the robust estimation of diverse sustainability indicators. By incorporating recent advances in machine learning, such as conformal prediction techniques, we provide not only point estimates but also rigorous prediction intervals, addressing a critical limitation of existing models and a crucial gap in the literature. These intervals improve the reliability and transparency of sustainability data, meeting the needs of regulators, financial institutions, and MNEs. Furthermore, we demonstrate that model performance varies across temporal, regional, and sectoral dimensions, offering nuanced insights into the dynamics of sustainability metrics.

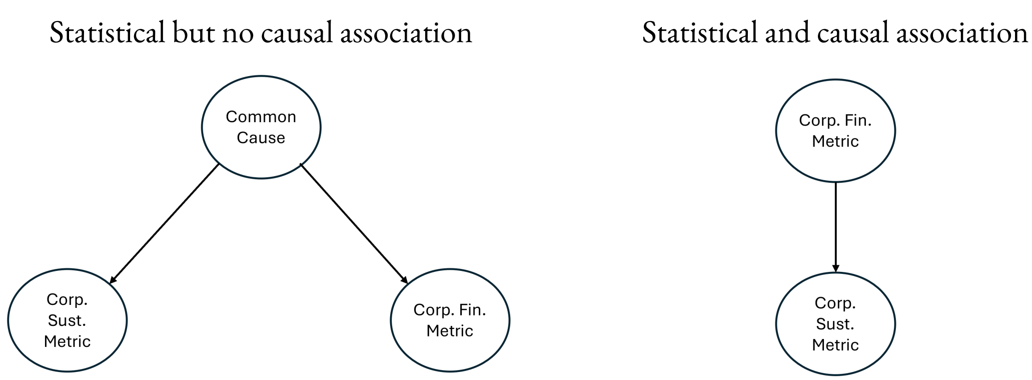
The remainder of the paper is structured as follows. The next section outlines the methodology, including the introduction of the uncertainty measure. Section III presents the results. Section IV concludes.

1.1 Methodology

Predicting cardinal sustainability data is a supervised ML regression task. Here, we suggest a versatile approach to using regression-based machine learning to predict a variety of company-level sustainability data only from reported financial and fundamental data.

Machine learning and hence our methodology differ substantially from common empirical approaches in business and finance research. Common empirical approaches, especially econometrics, traditionally emphasize hypothesis-driven analysis, seeking to identify causal relationships by imposing strong parametric assumptions and leveraging techniques like instrumental variables or structural modeling. The aim is to understand ”why” a relationship exists and to make policy recommendations. In contrast, machine learning, and therefore our methodology prioritizes predictive accuracy by exploring complex, non-linear relationships in data through algorithmic flexibility and minimal assumptions about underlying structures. While econometrics excels in causal inference, machine learning is better suited to generate high-quality predictions, especially in data-rich environments with complex interactions.

Figure 1.1: Stylized Representations of Associations between Variables



This distinction is visually represented in Figure 1.1. The left image illustrates a stylized statistical but non-causal association, reflecting the type of complex relationships machine learning algorithms can effectively exploit for prediction. The right image, on the other hand, depicts a combination of statistical and causal associations that econometric approaches typically focus on identifying. Our methodology takes advantage of both types of relationships to maximize prediction performance. As such, the approach is agnostic to whether a relationship is based on causality or correlation.

1.1.1 Model Space

A model is defined as a sequence of preprocessing steps and followed by a regression algorithm (learner). To ensure the versatility of our approach, we define a large model space that we search using a Bayesian approach* to maximize our chance of capturing the "best" model for a given sustainability metric. We maximize the coverage of the model space by first training and optimizing a large set of models (running up to 9,600 trials per sustainability metric†), then optimizing the best-performing model configurations, and finally using them in meta model training, see Figure 1.2. We evaluate the performance throughout the process using the Mean Squared Error (MSE) and double 10-fold cross-validation.

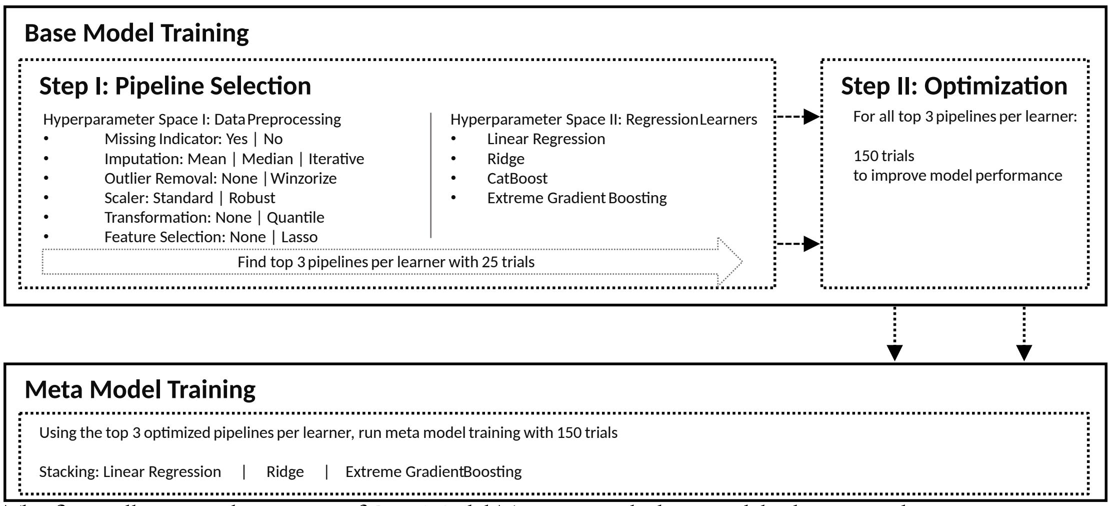
Base Model Training - Model Selection: The first step of base model training consists of the search for suitable model configurations for the sustainability metric at hand by exploring a variety of data preprocessing techniques along with different regression learners as input to hyperparameter optimization. In this step, we run up to 25 optimization trials per model configuration.

Data preprocessing is an essential aspect of the modeling process as it can significantly influence the performance of predictive models. In the literature on sustainability data prediction, this step is usually treated separately from the actual model training. Here, we use data preprocessing as a hyperparameter for optimization in itself. In doing so, we expand the considerations of the no free lunch

*Unlike grid or random search, Bayesian optimization utilizes past evaluation results to choose the next set of hyperparameters, efficiently narrowing down to the best possible model settings (Snoek et al., 2012).

†We have devised an early stopping mechanism to boost computational efficiency. For more information, see Appendix A.

Figure 1.2: Machine Learning Approach



The figure illustrates the process of Base Model Training, including model selection and optimization using Bayesian hyperparameter tuning, followed by Meta Model Training with a stacked regression approach. Evaluation uses Mean Squared Error (MSE) and double 10-fold cross-validation. Base model training involves selecting top pipelines per learner, followed by further optimization. Meta model training uses the top pipelines in different stacking configurations.

(NFL) theorem (Wolpert and Macready, 1997) to preprocessing in our setup. The options for data preprocessing in our setup span missing indicator flags, imputation methods (mean, median, iterative), outlier removal strategies (none, winsorization), scaling techniques (standard, robust), transformation approaches (none, quantile) and feature selection methods (none, Lasso). We introduce the missing indicator flag (a binary feature) to allow the model to learn from the reporting behavior of a company. The imputation methods are relevant for handling missing data, a common issue in financial datasets. Imputation strategies such as mean and median are simple and widely used, while iterative methods can provide a more sophisticated approach that utilizes correlations between features (van Buuren, 2007). Outlier removal and scaling enhance the robustness and stability of the models, particularly in financial applications where outliers can represent noise (Aggarwal, 2013). Feature engineering and selection further refine the model by introducing new features that could capture non-linear relationships or selecting the most relevant features to avoid overfitting (Iguyon and Elisseeff, 2003).

In the space of regression learners, the approach contemplates linear regression, ridge regression, extreme gradient boosting (XGBoost) and CatBoost. Linear regression and ridge are fundamental techniques with ridge introducing regularization to manage overfitting (Hoerl and Kennard, 1970). Linear regression is relevant in this study to compare training outputs with methods that are used regularly in econometrics. However, it is unlikely that this learner form the basis of the "best" performing models in the realm of machine learning. On the other hand, Gradient Boosting algorithms, including XGBoost (Chen and Guestrin, 2016) and CatBoost (Prokhorenkova et al., 2018), are powerful ensemble methods that have shown high performance on a wide range of prediction tasks, particularly in the presence of non-linear and complex relationships.

Compared to Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), neural networks, and simpler tree methods, XGBoost and CatBoost bring a blend of depth and breadth to the modeling process. SVMs, while effective for small to medium-sized datasets, can be outperformed by tree-ensemble methods in handling large and complex data sets (Fernández-Delgado et al., 2014). KNN suffers from the curse of dimensionality and is inherently slower in making predictions due to its instance-based nature (Beyer et al., 1998). Neural networks, although powerful for large-scale and complex non-linear relationships, require extensive tuning and larger datasets to generalize effectively without overfitting (LeCun et al., 2015). This could reduce the versatility of our setup. Simpler tree methods such as CART or C4.5 can provide interpretable models but usually lack the predictive power of boosted ensembles, which aggregate multiple trees to reduce variance and bias (Breiman, 1996). Therefore, for our regression tasks using financial and fundamental data, where feature relationships are likely complex, XGBoost and CatBoost are likely to be good fits.

Base Model Training - Optimization: The second step involves optimizing the top three model configurations per learner and target variable, selected according to their initial performance in Step I. Each model configuration undergoes 150 Bayesian hyperparameter optimization trials. With this step, we substantially expand the optimization efforts to ensure that the model hyperparameters are chosen close to ”best”.

Meta Model Training: Finally, meta model training is applied using the three best-performing models per learner. The approach employs stacking, which combines the predictions of multiple models by training a meta learner, often leading to performance improvements (Wolpert, 1992). We use linear regression, ridge, and XGBoost models in this step but do not repeat the use CatBoost. In our setting, CatBoost is computationally very costly compared to XGBoost while yielding similar results. The exclusion is thus based on pure efficiency considerations.

1.1.2 Model Performance Metrics

We evaluate the performance of the top three models from both base and all meta-training using performance assessment metrics as summarized in Table 1.1. We evaluate the point estimates using these metrics.

Global assessments encompass a set of quantitative and graphical measures designed to evaluate the prediction performance of global models. The metrics in this category include accuracy and error distribution between predicted and actual values. Accuracy measures include the mean absolute error (MAE) and the mean squared error (MSE) quantify the average prediction error and the average of squared errors, respectively, with MSE placing greater emphasis on larger errors. We use MSE as the metric in our loss function and thus as our main measure of model performance. The R-squared (R^2) measures the proportion of variance in the dependent variable that can be captured by the model, offering insight into the explanatory power of the model.

Local assessments show how the models perform in their operational contexts. This category includes quintile allocation, which evaluates the model’s ability to accurately rank predictions within specific quintile brackets. This could be useful when seeking best-in-class investment strategies (Edmans et al., 2022) or when reducing exposure to highly emitting companies in portfolios (Rink et al.,

Table 1.1: Performance Assessment Metrics for Machine Learning Models

Metric	Measure/Value	Description
Global Assessment		
Accuracy		
	Mean Absolute Error (MAE)	The average of the absolute errors between the predicted and actual values, representing average prediction error.
	Mean Squared Error (MSE)	The average of the squared errors, emphasizing larger errors more than MAE. Also used in the model training as loss function.
	R^2 (R-squared)	Measures the proportion of the variance in the dependent variable that is predictable from the independent variables.
	Quintile Deviation	The absolute difference in quintiles between the predicted quintile and the actual sample quintile.
Error Distribution	Graphical representation	Refers to the distribution of relative errors between predictions and actual values.
Local Assessment (Context)		
Sectoral Accuracy	MAE / MSE	Evaluation of model performance within different industry sectors.
Temporal Accuracy	MAE / MSE	Evaluation of model performance over different time periods.
Spatial Accuracy	MAE / MSE	Evaluation of model performance across different geographical locations.

This table reports a summary of the performance metrics used to assess the point estimates of trained models. Global and local in this context do refer to full or partial results of the model, not to geographic coverage.

2024). The context examines the performance of the model in sector, space, and time. This should ensure transparency about performance differences prevalent in other sustainability data sets (Dobrick et al., 2023).

1.1.3 Prediction Uncertainty

Estimating sustainability data from corporate financial data is a task inherently characterized by uncertainty. Point estimates generated by classical statistical or machine learning models represent the conditional expectation of the target variable - in our case the conditional mean - but do not provide information about the uncertainty associated with the predicted value. However, quantifying this uncertainty is crucial to make reliable statements about the accuracy of the estimation and associated risks, to possibly exclude certain predictions from use (*measure not estimate*), or to opt for more conservative or optimistic values instead of the point estimates of the conditional mean.

A key challenge in accurately and consistently assessing the uncertainty of different models is the construction of valid prediction intervals. Our selection of approaches and methods for generating prediction intervals is, therefore, guided by the goal of achieving (sufficiently) accurate marginal coverage and conditional coverage.

Marginal coverage refers to the probability that, on average across all predictions, the actual value of the target variable lies within the prediction interval. This property ensures that the prediction intervals are correct on average across the entire distribution of input data. It is particularly useful for making consistent statements about uncertainty across different models and is relevant in scenarios where models are applied for multiple predictions. Marginal coverage does not guarantee accurate coverage for every individual prediction, but ensures that the average coverage meets the desired level.

Conditional coverage refers to the probability that the true value of the target variable lies within the predicted interval for a specific set of input values. This property is stronger than marginal coverage and is crucial when individual-level uncertainty quantification is needed, such as in company-specific predictions. Achieving conditional coverage requires that the prediction intervals are accurately calibrated for each possible input, capturing the uncertainty for that particular instance.

In our data-driven approach, where financial data are used as predictors of sustainability-related information, additional challenges arise due to the unknown relationship between these variables (absence of theory). This suggests a preference for methods that do not rely on strong assumptions about the joint distribution.

In the literature on uncertainty quantification, there are various approaches to quantifying uncertainties of model prediction (Soize, 2017; Abdar et al., 2021). A common method involves using scalar uncertainty measures, such as the standard deviation (error), which provides a general measure of the spread of predictions. However, these methods offer only a global perspective on the underlying uncertainty and typically fail to adequately account for the variability of uncertainty across different areas of the distribution. Moreover, theoretical guarantees regarding marginal coverage and conditional coverage are only available under strong assumptions about the distribution and are typically not empirically validated (Palmer et al., 2022).

Quantile regression (Koenker and Bassett, 1978) offers an alternative approach that allows the calculation of prediction intervals using the estimation of quantiles instead of the conditional mean of the target variable. This method is particularly useful when asymmetric uncertainties in predictions cannot be ruled out. A central advantage of quantile regression is that it asymptotically ensures both marginal coverage and conditional coverage for sufficiently large sample sizes (Chernozhukov et al., 2009; Romano et al., 2019). In Appendix A, we provide a short demonstration of the properties of quantile regressions.

A relatively new framework, useful for prediction uncertainty quantification is conformal prediction (Vovk et al., 2005; Lei and Wasserman, 2014; Lei et al., 2018). The underlying methods provide theoretical guarantees for marginal coverage in finite samples without making strong assumptions about the distribution.[‡]

We employ a conformalized version of the quantile regression (Romano et al., 2019). This approach retains the favorable properties of quantile regression concerning the adaptivity of the prediction intervals and (asymptotically) conditional coverage, while also providing theoretical guarantees for marginal coverage in finite samples under the assumption of i.i.d. data. As with our systematic approach to identifying the optimal model for predicting the conditional mean, this approach to uncertainty quantification aims to be sufficiently close to optimal to allow meaningful conclusions.

Specifically, our approach involves generating symmetric prediction intervals with a target coverage rate of $\tau \in \{68\%, 95\%\}$ to assess prediction uncertainty. Given the size of the datasets, we employ a split method in which the test data set used for point estimates is divided into a calibration set and a uncertainty test set. This approach is intended to balance the trade-off between statistical efficiency and computational efficiency. The training of the models using an adapted loss function is performed on the training set. The calibration set is then used to compute conformal scores, which are subsequently employed to construct prediction intervals that achieve the desired coverage levels. The test set is used to evaluate the coverage and analyze prediction uncertainty. We implement this approach in four steps:

1. *Quantile Regression:* We train the best base models for each learner as well as the meta models on the training data set using the loss function

$$L_\alpha\left(\hat{y}_\alpha, y\right) = \begin{cases} \alpha\left(y - \hat{y}_\alpha\right) & \textit{if} \quad y > \hat{y}_\alpha \\ (1-\alpha)\left(\hat{y}_\alpha - y\right) & \textit{if} \quad y \leq \hat{y}_\alpha \end{cases}$$

   with $\alpha \in \{(1-\tau)/2, (1+\tau)/2\}$. Here, y is the actual value of the target variable, $\hat{y}_\alpha = \hat{y}_\alpha(x)$

[‡]Our approach builds on work that assumes exchangeability, which is satisfied under the assumption of i.i.d. data. For conformalized prediction approaches beyond exchangeability, see Tibshirani et al. (2019) and Barber et al. (2023).

is the quantile prediction of the target variable as a function of the features $\mathbf{x}$.

2. *Quantile Prediction:* We then use the trained models to predict the conditional quantiles $\hat{y}_\alpha\,(x)$ for each observation in the calibration data set. x is a vector of the predictor variables for each observation.

3. *Conformal Scores:* Based on these quantile predictions, we determine conformal scores, $c(\mathbf{x}, y) = \max\{\hat{y}_{(1-\tau)/2}(\mathbf{x}) - y, y - \hat{y}_{(1+\tau)/2}(\mathbf{x})\}$ for each observation in the calibration data set.

4. *Rectifying Quantiles:* Defining $\hat{r} = \text{Quantile}\left(\frac{\lceil (n_{cal}+1)\tau \rceil}{n_{cal}}, \{c_1, \ldots, c_{n_{cal}}\}\right)$ we can derive conditional prediction intervals

$$I(\mathbf{x}) = \left[\hat{y}_{\tau/2}(\mathbf{x}) - \hat{r}, \hat{y}_{1-\tau/2}(\mathbf{x}) + \hat{r}\right]$$

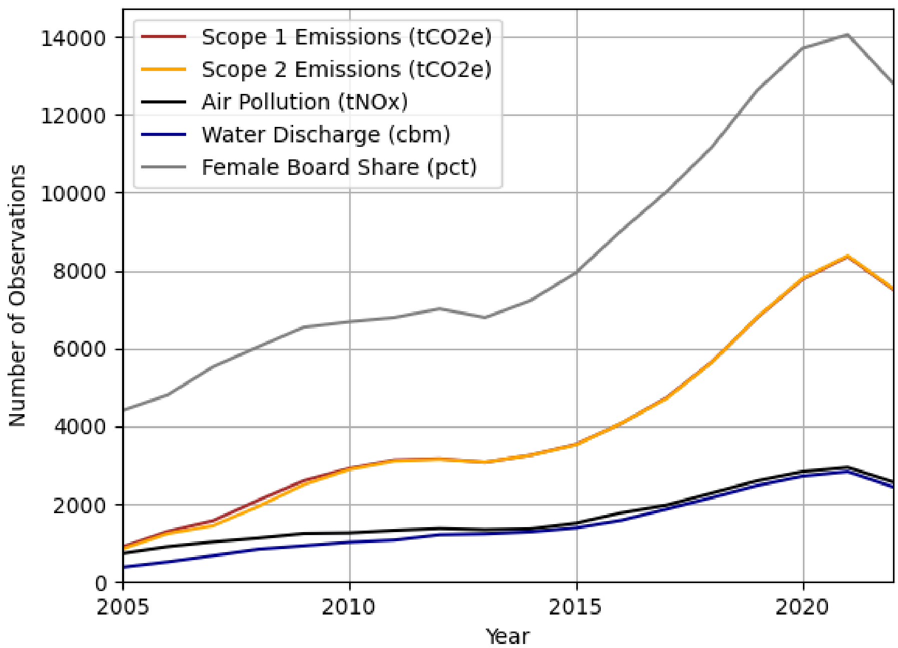
for each observation.

1.1.4 Data

Our data set comprises a comprehensive collection of company-year observations for listed equities obtained from the London Stock Exchange Group (LSEG) Data and Analytics database. This data set is global in scope, encompassing data from 95 countries, which provides a diverse and extensive foundation for modeling and analysis. To maintain the integrity and reliability of the results, only reported sustainability data are included in this study, thereby avoiding the potential biases introduced by the LSEG Data and Analytics' estimation models or unaudited data. This conservative approach ensures that the analysis is based solely on real and verifiable metrics.

As shown in Figure 1.3, the data set includes key sustainability indicators such as Scope 1 and Scope 2 emissions, air pollution, water discharge, and female board share (our ”target variables”). Data availability has recently increased substantially, enabling ML applications in the field.

Figure 1.3: Reported Sustainability Data over Time



The figure illustrates the availability of reported sustainability data by listed companies over time.

Table 1.2 provides a detailed summary of the data, highlighting the breadth and depth of the data set. The data set time period runs from 2005 to 2022.

- Scope 1 and Scope 2 Emissions: The dataset contains nearly 50,000 observations each for these emissions categories, covering 83 sectors across 83 countries, with data available for more than 8,000 companies. We select these indicators to benchmark against other studies and due to the relevance of climate change to business.
- Air Pollution and Water Discharge: These variables have fewer observations, reflecting the more limited availability of environmental data. However, they still provide significant coverage, with data on more than 3,000 companies from more than 60 countries. These indicators

are included to reflect emerging topics in business and finance research such as biodiversity, blue economy, and livable cities.

- Female Board Share: This social governance indicator is well-represented, with over 100,000 observations across 95 countries and 86 sectors, providing the richest data set in our analysis. It should demonstrate that our approach is applicable beyond environmental sustainability data.

The data set includes 211-255 predictor variables, depending on the specific sustainability metric, with data completeness ranging from 57% to 65%. This breadth of variables offers a comprehensive view of company characteristics and operational contexts.

Table 1.2: Summary Statistics

Dataset	Scope 1 Emissions	Scope 2 Emissions	Air Pollution	Water Discharge	Female Board Share
General Information					
Number of observations	47685	47320	20980	18426	108834
Number of sectors	83	83	76	74	86
Number of countries	83	83	63	63	95
Number of companies	8391	8335	3389	3098	14406
Start year	2005	2005	2005	2005	2005
End year	2022	2022	2022	2022	2022
Number of predictor variables	240	240	213	211	255
Data completeness (in %)	63.86	63.77	65.72	65.62	57.92
Target Variable Information					
Mean	3786965	1051686	19914	187082423	16.00
Standard deviation	26440465	48614503	179304	1318742226	14.00
Minimum	0.00	0.00	0.00	0.00	0.00
Maximum	4421000000	7386660000	14042000	26877900000	100.00
Target Variable Information					
Log (1+value) Mean	10.75	11.07	6.31	14.98	2.17
Log (1+value) Std	3.55	2.72	3.28	3.60	1.40
Log (1+value) Min	0.00	0.00	0.00	0.00	0.00
Log (1+value) Max	22.21	22.72	16.46	24.01	4.62

This table presents summary statistics for the dataset, including Scope 1 and Scope 2 emissions, air pollution, water discharge, and female board share. The table details general information such as the number of observations, sectors, countries, companies, the time period (2005-2022), and data completeness rates. It also includes target variable information, such as means, standard deviations, and the range (minimum to maximum) of the absolute and log-transformed values.

The features selected for this study focus on fundamental and financial data, excluding direct sustainability-related metrics (e.g., energy use) to challenge the model's ability to infer sustainability data solely from financial and fundamental data. The feature set includes the following.

- Financial data (e.g., income statement, balance sheet, cash flow metrics), capturing idiosyncratic company characteristics such as size, profitability, innovative capacity, and asset intensity.
- Fundamental data
  - Industry indicators to account for general trends in emission intensity within specific sectors.
  - Spatial variables that reflect policy and socio-economic operating conditions.
  - Company age that reflects the general development stage of a company.
- Temporal effects captured by the inclusion of year variables.

A list of all variables including summary statistics is presented in Appendix A.

Data preprocessing steps included retrieving data via the LSEG Data and Analytics API, filtering out non-listed equity observations, and excluding entries without date variables or those with quarterly reporting. The target variables were logarithmically transformed to improve predictive performance. For highly correlated features (correlation >= 99%) only one feature is retained based on the highest number of observations to mitigate high multicollinearity. Furthermore, features with very low data availability (missingness >= 99%) were excluded, as imputation was not feasible in these cases.

This rigorous data selection and processing framework prior to the pipeline preprocessing steps ensures that the resulting model is robust and reliable, providing information on how financial metrics can be used to predict sustainability data.

1.2 Results

1.2.1 Global model assessment

Our analysis reveals that sustainability data can be predicted from corporate financial data with a high degree of accuracy[§]. Complex and non-parametric machine learning models significantly outperform linear models in predicting sustainability data from financial data, see Table 1.3. This indicates that the underlying structure of sustainability data is quite complex and cannot be adequately captured by simple linear relationships.

Table 1.3: Global Model Performance

		Base Learner				Meta Learner		
Target Variable	Metric	Linear Regression	Ridge	CatBoost	XGBoost	Linear Regression	Ridge	XGBoost
	MAE	1.261	1.240	0.648	0.662	0.610	0.609	0.589
Scope 1 Emissions (tCO2e)	MSE	3.401	3.252	1.579	1.617	1.622	1.622	1.589
	R2	0.713	0.726	0.867	0.864	0.863	0.863	0.866
	MAE	1.252	1.118	0.513	0.627	0.556	0.556	0.527
Scope 2 Emissions (tCO2e)	MSE	3.400	2.959	1.163	1.269	1.275	1.275	1.204
	R2	0.540	0.599	0.842	0.828	0.827	0.827	0.837
	MAE	1.501	1.444	0.695	0.905	0.672	0.672	0.650
Air Pollution (tNOx)	MSE	4.598	4.320	1.923	2.262	1.907	1.907	1.909
	R2	0.564	0.590	0.818	0.786	0.819	0.819	0.819
	MAE	1.782	1.782	0.278	0.623	0.275	0.275	0.273
Water Discharge (cbm)	MSE	7.528	7.522	1.055	1.526	1.063	1.063	1.053
	R2	0.443	0.443	0.922	0.887	0.921	0.921	0.922
	MAE	0.876	0.876	0.473	0.501	0.448	0.448	0.428
Female Board Share (pct)	MSE	1.253	1.249	0.598	0.638	0.595	0.595	0.592
	R2	0.347	0.349	0.688	0.667	0.690	0.690	0.691

This table reports the performance metrics of the machine learning models Linear Regression, Ridge, CatBoost, and XGBoost, used to predict sustainability data. The models are evaluated based on their Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R2) values in five target variables Scope 1 Emissions, Scope 2 Emissions, Air Pollution, Water Discharge, and Female Board Share. Target variable is in log + 1 format. The results are shown for the best performing pipeline, that is, the pipeline that "won" the horse race. In Appendix A, we provide a visual representation of the global results.

Specifically, our best-performing models achieve mean squared errors (MSE) in the range of 0.6-1.9 and mean absolute errors (MAE) between 0.3 and 0.7. These results are substantially better compared to a benchmark study on corporate carbon emissions by Nguyen et al. (2022), which reported

[§]For further information on the computational efficiency of our approach, see Appendix A

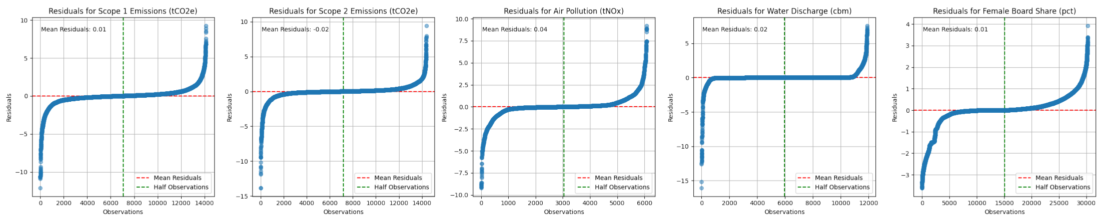
MAE values around 1.1 and 0.8 for Scope 1 and Scope 2 emissions where we achieve 0.6 and 0.5 respectively. Moreover, our models demonstrate high explanatory power. The best performing models consistently explain more than 85% of the variance in the sustainability data sample. This high level of performance underscores the potential of advanced machine learning techniques in enhancing the predictive accuracy of sustainability metrics based on financial data.

The performance of the prediction varies between the different sustainability metrics. The performance of models in predicting the female board share is weaker in relative terms compared to environmental variables. Although MAE and MSE for the female board share are not the highest among the target variables, its performance is the weakest compared to the low spectrum of values available for this variable (between 0 and 100 or 0 and 4.62 in log(1+value) terms). Given the fact that the female board share has the highest number of observations among our target variables, this indicates that prediction performance cannot always be improved to in our setting by increasing the sample size. It also highlights the difficulty that some models seem to have in dealing with truncated data (by definition, the female board share is scaled between 0% and 100%), see Appendix A for a visual representation.

For better readability, we show the results for the best-performing model for each of the sustainability metrics in subsequent analyses. These are base XGBoost models for Scope 1 and 2 emissions, a meta Ridge model for air pollution, and meta XGBoost models for water discharge and female board share.

The global models might bias towards over- or underestimating the target variables structurally. Figure 1.4 shows, however, that the residuals of the best performing models are evenly distributed between over- and underperformance in number of observations and in magnitude of the residuals. This is also reflected in the near-zero mean of the residuals. Only for female board share, we do not find fully symmetrical residuals. Hence, our models perform well for all target variables, especially for the environmental ones.

Figure 1.4: Ranked distribution of residuals



This figure shows the ranked distribution of residuals in the test dataset for five different variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share.

1.2.2 Local model assessment: Model Performance Varies

The relative errors in the predictions remain non-negligible. To show the applicability of the predicted data to different use cases, we dissect the results at the local level in the next step.

Quintile Analysis

First, we evaluate the performance of our models using a quintile-based approach. Specifically, we divide the data set into quintiles with roughly the same number of observations based on the size of the target variable[¶]. This allows us to assess how well our models perform across different ranges of sustainability metrics.

The quintile-based approach shows that the models generally perform the worst in the smallest quintile, which includes the lowest values of the target variables; see Table 1.4. This pattern is consistent in the five target variables analyzed. A key factor contributing to this performance disparity is the inherent difficulty in predicting values close to zero, which is only necessary in the smallest quintile.

The performance variation between the four remaining quintiles is relatively modest, with some target variables showing a slight decrease in performance in the fifth (largest) quintile. We do not observe any particular quintile consistently performing the best or second worst across all metrics,

[¶] Note that female board share has nearly 30% of observations equaling zero. Therefore, in this case, we manually adjusted the binning. As a result, more observations are in Quintile 1 than in the remaining four quintiles in this case.

Table 1.4: Performance of Best Models by Quintiles

Target Variable	Metric	Q1	Q2	Q3	Q4	Q5
Scope 1 Emissions (tCO2e)	MAE	1.112	0.571	0.476	0.466	0.618
	MSE	3.922	0.903	0.718	0.757	1.593
Scope 2 Emissions (tCO2e)	MAE	1.004	0.377	0.404	0.335	0.446
	MSE	3.517	0.413	0.500	0.405	0.982
Air Pollution (tNOx)	MAE	1.137	0.464	0.451	0.698	0.612
	MSE	4.074	0.780	0.803	2.015	1.861
Water Discharge (cbm)	MAE	0.532	0.222	0.205	0.185	0.221
	MSE	3.146	0.467	0.482	0.362	0.804
Female Board Share (pct)	MAE	0.692	0.301	0.315	0.344	0.401
	MSE	1.376	0.254	0.293	0.331	0.448

This table presents the performance metrics of the best-performing machine learning model across different quintiles of the target variables. The dataset is divided into quintiles based on the size of each sustainability metric Scope 1 Emissions, Scope 2 Emissions, Air Pollution, Water Discharge, and Female Board Share. Performance is measured using Mean Absolute Error (MAE) and Mean Squared Error (MSE) for each quintile, labeled Q1 through Q5, where Quintile 1 (Q1) represents the smallest values of the target variable, while Quintile 5 (Q5) represents the largest values. All input values are in log + 1 format. A visual representation of correct quintile match is available in Appendix A.

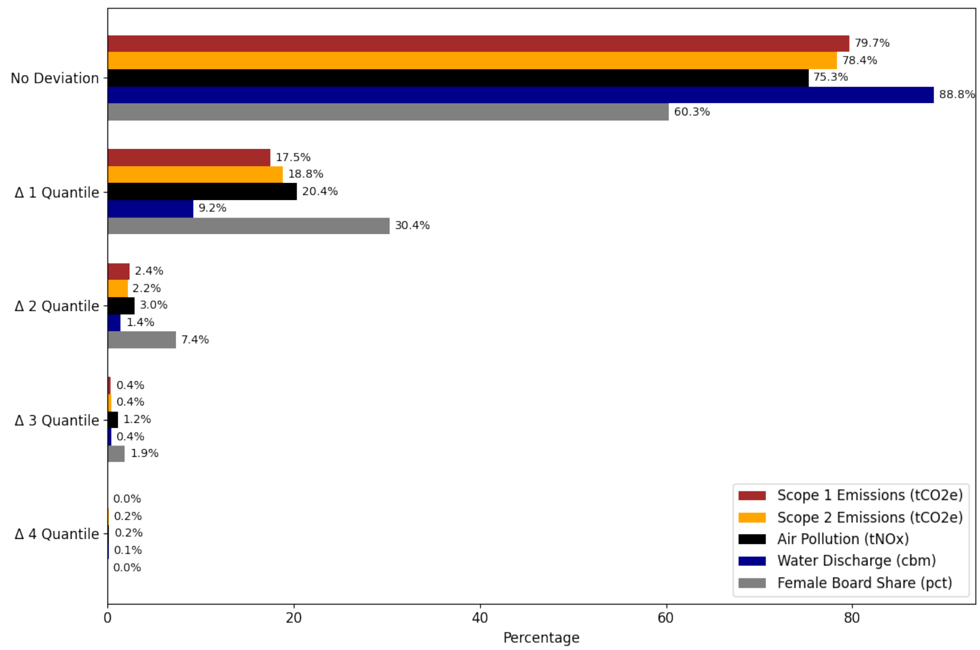
and the deviations in performance are generally small. This suggests that the models maintain a stable performance level in most of the predicted data distributions.

Finally, we categorically examine the degree of deviation between the predicted and actual quintiles. We find that our predictions fall into the right quintile 60.3% (female board share) to 88.8% (Scope 1 emissions) of the time, see Figure 1.5. In most cases of deviation, the predicted quintile deviates by only one quintile from the actual value. This underscores the overall robustness and performance of our models for categorizing companies based on our continuous predictions.

In practical terms, for an MNE, these findings indicate that the models are reliable for identifying high-impact areas within GVCs. This can be particularly useful for companies seeking to prioritize their strategic focus and allocate resources effectively to areas with the greatest impact on sustainability. Similarly, financial institutions can perform heat mapping or clustering exercises in their portfolios using the data.

Next, we analyze the performance of the model in the temporal, spatial, and sectoral dimensions

Figure 1.5: Number of Deviating Quintiles



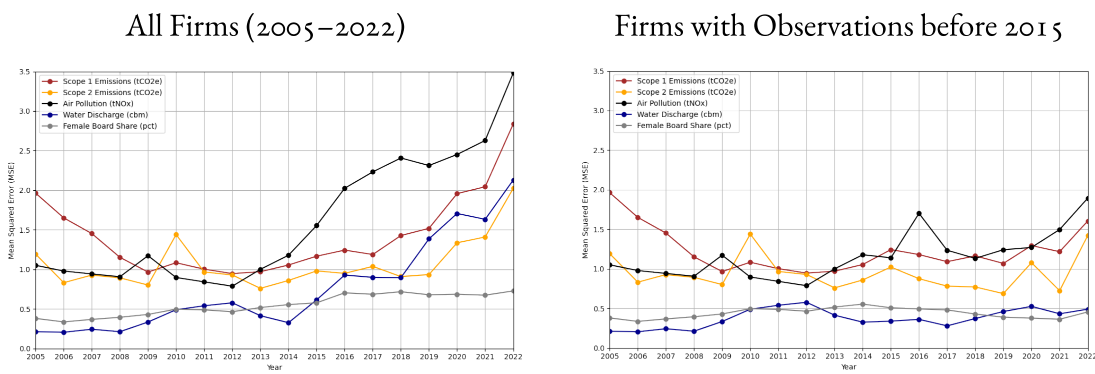
The pie charts display the proportion of observations of absolute deviating quintiles for the key variables: Scope 1 and Scope 2 emissions, air pollution, water discharge, and female board share.

to assess how our models perform under different conditions.

Temporal Dimension

Our analysis indicates that the models perform best during the period up to 2015, with a slight decrease in performance in subsequent years; see the left panel Figure 1.6. This decline is relatively minor for all target variables. We attribute it to the increased variability in the data set over time, that is, more companies reporting their sustainability data. Although more data should generally help in training machine learning models, higher heterogeneity among reporting companies (business models, sizes, technology mix, etc.) make it more difficult for the algorithm to predict with the same performance level, especially if the heterogeneity grows faster than the data availability. The flattened curves in the right panel of Figure 1.6 confirm this conjecture. It shows the same plots but for firms for which data are already available before 2015. We deduce from the comparison of the full set and the subset of the data that the heterogeneity of companies that started to report relatively recently drive the deterioration in prediction performance over time.

Figure 1.6: Temporal Model Performance



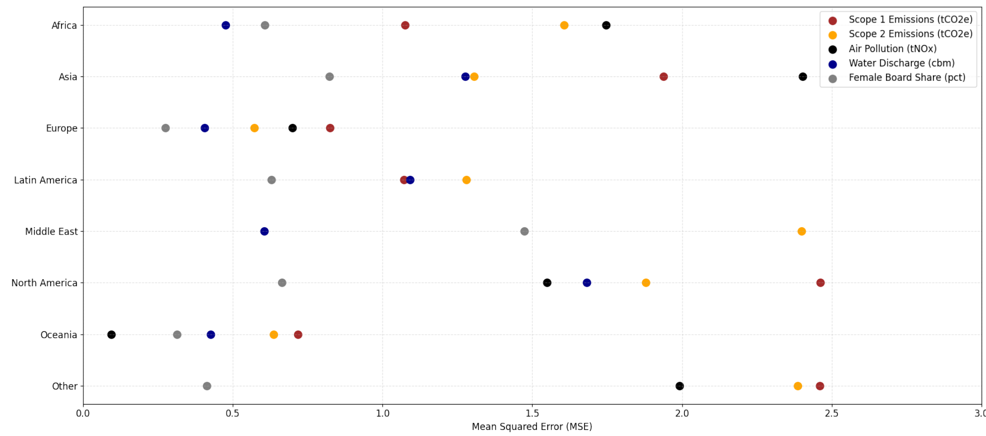
This figure illustrates the model performance over time (2005–2022) for five different variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share. The left panel shows results for all firms, while the right panel includes only firms with observations recorded before 2015. The ordinate represents the MSE, showing how prediction performance has evolved for each variable across the years.

When applying machine learning models to real-world scenarios, it is essential to consider these temporal variations. Users should ensure that the specific use case is well understood so that the models can be appropriately adapted. Particularly when focusing on current data, it might be necessary to apply variations or modifications to the models trained on older data. One potential approach is to incorporate a discount factor in the loss function that adjusts for temporal discrepancies.

Spatial Dimension

In the spatial analysis, we observe some variation in model performance between different geographic regions; see Figure 1.7. In particular, our models tend to perform better in Europe (and Oceania) than in other parts of the world. This discrepancy could be partially attributed to stricter and more comprehensive reporting regimes in Europe, resulting in a larger and more reliable dataset (Krueger et al., 2024), that is, reporting is more homogeneous due to mandatory guidelines that improve model performance in these regions (or reduce heterogeneity). However, despite these differences, the models still perform well in all regions. For MNEs looking to optimize global supply chains, our approaches are applicable, although some caution is advised.

Figure 1.7: Spatial Model Performance



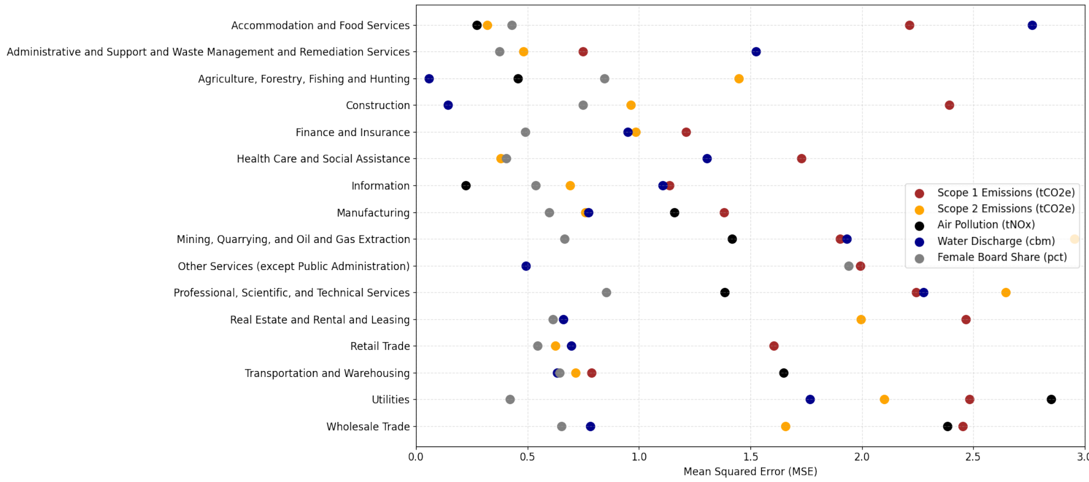
This figure shows the model performance across different global regions, as measured by the MSE for the five target variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share. Each region is represented along the ordinate, while the MSE values are plotted as dots.

Sectoral Dimension

Regarding the sectoral dimension, we find minor variations in model performance across different industries, with some outliers; see Figure 1.8. For most industries, the models perform reliably, suggesting that they are well suited for applications that involve analyzing portfolios spanning multiple sectors and industries, such as those of banks or asset managers. However, if a particular sector is of special importance to an economic actor, it may be beneficial to use a weighted loss function tailored to sectoral importance.

In summary, while there is some variation in the model performance across the temporal, spatial, and sectoral dimensions, the models generally perform well in all three areas. However, the variation underscores the importance of understanding the specific use case and tailoring the models accord-

Figure 1.8: Sectoral Model Performance



This figure displays the MSE of model predictions across industries for the five target variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share. Each dot represents the MSE for a particular variable within a specific industry.

ingly to ensure optimal performance for the task at hand. In Appendix A, we provide some recommendations for researchers on how to work with our approach and the predicted sustainability data given these variations.

1.2.3 Beware The Prediction Uncertainty

The analysis of prediction uncertainty across the target variables reveals heterogeneous patterns. For smaller coverage requirements, the uncertainty is generally negligible, whereas for larger coverage requirements, it becomes significant. Our conformalized quantile regression approach demonstrates empirically valid coverage (with an absolute difference between empirical and target coverage $\leq 0.68\%$ for all variables and coverage rates). The prediction uncertainty remains largely symmetrical, balancing under- or overestimation of prediction uncertainty compared to other standard uncertainty measures. In this section, we show the results for Scope 1 Emissions; see Appendix A for the results for the other target variables.

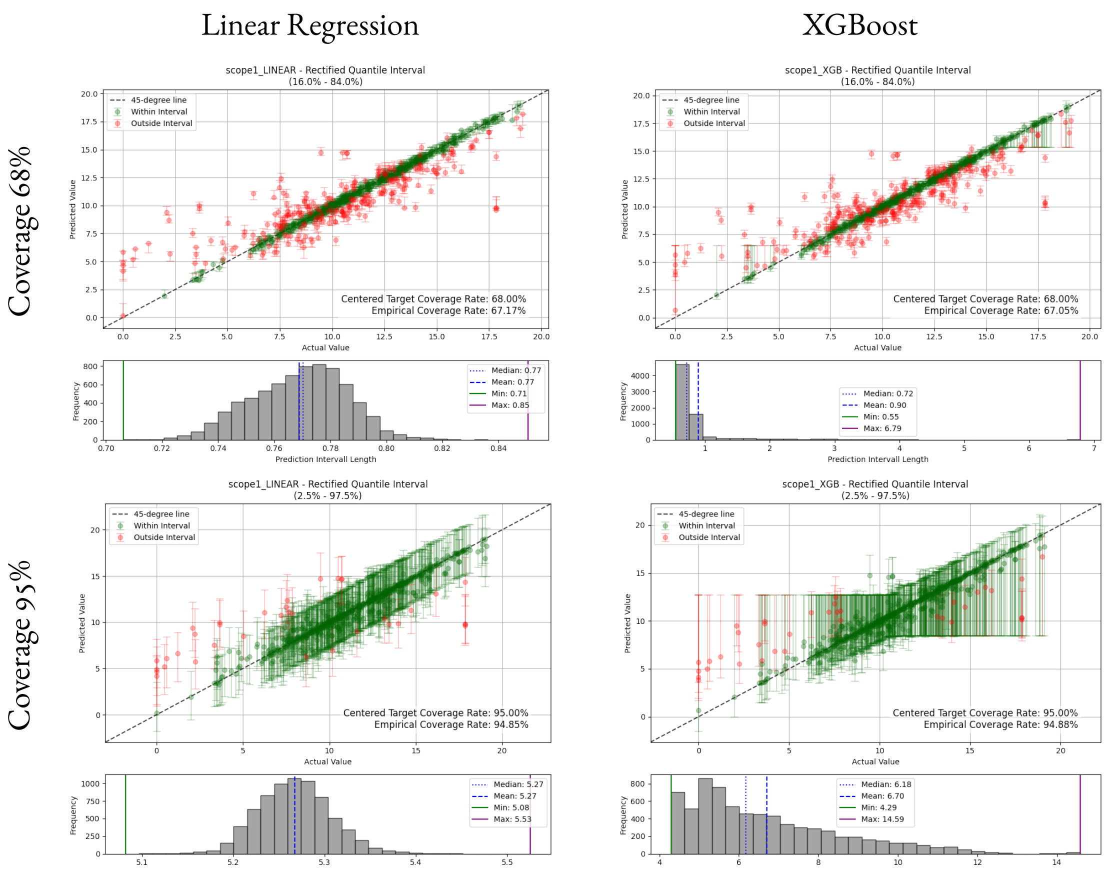
Figure 1.9 illustrates the prediction uncertainty in four settings, including conformalized quantile regression using linear regression and XGBoost and with coverage rates of 68% and 95%. The figure demonstrates that, while prediction uncertainty always exists, it is relatively low for the 68% coverage rate. This suggests that users who are not highly risk-averse can use the point estimates without encountering (on average) significant uncertainty. However, at the 95% coverage rate, uncertainty increases substantially, indicating a wider range of possible outcomes, which may be of concern to users who require greater confidence in their predictions.

In addition, the choice of the learner to estimate the uncertainty affects the results. Linear regression models tend to produce on average narrower prediction intervals with relatively constant interval lengths across the distribution of the target variable. In contrast, XGBoost exhibits a more adaptive behavior, with wider prediction intervals towards the extremes of the target variable values. For lower actual values, the uncertainty intervals become larger, particularly skewing toward values above the actuals. Similarly, for the largest values, the intervals widen, though skewed downward, toward lower-than-actual values.

Figure 1.10 further examines the distribution of the prediction intervals, confirming their general symmetries. In this figure, we use predictions of the conditional mean from the (best performing) XGBoost meta-leaner. Linear regression models show tighter distributions of interval lengths, while XGBoost produces more widely spread intervals.

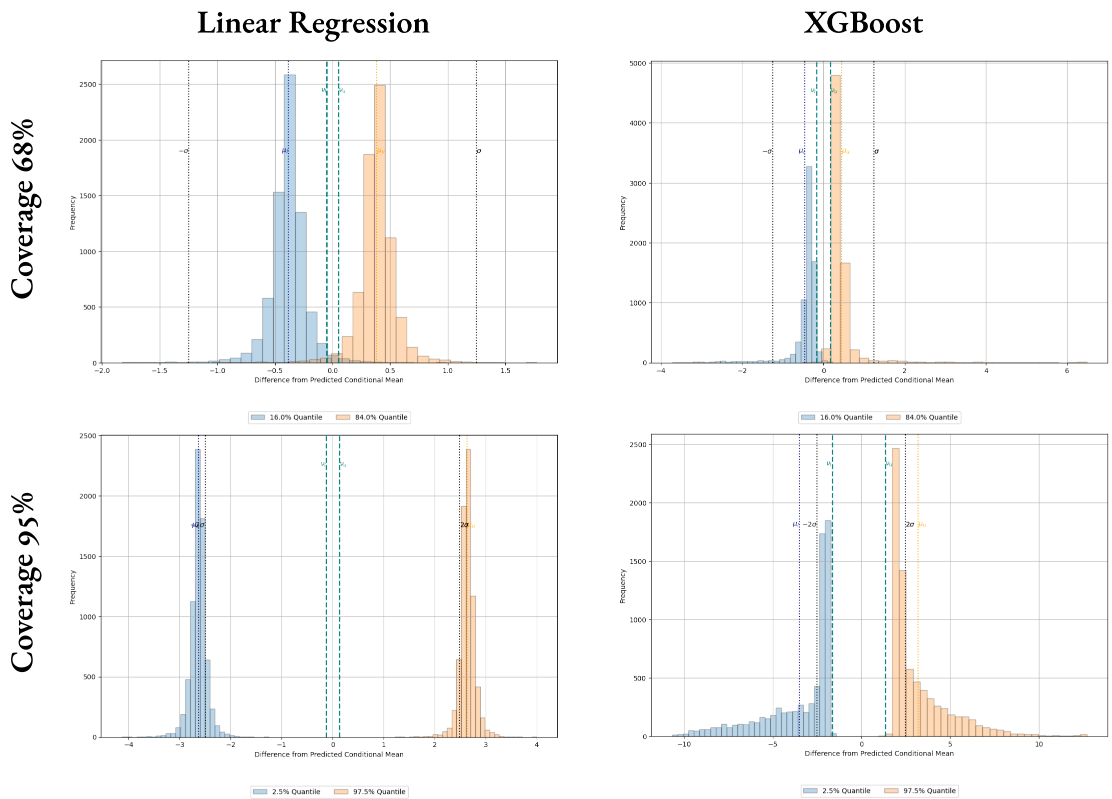
This figure also presents alternative uncertainty measures for comparison. In addition to the conformalized quantile-based measure, a more naive approach is shown using simple one- and two-standard deviations (σ) from the conditional mean, which are typically used for coverage levels 68% and 95%. This naive approach results in significantly larger intervals compared to the conformalized quantile-based method in most settings. In addition, an alternative method has been employed that uses (standard) quantile regression (ν). This method underestimates the uncertainty compared to our conformalized approach most of the time. This leads us to conclude that the conformalized quantile-based

Figure 1.9: Prediction Uncertainty in Different Settings for Scope 1 Emissions



This figure displays the prediction uncertainty for Scope 1 Emissions. The settings are for the learners linear regression and XGBoost and the target coverage rate of 68% and 95%. For better readability, the actual vs. predicted plots display only 2% of the total observations, randomly selected.

Figure 1.10: Deviation from Conditional Mean for Scope 1 Emissions



This figure displays the deviation from the predicted conditional mean for Scope 1 Emissions in different settings. The settings are for uncertainty estimates based on linear regression and XGBoost and for targeted coverage rates of 68% and 95%. In all settings, the conditional mean is predicted by the best-performing XGB meta model. The black dotted lines represent the prediction intervals using one and two standard deviations (σ), respectively. The green dashed lines represent the mean lower (upper) quantile prediction from standard quantile regression, ν_l (ν_u). Finally, the blue and orange bars show the distribution of quantile predictions for the lower and upper quantile from conformalized quantile regression. The mean of lower (upper) predictions is represented by the blue and orange dotted lines, μ_l (μ_u).

method is well suited to test prediction uncertainty.

The results of the uncertainty measures for other target variables than Scope 1 emissions show consistent results for environmental variables; however, for the variable representing the female board share (see Appendix A), which is truncated between zero and one, the uncertainty distributions differ, reflecting the specific characteristics of the data.

1.3 Conclusion

This study demonstrates that ML can serve as an effective tool for generating company-level sustainability data using only readily available financial and fundamental data. The findings of this research have several important implications for policymakers, MNEs, and the financial industry.

First, policymakers should reconsider the prevailing trend of relying solely on sustainability-related raw data within industry and the financial systems. Although the use of raw data has its merits, particularly in ensuring accuracy, there are instances where the transaction costs associated with obtaining such data are prohibitively high. In these cases, the use of machine learning-generated data offers a viable alternative to using generalized metrics, such as industry averages. This approach can improve the granularity and relevance of sustainability data for decision making.

Second, the study highlights the potential variations and uncertainties inherent in any prediction model, particularly those related to sustainability data. To address this, there is a need for increased transparency requirements for both data providers and companies when using machine learning or other modeling techniques to generate sustainability data. This transparency is crucial to ensure that the uncertainties associated with these models are well understood and that any biases in the underlying data are clearly communicated. Policymakers could enhance transparency standards, similar to the current efforts for ESG ratings in the European Union (General Secretariat of the Council, 2024), and extend these standards throughout the industry to ensure consistency and reliability.

Third, our research emphasizes the importance of considering the specific use case when applying machine learning models. The performance of these models can vary significantly depending on temporal, spatial, or sectoral factors, which must be taken into account to ensure the accuracy and relevance of the generated data. Adjustments to the loss function can improve the suitability of the model for specific applications, but these considerations should be made transparent to users, illustrating the methodology behind the data generation process.

It is important to acknowledge the limitations of our research. In particular, questions remain regarding the generalizability of our models as is the case for any data-generating process. In the absence of mandatory ESG reporting requirements (Krueger et al., 2024), many MNEs report voluntarily, which can lead to biases in the sample. In addition, the models developed in this study are trained primarily on data from MNEs, which may not be directly applicable to government organizations, non-profit entities, or small and medium-sized enterprises (SMEs)[‖]. These other parts of the economy may require different data sets, and it remains uncertain whether sufficient data is available to support the development of ML models in these contexts. Future research should explore these gaps, potentially identifying alternative approaches to address the limitations in data availability for these use cases.

In conclusion, this study illustrates that machine learning has a significant role to play in making sustainability data more accessible and cost-effective. By improving the availability and quality of sustainability data through ML, companies and policymakers can make better informed decisions, ultimately advancing sustainability initiatives throughout the global economy.

[‖] In Appendix A, we show that the prediction performance of our models for smaller companies tends to be worse.

The difference between what we do and what we are capable of doing would suffice to solve most of the world's problems.

Mahatma Gandhi

2

Consistency or transformation? Finance in climate agreements

The world economy needs to decarbonize to achieve the targets of the Paris Agreement. Finance plays a role in this process, which the Paris Agreement explicitly recognizes. Article 2.1c of the Agreement calls for making *"financial flows consistent with a pathway toward low green-*

house gas emissions and climate-resilient development" (United Nations, 2015). However, this statement is ambiguous on two dimensions: (i) scope of "financial flows" and (ii) role of finance in climate action. The scope ranges from compensatory payments for climate damages at the policy level to a complete reorientation of the global financial system to support the Paris Agreement targets. The role of financial flows results from the interpretation of "consistency". It can range from a (passive) provision of capital to green companies to an active role of the financial system in driving change in the real economy. This breadth of interpretation hampers the stringent and consistent implementation and monitoring of Article 2.1c.

In this paper, we provide evidence for a clearer definition of Article 2.1c by examining the role of responsible institutional investors in aligning financial flows with the Paris Agreement. Despite their self-perception as being within the scope of Article 2.1c, we show that their actual impact on decarbonizing the real economy is limited.

During the past decade, institutional investors have increasingly integrated sustainability into their investment strategies, as evidenced by the growth of initiatives such as the United Nations Principles for Responsible Investment (UN PRI), which had 5,345 signatories as of March 2024 (PRI, 2024). The Paris Agreement further accelerated this momentum, giving rise to climate investor coalitions such as Climate Action 100+, with roughly 700 signatories as of January 2023 (Climate Action 100+, 2023). The establishment of the Glasgow Financial Alliance for Net Zero (GFANZ) before COP26 underscores the financial sector's collective commitment to the Paris targets (GFANZ, 2024). These developments suggest that "Responsible Investors" consider themselves within the purview of Article 2.1c.

Responsible Investors have two primary levers to align financial flows with the Paris climate goals: (i) capital reallocation toward greener companies or away from carbon-intensive ones, and (ii) using their influence as shareholders to engage companies on their climate strategies, pushing for meaningful transition and decarbonization plans.

Capital reallocation by Responsible Investors sends a green preference signal (Pástor et al., 2021) and can affect capital costs (De Angelis et al., 2023), which should prompt companies to adjust their business models (Caldecott et al., 2022). Atta-Darkua et al. (2023) demonstrates that Responsible Investors have indeed begun to tilt their portfolios towards greener companies. However, for these signals to be effective in achieving the Paris targets, they must induce tangible changes in the real economy. The literature remains skeptical about this impact (Berk and van Binsbergen, 2021; Kahn et al., 2023). In addition, divesting from high-emission companies can raise their cost of capital, potentially hindering their ability to finance transition projects. Simultaneously, reallocating capital to already green companies has limited additional climate impact (Hartzmark and Shue, 2023). This suggests that capital reallocation reflects a passive interpretation of Article 2.1c, rather serving the reputation of the investor instead of supporting the decarbonization of the real economy.

Alternatively, Responsible Investors can leverage their influence through shareholder voting and engagement with company management. Given their significant share in global equity markets (Bas et al., 2023), this channel could be potent. Engagement has been shown to improve companies' climate performance and transparency (Cohen et al., 2023a; Ilhan et al., 2023) and reduce downside climate risks (Hoepner et al., 2024). If Responsible Investors actively used this strategy, they could assume an active role in aligning financial flows with the Paris climate objectives.

To understand whether Responsible Investors indeed have an aggregate impact through the channels, this paper empirically examines their global equity holdings and their relationship to the decarbonization of real economy companies. We use a global data set of institutional investor company holdings in which we systemically identify Responsible Investors according to their membership in the UN PRI. Using these data, we run our analyses at the company-level to directly estimate the relationship between responsible ownership and the decarbonization of real economy business models.

Our data show that Responsible Investors indeed hold a significant share of equity in capital markets. In recent years, they have built up ownership shares, so they are now holding roughly a third of all equity in global capital markets. Given this relevance by size, these investors can be considered within the scope of Article 2.1c. However, their size in capital markets does not necessitate any impact on climate strategies by companies in their portfolios. Therefore, we develop a view on their actual impact by analyzing Responsible Investor's capital allocation decisions and relationship to company decarbonization.

The analysis of Responsible Investors capital allocation shows lower allocation to brown and higher to already green or low-impact companies. Responsible Investors explicitly shun high-emitting companies more than the average institutional investor and more than other investors. This finding is in line with previous studies on responsible investor behavior (Atta-Darkua et al., 2023; Heath et al., 2023; Kahn et al., 2023). As a consequence of the result, Responsible Investors have lower leverage over these companies than the average investor, as such, reducing their influence on potential transition-related decisions within the company. Combined with the passive interpretation of the capital allocation channel, this leads to doubts about the role of Responsible Investors in making "financial flows consistent" with the targets of the Paris Agreement. In particular, it appears that Responsible Investors shun companies and industries with a large potential for transition finance, which further diminishes their potential leverage for climate action.

If the engagement channel is to work, Responsible Investors drive decarbonization in the companies in which they have higher ownership. However, our analysis shows that companies with higher ownership by Responsible Investors do not decarbonize faster. We do not find any relationship between responsible ownership and company decarbonization. This finding strongly speaks against an active role of Responsible Investors in making "financial flows consistent" with the targets of the Paris Agreement. In conjunction with the previous finding, we conclude that Responsible Investors prioritize a lower-emission portfolio over a Paris-aligned real economy, that is, low-emission portfolios over tangible change needed for climate action.

In contrast, we find that companies' ESG ratings improve significantly with higher responsible investor ownership. This highlights a focus of Responsible Investors on these widely used ESG metrics (Berg et al., 2021) instead of decarbonization of the real economy. Given the low correlation between ESG ratings and actual decarbonization of companies (Elmalt et al., 2021), this finding further corroborates the interpretation that Responsible Investors prioritize the perceived sustainability performance of their portfolio over decarbonization or any other tangible sustainability improvement in the real economy.

Our findings remain consistent across a range of robustness tests. Our main analysis is run on Responsible Investors defined as an institutional investor being a member of UN PRI. UN PRI is the longest existing initiative in the field, and thus allows for a more comprehensive panel data structure. However, UN PRI focuses on sustainability in general. We rerun our analyses using CA100+ membership as an indicator for Responsible Investor. This initiative is only dedicated to climate action. The results are robust. Second, capital allocation decisions by Responsible Investors in the past might affect company decarbonization potential in the future. For example, a greener company might have used all green technology available already at the moment when the Responsible Investor invests, and thus Responsible Investors might not be able to motivate the company to do more. We check for robustness on this issue by running a lagged regression model with robust results. Finally, we run variations on our main settings (e.g., by excluding low institutional ownership or big three ownership) to ensure that outliers or specific observations do not drive the results.

This paper contributes to two strands of the literature. First, we add to the discussion on the role of institutional investors and capital markets in the decarbonization of the real economy. Atta-Darkua et al. (2023) find that Responsible Investors do indeed decarbonize their portfolios; however, they achieve this mainly through portfolio tilting, which raises doubts about the impacts in the real economy. In a similar vein, Benz et al. (2021) and Heath et al. (2023) show that mutual funds tend to avoid high-impact companies. We uniquely add to these findings by assessing the impact of Responsible Investors in the real economy through a company level instead of a investor or fund-level analysis. This allows us to control for company characteristics, which might explain carbon emissions or ownership structures. Our analysis also changes the perspective from the often discussed return effects of carbon emissions (see, e.g., Bolton and Kacperczyk (2021), Aswani et al. (2024) and Bolton and Kacperczyk (2024)) to the impact of investors-company relationships in promoting climate action.

Second, we contribute to the literature on finance in climate agreements. Article 2.1c of the Paris Agreement is interpreted in different ways. Zamarioli et al. (2021) point out that the article implies a transformation of the global financial system. This is beyond transfer payments from the Global North to the Global South and requires the participation of non-state actors. Our paper is the first to explicitly target this question from an empirical point of view. We contribute by highlighting that the inclusion of non-state actors, institutional investors in this case, might not be highly effective in achieving the decarbonization of the real economy. As a result, regulators should be precise in the scope of finance in climate agreements and the role they assign to financial markets and specific types of financial institutions in global climate efforts.

The remainder of the paper is structured as follows. Section II outlines the methodology, Section III presents and discusses the results, and Section IV concludes.

2.1 Methodology

We apply an empirical approach based on an extensive institutional investor ownership data set and company-level data. We test the relationship between Responsible Investors and company decarbonization using ordinary least squares (OLS) regressions in different model specifications.

2.1.1 Data

We build a panel data set that contains company and investor data using different data sources.

We retrieve a broad universe of publicly listed companies, including their unique identifiers (RIC and ISIN) available in the Refinitiv database for the 2009-2023 period. We clean the data so that only primary listed equity of companies remains, as the data from Refinitiv contain other listed financial instruments, such as listed bonds. This ensures that each company appears only once in the data set.

Financial institutions differ in their role in climate action compared to real economy companies (Görgen et al., 2020). This is mainly the result of their main exposure to climate change via financed emissions (Scope 3). In contrast, climate-relevant sectors in the real economy (Battiston et al., 2017) exhibit more direct emissions (Scope 1 and Scope 2). To avoid measurement errors due to this different behavior and to measure the relationship between Responsible Investor ownership and real economy companies' Paris alignment, we remove financial institutions based on economic sector level classification by The Refinitiv Business Classification (TRBC) at the classification level 1.

For the remaining companies, we retrieve absolute and relative (greenhouse gas emissions divided by revenue) Scope 1 emissions from Refinitiv as independent variables for the analysis. We use reported emission data only to avoid inconsistencies in the modeled data (Busch et al., 2022; Aswani et al., 2024; Bolton and Kacperczyk, 2024). We focus on Scope 1 emissions, as these are under direct control of the company. Furthermore, following the classification by Battiston et al. (2017)[*], we introduce a dummy variable that indicates whether a company operates in a climate-relevant sector (Climate Policy Relevant Sector) and a dummy variable that indicates the 10% of observations with the highest Scope 1 emissions (Top 10% Scope 1 Emissions) in each year. This yields four different measures for the role of a company in the decarbonization, which we use in different regression settings.

We add yearly MSCI industry-adjusted ESG ratings, which allows us to control for ESG integration strategies and compare the emission development with the ESG rating development. MSCI ESG ratings provide a sufficiently historical time series, and practitioners rate them as one of the best ESG rating providers in terms of quality and usefulness in recent years (see, e.g., Wong and Petroy (2020) and Brock et al. (2023)). As a result, they should indicate the investment behavior of institutional

[*]We use a NACE to NAICS to TRBC matching for this procedure.

investors in the market. MSCI industry-adjusted ESG ratings range between values of 0 and 10 with higher values indicating ”greener” / ”more sustainable” performance of the respective company. To avoid any time- or distributional effects in the ratings, we normalize the ratings on an annual basis following Berg et al. (2022).

Furthermore, we collect a set of control variables based on Ferreira and Matos (2008). For this purpose, we obtain end-of-year data from Refinitiv that include company market value (in USD), return on assets (ROA), total debt (in USD), book-to-market ratio (BTMR), cash holdings (in USD), revenue (in USD), stock returns, stock return volatility, dividend yield, the TRBC industry classification, and headquarters location. Based on the company market value (in USD), we remove all company observations with values smaller than 25 mUSD to exclude micro-sized enterprises from the analysis.

For the institutional ownership data set, we retrieve end-of-year institutional ownership information for each company from the Refinitiv ownership database. This includes an investor-specific identifier (PermID) and the value of shares held by an investor in each company. Investor observations with missing values for the value of shares are removed. The same applies to all investor observations with the value of shares equal to zero. Refinitiv ownership data include entries from large private investors, inter alia, high-net-worth individuals and family offices. We remove all of these observations to ensure that we capture only institutional investors in our data. In addition, we remove all investor observations with aggregated portfolio values of less than 100 mUSD and number of companies held smaller five in a given year to avoid comparatively small or very specialized investors biasing the results.

We define ‘Responsible Investors’ as those institutional investors committed to action on climate change. To approximate this commitment, we use membership in sustainability-related institutional investor initiatives, namely, UN PRI and Climate Action 100+. Using public UN PRI Signatory and Climate Action 100+ membership data and Refinitiv’s name matching followed by a manual review process, we create two lists of Responsible Investors. In addition, we add subsidiaries of the signatories up to the third subsidiary level. We classify an investor as Responsible Investor from the year of signing up to the UN PRI. For the CA100+ member list, no signature date is published; therefore, we classify each member of the initiative as a CA100+ investor from the initialization of the initiative in the year 2017. In our main analysis, we use UN PRI as the proxy for Responsible Investor.

We calculate three ownership indicators for each company i in each year t. First, the Responsible Investor Share, which is the sum of value held by Responsible Investors in relation to the company's market value, see Equation 2.1. Second, the Institutional Investor Share, which is the sum of value held by all institutional investors divided by the company's market value, see Equation 2.2. Third, the Responsible Investor Ratio, which is the sum of holdings by Responsible Investors relative to the sum of holdings by institutional investors, see Equation 2.3. Using the Responsible Investor Ratio allows us to compare Responsible Investor preferences for company characteristics in relation to the average institutional investor behavior.

$$\text{Responsible Investor Share}_{i,t} = \frac{\sum \text{Responsible Investor Value}_{i,t}}{\text{Market Value}_{i,t}} \tag{2.1}$$

$$\text{Institutional Investor Share}_{i,t} = \frac{\sum \text{Institutional Investor Value}_{i,t}}{\text{Market Value}_{i,t}} \tag{2.2}$$

$$\text{Responsible Investor Ratio}_{i,t} = \frac{\sum \text{Responsible Investor Value}_{i,t}}{\sum \text{Institutional Investor Value}_{i,t}} \tag{2.3}$$

All continuous variables in the resulting data set are winorized at the levels 1% and 99%. We take the natural logarithm of control variables with strong tails or a higher skewness. The final data set contains 275,532 company-year observations coming from 25,050 unique companies; see Table 2.1 for summary statistics of selected variables. However, the number of observations available for regression analysis is often limited by the availability of Scope 1 emission data and ESG rating data.

Table 2.1: Summary Statistics

	count	mean	std	min	25%	50%	75%	max
Responsible Investor Ratio	276372	0.36	0.32	0.00	0.04	0.31	0.61	1.00
Responsible Investor Share	276238	0.08	0.13	0.00	0.00	0.02	0.09	1.00
CA100+ Ratio	276372	0.06	0.15	0.00	0.00	0.00	0.03	1.00
CA100+ Share	276238	0.01	0.03	0.00	0.00	0.00	0.00	0.75
Institutional Investor Share	276238	0.19	0.24	0.00	0.02	0.09	0.27	1.00
log(Scope 1 Emissions)	35028	10.92	3.41	0.00	8.76	10.93	13.18	19.75
log(Scope 1 Intensity)	34910	0.19	0.42	0.00	0.00	0.01	0.14	8.51
log(Scope 2 Emissions)	34638	10.89	2.69	0.00	9.44	11.22	12.72	22.72
log(Scope 2 Intensity)	34537	0.07	0.17	0.00	0.01	0.02	0.07	7.36
ESG Rating (MSCI)	47837	4.70	2.33	0.00	2.90	4.63	6.50	10.00
Climate Policy Relevant Sector	276372	0.58	0.49	0.00	0.00	1.00	1.00	1.00
log(Total Debt)	262632	2.10	4.25	-9.21	1.94	3.60	4.48	6.92
Return on Assets	269261	2.02	13.67	-48.97	0.89	4.10	7.89	33.05
log(Revenue)	262385	12.64	1.93	9.28	11.32	12.53	13.86	19.19
Book to Market Ratio	270079	0.81	3.79	-100.00	0.30	0.60	1.10	100.00
log(Cash Holdings)	253909	10.60	2.02	6.90	9.25	10.62	11.93	16.89
Stock Return	261823	13.97	52.58	-65.11	-18.36	4.14	32.23	206.87
log(Market Capitalization)	276238	6.02	1.77	3.85	4.48	5.85	7.15	12.92
Dividend Yield	276345	1.86	2.40	0.00	0.00	0.99	2.84	10.77
Historic Volatility	275532	0.45	0.21	0.13	0.30	0.41	0.56	0.99
North America	276372	0.18	0.38	0.00	0.00	0.00	0.00	1.00
European Union	276372	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Rest of World	276372	0.66	0.47	0.00	0.00	1.00	1.00	1.00

The table presents summary statistics for the financial and environmental metrics across our dataset of companies and their investors. Each metric's distribution is described by count, mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, and maximum values. Note that ESG Rating is displayed non-normalized here.

2.1.2 Statistical Analysis

We run the analysis at the company level. This setting allows us to investigate whether certain characteristics of the company affect the relationship between the company and the investor. Using this company-level approach rather than an investor portfolio-based approach (e.g., as in Atta-Darkua et al. (2023)) comes with the advantage that we can explicitly control for other company-specific characteristics that may influence the investment preferences of investors and the effects that those characteristics might have on the companies' strategic decisions to decarbonize.

First, we test whether companies with high relevance for the decarbonization are held less by Responsible Investors. The focus of this regression analysis is on the climate relevance of companies measured through absolute and relative Scope 1 emissions as well as the company being among the top 10% of high-emitting company observations ("Top 10% Scope 1 Emissions") and operating primarily in a climate-relevant sector ("Climate Policy Relevant Sector") (all represented by φ). In addition, we control for company-level ESG ratings to ensure that investment strategies such as ESG integration do not drive the results. We lag all independent variables by one year as the investor is very likely to need time to observe the company behavior and make informed investment decisions. We apply OLS regressions in the setting as depicted in Equation 2.4.

$$y_{i,t} = \beta_0 + \beta_1 \varphi_{i,t-1} + \beta_2 \text{ESG Rating}_{i,t-1} + \beta_X X_{i,t-1} + \text{FE} + \varepsilon_{i,t} \tag{2.4}$$

Here, the dependent variable, denoted by $y_{i,t}$, can be the Responsible Investor Ratio or the Institutional Investor Share for each company i in year t. The model includes an intercept β_0, and coefficients β_1 to capture the impact of climate relevance indicator φ and β_2 to capture the effect of the MSCI ESG Rating (ESG) on the dependent ownership variable. Furthermore, β_X and X denote the vectors for company-specific time-variant control variables. FE denotes fixed effects including time (year), sector (TRBC level 1) and headquarter location (Europe, North America or Rest of the World). ε is the error term.

Second, we test whether Responsible Investor ownership positively relates to decarbonization of the company, that is, whether companies with higher Responsible Investor ownership decarbonize faster. For this, we calculate Δ in all time-variant variables as changes of future years (1-5) versus the base year. We use Responsible Investor Share in this setting to account for the overall influence of Responsible Investors on the company. We focus on Scope 1 emissions in this setting, as these emissions are under direct control by the company and MSCI ratings to contrast our findings on decarbonization. We focus on absolute emissions, as they are mainly relevant for achieving the targets of the Paris Agreement. We use the following regression setup; see Equation 2.5.

$$\begin{aligned}\Delta y_{i,t} = \beta_0 &+ \beta_1 \text{Responsible Ownership}_{i,t-x} + \beta_2 \text{Institutional Ownership}_{i,t-x} \\ &+ \beta_3 \Delta \text{Responsible Ownership}_{i,t} + \beta_4 \Delta \text{Institutional Ownership}_{i,t} \\ &+ \beta_X X_{i,t-x} + \gamma_X \Delta X_{i,t} + \text{FE} + \varepsilon_{i,t} \end{aligned} \tag{2.5}$$

In this setup, the dependent variable, represented by $\Delta y_{i,t}$, denotes the change in ESG ratings or in Scope 1 emissions for each company i at time t. The model comprises an intercept β_0 and coefficients β_1 and β_2 to evaluate the impacts of the Responsible Investor Share (Responsible Ownership) and the Institutional Investor Share (Institutional Ownership) on the dependent variable of time $t-x$, where x represents the years of change versus the target year. β_3 is the coefficient for the change in ownership from the target year i to the base year x. Furthermore, X and Δ X denote the vectors for the company-specific time-variant control variables in time t and $t-x$ and β_X and γ_X their respective coefficients. FE denotes fixed effects including time (year), sector (TRBC level 1), and headquarter location (Europe, North America or Rest of the World). ε is the error term.

Third, the decision on portfolio allocation by Responsible Investors is largely endogenous. Investors may invest in or shun companies for specific reasons. For example, an investor might anticipate that high-emitting companies cannot decarbonize or choose specific companies that have the potential to do so. In contrast, a greener company might have used all the green technology available already at the moment when the Responsible Investor invests, and thus Responsible Investors might not be able to motivate the company to do more. That is, the decision of the investors in analysis I could affect the results of analysis II. To check for this endogeneity, we perform a lagged dependent variable regression to rule out concerns about the direction of results. In this model, we control for the shunning of high-emitting companies when assessing the future emission development of these companies. β_5 in Equation 2.6 captures the potential effect that emissions in t-1 could have on the results. The same setting is applied for MSCI ESG ratings.

$$\begin{aligned}\Delta y_{i,t} = {} & \beta_0 + \beta_1 \text{Responsible Ownership}_{i,t-x} + \beta_2 \text{Institutional Ownership}_{i,t-x} \\ & + \beta_3 \Delta \text{Responsible Ownership}_{\ i,t} + \beta_4 \Delta \text{Institutional Ownership}_{\ i,t} + \beta_5 y_{i,t-1} \\ & + \beta_X X_{i,t-x} + \gamma_X \Delta X_{i,t} + \text{FE} + \varepsilon_{i,t} \qquad (2.6)\end{aligned}$$

In this setup, the dependent variable $\Delta y_{i,t}$ denotes the change in ESG ratings or of Scope 1 emissions for each company i at time t. The model includes an intercept β_0, and coefficients β_1 and β_2 to evaluate the impacts of the Responsible Investor Share (Responsible Ownership) and the Institutional Investor Share (Institutional Ownership) on the dependent variable at time $t - x$, where x represents the years of change relative to the target year. The coefficient β_3 represents the change in responsible ownership from the base year to the target year, while β_4 captures the change in institutional ownership over the same period.

Furthermore, the model incorporates the lagged dependent variable $y_{i,t-1}$, with coefficient β_5, to capture the influence of the dependent variable of the previous period on the current period. The terms $X_{i,t-x}$ and $\Delta X_{i,t}$ denote the coefficient vectors for company-specific time-variant control variables at time $t - x$ and the change in these variables up to time t, respectively, with corresponding coefficients β_X and γ_X. Fixed effects (FE) are included to control for unobserved heterogeneity, covering factors such as time (year), sector (TRBC level 1), and headquarters location (Europe, North America, or Rest of the World). $\varepsilon_{i,t}$ is the error term.

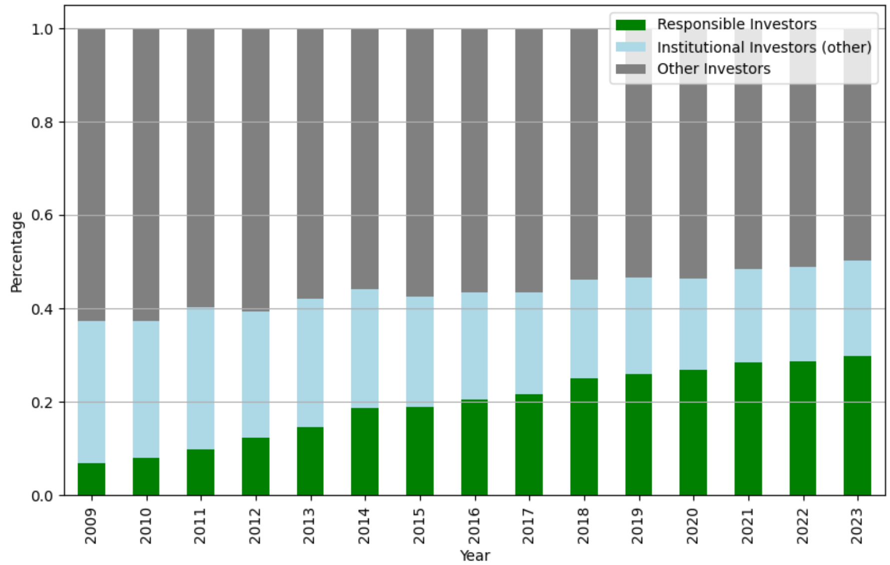
2.2 Results and Discussion

2.2.1 Responsible Investors' portfolio allocation

Responsible Investors represent a significant share of capital markets. Their relevance in the equity market has grown steadily and reached 28.7% in 2022, see Figure 2.1. Given this relevance by size, these investors are within the scope of Article 2.1c. If Responsible Investors were holding portfolios in line with the Paris climate targets, a major share of financial flows would actually go towards these targets. However, the size of Responsible Investors in capital markets does not necessitate any impact on climate strategies by companies in their portfolios, nor does it ensure that their holdings are aligned with the Paris climate targets.

Carbon intensities of Responsible Investor holdings are an indication of their exposure to (i) low carbon sectors, and (ii) high-emitting companies. In 2022, Responsible Investors hold approximately 17.7% of the reported financed greenhouse gas emissions through their equity holdings. Here, we assume a fair share distribution of greenhouse gas emissions in equity markets only. The divergence between the share of the total market held and the associated share of Scope 1 emissions held could be an indication of Responsible Investors' portfolio reallocation toward low-emitting companies and avoidance ("shunning") of high-emitting companies. In doing so, they could actually be re-allocating financial flows towards companies that are closer aligned with the Paris climate targets.

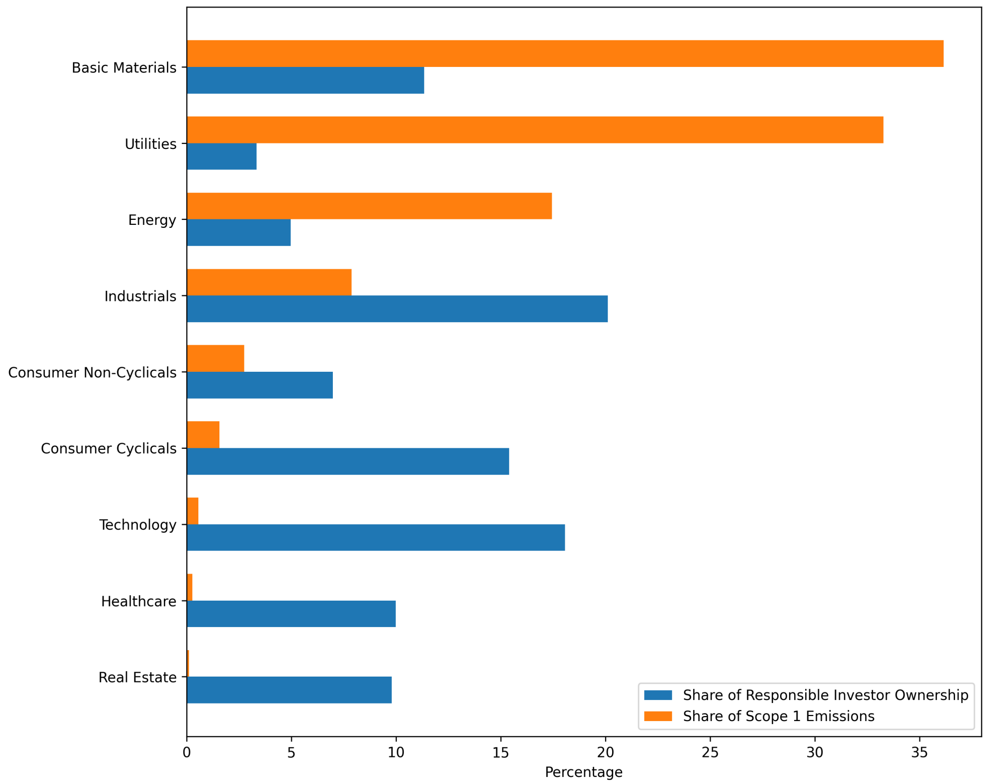
Figure 2.1: Temporal Relevance of Responsible and Institutional Investors



This Figure shows the relative share of Responsible Investors, institutional investors and other investors as shares of the total company market value over time.

Some sectors are more climate-relevant than others (Battiston et al., 2017). Thus, one strategy to achieve lower-emitting financial flows is through sectoral reallocation. Figure 2.2 contrasts the average share of Responsible Investors' equity holdings in the main sectors of the real economy and the share of greenhouse gas emissions from each of these sectors in 2022, respectively. It shows that the participation of Responsible Investors is, on average, higher for companies operating in less carbon-intensive sectors with very low holdings in the highest-emitting sectors, that is, Basic Materials (incl. cement, steel, chemicals), Utilities (incl. electricity and heat, sewerage), and Energy (incl. exploration, extraction, and refining of coal, oil, and gas). The distribution cannot be explained by the market value of the sectors alone. Over- and underinvestment of Responsible Investors compared to all institutional investors tends to be negatively correlated with the sectoral emission intensity.

Figure 2.2: Responsible Investor Holdings and Emission Distribution



This Figure shows the shares of (i) Scope 1 emissions and (ii) ownership by Responsible Investors per main economic sectors (TRBC Level 1 sectors) for the year 2022.

The descriptive findings indicate that Responsible Investors indeed hold substantial shares in the capital markets and, as such, could be considered within the scope of Article 2.1c of the Paris Agreement. The reallocation of capital away from companies in high-emitting sectors is a sign of a passive interpretation of the Article 2.1c on the side of Responsible Investors. That is, instead of working with high-emitting companies on transition strategies, they seem to shun them. In their own right, these descriptive results show the behaviour of Responsible Investor toward climate-related portfolio allocation. However, they can be driven by other company characteristics than climate characteristics that explain Responsible Investor's investment decisions. In the next step, we perform a regression analysis in which we control for company characteristics such as company size, leverage, or profitability, and their sector allocation in order to investigate whether the shunning persists.

2.2.2 High-emitting company shunning by Responsible Investors

To test whether Responsible Investors shun high-emitting companies, we characterize companies according to their emissions and their climate relevance. We use the indicators Scope 1 Absolute (continuous), Scope 1 Relative (continuous), Climate Policy Relevant Sector (binary), and Top-10% High Emitter (binary) to measure whether a company is climate relevant or even a high emitter as independent variables. The dependent variable is the ratio of company value held by Responsible Investors to all institutional investors ("the Responsible Investor Ratio"). Under the Responsible Investor Ratio, the regression coefficients can be interpreted as the relative difference in company ownership by the Responsible Investor versus the ownership of all institutional investors after controlling for company characteristics.

The regression results show that Responsible Investors shun companies with relevance for the decarbonization, see Table 2.2 columns 1-4. The shunning holds for the different measures of the contribution of companies to climate change. All coefficients are negative and statistically significant (α = 1%), indicating that Responsible Investors hold significantly less in high-emitting and climate-relevant companies than the average institutional investor. For example, an increase of Scope 1 emissions by one percentage point is associated with a decrease in the Responsible Investor Ratio by 0.3 percentage points on average. The significance of the results for Climate Policy Relevant Sector and Top 10% Scope 1 Emissions indicates that the results are robust beyond emission-reporting companies. These findings strongly show high-emitter shunning by Responsible Investors, indicating that they aim to make their financial flows consistent with the Paris Agreement through portfolio allocation. They corroborate results by Atta-Darkua et al. (2023) and Heath et al. (2023) at the company level.

ESG ratings are significantly positively related to the Responsible Investor Ratio in all four specifications. The inclusion of ESG ratings ensures that the regression models capture changes in capital allocation by Responsible Investors based on classical ESG integration approaches, which is common practice among institutional investors. The interpretation of these positive and significant coefficients is two-fold. First, companies with a better ”greenness” profile have a higher Responsible Investor Ratio. This means that Responsible Investors tend to favor companies with better ESG ratings more strongly than the average institutional investor. Second, the significant and negative relationship between the different company-level climate measures and the Responsible Investor Ratio is very likely to result from the shunning of high-emitting companies and is not solely attributable to the preference for highly ESG-rated companies.[†]

The debate about the role of institutional investors has intensified in recent years. With Article 2.1c of the Paris Agreement and the subsequent establishment of more dedicated investor initiatives and a growing participation (recall Figure 2.1), we expect the effects to increase over time. As Figure 2.3 shows, the shunning of high-emitting and climate-relevant companies becomes significant only after the Paris Agreement and is more strongly pronounced rather recently. This finding indicates that Responsible Investors react to the Paris Agreement and channel financial flows to lower-carbon companies. Note that statistical power in these biennial regressions is relatively low because of the low

[†]In Appendix B, we present the regression results without ESG rating.

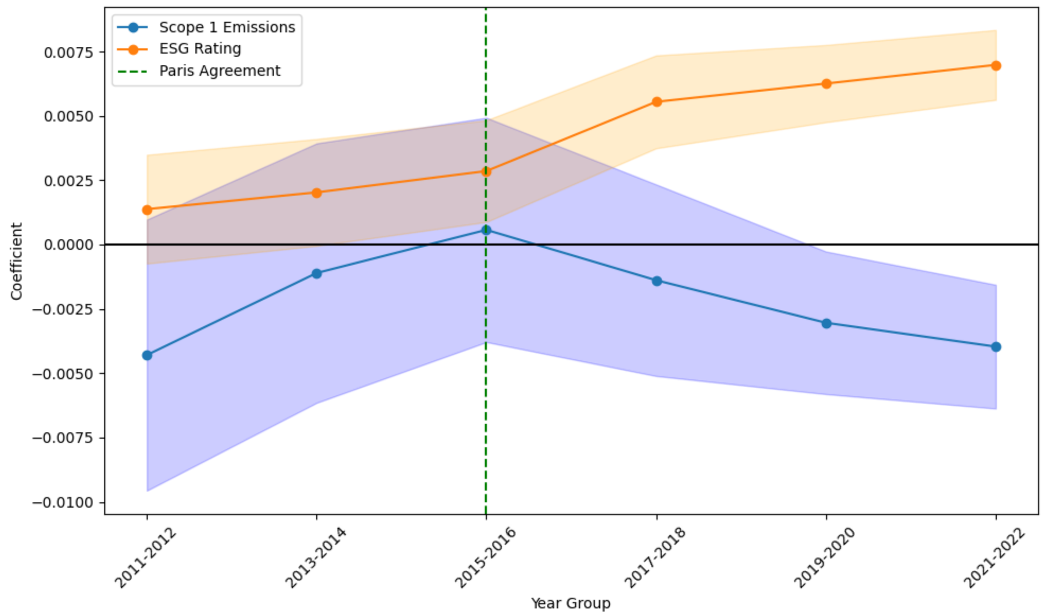
Table 2.2: High Emitter Shunning Regressions

	Responsible Investor Ratio				Institutional Investor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1 Emissions)	-0.003***				-0.002***			
	(0.001)				(0.001)			
log(Scope 1 Intensity)		-0.033***				-0.016***		
		(0.005)				(0.005)		
Climate Policy Relevant Sector			-0.008***				-0.019***	
			(0.002)				(0.003)	
Top 10% Scope 1 Emissions				-0.019***				0.006
				(0.005)				(0.005)
ESG Rating	0.020***	0.018***	0.019***	0.019***	0.029***	0.028***	0.032***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Book to Market Ratio	-0.005	-0.004	-0.004***	-0.004***	-0.046***	-0.046***	-0.010***	-0.010***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.005)	(0.005)	(0.001)	(0.001)
Dividend Yield	0.001*	0.001*	0.001	0.001	-0.009***	-0.009***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Historic Volatility	-0.087***	-0.087***	-0.067***	-0.068***	-0.104***	-0.104***	-0.094***	-0.098***
	(0.015)	(0.015)	(0.010)	(0.010)	(0.018)	(0.018)	(0.011)	(0.011)
log(ROA)	0.006***	0.006***	0.004***	0.004***	0.006***	0.006***	0.010***	0.010***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Revenue)	0.008***	0.004**	0.001	0.002	0.012***	0.009***	0.002*	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Total Debt to Equity)	-0.003***	-0.003***	-0.001*	-0.001*	-0.003***	-0.003***	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Stock Return	0.000***	0.000***	0.000*	0.000*	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Cash Holdings)	0.007***	0.007***	0.010***	0.009***	-0.004***	-0.004***	-0.002*	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Market Value)	-0.014***	-0.013***	-0.005***	-0.004***	-0.018***	-0.018***	0.009***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.424***	0.445***	0.356***	0.347***	0.441***	0.453***	0.244***	0.241***
	(0.018)	(0.018)	(0.013)	(0.013)	(0.021)	(0.021)	(0.013)	(0.014)
Observations	18207	18207	38934	38934	18207	18207	38934	38934
Adjusted R^2	0.277	0.279	0.246	0.246	0.398	0.398	0.443	0.442
F Statistic	7315.3***	7326.5***	11954.6***	12039.2***	3134.1***	3122.0***	5165.5***	5161.1***

This table presents the regression results for high-emitter shunning, showing the relationship between financial variables, ESG ratings, and climate factors in portfolio allocation by Responsible Investors and institutional investors. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI), while columns 5 through 8 pertain to general institutional investors. The dependent variable is the level of investment in the companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions and Scope 1 intensity, respectively, and Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company-year observation is among the highest 10% of absolute emissions). In addition to the control variables, all regression setups include region, year and industry fixed effects. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and are clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

number of observations per bucket. The significant positive relationship between ESG ratings and the ownership of Responsible Investors also increases over time, which is in line with the industry's increasing focus on ESG investing (Amir and Serafeim, 2018).

Figure 2.3: Biennial Investment Focus by Responsible Investors



This Figure shows portfolio allocation with respect to ESG ratings and absolute Scope 1 Emissions by Responsible Investors relative to all institutional investors over time. Regression coefficients are plotted on the y-axis with 5% confidence intervals. We repeat the regression setup from Table 2.2 but on a biennial basis. The significance levels are lower due to the lower availability of data in the stratified data sets in each regression.

Interestingly, all institutional investors also shun high-emitting and climate-relevant companies (Table 1, columns 5-8). We observe a significantly negative relation between the ownership share of institutional investors ("Institutional Investor Share") and absolute Scope 1 emissions, Scope 1 emission intensity, and climate policy relevant sector (α=1%). The effect disappears statistically for the dummy variable Top 10% Scope 1 emissions. ESG ratings are also significantly positive related to Institutional Investors Share (α=1%) as well. Again, indicating that institutional investors generally have a preference for companies with better ESG ratings.

The results at the institutional investor level allow us to draw two conclusions. First, the coefficients for Responsible Investors in Table 2.2 (columns 1 through 4) are conservative, as they do not reflect the general shunning of institutional investors by the construction of the indicator. Second, institutional investors generally tend to shift their portfolio allocation from high-emitting companies toward other parts of the capital market, that is, ”greener” companies. Hence, it is likely that there are other market actors willing to take higher levels of carbon emissions and transition relevant companies into their portfolios. This conclusion could be interpreted as supporting evidence for a split in capital markets between green and conventional / brown investors (Pástor et al., 2021). This raises questions as to whether (secondary) capital markets can help steer the real economy in line with the Paris climate objectives if there are sufficient buyers for the stocks of those companies (Berk and van Binsbergen, 2021).

2.2.3 Missing link between company decarbonization and Responsible Investor ownership

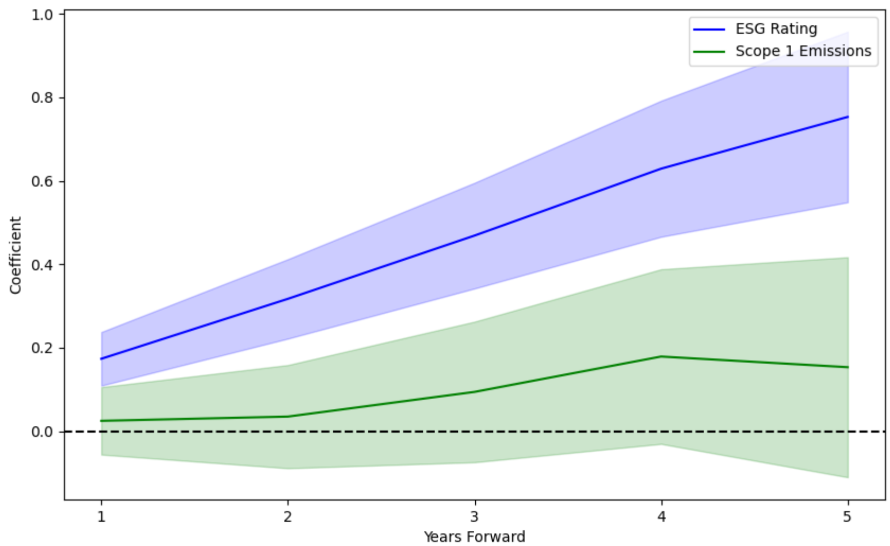
So far, we have shown that Responsible Investors seem to make financial flows consistent with the targets of the Paris Agreement by reallocating capital. Given the limited link between capital allocation and real economy decarbonization (e.g. Berk and van Binsbergen (2021) and Kahn et al. (2023)), these results only support the view that Responsible Investors play a passive role in achieving the Paris targets. That is, they reallocate capital to align their portfolios, but do not work with the real economy on actual reduction of carbon emissions. To better understand whether Responsible Investors also take a more active role, we turn to the question whether those companies with a higher Responsible Investors ownership decarbonize faster next.

For the analysis, we investigate how the shares that Responsible Investors hold in the company (”Responsible Investor Share”) relate to changes in company-level greenhouse gas emissions. In this setting, we use Responsible Investor Share as opposed to the Responsible Investor Ratio to better account for Responsible Investors' leverage on company decisions, e.g., voting power at general annual meetings or relevance as part of investor relations / closed-door engagements. The setup controls for company characteristics and institutional ownership. The control for institutional ownership is necessary to ensure that we do not capture general effects of institutional ownership at the company level, but only those by Responsible Investor ownership.

Figure 2.4 shows the change in emissions at the company level over time in relation to the Responsible Investor ownership. We do not find evidence that companies' Scope 1 emissions decline significantly with higher Responsible Investor ownership. This means that a higher ownership of Responsible Investors is not related to the decarbonization of companies. If anything, we find a statistically insignificant positive relationship between company level emission development and Responsible Investor ownership. As a consequence of this finding, we conclude that the engagement and voicing channel has limited effects on the decarbonization of companies at the aggregate global level. This supports the critical view on engagement at the system level by Berg et al. (2023). These findings call into question whether Responsible Investors take an active role in shaping a Paris-aligned real economy.

Interestingly, a very different picture emerges for changes in ESG ratings. If we run the regressions using ESG ratings, we find a significant positive relation of Responsible Investor ownership and changes in ESG ratings over time. This suggests a greater interest from Responsible Investors in improving the performance of the ESG rating than the decarbonization in the real economy. The strong use of ESG ratings and, therefore, the implicit or even explicit target setting using this metric, for example, as part of C-level compensation by some companies (Cohen et al., 2023b), could explain this result. Given the low correlation between ESG ratings and actual decarbonization of companies (Elmalt et al., 2021), this finding further corroborates the interpretation that Responsible Investors prioritize the perceived sustainability performance of their portfolio over decarbonization in the real economy.

Figure 2.4: Temporal Change of Sustainability in Companies in Relation to Responsible Investor Ownership



This Figure shows how ESG ratings and Scope 1 Emissions change in relation to the level of Responsible Investor ownership over time. Regression coefficients are plotted on the y-axis with 5% confidence intervals. Regressions are executed on an annual basis. The tables for the underlying regression are reported in Appendix B.

The Paris Agreement targets absolute emission reductions due to the physical limits of the carbon budget (Intergovernmental Panel on Climate Change (IPCC), 2021). Therefore, actual Paris-aligned business model transition should also target absolute emission reduction. However, it is possible that some companies with relatively carbon-efficient technologies need to increase their own absolute emissions to replace more inefficient competitors (Aswani et al., 2024). In this scenario, absolute emissions were to decrease at the macro-level, while company-level emissions would develop inconsistently. Responsible Investors aware of such situations could be willing to hold more carbon-efficient companies and would be willing to keep or even increase absolute in these companies for the "greater good". In this situation, they would rather work with companies to reduce relative emissions. We test for this by rerunning the analysis using Scope 1 emission intensities. Table 2.3 shows that the results remain insignificant, ruling out this explanation. This corroborates our conclusion that Responsible Investors do not pursue an active role under Article 2.1c.

Table 2.3: Scope 1 Intensity (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	0.0105	0.0081	0.0148	0.0342*	0.0336
	(0.0081)	(0.0122)	(0.0147)	(0.0180)	(0.0217)
Institutional Investor Share	-0.0009	0.0010	-0.0001	-0.0156	-0.0178
	(0.0059)	(0.0088)	(0.0105)	(0.0123)	(0.0142)
Time-variant company controls	Y	Y	Y	Y	Y
Δ Time-variant company controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0570	0.0825	0.0746	0.0819	0.0851
F-Statistic	12.76***	14.34***	13.49***	12.99***	11.51***

This table presents the regression results for the relationship between Scope 1 emission intensity and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. For the full regression table, see Appendix B. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

2.2.4 Robustness

The findings of this study challenge the prevailing narrative and communication from both the industry and many policy makers on the role of Responsible Investors in global climate efforts, making our results somewhat controversial. To ensure the econometric and conceptual robustness of our conclusions, we perform a series of robustness checks. We demonstrate that our findings are valid across different definitions of Responsible Investors, address endogeneity concerns related to their holdings in specific companies, and account for potential outliers in our sample. This confirms the validity of our results and supports the reliability of our conclusions.

Our main analysis is focused on Responsible Investors as defined by membership in the UN PRI. UN PRI is the longest existing initiative in the field, and thus allows for a more comprehensive panel data structure. However, UN PRI focuses on sustainability in general. Although much of the sustainability debate in developed countries is on climate change mitigation, we could introduce an error in the measurement through our decision. Therefore, we repeat the analysis on shunning and decarbonization using the Climate Action 100+ membership as an indication for Responsible Investors. According to their statutes, these investors focus mainly on the decarbonization of companies through engagement (Climate Action 100+, 2023).

Table 2.4 shows that CA100+ investors also shun high-emitting companies, although at a lower level. Contrary to UN PRI signatories, they actually hold more shares in companies in climate policy relevant sectors than the average institutional investor. However, due to the strong shuning by institutional investors in general, this still means that CA100+ investors shun these sectors compared to the average investor. The preference for companies with higher ESG ratings is also observable. Hence, the shunning is robust for this alternative definition of Responsible Investors.

A declared focus of CA100+ is on engaging with high-emitters to decarbonize their business models (Climate Action 100+, 2023). As a result, we would expect a relationship between CA100+ ownership and decarbonization of companies. However, Table 2.5 shows that CA100+ ownership is not associated with a decrease in the carbon emissions of companies. In Annex B, we also document robustness for no decrease in Scope 1 intensities and an improvement in ESG ratings in relation to CA100+ ownership. Again, this underscores that our main results are robust to the definition of a Responsible Investor.

Some caution in interpreting the results of the CA100+ analysis is warranted for two reasons. First, CA100+ does not provide signature year data for its members. In the absence of better data, we characterize all investors as CA100+ investors from the year the initiative was founded. Second, the initiative was only founded in 2017 limiting the periods available for the analysis of decarbonization.

The decision on the portfolio allocation by Responsible Investors is largely endogenous. Investors may invest in or shun companies for specific reasons. As such, capital allocation decisions by Respon-

Table 2.4: High-Emitter Shunning Using CA100+ Investors

	CA100+ Ratio			
	(1)	(2)	(3)	(4)
log(Scope 1 Emissions)	-0.001***			
	(0.000)			
log(Scope 1 Intensity)		-0.014***		
		(0.002)		
Climate Policy Relevant Sector			0.005***	
			(0.001)	
Top 10% Scope 1 Emissions				-0.009***
				(0.002)
ESG Rating	0.009***	0.008***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Time-variant company controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y
Observations	18207	18207	38934	38934
Adjusted R^2	0.301	0.302	0.299	0.299
F Statistic	570.2***	569.6***	1007.2***	1008.5***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors. Here, we use CA100+ Share membership as a proxy for Responsible Investor. The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector, and Top 10% Scope 1 Emissions . In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

Table 2.5: Scope 1 Emissions (Δ1 - Δ5)

	Δ 1 Year	Δ 2 Year	Δ 3 Year	Δ 4 Year	Δ 5 Year
	(1)	(2)	(3)	(4)	(5)
CA100+ Share	-0.1099	-0.1843	0.0497	0.2527	0.2994
	(0.0911)	(0.1404)	(0.1911)	(0.2563)	(0.3425)
Time-variant company controls	Y	Y	Y	Y	Y
Δ Time-variant company controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0139	0.0279	0.0403	0.0563	0.0779
F-Statistic	4.93***	7.68***	9.90***	10.93***	11.96***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is CA100+ Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

sible Investors in the past might affect company decarbonization potential in the future. For example, a greener company might have used all the green technology available already at the time when the Responsible Investor invests. Thus, Responsible Investors might not be able to motivate the company to do more to decarbonize their business models. This can affect the outcomes of the decarbonization in the following years. To account for this scenario, we run a lagged dependent variable model repeating the analysis in the main results.

The lagged dependent variable model shows that the main results are robust. Table 2.6 highlights that the ownership of Responsible Investors is not significantly related to changes in company-level emissions. Not surprisingly, the lagged Scope 1 emissions are negatively related to future emission changes as companies with higher ex-ante emissions might find it easier to decarbonize. The same result holds for Scope 1 intensities. The improvements in ESG ratings in relation to Responsible ownership are also robust. The regression tables for Scope 1 intensities and ESG ratings are reported in the Appendix B.

An additional concern with our use of the Responsible Investor Ratio is the potential influence of

Table 2.6: Scope 1 Emissions (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	-0.0370	-0.0704	-0.0779	-0.0705	-0.0112
	(0.0429)	(0.0676)	(0.0903)	(0.1136)	(0.1451)
Institutional Investor Share	-0.0282	-0.0420	-0.0866	-0.0778	-0.1746*
	(0.0280)	(0.0441)	(0.0580)	(0.0729)	(0.0918)
lag log(Scope 1 Emissions)	-0.0392***	-0.0794***	-0.1075***	-0.1408***	-0.1537***
	(0.0035)	(0.0059)	(0.0081)	(0.0101)	(0.0119)
Time-variant company controls	Y	Y	Y	Y	Y
Δ Time-variant company controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
Observations	17263	13474	10797	8730	7091
Adjusted R^2	0.0367	0.0744	0.0980	0.1356	0.1638
F-Statistic	6.96***	10.83***	12.76***	15.07***	15.82***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables in the dependent variable model, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *$p<0.1$; **$p<0.05$; ***$p<0.01$, with robust standard errors clustered at the company year level.

high ratios, which could disproportionately drive the results. High ratios might occur when a small number of institutional investors hold shares in a company, and those investors happen to be Responsible Investors. This situation could distort the analysis, as it may not accurately reflect a broader trend. As this situation is most likely to result from a low overall institutional ownership, we exclude all observations in which the share of institutional investors is equal to or below 10% of the company's market capitalization. This threshold helps ensure that the results are based on companies with a substantial level of institutional ownership, providing a more accurate assessment of the impact of Responsible Investors. As shown in Table 2.7, the results remain robust after this adjustment, indicating that our findings are not driven by cases of low overall institutional ownership.

Finally, the big three (BlackRock, State Street Global Advisors, Vanguard) have signed the UN PRI. Their strong presence on the capital markets (Bebchuk and Hirst, 2019) could inflate the size of responsible ownership in companies in the real economy. This could affect our results due to their universal ownership and their relatively high quantitative effect on our key variables. We run the anal-

Table 2.7: High-Emitter Shunning with Institutional Investor Shares $> 10\%$

	Responsible Investor Ratio			
	(1)	(2)	(3)	(4)
lag log(Scope 1 Emissions)	-0.003***			
	(0.001)			
lag log(Scope 1 Intensity)		-0.031***		
		(0.005)		
Climate Policy Relevant Sector			-0.007***	
			(0.002)	
Top 10% Scope 1 Emissions				-0.019***
				(0.005)
lag ESG Rating	0.023***	0.022***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
Time-variant company controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y
Observations	16701	16701	33475	33475
Adjusted R^2	0.288	0.290	0.278	0.278
F Statistic	7064.2***	7081.0***	11562.6***	11640.4***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors. The table highlights that results are robust after only keeping all observations with Institutional Investor Shares $> 10\%$. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI). The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

yses without the Big Three. The results are robust; see Tables 2.8 and 2.8.

Table 2.8: High-Emitter Shunning w/o Big Three

	Responsible Investor Ratio			
	(1)	(2)	(3)	(4)
lag log(Scope 1 Emissions)	-0.002***			
	(0.001)			
lag log(Scope 1 Intensity)		-0.024***		
		(0.004)		
Climate Policy Relevant Sector			-0.009***	
			(0.002)	
Top 10% Scope 1 Emissions				-0.019***
				(0.004)
lag ESG Rating	0.019***	0.019***	0.020***	0.020***
Time-variant company controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y
Observations	16701	16701	33475	33475
Adjusted R^2	0.244	0.245	0.234	0.234
F Statistic	3824.2***	3823.7***	6218.4***	6242.6***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors. The table highlights that results are robust after removing the Big Three (BlackRock, State Street Global Advisors, Vanguard) from the Responsible Investor Ratio. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI). The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

2.3 Conclusion

Our study reveals that Responsible Investors tend to shun companies with high emissions and significant roles in climate mitigation, instead favoring greener assets. Although this behavior aligns their portfolios more closely with the Paris Agreement's climate targets, it reduces their leverage to influence companies with substantial potential for emission reductions. Importantly, we find no evidence

Table 2.9: Scope 1 Emissions (Δ1 - Δ5) w/o Big Three

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share (w/o Big Three)	0.0461	0.0261	0.0864	0.1314	0.0808
	(0.0475)	(0.0715)	(0.0940)	(0.1151)	(0.1442)
Time-variant company controls	Y	Y	Y	Y	Y
Δ Time-variant company controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0140	0.0285	0.0412	0.0568	0.0780
F-Statistic	4.90^{***}	7.76^{***}	10.19^{***}	11.05^{***}	11.94^{***}

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Here, we exclude the Big Three (BlackRock, State Street Global Advisors, Vanguard) from the Responsible Investor Share. Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

that companies with higher ownership by Responsible Investors decarbonize faster. Instead, these companies show significant improvements in ESG ratings, a metric widely used in financial markets but arguably less connected to actual physical changes at the company level. These findings call into question the active role of institutional investors under Article 2.1c of the Paris Agreement.

Several reasons might explain our findings. First, the integration of climate change as part of the investment process has only recently reached the mainstream in finance. Processes and methodologies for Paris-aligned investment are still under development and implementation. Given that effects are likely to take some time to materialize in the real economy, our findings do not rule out that Responsible Investor ownership will relate to or even drive decarbonization in real economy companies in the future. However, other studies question the potential effect size for the future (Berk and van Binsbergen, 2021; Hartzmark and Shue, 2023).

Second, while most Responsible Investors regard themselves within the scope of Article 2.1c, they apply a passive interpretation of its role. That is, (i) they sell ”brown” assets to other actors in the financial system, and (ii) they aim to maximize return within their (slightly) greened portfolios. In the absence of existing and expected real economy regulation for decarbonization in accordance with Paris's climate objectives (Intergovernmental Panel on Climate Change (IPCC), 2021), it is very likely that maximization of risk-return is not achieved by urging companies to fully decarbonize in accordance with a Paris trajectory. Therefore, Responsible Investors may not use their ability to influence company decision-making on the Paris alignment to a full extent.

This study has limitations. First, our data are limited to mainly large and capital market-oriented corporations and exclude most small and medium-sized enterprises (SMEs) as well as private markets. The alignment of financial flows with the climate objectives could work differently for those companies due to their different financial structures and the lack of discipline induced by capital markets. Second, we do not investigate other asset classes that are usually used to finance large corporations, such as corporate bonds and syndicated loans, which could be effective in achieving company decarbonization. Third, (mandatory) corporate emission reporting has only recently become standard practice in developed economies. This significantly reduces the number of companies covered in our emission data set. Missing companies most likely show comparatively lower absolute Scope 1 emissions and operate in countries with fewer reporting requirements as well as lower climate policy ambitions.

The findings have implications for policy makers. Private finance has taken on an increasingly prominent role under the Paris Agreement. The findings indicate the need for a critical reflection on this prominent role. Given our findings, it is unlikely that private finance will become a key catalyst for emission reduction in the real economy. Policy makers should therefore consider (i) if they consider institutional investors to be within the scope of Article 2.1c, and (ii) whether they expect an active or passive interpretation of making "financial flows consistent" with the Paris objectives. If they expect an active role from institutional investors, they will need to adapt the regulatory environment, as the status quo is not conducive to this active contribution to Article 2.1c.

The reasonable man adapts himself to the world; the unreasonable one persists in trying to adapt the world to himself. Therefore, all progress depends on the unreasonable man.

George Bernard Shaw

3

Sustainable small business lending

Sustainability has become a central objective in economic development[*] and economic transformation around the world. This has two-fold consequences for the financial sector. First, financial institutions need to integrate sustainability information in their assessment of the fi-

[*]Throughout the paper, I define sustainability as contributions to environmental, social and governance (ESG) goals and resilience towards ESG risks.

nancial value of assets. Second, financial actors are increasingly being pressured to become, and also to portray themselves as, enablers of sustainable economic transformation. Starks (2023) contrasts those consequences as the value (financial effects) versus the values (non-financial considerations) perspectives.

These developments affect banks' small business lending activities. Banks are the main external source of financing for most small businesses (e.g., Boot and Thakor (2000)). As such, they can facilitate the sustainable transformation of business models among small businesses, while also being exposed to their sustainability risks. Traditional small business lending concepts such as relationship lending and soft information generation (e.g. Berger and Udell (2006), Berger and Black (2011)) may evolve, and novel concepts such as the provision of sustainability advisory networks or the provision of sustainability tools (Delrieu et al., 2022) may emerge. In this paper, I discuss the concept of sustainable small business lending that encompasses these aspects. For European banks, sustainable small business lending can affect more than half of its business lending portfolio (OECD, 2023).

Sustainable small business lending has the potential to make significant contributions to broader sustainable transformations and to improve economic resilience to sustainability effects due to the relevance of small businesses. In the case of the European Union (EU), small businesses represent a substantial portion of employment (64%), company count (>99%), and economic value added (52%). Small businesses also contribute significantly to environmental impacts. The share of small businesses in the carbon dioxide emissions of all EU companies is 63% (European Commission, 2022b).

Given this importance, banks and policy makers are increasingly communicating the need to work with small businesses in the context of sustainable finance (e.g., Delrieu et al. (2022) and European Commission (2023)). However, the literature does not provide a framework or empirical evidence for the effective implementation of sustainable small business lending. Therefore, the primary objective of this paper is to assess the current state of sustainable small business lending, first, by bringing together the sustainable finance literature with the small business lending literature, and second, by conducting a survey among German banks to evaluate whether and how sustainable small business lending practices are currently being implemented. In doing so, the paper expands the sustainable finance literature by adding relevant aspects of the small business lending literature.

The results of the survey show that banks are in the process of implementing sustainable small business lending practices. However, banks report greater progress in implementing sustainable finance practices for larger and capital market-oriented clients. Banks place greater emphasis on the value and risk perspective over transformation and values considerations in their efforts to implement sustainable small business lending. This becomes visible when comparing implementation timelines of different value and values use cases.

The results also highlight the relevance of sustainable relationship lending. A majority of banks use or implement sustainability-related dialogues with small businesses. Client interaction seems to be a relevant tool for collecting sustainability-related soft information from small businesses, that is, unmeasured or hardly measurable sustainability information. Still, banks show a preference for sustainability-related hard information, that is, measured sustainability data.

The findings have implications for banks and policymakers. Banks can use the findings to structure and adjust their sustainable small business lending practices. Furthermore, the banking industry may need to revise its communication on its role in supporting the transformation of economic activities by small businesses. Policymakers can use the results to shape sustainable finance policies for small business lending by incorporating the tendency of banks to follow value- and risk-oriented practices. They may support this development and formulate policies that allow banks to establish values-supporting activities for small businesses as part of broader efforts to achieve sustainability objectives.

The remainder of the paper is organized as follows. Section 2 adds elements of the small business lending literature to the sustainable finance literature. Section 3 details the survey design and the characteristics of the respondents. Section 4 presents the survey results, addressing the following issues: the perception of sustainable finance by banks generally, the role of each value and values in sustainable small business lending, and the link between relationship lending and sustainable small business lending. Section 5 concludes.

3.1 Literature

Banks can support the shift toward sustainability in the economy and help mitigate sustainability risks through their financial intermediation function. This role is increasingly discussed in the literature on sustainable finance. Typically, banks represent the main external source of financing for small businesses, discussed in the literature on small business lending. Here, I combine both strands of literature by adding elements of small business lending to sustainable finance.

3.1.1 Sustainable Finance: Value versus Values

Sustainable finance is a rapidly evolving field in both academia and practice. The definitions of what constitutes sustainable finance are diverse. Starks (2023) attempts to bring nuance to the debate by contrasting the 'value' with the 'values' perspective. Value refers to how sustainability aspects influence a financial institution's assets, accounting for risks and opportunities, that is, pecuniary aspects of sustainability. Values, on the contrary, integrate ethical considerations and non-pecuniary preferences like climate change mitigation into decision making, sometimes at the expense of returns. These concepts apply to bank lending.

In banking, evaluating sustainability-related value aspects of firm lending can affect credit conditions. Banks may charge different interest rates, change collateral requirements, introduce additional covenants, or decide not to provide capital at all. This is empirically observable, since banks have begun to price policy risks and policy uncertainty associated with climate change, in the form of carbon premiums on the Scope 1 emissions of firms (e.g., Ilhan et al. (2021) and Ehlers et al. (2022)) and exposure to stranding risks (Delis et al., 2023). Firm-level credit ratings also increasingly reflect their environmental performance (Seltzer et al., 2022).

The values perspective encompasses the bank's pursuit of sustainability targets as part of its lending strategy. Recently, many banks have publicly announced their support for climate and biodiversity targets by becoming signatories to respective initiatives, e.g., the United Nations Environment Program Finance Initiative (UNEP FI) Net Zero Banking Alliance. The operationalization of these objectives could involve engaging with clients, building green portfolios, and excluding non-sustainable activities (UNEP FI, 2021). The first evidence on values activities by banks suggests that banks can positively influence sustainability behavior by firms (Houston and Shan, 2022). European banks allocate capital away from carbon-intensive activities (Reghezza et al., 2022); however, without affecting the underlying economic activities (Kacperczyk and Peydro, 2022). The evidence on the effect of dedicated sustainable lending products on increasing sustainability in the economy is mixed. Flammer (2021) finds positive signaling effects by firms through green bond issuances and Dursun-de Neef et al. (2023) find positive effects of green bond issuances on firm environmental, social and governance (ESG) ratings. Auzepy et al. (2023) find no effect of sustainability-linked loans on firm environmental performance. If client dialogue by banks is as effective as investor engagement (e.g. Dimson et al. (2015), Sautner et al. (2023) and Hoepner et al. (2024)), it is likely to be an effective channel for values support by banks.

3.1.2 Sustainable Small Business Lending

So far, small business lending, that is, lending activities to predominantly unlisted and often informationally opaque firms with limited numbers of employees (Petersen and Rajan (1994), Boot (2000), and Berger and Black (2011)), has not been discussed in the literature on sustainable finance. This is despite the relevance of small businesses for sustainability. They are responsible for 63% of the firm emissions in the EU (European Commission, 2022b). They account for more than half of business lending in the European Union (OECD, 2023) and are mainly dependent on bank lending. The importance of small businesses for banks, the economy, and sustainable economic development makes sustainable small business lending inevitable.

Usually, banks employ two technologies in small business lending (Berger and Udell, 2006):

- Transaction lending, where banks use automatic processes to provide credit. This method relies on 'hard' information, such as financial statements and credit scores.

- Relationship lending, where small businesses and banks develop long relationships. This type of technology helps firms access credit that lack formal financial data and, thus, are informationally opaque to the bank (López-Espinosa et al., 2017). Usually relationship lending generates 'soft' information, that is, non-quantified or non-quantifiable information about the firm through the relationships.

Table 3.1 illustrates the potential dynamics between the two lending technologies and sustainable finance represented by the perspectives 'value' and 'values'. It highlights that, regardless of the sustainable finance perspective and lending technology, there is potential for interaction between both strands of literature.

The value perspective of sustainable small business lending involves banks understanding the sustainability risks of their small business clients. For transaction lending activities, this primarily means that banks find quantifiable measures for counterparty risk, for example, by surveying their small business clients or by running their own analyzes. Based on this information, a reassessment of risk and adjustments to credit conditions could follow. Relationship lending allows banks to understand the risks associated with the sustainability of the business model more strategically, partially avoiding the challenges of measuring sustainability (Edmans, 2023a). Relationship lending could also allow for more flexibility in adjusting credit conditions (Bolton et al. (2016) and Schäfer (2019)).

Small business lending could contribute to values creation by providing financial and non-financial resources to small businesses to transform their business models. Values-alignment is inevitable if

Table 3.1: Sustainable small business lending

		Sustainable Finance	
		Value	**Values**
Small Business Lending	**Transaction Lending**	**Quantification** of sustainability risks $\rightarrow$ **credit condition** adjustments	**Quantification** of counterparty sustainability $\rightarrow$ **in-/exclusion** based on fitness with own values
	Relationship Lending	Sustainability risk analysis of counterparty **business model** $\rightarrow$ **flexible terms** for business model development	Analysis of counterparty sustainability **strategy** $\rightarrow$ sustainability **objective alignment**

This table summarizes the intersection of the sustainable finance literature and the small business lending literature using value vs values and lending technologies, respectively, to represent each literature.

banks are to meet their sustainability commitments. Banks trying to achieve their own sustainability goals can use different alignment strategies depending on the deployed lending technology. Transaction lending is likely to produce more automatic capital shifts away from small businesses that do not match the banks' own values and toward those that do, leading to a capital shift as observed by Reghezza et al. (2022). Relationship lending, in contrast, is likely to result in more strategic approaches to align sustainability objectives, as suggested by industry publications (e.g., UNEP FI (2021) and Delrieu et al. (2022)).

Banks could assign a special role to sustainable relationship lending. Information asymmetries and opaqueness will remain an issue, as sustainability-related disclosure regulations primarily target large firms (European Commission, 2023). Long and established lending relationships could help banks understand sustainability-related aspects in small businesses, particularly through client dialogue. Relationship lending could benefit banks and small businesses as downside risks resulting from sudden sustainability-related policy changes could be lower for firms financed through the relationship channel (Bolton et al. (2016), Beck et al. (2018), and Schäfer (2019)). On the values side, relationship lending could contribute to the transition of business models, as it is positively associated with innovation and operational efficiency (Hombert and Matray (2017) and Yildirim (2020))[†].

The discussion of both strands of literature shows the potential dynamics of sustainable small business lending. So far, empirical evidence on these dynamics has been largely absent.

3.2 Survey

To evaluate whether and how sustainable small business lending practices are currently being implemented, I conducted a survey among German banks. Due to the field's nascence, archival data on sustainability in small business lending are scarce, creating the need for primary data collection. Surveys are regularly used in sustainable finance research to understand the positioning of stakeholders in nascent areas (e.g., Amir and Serafeim (2018), Krueger et al. (2020), and Stroebel and Wurgler (2021)).

3.2.1 Survey Development & Delivery

The development of the survey is based on the literature and expert judgment from exchanges with banks, industry experts, and scholars. The first draft of the survey was developed mainly based on the dynamics in Table 3.1. In an iterative process, it was refined with practitioners and scholars. The final version of the survey was tested for clarity with additional practitioners. Despite the preparatory steps, some participants struggled to distinguish the response options "under implementation" and "within less than six months" for timeline-related questions. Therefore, these are shown as "(near) implementation" throughout the paper. See Appendix A for the final survey instrument.

The survey was structured into three parts. In the first part, personal data were collected from participants. The survey participants were asked to name their employer, while their own name remained

[†]Increasing lending distances (e.g., DeYoung et al. (2008) and Agarwal and Hauswald (2010)) are unlikely to diminish these effects, as distances increase primarily for small transactional lending activities (Adams et al., 2023).

anonymous. Although this might create bias towards favorably answering questions, this decision was deliberated to add more data ex post to the survey results and reduce the questions to proprietary information only, that is, reducing the overall length of the survey with the prospect of a higher response rate. In addition, the names of the banks allowed me to ensure that each bank participated once. The second part of the survey was designed to understand to what extent banks have made progress in integrating sustainable finance aspects into their business among all client groups and departments, and the perceived relevance of the topic. The third part was a deep dive into sustainable small business lending practices. Throughout the survey, small businesses were defined as unlisted firms with fewer than or equal to 250 employees.

The survey was sent to banks operating in Germany. The German financial system and economic structure of the countries appear to be well suited to test sustainable small business lending. The German economy is heavily bank-financed (Behr and Schmidt, 2015), increasing the relevance of bank lending for sustainable finance compared to other large economies. Germany's Mittelstand is often dubbed the 'backbone' of its economy, and small businesses represent a major share of economic output, also in sectors of high relevance for environmental and social sustainability, such as manufacturing and construction (KfW Bankengruppe, 2023).

To deliver the survey, two employees from each of Germany's 314 largest banks by balance sheet size were identified with job titles that included Environmental, Social and Governance (ESG) or Sustainable Finance, paired with risk management, C-suite titles (CFO and/or CRO), or strategy. This focus was chosen to ensure that employees have the capacity to answer the questions, as exchanges with banks show that these departments steer the implementation of sustainable small business lending projects. Names were collected by hand through LinkedIn, Xing[‡] and the banks' websites. The list of banks contacted can be provided upon request. The selected employees were contacted in three waves:

[‡]Xing is a platform for professionals which remains quite popular amongst German employees.

1. Initial email: All employees were contacted by email at the beginning of August 2023.
2. Reminder email: After two weeks, a reminder email was sent to all employees whose bank did not participate until that point.
3. Follow-up by phone: After another three weeks, employees of banks who had started but did not finish the survey and large German banks who did not respond until then were contacted by phone.

The survey was shared in German and made available through the survey tool 'Qualtrics'. The last response was collected at the end of September 2023.

3.2.2 Response & Bias

The response rate to the survey was high. More than 200 participants started the survey, and 77 participants completed it. I manually checked each completed response to remove double responses from banks (1 observation) and banks without small business lending activities (14 observations). The final sample includes 62 banks. This is a final bank response rate of 19.8%[§]. All participating banks have their headquarters in former West Germany; see Appendix B for a map. Table 3.3 shows the characteristics of the participating banks.

Compared to the German banking landscape, responding banks tend to be larger and more advanced in sustainable finance. The potential size bias is reflected in the high share of significant institutions[¶], which represent 14.5% in my sample compared to 5.2% in Germany according to the ECB (2023a) list of significant institutions. This is also reflected in the distribution of bank types with an overly strong representation of savings banks (35.5% to 24.8%) and public banks (16.1% to 1.7%) banks and a low representation of cooperative banks (33.9% to 50.5%) compared to figures of

§ This response rate is calculated by dividing the number of final banks in the sample over all banks contacted.
¶ Significant institutions are those banks who are under direct supervision by the ECB.

Deutsche Bundesbank (2023a). Almost half of the participating banks (48.4%) have signed a voluntary climate commitment. Although official figures do not exist on the share of banks having signed such a commitment in Germany, this number appears high. Follow-ups by phone (wave three of the survey distribution) revealed that some banks stopped responding to the survey because they did not feel advanced enough in their sustainable finance integration to answer the questions appropriately. Therefore, the survey results could bias towards the more advanced banks in sustainable finance compared to the German banking sector.

The survey participants predominantly work in strategy (33.9%) and risk management (30.7%) departments, indicating that the contacted employees responded. Technical level employees (38.7%), middle management (27.4%) and senior management (29.0%) responded mainly, but also the C-level management participated in the survey (4.8%). Entry-level employees did not participate. More responses come from men (70.5%), which is representative of the gender distribution in the German banking sector compared to the coverage of the topic in the media. The decision to contact employees working on sustainable finance might have biased the relevance of sustainable small business lending upward due to relevance to their own work and, potentially, their belief system. In addition, some respondents might suffer from social desirability or recency bias, again biasing the results toward more progress in the implementation than is actually achieved.

The availability of bank names allows me to match the bank financial data with the survey results. I retrieved the data from the Bureau van Dijk (BvD) Orbis Financials for Banks database after manually matching bank names with BvD Orbis identifiers. Data are available for most of the banks in the sample; see Table 3.4. I take a three-year average of the data (2019-2021) as one-year cross sections contain a higher number of missing values and to smooth potential one-off effects in the data. The data show that the sample includes banks with all levels of financial strength. Key ratios such as the Tier 1 ratio appear representative compared to ECB (2023b). The sample contains 34.4% of the total German banking assets in 2021 (relating the figures in my sample to figures by Deutsche Bundesbank

Table 3.3: Bank and respondents characteristics

Bank Type (N = 62)		**Significant Institutions (N = 62)**	
Savings	35.5%	Less Significant Institution	77.4%
Cooperative	33.9%	Significant Institution	14.5%
Public	16.1%	not applicable	8.1%
Private	14.5%		
Climate commitment (N = 62)		**Listed bank (N = 58)**	
No	51.6%	Unlisted	89.7%
National	45.2%	Listed	6.9%
International	3.2%	Delisted	3.5%
Bank size employees (N = 58)		**Gender (N = 61)**	
Medium	60.3%	Male	70.5%
Large	29.3%	Female	29.5%
Small	10.3%		
Department (N = 62)		**Level (N = 62)**	
Strategy	33.9%	Technical expert	38.7%
Risk management	30.7%	Senior management	29.0%
Market department	16.1%	Middle management	27.4%
Risk controlling / back-office	16.1%	C-level	4.8%
Regulatory affairs / compliance	3.2%		

This table presents a summary of the characteristics of the banks and the respondents in the final sample of 62 banks. The categories under 'Bank Type', 'Significant Institutions', 'Climate commitment', 'Listed bank', 'Bank size employees', 'Gender', 'Department', and 'Level' represent the distribution of these characteristics within the sample. The percentages are calculated on the basis of the total number of responding banks in each category. Missing or incomplete data are not represented in the percentages. 'Significant Institutions' and 'Climate commitment' are hand-collected from the ECB and bank websites. 'Listed bank' and 'Bank size employees' are based on data from BvD Orbis where some banks' data are not available. 'Bank size employees' is classified as follows: 'Small' if $=<250$ employees, 'Medium' if $251-1000$ employees and 'Large' if >1000 employees.

Table 3.4: Bank financials

	count	mean	std	min	25%	50%	75%	max
Tier 1 ratio (%)	53.0	15.63	3.81	10.13	13.72	15.07	16.22	36.09
Profit margin (%)	57.0	17.32	12.18	-28.66	12.21	15.76	21.71	56.81
Return on assets (%)	58.0	0.20	1.11	-7.83	0.23	0.34	0.44	1.01
Total assets (bn USD)	58.0	52.56	171.07	0.40	4.90	7.48	16.12	1082.41
Loans on book (bn USD)	58.0	23.63	66.05	0.00	2.90	4.92	10.51	415.67

This table provides a statistical summary of key financial indicators for the final bank sample, with data sourced from BvD Orbis. It includes data for 58 of the 62 responding banks, although the count for each financial indicator varies slightly as indicated in the 'count' column. The financial indicators are the Tier 1 ratio, profit margin, return on assets, total assets, and loans on book. For each indicator, the table presents the counts (number of banks for which data are available), mean, standard deviation (std), minimum (min), 25th percentile (25%), median (50%), 75th percentile (75%) and maximum values (max). These metrics provide an overview of the financial health and performance of the banks in the sample. All values are based on an average of vales per bank for the period 2019 - 2021 to close data gaps and reduce the influence of one-off effects on the data.

(2023b)) and therefore represents a major share of German banking assets. Note that the estimate of this share is conservative as figures by Bundesbank include banks without small business lending operations.

3.3 Results & Discussion

The results of the survey show that banks are in the process of implementing sustainable small business lending. I discuss the results along the questions how banks have progressed in implementing sustainable finance in general, how they are implementing the value and the values channels in sustainable small business lending, and how relationship lending and sustainability are linked.

3.3.1 How do German banks perceive sustainable finance?

First, I assess how banks perceive the relevance of sustainable finance and how they progress in implementing sustainable finance throughout the bank. This step helps contextualize subsequent responses to the survey in the banks' overarching view on sustainable finance. In the survey, banks were asked to evaluate the relevance of sustainable finance data for their bank (Question II-1), for example, ESG ratings in risk management, and the banks' progress in using sustainability data (Question II-2), such as ESG data integration in product development. For both relevance and progress, banks rated themselves on a scale from 1 (low relevance / progress) to 6 (high relevance / progress) in the following domains: risk management, strategy, reporting, product sales, product development, and client dialogue. By averaging the responses from the different domains, I construct a relevance and a progress indicator for each bank; see Figure 3.1.

Figure 3.1: Importance of sustainable finance for participating banks

(a) Relevance of implementing sustainable finance

(b) Progress in implementing sustainable finance

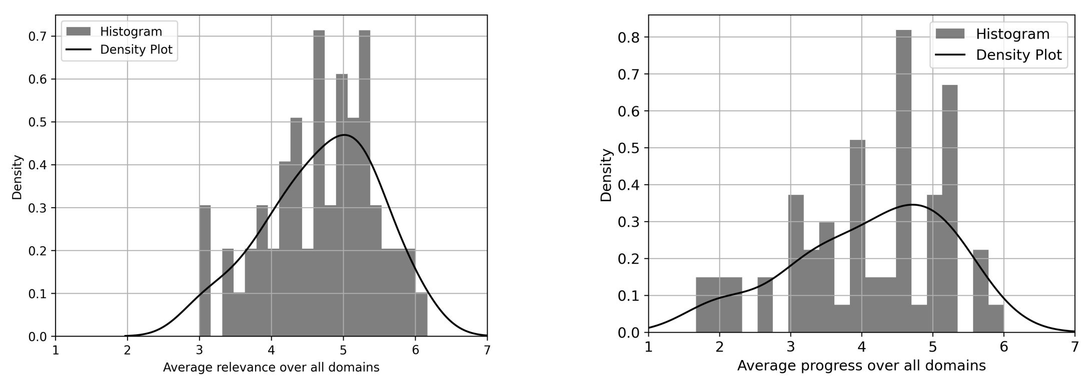


Figure 3.1 indicates that all participating banks consider sustainable finance to be relevant, with a majority rating it highly relevant. The progress indicator presents a more heterogeneous picture. Some banks report substantial progress, others report minimal progress. The progress indicator is likely biased towards more progress due to the survey setup and the respondent characteristics, see Chapter 3.2.2. Therefore, unbiased results would likely show a more left-skewed picture.

Progress but not relevance also affects how banks answer subsequent questions; see Table 3.5. Banks that have made more progress in sustainable finance are more likely to adjust credit conditions for small businesses and expect a higher level of sustainability risk to materialize. Not surprisingly, these banks are also more advanced in implementing specific sustainable small business lending use cases. For example, being one category more advanced on the progress score is related to being 0.7 categories more advanced in implementing client dialog. Hence, banks making general progress on the implementation of sustainable finance also progress on the implementation of sustainable small business lending activities with an elasticity of 0.3 to 0.7. This finding underscores a general consistency in responses throughout the survey while pointing to some variation in the sample.

In the regressions of Table 3.5, I control for the return on assets, the Tier 1 ratio, and the logarithm of total assets for the following reasons. More profitable banks might be able to invest more in their sustainability strategy (Artiach et al., 2010), which I control for using Return on Assets. The Tier 1 ratio, a measure of the financial health of a bank, ensures that the financial stress of bank does not affect the results (Hartzmark and Shue, 2023). Finally, Total Assets control for the relevance of small businesses for the banks business model as small business lending is more relevant for smaller banks (Berger et al., 2019).

The survey then inquired about the timing of the integration of sustainable finance between different types of companies, including listed and unlisted large companies, firms with high exposure to sustainability risks, and small businesses (Question II-3). To proxy the timelines with a tangible issue for practitioners, banks were asked about the timing of applying ESG data across these types. The results in Figure 3.2 show that the implementation is ongoing for all types of firms. However, small business lending is noticeably behind[‖]. This appears to be a matter of timing rather than relevance of small business clients for sustainable finance among participating banks. Figure 3.2 (b) shows that only a small share of banks do not plan to integrate sustainable finance into their small business lending

[‖]The differences in means between small businesses and all other firm categories are statistically significant. The respective p-values for the t tests and the Mann-Whitney U tests are the following: for large firms p=.00 and p=.00, for firms with high sustainability risk exposure p=.00 and p=.00, and for unlisted large firms p=.01 and p=.02.

Table 3.5: Relation of relevance and progress to aspects of sustainable small business lending

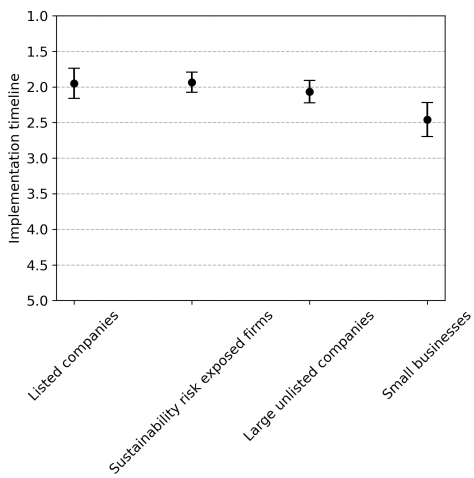
	(1)	(2)	(3)	(4)	(5)	(6)
Progress	4.0***	0.4*	0.6***	-0.3	-0.7**	-0.6***
	(1.5)	(0.2)	(0.2)	(0.2)	(0.3)	(0.2)
Relevance	1.3	-0.0	0.1	0.1	0.3	0.5*
	(1.5)	(0.2)	(0.2)	(0.3)	(0.3)	(0.3)
Return on assets	11.4**	-0.4	-1.0*	-0.5	0.5	-1.0
	(5.2)	(0.7)	(0.6)	(0.7)	(1.0)	(0.8)
Tier 1 ratio	-1.0**	-0.1*	-0.1***	-0.0	0.1***	-0.0
	(0.5)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
log(total assets)	0.3	-0.1	-0.3	0.0	0.2	-0.4***
	(0.8)	(0.2)	(0.2)	(0.1)	(0.2)	(0.1)
Department FE	Y	Y	Y	Y	Y	Y
Observations	53	51	51	52	47	50
Adjusted / Pseudo R^2	0.59	0.14	0.36	0.01	0.12	0.23

The table reports the relationship between the dependent variables that are of interest for the subsequent discussion and the relevance and progress indicators. Independent variables are: (1) Effect on credit for small businesses today (Question II-4-b), (2) Perceived ESG risk in small business lending portfolios today (Question III-1-a) , (3) Expected ESG risk materialization over more than two years (Question III-1-c), (4) Timeline to implement transition risk analysis (Question III-2-a), (5) Timeline to implement ESG related management of small business portfolios (Question III-2-g), and (6) Timeline to implement sustainability-related client dialogue (Question III-2-f). Control variables are bank size and thus relevance of small business lending (represented by logarithmic (total assets)), profitability (represented by the return on assets), financial health (represented by tier 1 ratio) and respondents' department fixed effects. All regressions are ordinary least squares except (1), which is logit due to the binary nature of the independent variable. Note that timelines are shown on an inverted scale, that is, most progress equals 1 whereas least progress equals 5. Therefore, a negative statistical relationship indicates a positive relationship. The results show heteroskedasticity-consistent standard error estimators based on MacKinnon and White (1985). *p<0.1; **p<0.05; ***p<0.01

operations. However, the one- to two-year difference in the rollout of sustainable finance could affect small businesses implementation of value and values aspects in their business models with potential repercussions for the banks' resilience and sustainability strategy.

Figure 3.2: Timeline of sustainable finance integration by different firm types

(a) Aggregated view



(b) Disaggregated bar chart view

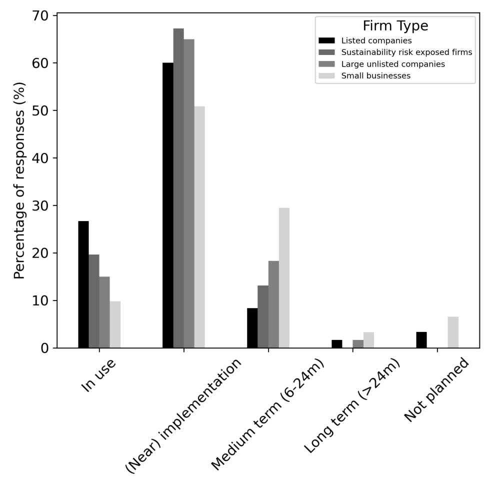


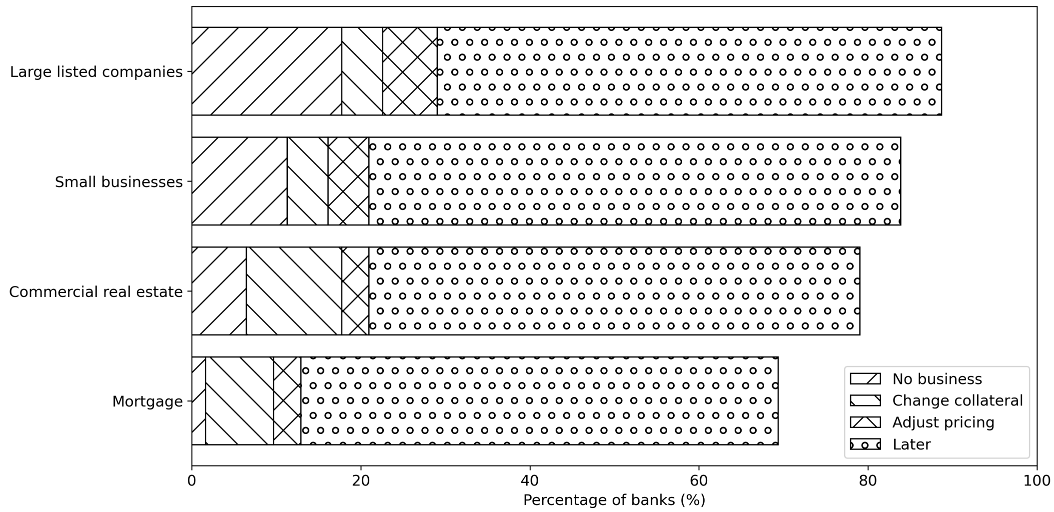
Figure (a) and (b) show the same data in different formats. Figure (b) reports the raw data whereas figure (a) shows the data aggregated by type of firm with 95% confidence interval. The values 1 to 5 are assigned based on the categories shown in (b) (e.g., 1 = 'In use'). A value of 2 in figure (a) indicates that on average, banks are '(Near) implementation'.

Finally, I explore whether and how sustainability considerations influence banks' credit supply today measured as forgone business, changes to demands for collateral, and adjustments to credit pricing (Question II-4). Banks were asked to report any changes in their lending practices due to sustainability aspects in various types of credit, including credit to large companies, credit to small businesses, commercial real estate lending, and mortgages.

Figure 3.3 shows that banks have changed credit supply to large companies slightly more than in other lending activities[**]. Some banks have already begun to adjust the credit supply to small busi-

[**]The remaining empty space in the figure is due to the answers 'no adjustment expected' and 'don't know'.

Figure 3.3: Sustainability aspects in credit decisions by firm type



nesses (21.0%). For both large corporations and small businesses, excluding business is currently the preferred strategy for banks to deal with sustainability aspects. This is in line with Reghezza et al. (2022) who show that European banks allocate capital away from carbon-intensive industries. A majority of banks anticipate changes in credit conditions in the future (62.9% in the case of small businesses). Firm lending appears to be potentially more affected than mortgages, although mortgages are also potentially exposed to sustainability risks such as climate risks (Emambakhsh et al., 2023).

The first set of questions establishes that sustainable finance is important for banks. They are actively working toward its integration and anticipate that it will alter their credit supply to clients, including small businesses. Although progress on lending activities to large and capital market-oriented firms is larger, the findings underscore the growing relevance of sustainable small business lending in the banking industry.

3.3.2 What is the role of value in sustainable small business lending?

Risk management increasingly encompasses understanding sustainability-related risks, that is, understanding value aspects. From the survey, I find that banks expect sustainability risks to increasingly materialize over time in small business lending portfolios and are in the process of implementing risk management instruments in small business lending.

To explore how banks perceive the effect of materialization of sustainability risk in their small business lending portfolios, banks were asked to rate the effect of ESG risks on their small business lending today, over the next two years, and beyond the two years (Question III-1), on a Likert scale from 1 (low) to 6 (high). The findings in Figure 3.4 indicate a moderate perception of sustainability risks in small business portfolios today, with expectations of an increase in the medium to long term[††]. This highlights the relevance of implementing value-based approaches for small business lending throughout the banking sector to manage these risks. The increase in anticipated risk is independent of the perceived relevance of sustainable finance by banks, but significantly positively related to progress (see Table 3.5). This could be interpreted as higher levels of implementation, and thus a better understanding of sustainability aspects, resulting in higher risk perception, or vice versa, as higher perceived risks motivate banks to progress faster in their value implementation.

Sustainability risks can be assessed using different instruments, such as transition risk analysis, physical risk analysis, sustainability-related stress tests, implementation of internal ESG ratings, and risk adjustments in models based on sustainability aspects. I inquire about the implementation timelines of the instruments for small business lending (Question III-2). Some banks use these instruments today for their small business lending, while most banks are implementing or planning to implement them within the next 24 months, see Figure 3.5. Risk analysis and stress testing are more advanced, probably due to regulatory emphasis.

[††]Differences between perceived risk today and expected risks in the future are statistically significant at $p=.00$ for t-tests and Mann-Whitney U tests.

Figure 3.4: Expected materialization of sustainability risks in small business lending over time

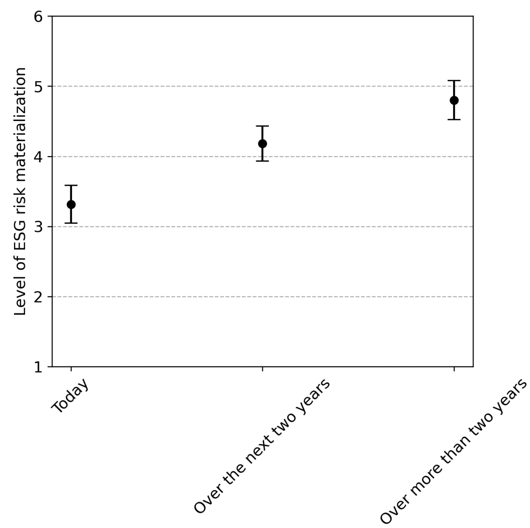
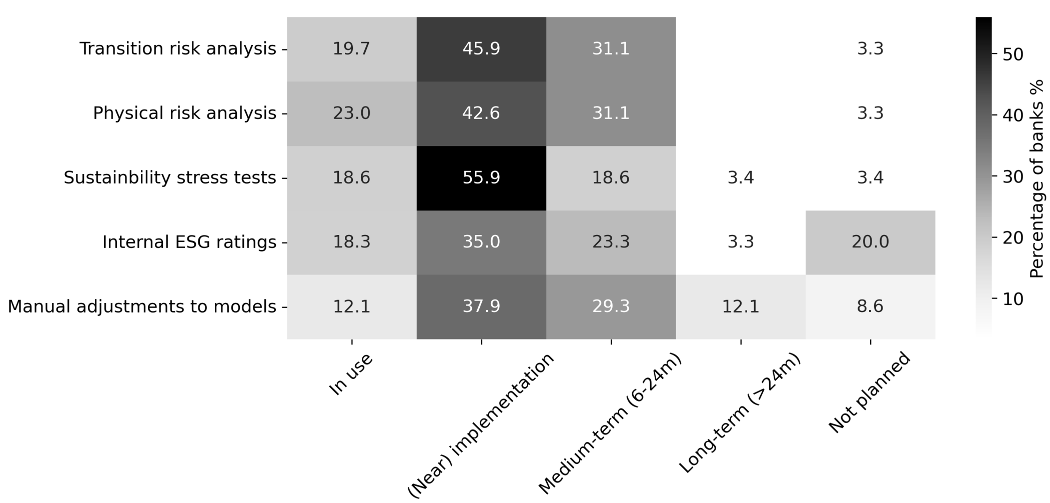


Figure 3.5: Timeline for implementing different instruments for value assessment in small business lending



Internal ESG ratings and risk adjustments in models based on sustainability aspects are less advanced. 20.0% of the participating banks do not plan to implement internal ESG ratings, contrasting with the widespread use of these ratings in asset management and corporate banking (Berg et al., 2022). This discrepancy raises questions about the applicability of ESG ratings for small business portfolios, given the lower economies of scale that external ESG rating providers can expect when supplying such ratings.

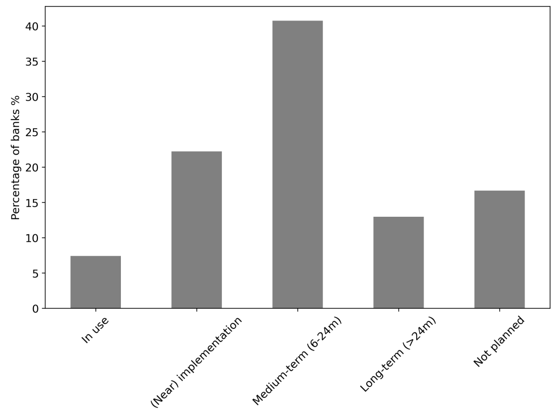
In summary, banks expect a significant increase in the materialization of sustainability risks, highlighting the relevance of value aspects for sustainable small business lending. Progress in implementing specific use cases is advanced but not uniformly, with regulatory-driven use cases slightly ahead of others.

3.3.3 What is the role of values in sustainable small business lending?

Banks are increasingly claiming to work toward sustainability goals, such as climate action and biodiversity restoration, and have made commitments to these objectives (UNEP FI, 2021). This raises the question whether these commitments and other values initiatives by banks affect small business lending and how they support small businesses transforming business models in line with sustainability objectives.

Banks were asked about their progress in implementing sustainability-related portfolio management in small business lending (Question III-2-g). Banks could implement this by tilting the small business lending portfolio towards or away from small businesses with specific sustainability characteristics, potentially affecting liquidity and capital costs for small businesses. Figure 3.6 shows that only a minority (7.4%) of banks are currently using or implementing (22.2%) such approaches. Surprisingly, 29.6% of the banks consider it a long-term issue or do not have implementation plans. This low usage rate is notable, especially compared to the rate of changes in credit supply (recall Figure 3.3), which potentially implies that credit supply is affected primarily through the value channel and not

Figure 3.6: Implementation timeline of sustainability-related management of small business lending portfolios

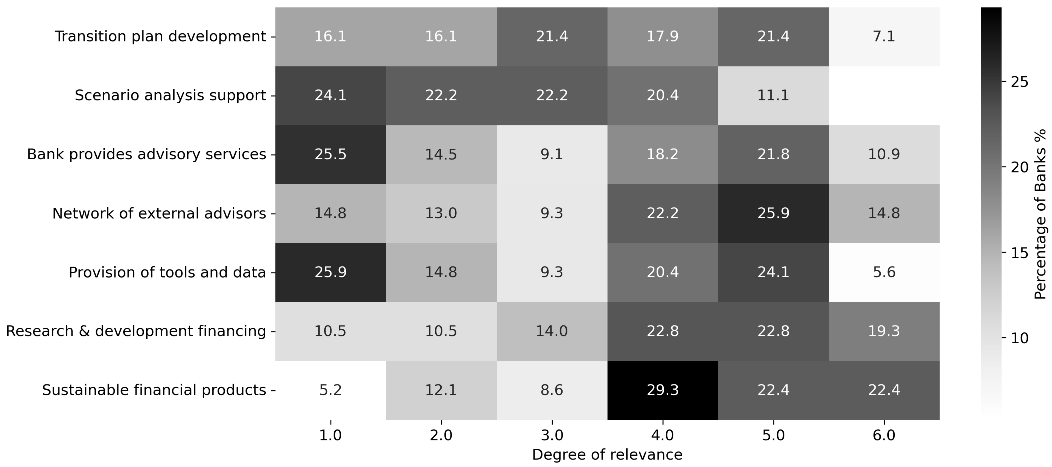


the values channel. The lack of sustainability data from small businesses could also play a role (see Figure 3.9).

Next, I explore the level of relevance of values in sustainable small business lending practices. Several use cases that would position banks as enablers of the transformation of small businesses were examined. Those include support in the development of transition plans, scenario analysis as a service for small businesses, provision of internal and external advisory services, provision of data and tools, and supply of sustainable financial products such as green loans, sustainability-linked loans, as well as financing of sustainability-related research and development (Question III-6).

Figure 3.7 shows that while most of these use cases are somewhat relevant, their relevance is heterogeneous. Banks seem to prioritize financing activities over additional advisory services. This means that banks focus on their core business instead of developing auxiliary products and services. Within these additional services, some, such as external advisory services, are considered more important than others, such as transition plan development or scenario analysis. With research pointing to a mixed effect of dedicated sustainability products on increasing sustainability among financed firms (Flammer (2021), Auzepy et al. (2023)), the effectiveness of the values channel in sustainable small business lending remains opaque. This puts into question whether banks actively support sustainability inte-

Figure 3.7: Relevance of values activities for sustainable small business lending



gration in the small business segment.

Finally, Table 3.6 shows that climate commitments by banks, which are a public communication of the climate mitigation values, have little or no effect on how banks pursue and perceive values-related practices in their small business lending activities. In the regression analysis, I show that the eight values cases from Figure 3.7 are not structurally more (or less) relevant to those banks that have committed to align their portfolios with climate goals than to non-committed banks. Only the provision of sustainability-related tools and data shows a statistically significant positive relationship with climate commitments (at the 5%-level). This calls into question the effectiveness of voluntary climate commitments in delivering a sustainable impact on the economy, which is consistent with the findings of Sastry et al. (2024). In addition, the finding hints at contradictory signals that banks send to their small business clients. On the one hand, they send strong strategic signals for climate action through their climate commitment, and on the other hand, they do not follow through with this signal at the point of client interaction.

The results on values show that banks take a restrained position towards the values perspective in sustainable small business lending. There is some progress and recognition of its importance, but

Table 3.6: Effects of climate commitments on values integration in small business lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate commitment	-0.6	0.4	0.1	0.6	0.8	1.1**	0.4	-0.0
	(0.4)	(0.4)	(0.4)	(0.6)	(0.5)	(0.4)	(0.5)	(0.6)
Progress	-0.4*	0.5*	0.3	0.1	0.3	0.2	0.0	0.4
	(0.2)	(0.3)	(0.3)	(0.3)	(0.4)	(0.3)	(0.3)	(0.4)
Return on assets	0.3	-1.3	-1.4	-1.7	-1.2	-0.8	0.2	0.4
	(1.1)	(1.4)	(1.0)	(1.4)	(1.3)	(1.0)	(1.5)	(1.2)
Tier 1 ratio	0.1***	0.0	-0.1	-0.0	0.0	-0.1**	0.1*	-0.0
	(0.0)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)
log(total assets)	0.1	-0.4	-0.5**	-0.4	0.0	-0.4*	0.3	0.3
	(0.2)	(0.3)	(0.3)	(0.4)	(0.3)	(0.2)	(0.3)	(0.3)
Department FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	47	48	46	47	45	46	48	49
Adjusted R^2	0.17	0.07	0.08	0.02	0.12	0.21	-0.05	-0.05

The table reports the relationship between the Climate Commitment indicators and the values cases as independent variables. Independent variables are (1) Timeline to implement ESG-related portfolio management, (2) Relevance of supporting small businesses in developing transition plans, (3) Relevance of supporting small businesses with scenario analysis, (4) Relevance of providing bank internal advisory services to small businesses, (5) Relevance of providing a network of external advisors to small businesses, (6) Relevance of providing sustainability-related tools and data to small businesses, (7) Relevance of providing financing for research & development, and (8) Relevance of providing sustainable financial products (Question III-6). Control variables are progress (represented by the progress indicator), size of the bank and thus relevance of small business lending (represented by log(total assets)), profitability (represented by return on assets), financial health (represented by tier 1 ratio) and respondents' department fixed effects. All regressions are ordinary least squares. Note that the timeline in (1) is shown on an inverted scale, that is, most progress equals 1 whereas the least progress equals 5. Therefore, a negative statistical relationship indicates a positive relationship. The results show heteroskedasticity-consistent standard error estimators based on MacKinnon and White (1985). *p<0.1; **p<0.05; ***p<0.01

values approaches are viewed heterogeneously across the German banking sector. It appears that financing activities are of greater relevance than additional services. This finding contrasts the narrative of the bank as an enabler of the transformation among small businesses, which is repeatedly presented by the European banking industry (Delrieu et al., 2022).

3.3.4 How are relationship lending and sustainable small business lending currently linked?

Relationship lending could become a relevant aspect of sustainable small business lending. Given the opaque nature of sustainability in small businesses, which is likely to remain (European Commission, 2023), and the difficulties in quantifying some sustainability dimensions (Edmans, 2023a), there is a potential case for the importance of soft information typically obtained through relationship lending. In addition, banks may be interested in engaging in value- and values-based exchanges with their small business clients. To explore the role of relationship lending in this field, the survey examines client dialogue and data sources.

Figure 3.8 shows the timeline to implement the sustainability-related client dialogue with small businesses (Question III-2-f). 19.6% of the banks already employ this kind of dialogue in their relationships with small businesses. Most banks are currently implementing or planning to implement client dialogue on sustainability-related measures within the next 24 months (69.6%), with only a minority viewing it as a long-term or irrelevant issue. This finding highlights a potential need for exchange on value and values as well as a potential role for soft information in the assessment of the sustainability profile of small businesses.

To improve the understanding of whether banks seek hard or soft sustainability information, the survey investigates the challenges banks face in acquiring sustainability-related data from small businesses (Question III-4) and the likelihood of using specific data sources (Question III-5). Both blocks of questions were formulated using a Likert scale from 1 (unlikely / low) to 6 (very likely / high).

Figure 3.8: Implementation timeline of sustainability related client dialog with small businesses

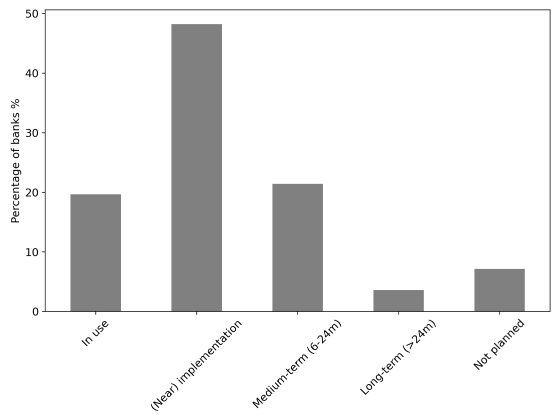


Figure 3.9 (a) shows that relevant data challenges include data availability, quality, comparability, cost, and materiality. These findings highlight that sustainability data from small businesses are not available in many cases to banks today. Interestingly, perceived damage to client relationships as a result of sustainability data acquisition is reported to be less relevant than other challenges[‡‡]. This suggests that the commonly stated concern about banks' inability to collect client data for competition reasons may not be as substantial as perceived by practitioners.

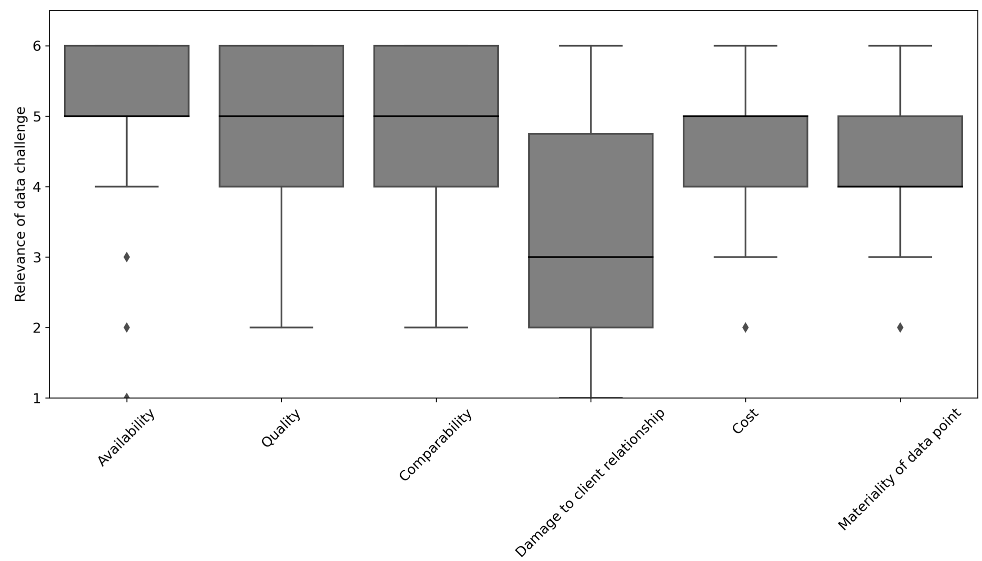
When asked about the likelihood of using different data sources (see Figure 3.9 (b)), banks state that the data provided by small businesses are a major source. Data vendors are also considered a significant source, suggesting the reliance on hard information for analysis. This is in line with the literature on the "hardening" of information in small business lending (Liberti and Petersen, 2019). The likelihood of using data vendors as a data source is surprising given the unlikely availability of widespread ESG ratings or similar data sources for small businesses from such vendors, at least based on data originating from the small business.

In addition, banks' own assessments and the role of relationship managers are likely to be used for

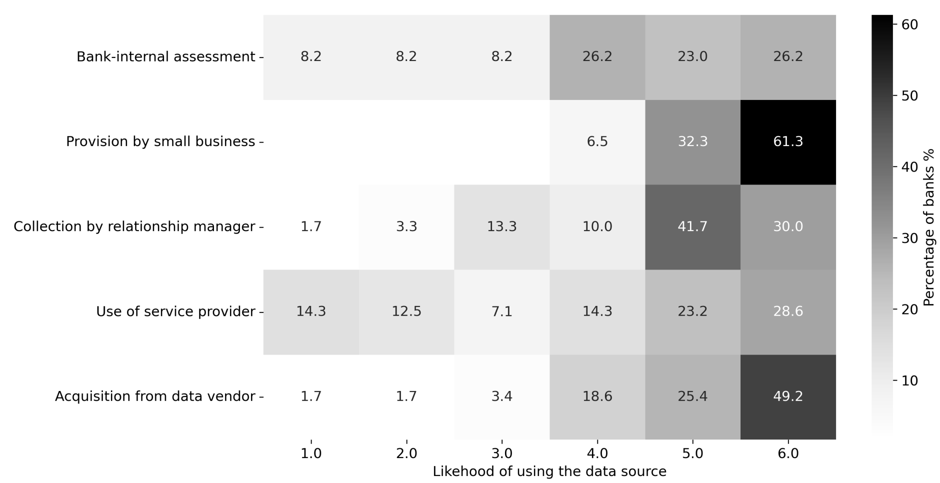
[‡‡]All other data challenges are statistically significant different from damage to client relationship with p=.00 for t-tests and Mann-Whitney U tests.

Figure 3.9: Sustainability data challenges and sources

(a) Data challenges



(b) Likely data sources



data acquisition, though this is not as pronounced as the hard information channels. This finding underscores the relevance of relationship lending as a means of generating soft information on the sustainability aspects of small businesses, albeit in a complementary role.

In summary, the findings suggest that relationship lending is becoming part of sustainable small business lending. The exchange with small businesses on sustainability issues appears to be relevant. Relationship lending as a means to generate soft information seems to be rather complementary to the use of hard information, which is the main data source in sustainable small business lending.

3.4 Conclusion

This paper discusses sustainable small business lending through a survey in the German banking market. The results reveal a trend toward the integration of sustainable small business lending practices. More progress is observable for the value as opposed to the values aspects. This could be explained by expectations of increased sustainability risk materialization over time and the pressure of regulators. Banks implement sustainable relationship lending, in particular through dialogue with small businesses on sustainability. This is likely to generate sustainability-related soft information while banks prefer hard information. In general, banks have made more progress in implementing sustainable finance for large and listed firms than for small businesses.

The study is not without limitations. First, the survey focuses on banks, which offers insight into the lenders' perspective but potentially omits the perspective of small businesses. They are instrumental in implementing sustainable practices and sustainability risk mitigation strategies. Informal exchanges with chief financial officers of small businesses show a rather critical perspective on the current state of sustainable finance. Second, the survey's broad definition of sustainability may have skewed the emphasis on certain sustainability aspects over others. Informal discussions with representatives of a subset of participating banks show a strong focus on climate aspects at the moment. Thus, the results might primarily show banks' positions on this particular topic. Third, the geographical confinement of the study to Germany may not accurately represent the conditions in other banking markets with different levels of capital market integration and cultural characteristics. Future research should aim to broaden this scope. As sustainable small business lending becomes increasingly practiced, future research should employ various empirical methods to deepen our understanding of sustainable small business lending and the role of different stakeholders in this context.

The findings have implications for banks and policymakers. Banks can use the findings to structure and adjust their sustainable small business lending practices. Furthermore, the banking industry may need to revise its communication on its role in supporting the transformation of economic activities by small businesses. Policymakers can use the results to shape sustainable finance policies for small business lending by incorporating the tendency of banks to follow value and risk-oriented practices. They may establish policies to support this development. Additionally, they may consider developing policies that allow banks to establish values and transformative supporting activities for small businesses as part of broader efforts to achieve sustainability objectives.

The difficulty lies not so much in developing new ideas as in escaping from old ones.

John Maynard Keynes

4

Disaggregating confusion? The EU Taxonomy and its relation to ESG rating

The financial system, as the provider of capital, has been assigned a central role in the sustainable transformation of the global economy (Battiston et al. 2021; Steffen and Schmidt 2021). Investors increasingly integrate sustainability considerations into decision making (Dimson et al., 2020; Ilhan et al., 2021; Shanaev and Ghimire, 2022). Thus, information on the sustainability performance of firms is becoming increasingly important. Environmental, social, and governance (ESG) ratings are a widely used external source of such information (Dimson et al., 2020; Krueger et al., 2020). However, ESG ratings diverge in assessing firm sustainability performance. In this paper, we analyze how the EU Taxonomy (Taxonomy), a classification system for sustainable economic activities, relates to the environmental part of ESG ratings (E ratings) and discuss how it could help reduce their divergence. Using tobit regressions, we find a significantly positive relation between the Taxonomy and E ratings for three out of four ESG data providers.

ESG ratings can affect capital allocation and firm cost of capital, among others, by changing return expectations (Gibson et al., 2019) and divestment (Krueger et al., 2020). The evolving regulatory landscape could increase the magnitude of these effects. For example, ESG ratings are likely to become a data source for risk evaluations in the European banking sector (Bundesanstalt für Finanzdienstleistungsaufsicht, 2020; European Banking Authority, 2021) and to determine capital requirements under Basel III / IV (Basel Committee on Banking Supervision, 2021; European Banking Authority, 2022).

However, scholarly work reveals inconsistencies between ESG ratings. Dorfleitner et al. (2015) find an "evident lack of convergence of ESG measures". Chatterji et al. (2016) show "strong evidence of low commensurability of SRI ratings". (Berg et al., 2022) coin the term aggregate confusion based on the weak correlation between different ESG ratings. They attribute aggregate confusion to scope divergence (that is, attributes that constitute the definition of sustainability) and measurement divergence (that is, indicators used to measure a given attribute) (Berg et al., 2022). Those inconsistencies can reinforce the effects on capital allocations and the cost of capital of firms (Gibson et al., 2019), which may result from uncertainty in the Knightian sense (Knight, 2012).

The European Union (EU) develops the Taxonomy with the objective to harmonize the definition of sustainability and its measurement. The Taxonomy consists of technical screening criteria defining substantial contributions (SC) to the six EU environmental objectives, do no significant harm criteria for the EU environmental objectives, and minimum social safeguards. SC criteria can be understood as the EU's definition of activities that support the ecological transition of the economy. The criteria should be science-based. So far, the Climate Delegated Act and the Complementary Delegated Act describe technical screening criteria defining SC to climate change mitigation and climate change adaptation, do no significant harm criteria for all six EU environmental objectives, and minimum social safeguards (European Commission, 2021, 2022a). The definitions of the technical screening criteria for SC to the remaining four EU environmental objectives should follow by the end of 2022. The Taxonomy is a key policy initiative within the finance part of the EU Green Deal (European Commission, 2019).

The Taxonomy could help disaggregate the confusion of the environmental part of ESG ratings (E ratings) by harmonizing measurement of sustainable economic activities, hence reducing measurement divergence. For this to materialize, E ratings would need to reflect the Taxonomy. Through this transmission channel, the Taxonomy can decrease uncertainty in investment decisions, which ultimately increases market efficiency and reduces the average cost of capital of firms. The Taxonomy's central role in the European sustainability ambitions and its informative value should foster this process (Lucarelli et al., 2020). Although those effects should unfold mainly in the near future, the E ratings may already reflect the Taxonomy since ESG data providers had access to relevant information during the Taxonomy development process and investors already have the need for Taxonomy-related data in light of the evolving regulatory landscape (Pacces, 2021). Thus, we hypothesize that technical screening criteria for SC to climate change mitigation could have an impact on climate change-related aspects in existing E ratings. The Taxonomy could be an explicit part of E rating methodologies or, more likely, implicitly be integrated during the firm's rating process.

In this paper, we demonstrate that there is a positive relationship between Taxonomy and E ratings already exists for MSCI ESG Research LLC (MSCI), Refinitiv, and V.E, part of Moody's ESG

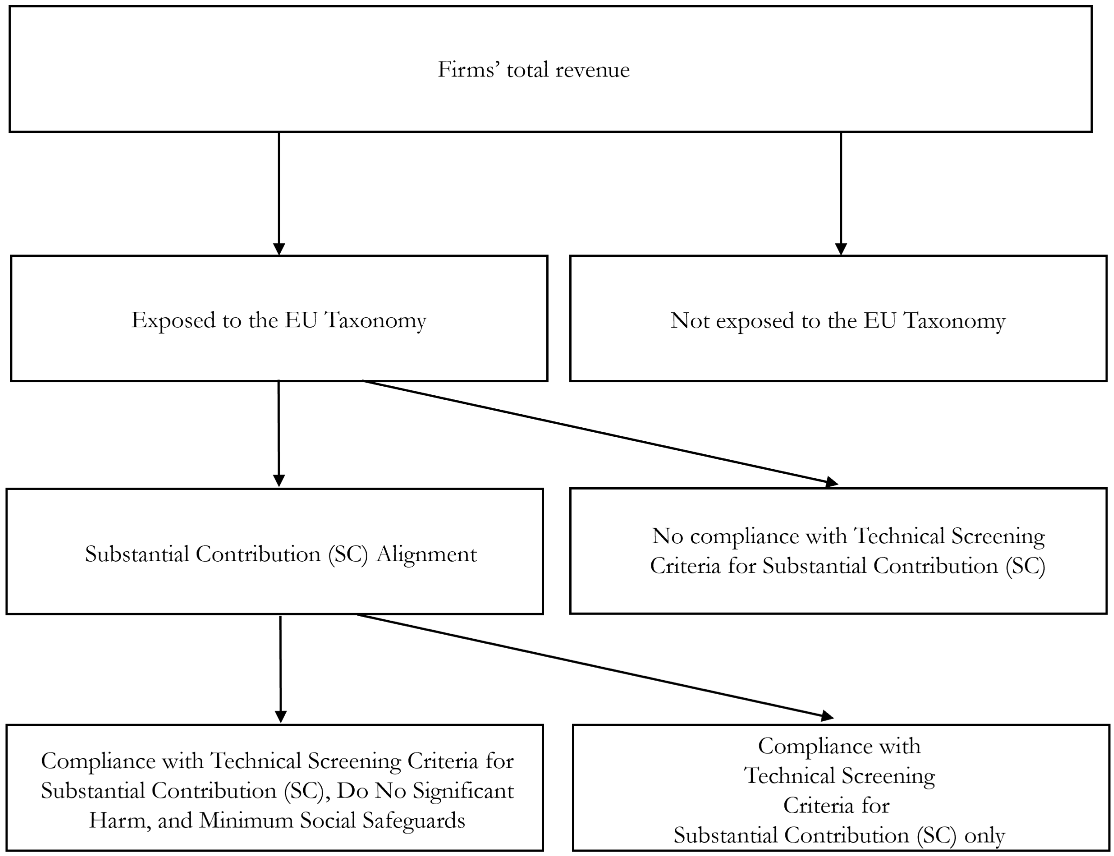
Solutions (V.E). Although the relationship is not significantly positive for Standard & Poor's (S&P) E ratings. In addition, we find that the relation between Taxonomy and E ratings is stronger pronounced for firms with fully Taxonomy-exposed revenue. To the best of our knowledge, we are the first to use Taxonomy-related firm data in an ESG rating context. Our findings have implications for investors in anticipating financial implications of the Taxonomy, ESG data providers aiming to reduce measurement divergence in E ratings, and policymakers for developing effective sustainable finance regulations. The following section describes the data and methodology. Section 3 discusses the results, and section 4 concludes.

4.1 Data and Methodology

We use a Taxonomy dataset from Institutional Shareholder Services (ISS) ESG that applies the Taxonomy's technical screening criteria to firm revenues. The dataset focuses on SC to climate change mitigation, that is, only those revenue-generating activities that substantially contribute to mitigating climate change are further screened for compliance with do no significant harm criteria and minimum social safeguards. The dataset provides information on the firms' share of revenue that complies with the technical screening criteria for SC to climate change mitigation (SC Alignment) and the firms' share of revenue that complies with technical screening criteria for SC, do no significant harm, and minimum social safeguards, see Figure 1. The dataset is among the first of its kind, and we are the first to use it in an ESG rating context.

We analyze the relation between the SC Alignment and E ratings from MSCI, Refinitiv, S&P, and V.E. These E ratings measure a firm's environmental sustainability, that is, they primarily follow an inside-out perspective. This is in line with the impact perspective of the Taxonomy, i.e. measuring SC to an environmental objective. E ratings substantially reflect climate change-related aspects according to their methodology papers (MSCI, 2020; V.E, 2020; Refinitiv, 2021; S&P, 2021). To ensure com-

Figure 4.1: Firm revenue split by level of alignment with the Taxonomy



parability, we standardize the ratings between 0 and 100. E ratings provided by Refinitiv and V.E do not fully utilize the range in our dataset, see Table 1.

The firm's share of Taxonomy-exposed revenue determines the maximum SC Alignment. This might distort the models since a firm that has maximized its SC Alignment within a low share of Taxonomy-exposed revenue is treated the same as a firm with the same SC Alignment within a higher share of Taxonomy-exposed revenue. We control for this effect by applying the Relative SC Alignment, which is calculated by dividing the firm's SC Alignment by its Taxonomy-exposed revenue, see Equation 4.1. Multiplying the result by 100 yields a Relative SC Alignment ranging between 0 and

Table 4.1: Summary Statistics

	N	Mean	SD	Median	0.25	0.75	Min	Max
MSCI E Rating	1,566	52.08	18.47	51	39	64	0	100
S&P E Rating	1,722	40.66	28.29	34	17	62	0	100
Refinitiv E Rating	1,721	50.30	27.28	53.94	28.70	72.48	0	99.05
V.E E Rating	1,126	34.82	16.93	34	22	46	0	84
Taxonomy Exposure	1,813	54.15	39.41	55.65	12	99.98	0	100
Relative SC Alignment	1,813	13.80	26.63	0	0	20	0	100
ln(Market Capitalization)	1,809	9.46	2.72	9.03	7.50	11.07	2.54	19.04

This table provides the summary statistics for the used variables. The following variables are presented: total number of observations (N), the mean, the standard deviation (SD), the median, the 25 percent quartile (0.25), the 75 percent quartile (0.75), the minimum (Min), and the maximum (Max).

100.

$$\text{Relative SC Alignment}_i = \frac{\text{SC Alignment}_i}{\text{Firm's Taxonomy-exposed revenue}} \times 100 \tag{4.1}$$

We follow three steps to analyze how the Taxonomy, as the central and regulatory framework for measuring and assessing SC to climate change mitigation, relates to E ratings in order to determine its potential for reducing measurement divergence. Firstly, we generate the correlation matrix to obtain a first indication of the relationship between E ratings and Relative SC Alignment. Secondly, since the standardized E ratings range from 0 to 100, we run a tobit regression model on the cross-section of E ratings. We control for the firm characteristics size, domicile, and industry to avoid biased estimates. Size bias should persist for Taxonomy assessment by third party providers as it represents another form of ESG assessment (Drempetic et al., 2020). The Taxonomy cross-references EU legislation, which should improve the Taxonomy's ease of applicability in the EU compared to the global average. In addition, firms domiciled in countries with more ambitious climate change policies should have higher Relative SC Alignments (Gyönyörová et al., 2023). The level of difficulty in fulfilling the Taxonomy's technical screening criteria differs between industries, thus we control for it.

We apply the following tobit regression model (Model I):

$$\text{E rating}_i = \alpha_1 + \beta_1 \text{Relative SC Alignment}_i + \gamma' \text{Controls}_i + \varepsilon_i \tag{4.2}$$

where E rating_i is the environmental rating of firm i, Relative SC Alignment_i is firm i's SC Alignment relative to its Taxonomy-exposed revenue (see Equation 4.1), and Controls_i capture the control variables, that is, firm size, domicile, and industry classification (NACE).

Thirdly, we expand Model I by further including a dummy variable (Full Taxonomy Exposure) indicating full Taxonomy-exposed revenue and an interaction term between Relative SC Alignment and Full Taxonomy Exposure (Model II). 440 firms have revenue that can be completely mapped to the Taxonomy, representing 24.27% of the full sample. The introduction of the dummy variable Full Taxonomy Exposure should correct for the fact that ESG data providers assess the entire firm while we analyze the Relative SC Alignment. Assuming the E ratings and the Taxonomy are related, we would expect that the relation between Relative SC Alignment with the E ratings to be higher on average for firms with full Taxonomy exposure.

4.2 Findings and Discussion

Our analysis suggests that aggregate confusion persists. The correlations between the E ratings by MSCI, S&P, Refinitiv, and V.E range from 0.29 to 0.65 (see Table 4.2). In line with the findings by Dorfleitner et al. (2015) and Chatterji et al. (2016), correlations are significant but do not uniformly show the same level of environmental performance. The size bias in the E ratings highlighted by Drempetic et al. (2020) is significant as well.

The E ratings from MSCI, Refinitiv, S&P, and V.E significantly positively correlate with the Relative SC Alignment, indicating a reflection of the SC criteria in the E ratings. The magnitude of the correlations differs between the ESG data providers. E ratings from S&P and Refinitiv are sig-

Table 4.2: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) MSCI E Rating	1.00						
(2) S&P E Rating	0.29***	1.00					
(3) Refinitiv E Rating	0.29***	0.65***	1.00				
(4) V.E E Rating	0.39***	0.60***	0.59***	1.00			
(5) Taxonomy Exposure	0.03	-0.14***	-0.11***	0.04	1.00		
(6) Relative SC Alignment	0.15***	0.07***	0.18***	0.19***	-0.05**	1.00	
(7) ln(Market Capitalization)	0.07***	0.34***	0.35***	0.05*	-0.21***	0.05**	1.00

This table presents the Bravais-Pearson pairwise correlation coefficients between the E ratings of the four data providers, Taxonomy Exposure, Relative SC Alignment, and logarithmized market capitalization. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

nificantly negatively correlated with the firm's share of Taxonomy-exposed revenue. This finding is in line with expectations since the current coverage of the Taxonomy focuses on emission-intensive industries, meaning that a higher share of Taxonomy-exposed revenue indicates higher revenue generation in these industries. Firm size is negatively correlated with a firm's share of revenue exposed to the Taxonomy. Thus, larger firms seem to be less exposed to the Taxonomy.

The results of Model I confirm the findings of the correlation analysis; see Table 4.3. Our results suggest a significantly positive relation of the Relative SC Alignment and the E ratings from MSCI, Refinitiv, and V.E. Contrary to the correlation matrix, we cannot confirm a significant relation of Relative SC Alignment and E ratings from S&P. We ascribe this effect to the inclusion of control variables, which correct for unobserved bias in the correlation coefficients. Other factors such as domicile, industry, or firm size have significant explanatory value for E ratings as well.

Model II confirms the hypothesis of a positive relation between the level of Taxonomy-exposed revenue and the effect of the Taxonomy on E ratings. The Taxonomy has a stronger explanatory value for E ratings of fully Taxonomy-exposed firms. This finding could indicate that the Taxonomy has a higher potential for reduction of measurement divergence for firms with highly Taxonomy-exposed revenue. We observe this effect for E ratings from MSCI, Refinitiv, and S&P, i.e., the respective in-

Table 4.3: Regression results of Model I

	MSCI E Rating	S&P E Rating	Refinitiv E Rating	V.E E Rating
Relative SC Alignment	0.105***	0.031	0.125***	0.066***
	(0.017)	(0.027)	(0.022)	(0.016)
ln(Market Capitalization)	0.989***	3.979***	4.116***	1.000***
	(0.212)	(0.317)	(0.295)	(0.197)
Domicile Dummies				
EU27	9.230***	18.730***	20.112***	16.265***
	(1.319)	(1.987)	(1.742)	(1.451)
North America	-0.033	-2.873*	-1.786	-2.977**
	(1.160)	(1.702)	(1.629)	(1.185)
Rest of the World	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Constant	24.631***	-8.596**	3.626	13.461***
	(3.464)	(3.672)	(4.361)	(2.524)
Observations	1,563	1,719	1,718	1,124

This table shows the results of the tobit regression model. The dependent variables are the E ratings from the four ESG data providers (columns 1 - 4). The independent variable is the Relative SC Alignment, which measures the SC Alignment in relation to the Taxonomy-exposed revenue of a firm, see Equation 4.1. We control for firm characteristics that have been shown to affect E Ratings, namely logarithmized market capitalization, domicile dummies (EU27; North America and Rest of the World), as well as industry classification dummies (NACE). For reasons of readability, we do not display the coefficients of all NACE industry classification dummies. Robust standard errors as per Huber (1967) and White (1980) are presented in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

teraction terms show a significantly positive relationship, see Table 4.4. In addition, we find that the Taxonomy retains a significantly positive relation with E ratings from those ESG data providers for the remaining sample. Interestingly, the Taxonomy does not show a significantly positive relation with E ratings from S&P even for fully Taxonomy-exposed firms.

The Taxonomy was not in place when ESG data providers developed the E ratings utilized in our analysis. Nevertheless, we find a positive relation between E ratings and Relative SC Alignment and stronger effects for firms with fully Taxonomy-exposed revenue. Our findings suggest that a potential of the Taxonomy to reduce measurement divergence of E ratings exists, which could reduce greenwashing risks in the financial system. This potential could also exist for social aspects of the ESG

Table 4.4: Regression results of Model II

	MSCI E Rating	S&P E Rating	Refinitiv E Rating	V.E E Rating
Relative SC Alignment	0.080***	0.021	0.113***	0.052***
	(0.017)	(0.030)	(0.024)	(0.016)
Full Taxonomy Exposure	-2.181	-7.051***	-6.849***	-3.272
	(1.370)	(2.141)	(2.223)	(2.032)
Full Taxonomy Exposure x Relative SC Alignment	0.164***	0.090	0.110*	0.138**
	(0.046)	(0.066)	(0.057)	(0.063)
ln(Market Capitalization)	0.981***	3.879***	4.036***	0.995***
	(0.213)	(0.320)	(0.296)	(0.198)
Domicile Dummies				
EU27	9.161***	18.603***	19.996***	16.109***
	(1.314)	(1.982)	(1.741)	(1.444)
North America	-0.111	-2.893*	-1.757	-3.062**
	(1.152)	(1.703)	(1.633)	(1.187)
Rest of the World	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Constant	25.123***	-6.688*	5.259	13.509***
	(3.534)	(3.706)	(4.506)	(2.533)
Observations	1,563	1,719	1,718	1,124

This table presents the results of the tobit regression model. The dependent variables are the E ratings from the four ESG data providers (columns 1 – 4). The independent variable is the Relative SC Alignment, which measures the SC Alignment in relation to the Taxonomy-exposed revenue share of a firm, see Equation 4.1. In addition to Model I, we consider Full Taxonomy Exposure and the interaction between Full Taxonomy Exposure and Relative SC Alignment. Full Taxonomy Exposure takes a value of 1 if a firm's share of revenue is fully Taxonomy-exposed and 0 otherwise. Including this interaction term corrects for the fact that ESG data providers assess the entire firm while we analyze Relative SC Alignment. As in Model 1, we control for firm characteristics that have been shown to affect E Ratings, namely logarithmized market capitalization, domicile dummies (EU27; North America and Rest of the World), as well as industry classification dummies (NACE). For reasons of readability, we do not display the coefficients of all NACE industry classification dummies. Robust standard errors as per Huber (1967) and White (1980) are presented in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

ratings, which could further reduce the measurement divergence between ESG ratings. The Platform on Sustainable Finance has already published recommendations on the structure of an EU Social Taxonomy, which the European Commission still needs to translate into legislation (Platform on Sustainable Finance, 2022). The non-significant relation between the Taxonomy and S&P E ratings suggests that the potential for the reduction in measurement divergence has not yet fully materialized. Finally, the stronger relation for firms with highly Taxonomy-exposed revenue might indicate that the Taxonomy could have the strongest effect on reducing measurement divergence amongst E ratings of pure players and less diversified firms.

Our findings are subject to limitations. Firstly, a time series is necessary to assess a potential reduction in divergence of E ratings once firms have reported Taxonomy data for several years. Secondly, three out of four E ratings show a significant relation to the Taxonomy, leaving some uncertainty as to whether and how the entire ESG rating market might be utilizing the Taxonomy. Thirdly, the Taxonomy data used in this paper was generated by a third party, which might not fully align with the Taxonomy data that firms will ultimately report. Fourthly, the current development stage of the Taxonomy includes primarily climate change aspects. Future policy developments will allow researchers to advance the focus of this manuscript as soon as the technical screening criteria for all six EU environmental objectives are available. At this point, the Taxonomy's technical screening criteria should closely resemble the indicators currently used in E ratings.

Future research might help overcome these limitations by analyzing a time series once it becomes available (potentially through the European Single Access Point), testing the effect of the Taxonomy on other parts of the ESG rating market (for example, on risk-related ratings) and by running a similar study to ours once the Taxonomy is fully developed. In addition, further research could incorporate components of financial performance to these findings, including the Taxonomy's direct effects on capital allocation and cost of capital. For instance, financial effects of first public disclosure by firms on the Taxonomy may be of interest to the accounting literature. Other research in the field of ESG ratings and sustainability measurement might utilize our perspective on the Taxonomy as a measure to disaggregate confusion of ESG ratings for their purposes.

4.3 Conclusion

This paper shows a significantly positive relation between E ratings and firm-level Taxonomy performance. Our findings are relevant for practitioners and policymakers: Investors might anticipate potential implications of the Taxonomy on their investments such as changes in cost of capital or capital reallocations by other investors. ESG data providers can use our findings in the process of reducing measurement divergence in E ratings to strengthen reliability and credibility as well as to pre-empt regulation. Policymakers can build on our findings to develop an effective sustainable finance regulation that improves the quality of ESG information in the market.

A

Appendix to Chapter 1

Publication Status

The paper is ready for submission.

Co-Authors

The following authors contributed to Chapter 1 (share of contribution in parentheses):

- Christian Haas, Frankfurt School of Finance & Management (40%)
- Ulf Moslener, Frankfurt School of Finance & Management (20%)
- Sebastian Rink, Frankfurt School of Finance & Management (40 %)

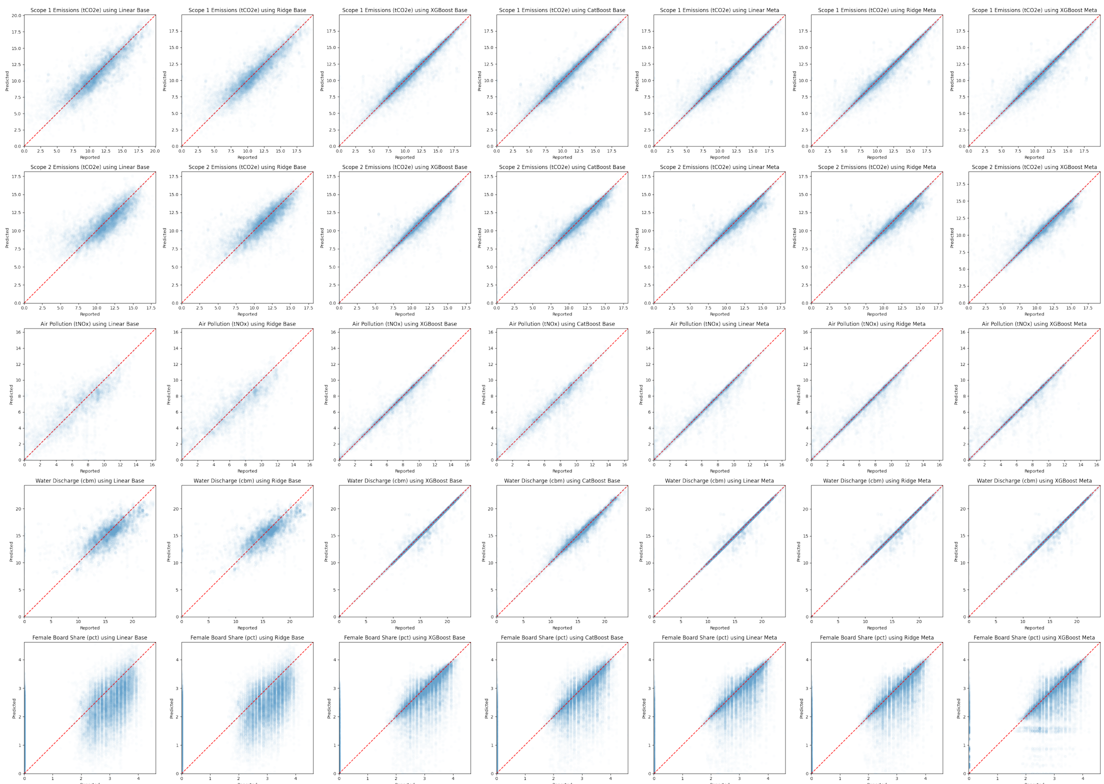
Paper Abstract

Sustainability data is increasingly relevant for multinational enterprises (MNEs), financial institutions, and researchers. However, sustainability data remain incomplete, fragmented, or scarce. In our paper, we propose a novel approach to address this challenge using machine learning (ML) to predict sustainability metrics from readily available financial data. This method allows for a more detailed and accurate assessment of sustainability in MNEs and their global value chains. Our approach is tested using a comprehensive dataset of financial and sustainability information at the company level. The results indicate that ML is effective in predicting key sustainability metrics, such as corporate carbon emissions and water discharge. However, users should reflect on the specific use case when applying ML since model performance can vary sectorally, spatially, and temporally. In addition, we develop a metric to assess the uncertainty of the predictions and find that it can substantially affect the model output. Regulators should build on our findings to encourage the use of ML-generated sustainability data while also requiring more transparency from data providers and model users.

Model Performance: Reported vs. Predicted Values

Figure A.1 presents a comparison between reported and predicted values within our test data set for both baseline and meta models in the five sustainability metrics. This comparison reaffirms that more complex models, such as XGBoost and CatBoost, as well as the meta models, consistently outperform linear models like OLS and Ridge by a significant margin.

Figure A.1: Plots reported vs predicted for best model per target variable and learner

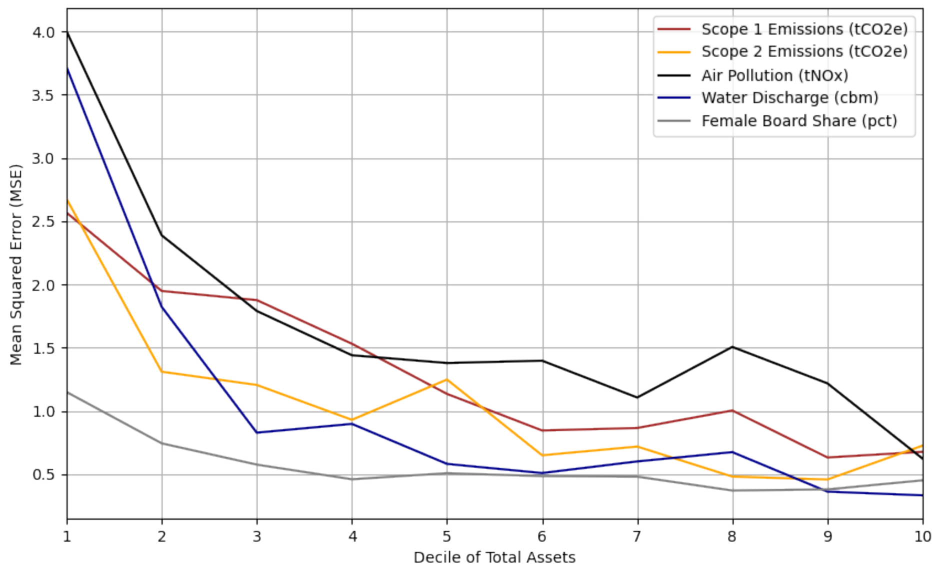


This figure displays the plots of the reported vs predicted variables for the five target variables vertically (Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share) and the best performing model per learner horizontally (linear regression, ridge, CATBoost, XGBoost, meta-linear, meta-ridge, meta-XGBoost).

Model Performance by Company Size

Figure A.2 illustrates the variation in model performance relative to company size, represented by deciles of company size and the corresponding mean squared error (MSE) per decile. The results indicate that model performance is notably poorer in the lowest decile, which includes the smallest companies. Despite this, the performance remains superior compared to previous studies even in this decile. Following the initial decile, there is a sharp improvement in model performance, which then levels off with only minor variations around deciles 7 to 9.

Figure A.2: Model Performance by Company Size

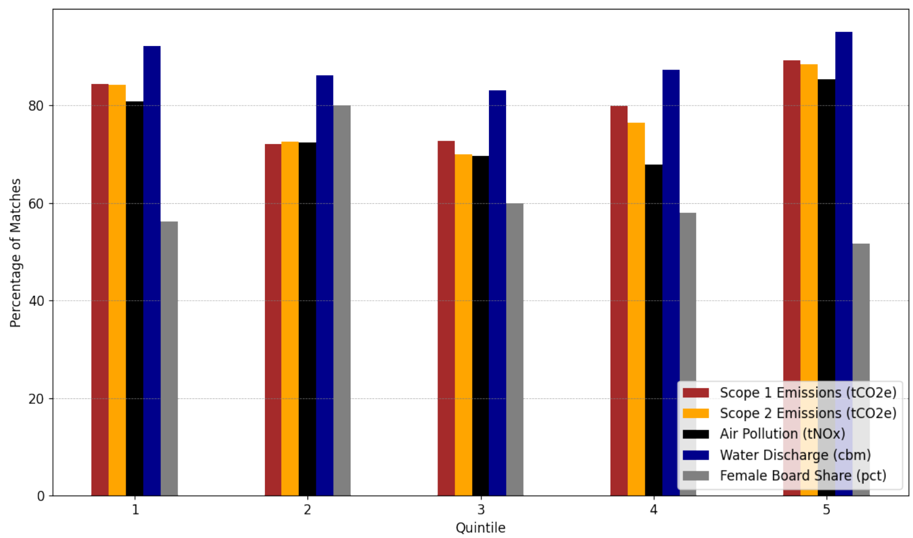


This figure displays the MSE of model predictions for company-size deciles for the the five target variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share.

Quintile Analysis of Sustainability Metrics

Figure A.3 presents the quintile results, also discussed in the main body of the paper, showing the percentage of matches for each sustainability metric within their respective quintile brackets. The primary finding is that the variation in model fit across quintiles is generally minimal for most sustainability metrics, with the exception of the female board share metric, where substantial variation is observed among the quintiles. This suggests that the predictive accuracy for the female board share is more sensitive to the distribution of data between different quintiles compared to other sustainability metrics.

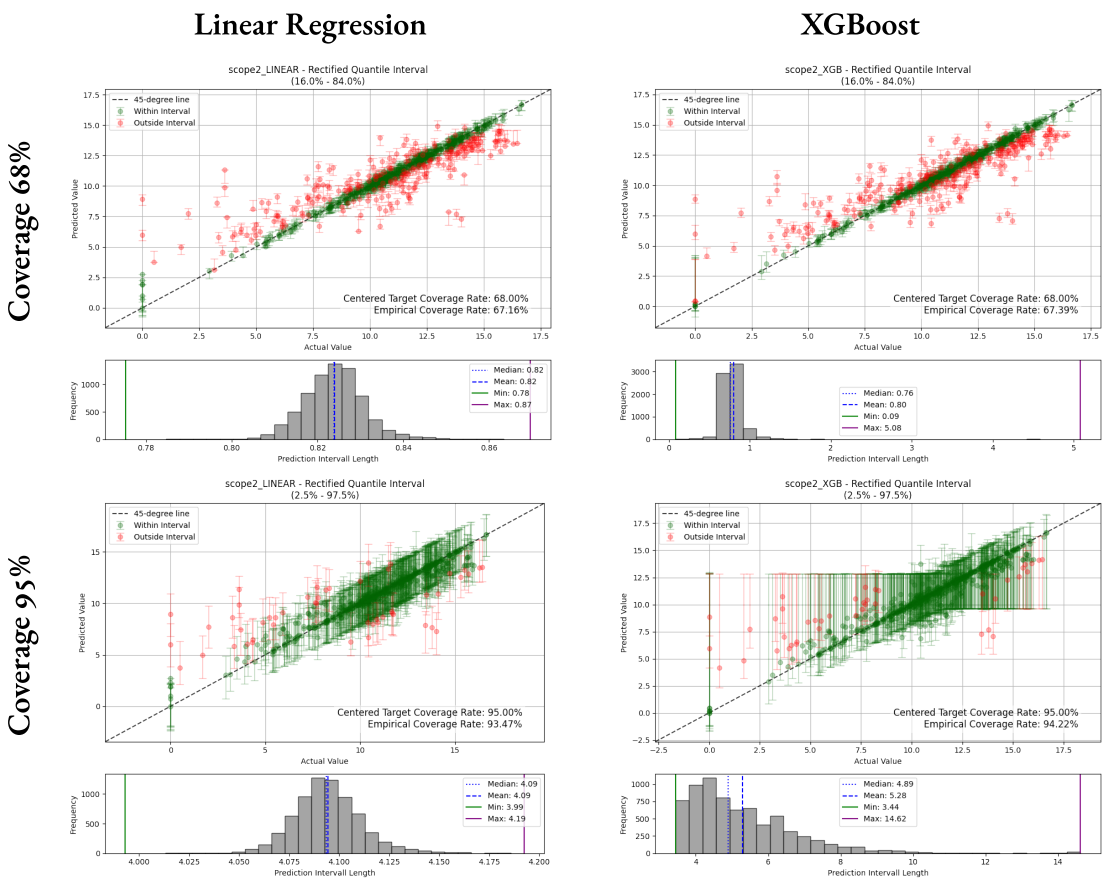
Figure A.3: Percentage of Quintile Matches



This figure displays the percentage of correctly allocated observations (predicted vs actual) per quintile for the five target variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share.

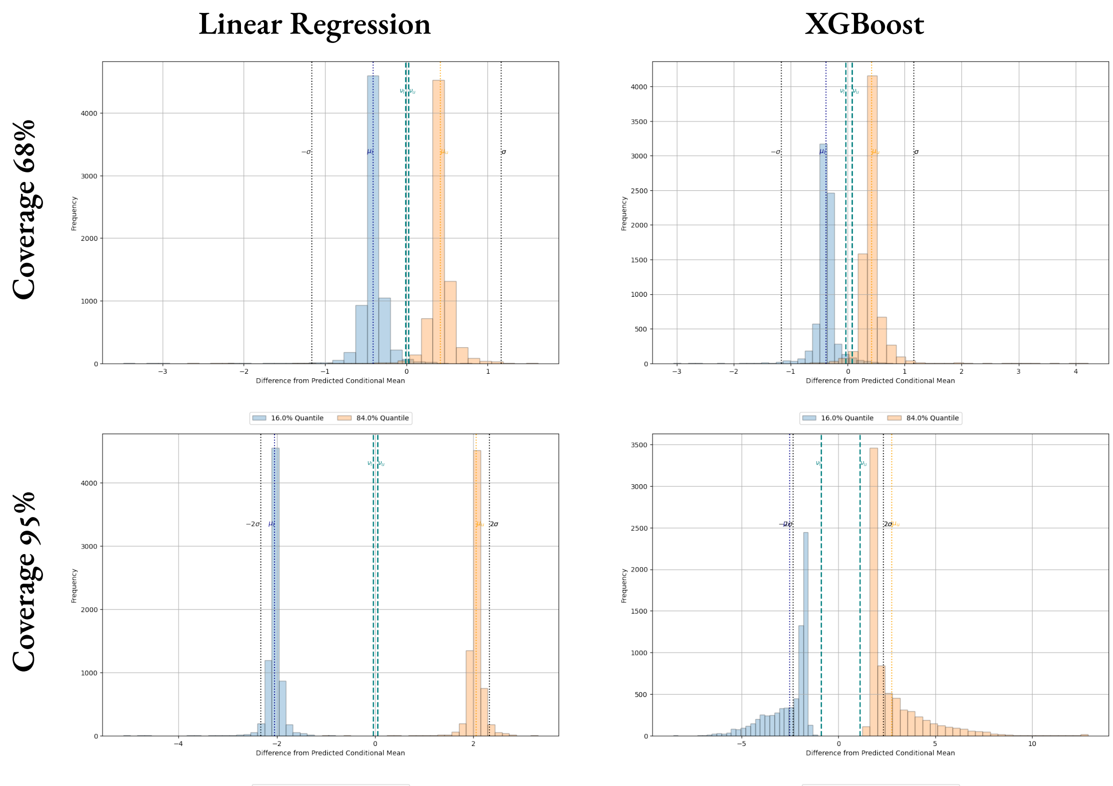
Scope 2 Emissions

Figure A.4: Conformalized Prediction Uncertainty in Different Settings for Scope 2 Emissions



This figure displays conformalized prediction uncertainty for Scope 2 Emissions. The settings are for the learners linear regression and XGBoost and the coverage of 68% and 95%. For better readability, the figure shows 2% of total observations which are randomly selected.

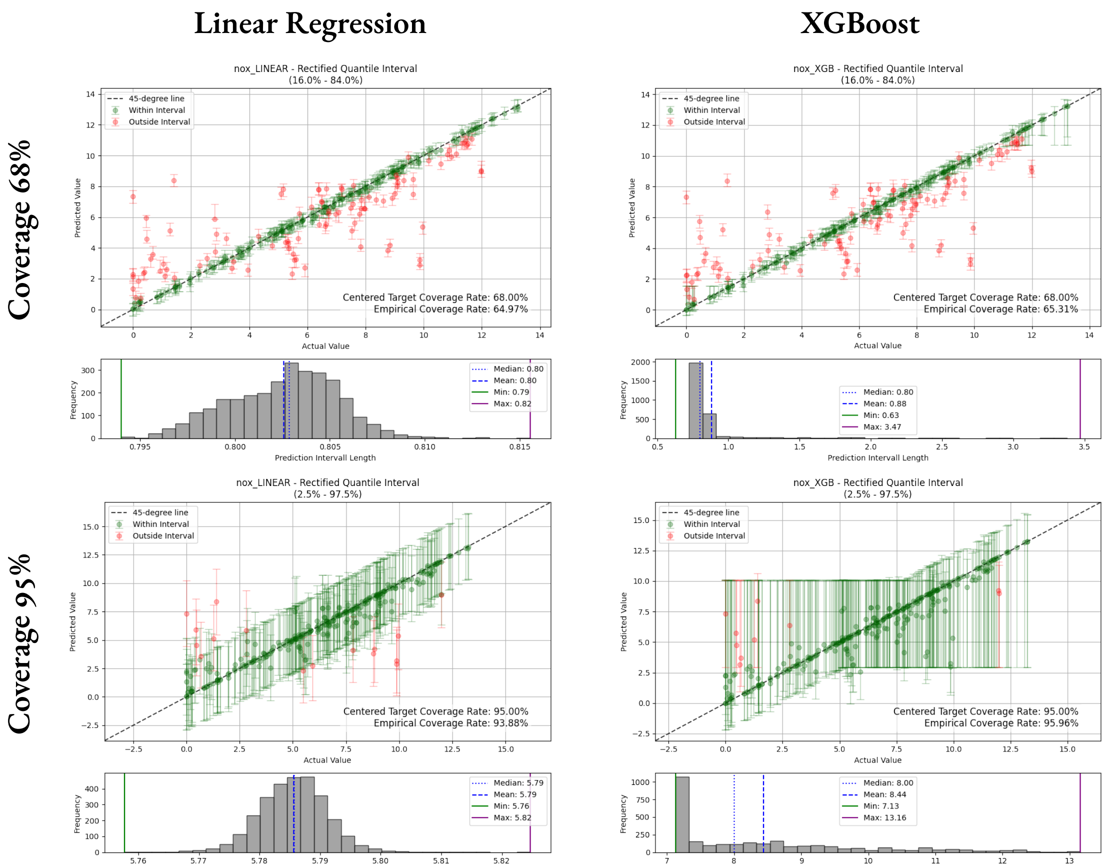
Figure A.5: Deviation from Conditional Mean for Scope 2 Emissions



This figure displays the deviation for the conditional mean for Scope 2 Emissions in different settings. The settings are for uncertainty estimates based on linear regression and XGBoost and for targeted coverage rates of 68% and 95%. In all settings, the conditional mean is predicted by the best-performing XGB meta model. The black dotted lines represent the prediction intervals using one and two standard deviations (σ), respectively. The green dashed lines represent the mean lower (upper) quantile prediction from standard quantile regression, ν_l (ν_u). Finally, the blue and orange bars show the distribution of quantile predictions for the lower and upper quantile from conformalized quantile regression. The mean of lower (upper) predictions is represented by the blue and orange dotted lines, μ_l (μ_u).

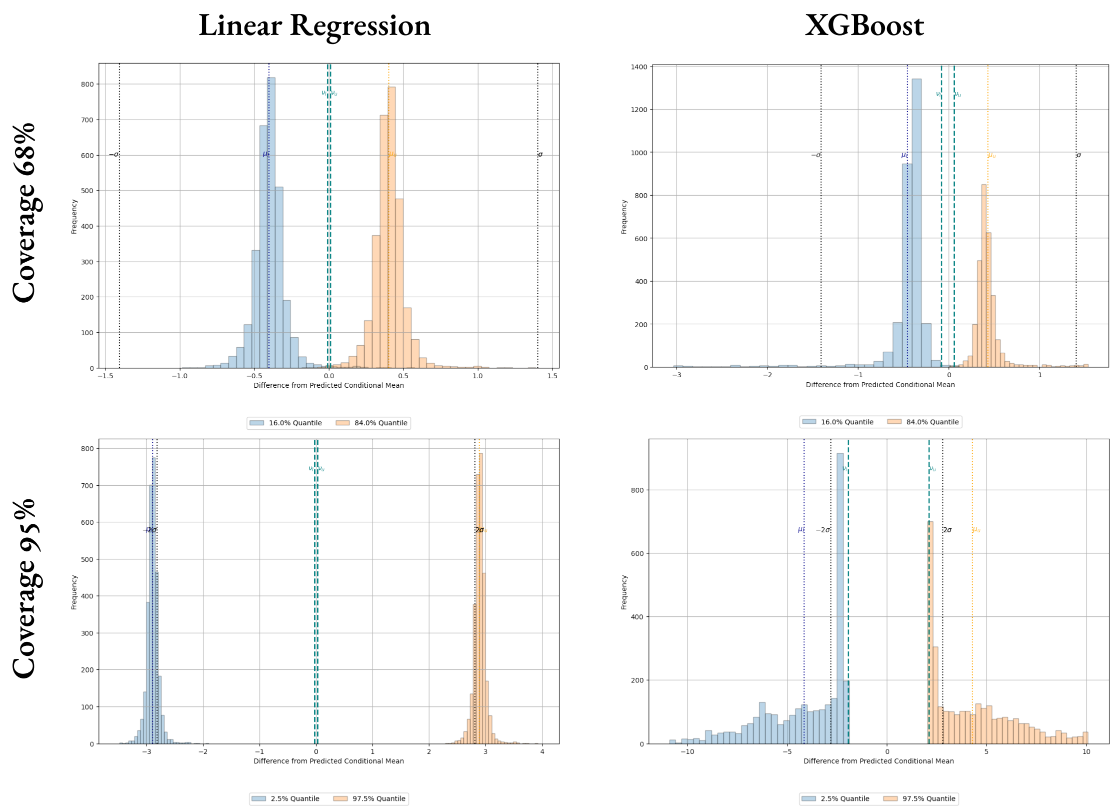
Air Pollution

Figure A.6: Conformalized Prediction Uncertainty in Different Settings for NOx Emissions



This figure displays conformalized prediction uncertainty for NOx Emissions. The settings are for the learners linear regression and XGBoost and the coverage of 68% and 95%. For better readability, the figure shows 2% of total observations which are randomly selected.

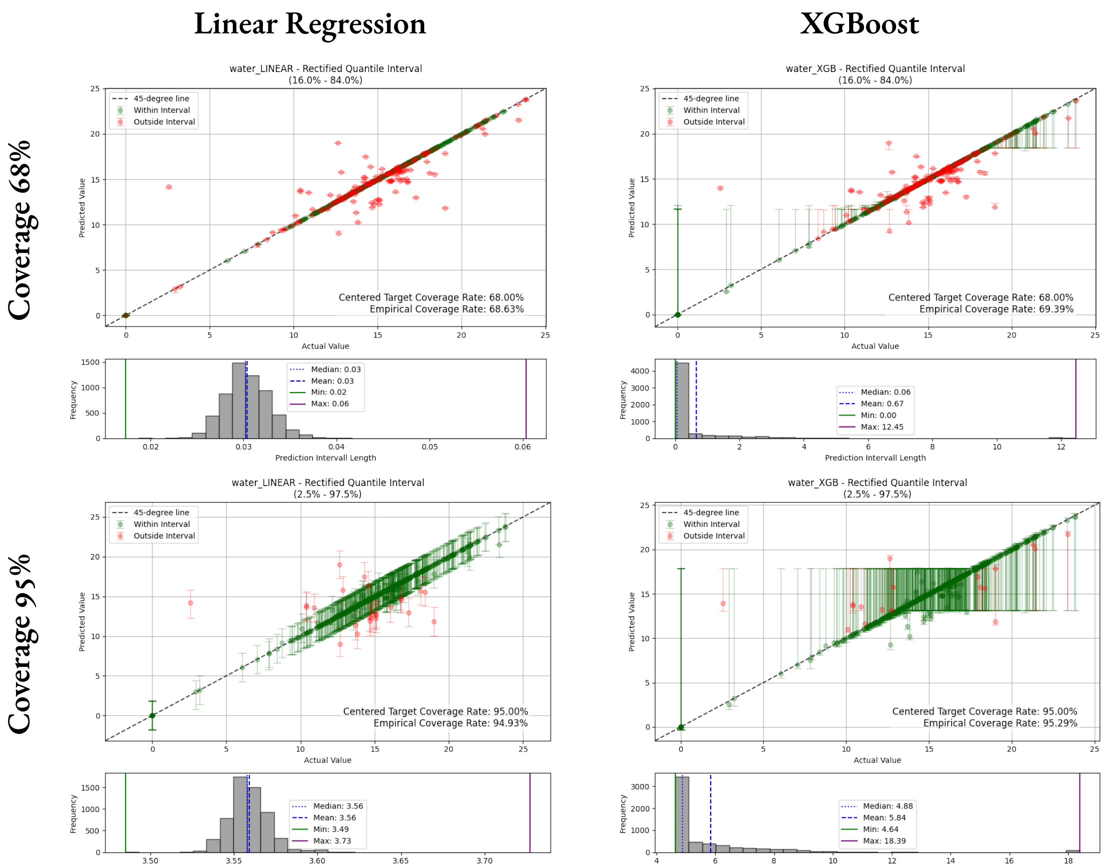
Figure A.7: Deviation from Conditional Mean for NOx Emissions



This figure displays the deviation for the conditional mean for NOx Emissions in different settings. The settings are for uncertainty estimates based on linear regression and XGBoost and for targeted coverage rates of 68% and 95%. In all settings, the conditional mean is predicted by the best-performing XGB meta model. The black dotted lines represent the prediction intervals using one and two standard deviations (σ), respectively. The green dashed lines represent the mean lower (upper) quantile prediction from standard quantile regression, ν_l (ν_u). Finally, the blue and orange bars show the distribution of quantile predictions for the lower and upper quantile from conformalized quantile regression. The mean of lower (upper) predictions is represented by the blue and orange dotted lines, μ_l (μ_u).

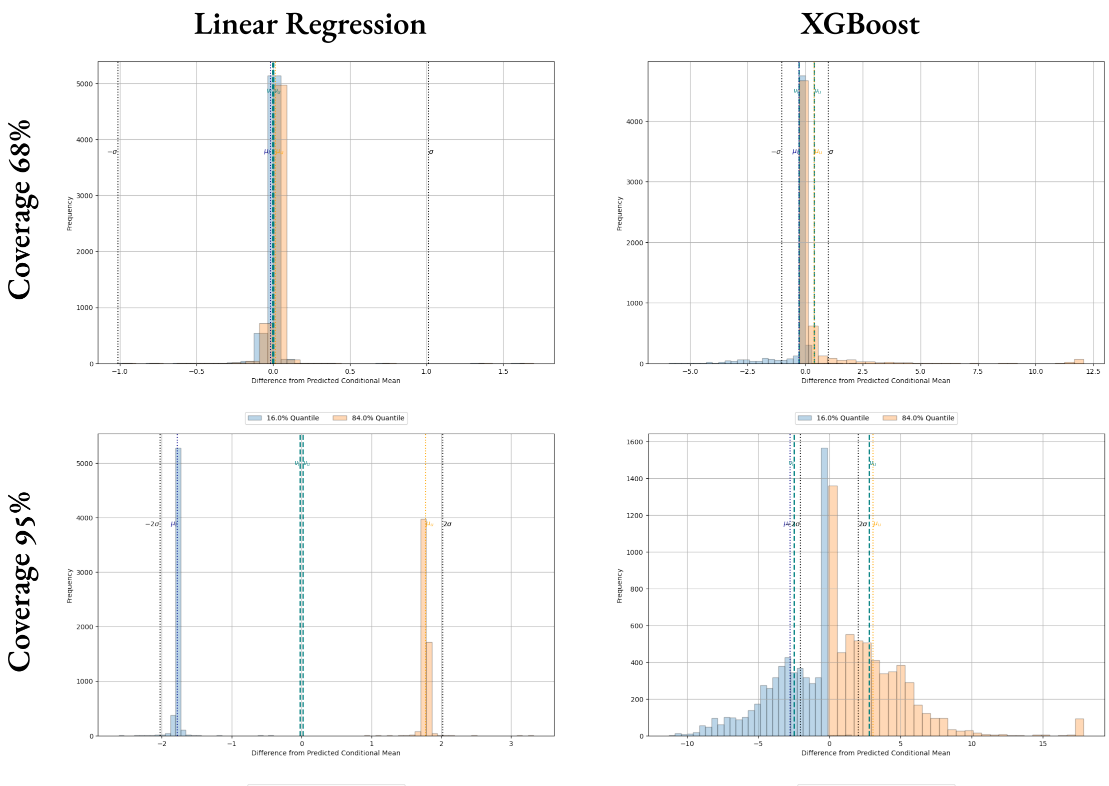
Water Discharge

Figure A.8: Conformalized Prediction Uncertainty in Different Settings for Water Discharge



This figure displays conformalized prediction uncertainty for Water Discharge. The settings are for the learners linear regression and XGBoost and the coverage of 68% and 95%. For better readability, the figure shows 2% of total observations which are randomly selected.

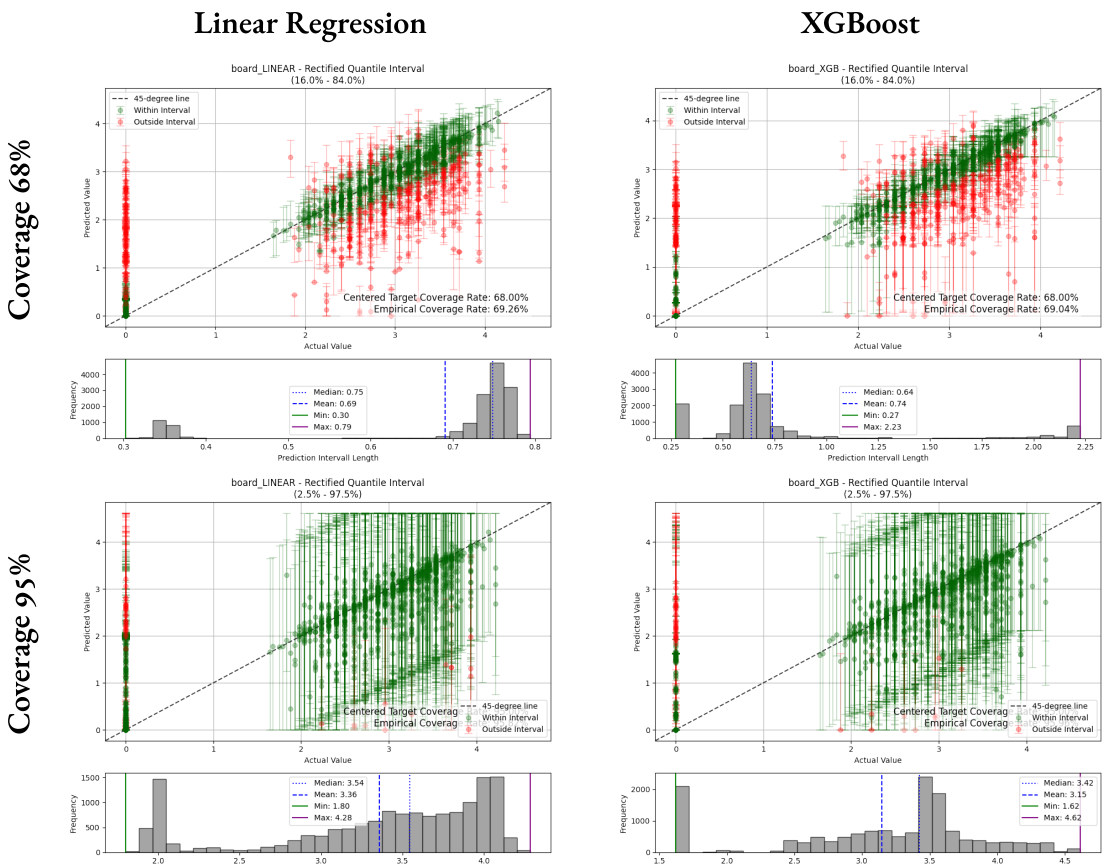
Figure A.9: Deviation from Conditional Mean for Water Discharge



This figure displays the deviation for the conditional mean for Water Discharge in different settings. The settings are for uncertainty estimates based on linear regression and XGBoost and for targeted coverage rates of 68% and 95%. In all settings, the conditional mean is predicted by the best-performing XGB meta model. The black dotted lines represent the prediction intervals using one and two standard deviations (σ), respectively. The green dashed lines represent the mean lower (upper) quantile prediction from standard quantile regression, ν_l (ν_u). Finally, the blue and orange bars show the distribution of quantile predictions for the lower and upper quantile from conformalized quantile regression. The mean of lower (upper) predictions is represented by the blue and orange dotted lines, μ_l (μ_u).

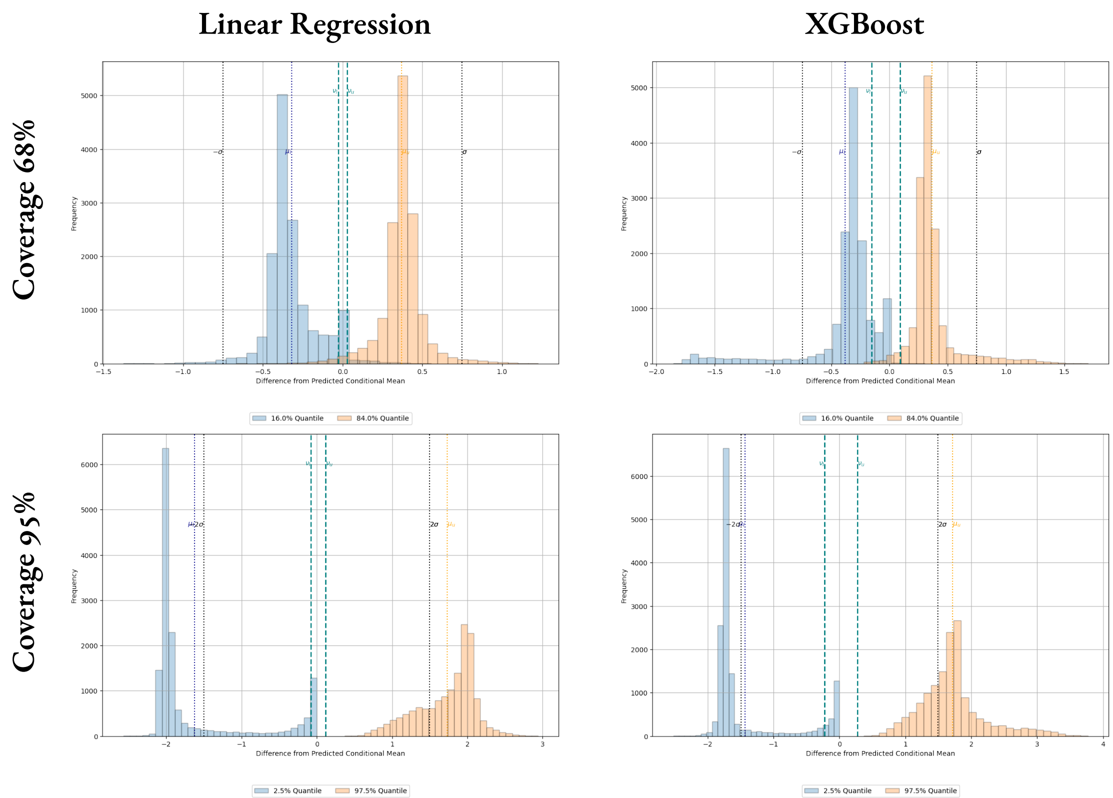
Female Board Share

Figure A.10: Conformalized Prediction Uncertainty in Different Settings for Female Board Share



This figure displays conformalized prediction uncertainty for Female Board Share. The settings are for the learners linear regression and XGBoost and the coverage of 68% and 95%. For better readability, the figure shows 2% of total observations which are randomly selected.

Figure A.11: Deviation from Conditional Mean for Female Board Share



This figure displays the deviation for the conditional mean for Female Board Share in different settings. The settings are for uncertainty estimates based on linear regression and XGBoost and for targeted coverage rates of 68% and 95%. In all settings, the conditional mean is predicted by the best-performing XGB meta model. The black dotted lines represent the prediction intervals using one and two standard deviations (σ), respectively. The green dashed lines represent the mean lower (upper) quantile prediction from standard quantile regression, ν_l (ν_u). Finally, the blue and orange bars show the distribution of quantile predictions for the lower and upper quantile from conformalized quantile regression. The mean of lower (upper) predictions is represented by the blue and orange dotted lines, μ_l (μ_u).

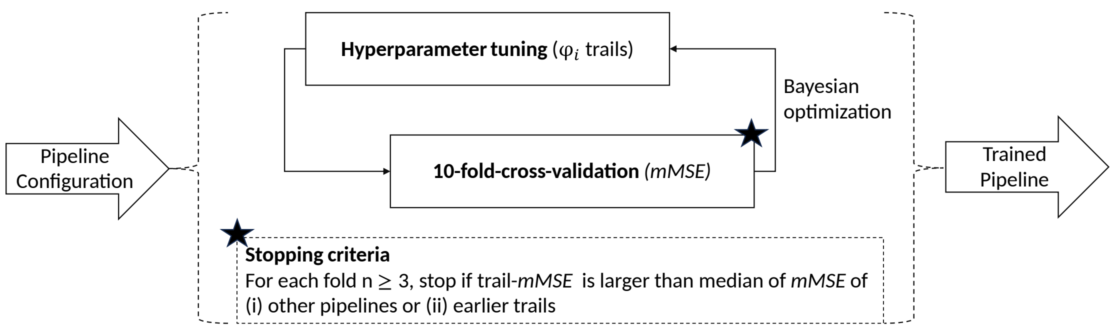
Early Stopping

In our efforts to improve computational efficiency during model training, we implemented an early stopping mechanism. This mechanism is designed to reduce unnecessary computations during the hyperparameter tuning process, specifically within the ten-fold cross-validation phase of each trial.Figure A.12 visually represents the early stopping process.

The early stopping approach is structured as follows:

1. Initialization of Trials: During the hyperparameter tuning process, each trial undergoes a ten-fold cross-validation to evaluate the model's performance under different parameter settings.
2. Minimum Trial Requirement: To ensure that the model has sufficient opportunity to learn and stabilize, the early stopping mechanism is only considered after the first three folds of the cross-validation process have been completed.
3. Performance Comparison: After the third fold, the mechanism compares the mean squared error (MSE) obtained in the current fold with the median MSEs of previously evaluated models or earlier trials of the same model configuration.
4. Activation of Early Stopping: If the MSE of the current trial exceeds the average MSEs of the previous trials, the early stopping mechanism is triggered. When activated, this mechanism halts the remaining cross-validation folds for the current trial and proceeds directly to the next model configuration. This avoids further computation on a model configuration that is unlikely to outperform existing configurations.

Figure A.12: Early Stopping Approach



This figure displays the early stopping mechanism that is applied throughout the code.

Computational Efficiency vs. Comprehensiveness Trade-off in Model Development

In this section, we elaborate on the trade-offs we encountered between computational efficiency and the comprehensiveness of our approach in model development.

Our approach to model configuration deliberately incorporates a trade-off between computational demands and the comprehensiveness of the analysis. By treating preprocessing steps as additional hyperparameters and employing a wide range of models and configurations, we place a significant burden on computational resources. This strategy, while resource-intensive, is aimed at enhancing the replicability of our results and ensuring that our methods are broadly applicable, independent of specific institutional contexts in which the data are generated.

The versatility offered by this approach can be valuable to the research community, as it allows for more generalized and adaptable modeling techniques.

However, this versatility comes at the cost of computational efficiency. Despite implementing early stopping mechanisms to reduce unnecessary calculations, the overall process remains resource-demanding. In the following, we provide an overview of the computational resources required for our approach:

- CPU: **2 x AMD EPYC Milan 7713 - 64-Core**
- GPU: **NVIDIA RTX Ada A6000**
- Time Consumption: **19.01 days** *(assuming serial execution)*
- Electricity Consumption: **87.94 kWh** *(estimation)*
- Early Stopping Effect: **active in 37.86% of 59,250 trials**

The above specifications highlight the scale of computational resources needed to execute our models effectively. The use of powerful CPUs and GPUs is essential to manage the large datasets and numerous trials involved in our comprehensive approach to discovering best performing models. Even with these resources, the time required to complete the model runs is considerable, emphasizing the trade-off between the depth of analysis and computational efficiency.

The introduction of early stopping mechanisms plays a crucial role in mitigating some of the computational burdens. As detailed in Annex B, early stopping is activated in approximately 30.02% of the 59,250 trials, significantly reducing the time and energy required to train the models. This not only improves efficiency but also ensures that computational resources are allocated more effectively towards promising model configurations.

Insights and Recommendations for Future Researchers

In this annex, we provide guidance for future researchers who aim to replicate or build on our findings with reduced computational effort. By analyzing the performance of various model configurations and the factors that contribute to the best results, we draw several conclusions that can inform more efficient model development in similar studies. In addition, we provide guidance on the use of our data.

Applying our method

Table A.1 summarizes the configurations of the best-performing models for each target variable based on the mean squared error (MSE) in the test data set. These best performing models reflect the combination of preprocessing steps and learner choices that yielded the most accurate predictions.

Table A.1: Summary of Winning Model Configurations

Target Variable	Missing Indicator		Imputation			Outlier Removal		Scaler		Transformation		Feature Selection	
	No	Yes	Mean	Median	Iterative	None	Winzorize	Standard	Robust	None	Quantile	None	Lasso
Scope 1 Emissions (tCO2e)	6	6	4	6	2	11	1	6	6	5	7	12	0
Scope 2 Emissions (tCO2e)	2	10	5	7	0	5	7	4	8	5	7	12	0
Air Pollution (tNOx)	4	7	5	6	0	8	3	1	10	8	3	11	0
Water Discharge (cbm)	3	9	8	2	2	10	2	4	8	7	5	12	0
Female Board Share (pct)	4	8	5	6	1	4	8	3	9	10	2	12	0

This table summarizes the best performing model setups along the dimensions missing indicator, imputation, outlier removal, scaler, transformation and feature selection for the five target variables: Scope 1 emissions, Scope 2 emissions, air pollution, water discharge, and female board share.

The analysis of the best performing models reveals several insights that can guide future research.

- Meta Learners and Complex Models: As stated in the main body of the paper, more complex models, such as meta learners, tend to outperform simpler linear models. Researchers should consider including these advanced techniques in their pipelines to achieve better performance.

- Pipeline Options: The study shows that there is no universal best configuration across all preprocessing steps. This suggests that researchers working with different data sets or in different use cases may need to experiment with the full range of pipeline options, rather than relying on a predetermined set of configurations. For example, there is no clear trend that favors a particular missing indicator or scaling method in all target variables.

- Imputation and Transformation Methods: While there are slight trends in the performance of certain imputation and transformation methods, these trends are not strong enough to recommend a specific approach universally. Researchers should evaluate the effectiveness of these methods on a case-by-case basis, as different variables may respond differently to the same preprocessing techniques.

- Feature Selection: The analysis indicates that in our case, model configurations without feature selection generally performed better. This finding suggests that including more features, rather than reducing them, can enhance model performance. Future researchers should be cautious about overly aggressive feature selection, particularly when working with rich datasets, as it might lead to the loss of valuable information.

In addition to these findings on pipeline buliding, researchers might want to implement early stopping mechanisms, as discussed in Annex A, to reduce computational burden while ensuring that only the most promising configurations are fully explored.

Using our data When using our data, researchers should consider model variation and prediction uncertainty.

Understand and adapt to model variations:

- Temporal Dynamics: Recognize that the quality of the model predictions may vary over time. For example, earlier periods in datasets may yield better predictions than more recent ones, potentially due to differences in data completeness or quality. Researchers should explore temporal segmentation in their analyses and adjust the models accordingly.

- Regional Variations: Consider the regional context of the data. Prediction accuracy may differ significantly across geographic regions, with some regions (e.g., Europe) performing better. Adapt the models to account for regional data availability and variability.

- Sectoral Differences: Different sustainability indicators (e.g., water discharge, air pollution) exhibit sector-specific prediction performance. Researchers should analyze sectoral characteristics and adapt models to suit the particularities of each sector.

Researchers may achieve this either by retraining the model (i.e. adapting the loss function to their needs) or by making sure that the model specifications in their research capture those variations.

Use of prediction uncertainty in research:

- Reliability: Prediction uncertainty, specifically through conformal prediction intervals, enhances the reliability of sustainability data by quantifying the confidence level of each prediction. For example, a 95% conditional coverage interval indicates that for a given company, there is a 95% probability that its actual datum lies within the estimated range. This provides researchers with a transparent measure of the quality and trustworthiness of the imputed data, especially in contexts where decision-making depends on accurate sustainability metrics.

- Robustness: By explicitly incorporating uncertainty measures, researchers can assess the robustness of their models in various scenarios. For example, when conducting sensitivity analyses or stress tests, prediction intervals provide a range of plausible outcomes rather than relying on single-point estimates, which might be overly optimistic or pessimistic. This allows researchers to account for data imperfections and ensure that their findings hold under different levels of risk tolerance (e.g., using narrower 68% intervals for moderate scenarios and wider 95% intervals for extreme cases).

Property of the Quantile Regression Loss Function

We minimize the expected loss function with respect to $\hat{y}_\alpha$ for the quantile level α.

$$\mathbb{E}\left[L_\alpha(y, \hat{y}_\alpha)\right] = \alpha \int_{\hat{y}_\alpha}^{\infty} (y - \hat{y}_\alpha) f(y)\, dy + (1-\alpha) \int_{-\infty}^{\hat{y}_\alpha} (\hat{y}_\alpha - y) f(y)\, dy$$

Taking the derivative with respect to $\hat{y}_\alpha$:

$$\frac{\partial \mathbb{E}(.)}{\partial \hat{y}_\alpha} = \alpha \int_{\hat{y}_\alpha}^{\infty} \frac{\partial}{\partial \hat{y}_\alpha} (y - \hat{y}_\alpha) f(y)\, dy + (1-\alpha) \int_{-\infty}^{\hat{y}_\alpha} \frac{\partial}{\partial \hat{y}_\alpha} (\hat{y}_\alpha - y) f(y)\, dy$$

Applying the Leibniz rule for differentiation under the integral sign:

$$\begin{aligned} &= \alpha \left[\int_{\hat{y}_\alpha}^{\infty} \frac{\partial}{\partial \hat{y}_\alpha} (y - \hat{y}_\alpha)\, dy + (\hat{y}_\alpha - y) f(y) \Big|_{y=\hat{y}_\alpha} \cdot \frac{d\hat{y}_\alpha}{d\hat{y}_\alpha} \right] \\ &\quad + (1-\alpha) \left[\int_{-\infty}^{\hat{y}_\alpha} \frac{\partial}{\partial \hat{y}_\alpha} (\hat{y}_\alpha - y)\, dy + (\hat{y}_\alpha - y) f(y) \Big|_{y=\hat{y}_\alpha} \cdot \frac{d\hat{y}_\alpha}{d\hat{y}_\alpha} \right] \end{aligned}$$

Simplifying further, we obtain:

$$= -\alpha \int_{\hat{y}_\alpha}^{\infty} f(y)\, dy + (1-\alpha) \int_{-\infty}^{\hat{y}_\alpha} f(y)\, dy$$

Let $F(\hat{y}_\alpha)$ denote the cumulative distribution function (CDF) of $f(y)$:

$$\begin{aligned} \Rightarrow \frac{\partial \mathbb{E}(.)}{\partial \hat{y}_\alpha} &= -\alpha(1 - F(\hat{y}_\alpha)) + (1-\alpha) F(\hat{y}_\alpha) \\ &= -\alpha + \alpha F(\hat{y}_\alpha) + F(\hat{y}_\alpha) - \alpha F(\hat{y}_\alpha) \\ &= F(\hat{y}_\alpha) - \alpha \end{aligned}$$

Setting this derivative to zero to find the minimum:

$$\frac{\partial \mathbb{E}(.)}{\partial \hat{y}_\alpha} = 0 \Rightarrow F(\hat{y}_\alpha) - \alpha = 0$$

Thus, at the optimal point:

$$F(\hat{y}_\alpha) = \alpha$$

Summary Statistics Predictors

Table A.2: Summary statistics of predictor variables

The table presents summary statistics for the predictor variables. These statistics include the count of observations, the mean, standard deviation, minimum, maximum, and percentiles (25%, 50%, 75%) for each variable. The units for each variable are indicated in the ”Unit” column, with common abbreviations such as B for billions, M for millions, and K for thousands.

	count	mean	std	min	25%	50%	75%	max	Unit
Accounts Payable - Long Term	18316	38.90	467.62	-7.88	0.01	0.11	0.93	18479.00	B
Avg. Payables Payment Days	80527	303.08	23949.38	-32528.25	35.47	56.43	93.25	5769517.74	Unit
Brands, Patents, Trademarks, Marketing (Gross)	27924	8.91	112.41	-0.02	0.01	0.08	0.49	5118.16	B
Capital Expenditures (Total)	101362	79.14	1009.41	-4.17	0.05	0.34	2.94	75161.53	B
Cash & Cash Equivalents	94014	155.92	1722.84	-7.43	0.10	0.66	6.18	110763.21	B
Cash & Cash Equivalents (Total)	103303	223.49	2980.01	-7.43	0.11	0.79	8.87	202104.93	B
Cash & Short-Term Investments	98451	222.83	2579.73	-0.01	0.15	0.95	9.98	124652.84	B
Computer Software (Net)	32490	11.22	113.29	-527.61	0.01	0.07	0.59	5744.00	B
Long Term Debt Issued (Cash Flow)	59479	193.77	2415.98	-111.28	0.08	0.85	8.18	145183.14	B
Long & Short Term Debt Issued (Cash Flow)	19552	1839.72	48455.29	-24.76	0.10	0.95	5.65	1787877.77	B
Short Term Debt Issued (Cash Flow)	11008	471.55	4511.91	-12.11	0.02	0.51	17.66	192778.56	B
Long Term Debt (Total)	96939	342.28	3355.23	-1302.34	0.23	1.95	15.46	183775.07	B

Continued on next page

	count	mean	std	min	25%	50%	75%	max	Unit
Total Debt	99726	556.41	4952.84	-0.12	0.35	2.78	24.86	205362.30	B
Depreciation & Amortization	13845	30.52	442.09	-6.14	0.03	0.18	1.05	14863.00	B
EBIT	104120	108.47	1348.85	-30329.63	0.08	0.66	5.65	60569.45	B
Part-Time Employees	3661	7.23	23.04	0.00	0.03	0.35	3.59	444.55	K
Equity Earnings/Loss (Pre-Tax, Nonrecurring)	41519	12.19	157.91	-2483.34	-0.00	0.01	0.24	7087.00	B
Short-Term Financial Assets	18291	203.63	2887.98	-738.25	0.01	0.17	1.93	92441.70	B
Net Financing Income/Expense	92886	-6.24	128.64	-10670.09	-0.24	-0.02	0.00	4740.00	B
Goodwill (Gross)	22899	46.16	313.86	-0.40	0.14	0.75	4.26	6958.30	B
Impairment - Financial Investments	14263	6.74	82.03	-459.28	0.00	0.01	0.15	2242.53	B
Impairment - Fixed Assets	50314	4.92	83.93	-1709.81	0.00	0.03	0.39	11072.70	B
Income Taxes	101788	28.05	340.50	-1855.99	0.01	0.12	1.23	16990.40	B
Intangible Assets (Accum. Amort. & Impair.)	34239	49.82	424.81	-52.59	0.04	0.26	1.55	18254.57	B
Intangible Assets (Gross)	34632	122.90	907.03	-60.63	0.17	1.08	6.80	37612.29	B
Intangible Assets (Net Cash Flow)	4464	18.25	193.18	-136.28	0.00	0.01	0.11	5615.31	B
Long-Term Investments	66338	105.56	1678.63	-1246.24	0.03	0.52	8.03	126930.42	B
Total Investments	85989	618.23	6893.10	-230.94	0.09	1.27	25.76	442925.68	B
Lending & Long-Term Deposits	7493	714.66	6413.50	-42.61	0.73	10.50	53.20	242431.95	B
Short-Term Loans & Receivables (Net)	40189	267.76	2113.23	-5.18	0.33	1.68	11.65	97072.45	B

Continued on next page

	count	mean	std	min	25%	50%	75%	max	Unit
Total Loans & Receivables	102232	1126.53	21694.84	-38.63	0.20	1.44	18.53	2531993.14	B
Net Cash Flow - Financing	103774	11.49	961.89	-27753.00	-0.97	-0.05	0.16	121530.63	B
Net Cash Flow - Investing	103526	-115.48	1569.11	-132477.05	-4.01	-0.40	-0.04	25880.94	B
Net Cash Flow - Operating	103874	128.39	1942.81	-80142.33	0.07	0.60	5.42	125791.99	B
Net Financial Income/Expense (Other)	17440	-1.20	29.88	-1517.46	-0.06	-0.01	-0.00	299.66	B
Net Income (After Tax)	51281	101.89	1246.50	-40408.49	0.11	0.86	6.74	44344.86	B
Nonrecurring Income/Expense	86092	-1.47	174.77	-10939.90	-0.24	-0.01	0.00	29391.89	B
Total Operating Expenses	99953	760.55	6541.08	-1143.05	0.68	4.23	31.37	227970.94	B
Total Other Assets	100956	122.21	1323.71	-41897.01	0.04	0.42	5.69	69247.18	B
Total Other Current Assets	30798	29.04	260.52	-14527.45	0.03	0.30	4.92	13300.06	B
Total Other Current Liabilities	89942	102.06	1122.25	-12625.25	0.04	0.40	4.97	150865.89	B
Total Other Noncurrent Liabilities	42108	115.75	2088.40	-1290.92	0.09	0.68	7.05	145414.99	B
Payables & Accrued Expenses	100432	131.24	1145.48	-0.69	0.14	0.94	8.45	77457.92	B
Plant, Machinery & Equipment (Gross)	73124	525.67	6823.00	-105.61	0.15	1.20	11.25	305445.00	B
PPE (Accum. Depreciation & Impairment)	88596	399.03	4681.38	-10168.69	0.16	1.27	11.25	227543.45	B
PPE (Gross)	92792	855.02	8895.91	-4920.35	0.46	3.59	33.30	377471.99	B
PPE (Net)	100907	437.36	4442.67	-991.57	0.20	1.84	17.45	207052.67	B
Other PPE (Gross)	65438	120.92	1761.60	-3128.77	0.03	0.31	3.70	169436.18	B

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	count	mean	std	min	25%	50%	75%	max	Unit
Total Provisions	89472	79.50	778.60	-166.19	0.06	0.49	4.88	44491.12	B
Long-Term Receivables & Loans	40536	100.80	1385.81	-31.92	0.01	0.14	1.48	46311.56	B
R&D Expense	32492	40.82	630.29	-136.86	0.04	0.20	1.99	22401.73	B
R&D Costs (Gross)	10642	75.39	592.23	-0.00	0.02	0.09	0.73	10374.45	B
Short-Term Debt & Notes Payable	54238	267.85	2309.18	-168.57	0.06	1.15	20.76	104779.30	B
Total Short-Term Investments	52532	131.21	1936.84	-3.40	0.03	0.33	3.48	95270.26	B
Total Assets	103976	2732.62	30953.65	0.00	2.05	12.61	137.79	1808429.76	B
Total Book Capital	103954	1154.24	10028.24	-66.81	1.29	7.70	73.41	442390.86	B
Total Current Assets	89457	505.03	4941.26	-57.13	0.50	3.03	26.51	283116.65	B
Total Current Liabilities	44789	516.29	3918.81	0.00	0.80	4.49	40.21	298411.51	B
Total Fixed Assets (Net)	82720	737.86	6722.46	-17420.67	0.59	3.86	31.22	283593.15	B
Total Liabilities	103952	2045.66	26076.03	-20.44	0.99	6.76	75.56	1700262.11	B
Total Shareholders' Equity	99822	689.10	7064.58	-11055.62	0.75	4.17	34.21	304899.93	B
Working Capital Change (Cash Flow)	98107	-26.13	623.51	-31484.37	-0.38	-0.01	0.08	35264.41	B
Avg. Receivables Collection Period (Days)	43635	95.47	919.42	-17463.43	41.87	63.48	90.74	152776.77	Unit
Full-Time Employees	79275	323.43	52542.63	0.00	1.68	6.93	23.05	10785002.89	K
R&D as % of Revenues	43026	287.33	8230.36	-34.17	0.68	2.58	7.06	598611.42	Unit
Turnover	62282	2.12	108.80	-17573.65	0.00	0.02	0.23	19941.57	B

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	count	mean	std	min	25%	50%	75%	max	Unit
Date of Incorporation	105929	1.98	0.03	1.81	1.97	1.99	2.00	2.02	K
Year	109085	2.01	0.01	2.00	2.01	2.02	2.02	2.02	K
Parent Shareholders' Equity (Total)	4123	482.85	1871.17	-63.52	6.26	55.35	326.36	37441.42	B
Business Financing Revenue (Other)	4278	45.33	542.50	-8261.00	0.00	0.04	1.33	11075.05	B
Inventories (Finished Goods)	22867	48.84	497.25	-4.83	0.03	0.22	1.57	17537.84	B
Long-Term Loans	9204	62.72	938.79	-0.00	0.01	0.19	1.91	28704.25	B
Short-Term Loans	10735	33.42	370.27	-0.00	0.01	0.22	1.96	21022.04	B
Total Noncurrent Liabilities	41426	202.81	2583.53	-99.82	0.10	0.85	6.30	131277.39	B

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B

Appendix to Chapter 2

Publication Status

The paper is ready for submission.

Co-Authors

The following authors contributed to Chapter 2 (share of contributions in parentheses):

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- Youri Matheis, Frankfurt School of Finance & Management (16.6%)

Paper Abstract

Using global institutional ownership data, we examine how Responsible Investors contribute to the decarbonization of the real economy. Despite holding approximately one-third of global equities, Responsible Investors allocate less capital to high-emission firms and more to already green companies, thereby reducing their leverage for engagement over firms with significant potential for emission reductions. We find no evidence that companies with higher ownership by Responsible Investors decarbonize faster. Instead, companies with greater Responsible Investor ownership exhibit significant improvements in ESG ratings, suggesting a focus on perceived sustainability rather than actual emission reductions. Our findings indicate that Responsible Investors prioritize lower-emission portfolios over facilitating real-economy decarbonization, casting doubt on their role in aligning global financial flows with the Paris Agreement's targets. The study highlights the need for clearer regulatory guidance on the role of finance in achieving global climate objectives.

Supplementary Tables

Shunning without ESG rating

Table B.1: High-Emitter Shunning by Responsible Investors w/o ESG Ratings

	Responsible Investor Ratio				Institutional Investor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1 Emissions)	-0.003***				-0.005***			
	(0.001)				(0.001)			
log(Scope 1 Intensity)		-0.030***				-0.031***		
		(0.004)				(0.004)		
Climate Policy Relevant Sector			-0.005***				-0.022***	
			(0.002)				(0.001)	
Top 10% Scope 1 Emissions				-0.025***				-0.028***
				(0.004)				(0.005)
Book to Market Ratio	0.004	0.004	0.004***	0.004***	-0.033***	-0.032***	-0.002**	-0.002**
	(0.003)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.001)
Dividend Yield	0.001*	0.001**	0.002***	0.002***	-0.006***	-0.006***	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
European Union	0.040***	0.039***	0.054***	0.055***	0.124***	0.123***	0.113***	0.115***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Historic Volatility	-0.072***	-0.070***	-0.022***	-0.023***	-0.077***	-0.075***	-0.122***	-0.124***
	(0.013)	(0.013)	(0.005)	(0.005)	(0.014)	(0.014)	(0.003)	(0.003)
log(ROA)	0.005***	0.005***	0.004***	0.004***	0.006***	0.006***	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Revenue)	0.004**	0.001	0.022***	0.022***	0.016***	0.011***	0.020***	0.020***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Total Debt to Equity)	-0.002***	-0.002***	-0.000	-0.000*	-0.003***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
North America	0.021***	0.021***	0.039***	0.040***	0.402***	0.402***	0.373***	0.376***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Stock Return	0.000*	0.000*	0.000***	0.000***	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Cash Holdings)	0.008***	0.007***	0.008***	0.008***	-0.006***	-0.006***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
log(Market Value)	-0.003*	-0.003	-0.002*	-0.001*	0.003	0.003	0.034***	0.034***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.365***	0.385***	-0.005	-0.011	0.223***	0.248***	-0.208***	-0.226***
	(0.015)	(0.015)	(0.007)	(0.007)	(0.016)	(0.017)	(0.005)	(0.005)
Observations	27006	27006	172284	172284	27006	27006	172284	172284
Adjusted R^2	0.228	0.230	0.171	0.171	0.372	0.373	0.452	0.451
F Statistic	9425.3***	9416.0***	17232.7***	17260.7***	3776.9***	3758.7***	7795.8***	7787.7***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial and climate factors on the portfolio allocation by Responsible Investors and institutional investors. The table highlights that results are robust after removing ESG ratings. The results get stronger for institutional investors. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI), while columns 5 through 8 pertain to general institutional investors. The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *$p<0.1$; **$p<0.05$; ***$p<0.01$.

Shunning with high institutional ownership

Table B.2: High-Emitter Shunning with Institutional Investor Shares $> 10\%$

	Responsible Investor Ratio				Institutional Investor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1 Emissions)	-0.003***				-0.001			
	(0.001)				(0.001)			
log(Scope 1 Intensity)		-0.031***				-0.012**		
		(0.005)				(0.006)		
Climate Policy Relevant Sector			-0.007***				-0.020***	
			(0.002)				(0.003)	
Top 10% Scope 1 Emissions				-0.019***				0.004
				(0.005)				(0.006)
ESG Rating	0.023***	0.022***	0.023***	0.023***	0.021***	0.020***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Book to Market Ratio	-0.015***	-0.014***	-0.016***	-0.015***	-0.039***	-0.039***	-0.028***	-0.029***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Dividend Yield	0.000	0.000	0.000	0.000	-0.008***	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
European Union	0.021***	0.021***	0.018***	0.019***	0.091***	0.091***	0.096***	0.096***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Historic Volatility	-0.099***	-0.100***	-0.105***	-0.106***	-0.089***	-0.090***	-0.050***	-0.055***
	(0.016)	(0.016)	(0.010)	(0.010)	(0.018)	(0.018)	(0.011)	(0.011)
log(ROA)	0.004**	0.004**	0.003**	0.003**	0.008***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log(Revenue)	0.009***	0.006***	0.004***	0.005***	0.008***	0.007***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log(Total Debt to Equity)	-0.003***	-0.003***	-0.001***	-0.001***	-0.002**	-0.002***	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
North America	0.021***	0.021***	0.024***	0.025***	0.368***	0.368***	0.374***	0.376***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Stock Return	0.000**	0.000**	0.000***	0.000***	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Cash Holdings)	0.006***	0.006***	0.010***	0.009***	-0.003*	-0.003*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Market Value)	-0.016***	-0.015***	-0.009***	-0.008***	-0.016***	-0.015***	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.436***	0.457***	0.364***	0.355***	0.461***	0.470***	0.319***	0.315***
	(0.019)	(0.018)	(0.013)	(0.013)	(0.021)	(0.021)	(0.014)	(0.014)
Observations	16701	16701	33475	33475	16701	16701	33475	33475
Adjusted R^2	0.288	0.290	0.278	0.278	0.374	0.374	0.414	0.413
F Statistic	7064.2***	7081.0***	11562.6***	11640.4***	3484.6***	3477.1***	6081.4***	6071.7***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors and institutional investors. The table highlights that results are robust after only keeping all observations with Institutional Investor Shares $>$ 10%. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI). The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p$<$0.1; **p$<$0.05; ***p$<$0.01.

Shunning without Big Three

Table B.3: High-Emitter Shunning w/o Big Three

	Responsible Investor Ratio				Institutional Investor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1 Emissions)	-0.002***				-0.001			
	(0.001)				(0.001)			
log(Scope 1 Intensity)		-0.024***				-0.012**		
		(0.004)				(0.006)		
Climate Policy Relevant Sector			-0.009***				-0.020***	
			(0.002)				(0.003)	
Top 10% Scope 1 Emissions				-0.019***				0.004
				(0.004)				(0.006)
ESG Rating	0.019***	0.019***	0.020***	0.020***	0.021***	0.020***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Book to Market Ratio	-0.015***	-0.014***	-0.013***	-0.013***	-0.039***	-0.039***	-0.028***	-0.029***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Dividend Yield	-0.004***	-0.004***	-0.003***	-0.003***	-0.008***	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
European Union	0.027***	0.026***	0.022***	0.022***	0.091***	0.091***	0.096***	0.096***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Historic Volatility	-0.101***	-0.102***	-0.109***	-0.110***	-0.089***	-0.090***	-0.050***	-0.055***
	(0.014)	(0.014)	(0.009)	(0.009)	(0.018)	(0.018)	(0.011)	(0.011)
log(ROA)	0.004**	0.004**	0.004***	0.004***	0.008***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log(Revenue)	0.005***	0.002	-0.001	-0.001	0.008***	0.007***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log(Total Debt)	-0.003***	-0.003***	-0.000	-0.000	-0.002**	-0.002***	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
North America	-0.047***	-0.047***	-0.066***	-0.065***	0.368***	0.368***	0.374***	0.376***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Stock Return	0.000	0.000	0.000**	0.000**	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Cash Holdings)	0.007***	0.007***	0.010***	0.009***	-0.003*	-0.003*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Market Capitalization)	-0.031***	-0.031***	-0.020***	-0.020***	-0.016***	-0.015***	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.497***	0.514***	0.427***	0.418***	0.461***	0.470***	0.319***	0.315***
	(0.017)	(0.017)	(0.012)	(0.012)	(0.021)	(0.021)	(0.014)	(0.014)
Observations	16701	16701	33475	33475	16701	16701	33475	33475
Adjusted R^2	0.244	0.245	0.234	0.234	0.374	0.374	0.414	0.413
F Statistic	3824.2***	3823.7***	6218.4***	6242.6***	3484.6***	3477.1***	6081.4***	6071.7***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors and institutional investors. The table highlights that results are robust after removing the Big Three (BlackRock, State Street Global Advisors, Vanguard) from the Responsible Investor Ratio. Columns 1 through 4 show the results for Responsible Investors who are signatories of the United Nations Principles for Responsible Investment (UN PRI). The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

Table B.4: ESG Rating (Δ1 - Δ5)

	Δ 1 Year	Δ 2 Year	Δ 3 Year	Δ 4 Year	Δ 5 Year
	(1)	(2)	(3)	(4)	(5)
Responsible Investor Share	0.1735***	0.3172***	0.4687***	0.6290***	0.7530***
	(0.0327)	(0.0486)	(0.0646)	(0.0832)	(0.1043)
Institutional Investor Share	-0.0026	0.0117	0.0212	0.0212	0.0150
	(0.0207)	(0.0308)	(0.0407)	(0.0517)	(0.0636)
Book to Market Ratio	-0.0032	-0.0043	-0.0064	-0.0118	-0.0492**
	(0.0024)	(0.0032)	(0.0046)	(0.0108)	(0.0210)
European Union	0.0206***	0.0274***	0.0538***	0.0672***	0.0886***
	(0.0068)	(0.0099)	(0.0128)	(0.0162)	(0.0197)
log(ROA)	0.0122***	0.0175***	0.0254***	0.0299***	0.0263*
	(0.0042)	(0.0066)	(0.0084)	(0.0109)	(0.0135)
log(Revenue)	-0.0019	-0.0138**	-0.0234***	-0.0275***	-0.0320***
	(0.0036)	(0.0054)	(0.0071)	(0.0092)	(0.0116)
log(Total Debt to Equity)	0.0020**	0.0052***	0.0069***	0.0090***	0.0105***
	(0.0009)	(0.0015)	(0.0019)	(0.0025)	(0.0033)
North America	-0.0093	-0.0383***	-0.0433***	-0.0573***	-0.0751***
	(0.0085)	(0.0124)	(0.0157)	(0.0196)	(0.0241)
Stock Return	-0.0002	0.0000	-0.0005**	-0.0005*	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
log(Cash Holdings)	0.0021	0.0084**	0.0090*	0.0070	0.0084
	(0.0024)	(0.0036)	(0.0047)	(0.0061)	(0.0076)
log(Market Value)	0.0014	0.0043	0.0125*	0.0180*	0.0167
	(0.0036)	(0.0055)	(0.0072)	(0.0094)	(0.0120)
Book to Market Ratio Δ1 - Δ5	0.0027	0.0110	0.0268*	0.0266	0.0074
	(0.0125)	(0.0079)	(0.0163)	(0.0188)	(0.0212)
Institutional Share Δ1 - Δ5	0.0470	0.1053*	0.1844***	0.2168***	0.1238
	(0.0535)	(0.0605)	(0.0691)	(0.0825)	(0.0960)
log(ROA) Δ1 - Δ5	0.0039	0.0137**	0.0315***	0.0210**	0.0086
	(0.0044)	(0.0059)	(0.0074)	(0.0090)	(0.0112)
log(Revenue) Δ1 - Δ5	0.0136	-0.0241	-0.0354*	-0.0409*	-0.0078
	(0.0159)	(0.0178)	(0.0200)	(0.0219)	(0.0236)
log(Total Debt to Equity) Δ1 - Δ5	0.0008	0.0040*	0.0033	0.0042	0.0043
	(0.0018)	(0.0021)	(0.0025)	(0.0031)	(0.0038)
Stock Return Δ1 - Δ5	-0.0001	-0.0001	-0.0003*	-0.0005**	-0.0004
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Responsible Investor Share Δ1 - Δ5	-0.0271	0.0527	0.0166	0.1356	0.2954**
	(0.0724)	(0.0788)	(0.0881)	(0.1005)	(0.1165)
log(Cash Holdings) Δ1 - Δ5	0.0035	0.0041	0.0041	0.0009	0.0083
	(0.0040)	(0.0049)	(0.0058)	(0.0071)	(0.0086)
log(Market Value) Δ1 - Δ5	0.0228	0.0291**	0.0543***	0.0912***	0.0811***
	(0.0161)	(0.0139)	(0.0157)	(0.0175)	(0.0194)
Constant	-0.0449	0.0824	0.2570***	0.3067***	0.3742***
	(0.0413)	(0.0633)	(0.0779)	(0.0946)	(0.1133)
Observations	29780	23934	19210	15110	11997
Adjusted R^2	0.0102	0.0160	0.0278	0.0338	0.0403
F-Statistic	8.22***	9.46***	14.07***	14.77***	14.76***

This table presents the regression results for the relationship between ESG ratings and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Table B.5: Scope 1 Emissions (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	0.0248	0.0350	0.0941	0.1789*	0.1533
	(0.0412)	(0.0631)	(0.0859)	(0.1068)	(0.1345)
Institutional Investor Share	-0.0368	-0.0881**	-0.1586***	-0.2188***	-0.2176**
	(0.0271)	(0.0415)	(0.0566)	(0.0686)	(0.0854)
Book to Market Ratio	-0.0032	-0.0059	-0.0210	-0.0052	-0.0144
	(0.0135)	(0.0179)	(0.0245)	(0.0329)	(0.0410)
European Union	-0.0350***	-0.0765***	-0.1042***	-0.1325***	-0.1554***
	(0.0097)	(0.0144)	(0.0188)	(0.0233)	(0.0275)
log(ROA)	-0.0085	-0.0130	-0.0107	-0.0118	-0.0038
	(0.0071)	(0.0112)	(0.0142)	(0.0180)	(0.0217)
log(Revenue)	-0.0043	-0.0008	0.0021	-0.0028	-0.0196
	(0.0065)	(0.0095)	(0.0124)	(0.0159)	(0.0182)
log(Total Debt to Equity)	0.0025	0.0030	0.0034	0.0061	0.0098
	(0.0020)	(0.0026)	(0.0036)	(0.0045)	(0.0060)
North America	-0.0242*	-0.0604***	-0.0755***	-0.0765***	-0.0969***
	(0.0135)	(0.0185)	(0.0244)	(0.0284)	(0.0335)
Stock Return	-0.0002	-0.0001	-0.0002	0.0006	-0.0001
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0005)
log(Cash Holdings)	-0.0034	-0.0036	-0.0052	-0.0034	0.0138
	(0.0040)	(0.0059)	(0.0077)	(0.0092)	(0.0116)
log(Market Value)	0.0059	0.0001	-0.0039	-0.0061	-0.0124
	(0.0061)	(0.0092)	(0.0121)	(0.0149)	(0.0171)
Book to Market Ratio Δ1 - Δ5	-0.0096	0.0135	0.0551*	0.1027**	0.0946*
	(0.0282)	(0.0280)	(0.0315)	(0.0442)	(0.0517)
Institutional Share Δ1 - Δ5	0.0414	-0.1785**	-0.2497**	-0.2413**	-0.1873
	(0.0789)	(0.0892)	(0.1023)	(0.1040)	(0.1220)
log(ROA) Δ1 - Δ5	-0.0081	-0.0283***	-0.0221*	-0.0345**	-0.0538***
	(0.0066)	(0.0100)	(0.0113)	(0.0142)	(0.0165)
log(Revenue) Δ1 - Δ5	0.3123***	0.3994***	0.4995***	0.5674***	0.6432***
	(0.0392)	(0.0411)	(0.0403)	(0.0460)	(0.0543)
log(Total Debt to Equity) Δ1 - Δ5	0.0093**	0.0066	0.0086*	0.0077	0.0049
	(0.0043)	(0.0044)	(0.0049)	(0.0055)	(0.0067)
Stock Return Δ1 - Δ5	-0.0004**	-0.0005*	-0.0006**	-0.0002	-0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Responsible Investor Share Δ1 - Δ5	0.0223	0.2687**	0.2593**	0.2035	0.0389
	(0.1094)	(0.1116)	(0.1275)	(0.1378)	(0.1566)
log(Cash Holdings) Δ1 - Δ5	-0.0077	-0.0112	-0.0166*	-0.0093	0.0028
	(0.0067)	(0.0077)	(0.0095)	(0.0113)	(0.0139)
log(Market Value) Δ1 - Δ5	0.0297	0.0203	0.0223	0.0318	0.0626**
	(0.0301)	(0.0265)	(0.0262)	(0.0288)	(0.0311)
Constant	0.0584	0.1055	0.1373	0.2312	0.4016**
	(0.0675)	(0.0967)	(0.1223)	(0.1568)	(0.1751)
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0139	0.0281	0.0405	0.0565	0.0779
F-Statistic	4.92***	7.63***	9.92***	10.94***	11.91***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Table B.6: Scope 1 Intensity ($\Delta 1$ - $\Delta 5$)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	0.0105	0.0081	0.0148	0.0342*	0.0336
	(0.0081)	(0.0122)	(0.0147)	(0.0180)	(0.0217)
Institutional Investor Share	-0.0009	0.0010	-0.0001	-0.0156	-0.0178
	(0.0059)	(0.0088)	(0.0105)	(0.0123)	(0.0142)
Book to Market Ratio	-0.0042***	-0.0084***	-0.0184***	-0.0206***	-0.0283***
	(0.0016)	(0.0028)	(0.0038)	(0.0055)	(0.0076)
European Union	-0.0026*	-0.0069***	-0.0142***	-0.0197***	-0.0276***
	(0.0015)	(0.0023)	(0.0028)	(0.0035)	(0.0044)
log(ROA)	-0.0036***	-0.0007	-0.0047*	-0.0016	-0.0025
	(0.0013)	(0.0021)	(0.0026)	(0.0029)	(0.0041)
log(Revenue)	-0.0008	0.0014	0.0008	0.0006	-0.0050
	(0.0012)	(0.0018)	(0.0024)	(0.0032)	(0.0040)
log(Total Debt to Equity)	-0.0003	-0.0003	-0.0006	0.0000	0.0004
	(0.0002)	(0.0004)	(0.0004)	(0.0006)	(0.0007)
North America	-0.0031	-0.0086**	-0.0189***	-0.0227***	-0.0322***
	(0.0022)	(0.0037)	(0.0040)	(0.0050)	(0.0063)
Stock Return	-0.0001	-0.0001	-0.0001*	-0.0000	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(Cash Holdings)	-0.0006	-0.0017*	-0.0023*	-0.0011	0.0012
	(0.0007)	(0.0010)	(0.0013)	(0.0016)	(0.0022)
log(Market Value)	0.0019*	-0.0000	0.0017	0.0003	0.0026
	(0.0011)	(0.0015)	(0.0022)	(0.0027)	(0.0035)
Book to Market Ratio $\Delta 1$ - $\Delta 5$	0.0039	0.0077	0.0169***	0.0174***	0.0208**
	(0.0039)	(0.0051)	(0.0049)	(0.0064)	(0.0085)
Institutional Share $\Delta 1$ - $\Delta 5$	0.0027	-0.0408***	-0.0452**	-0.0493**	-0.0400*
	(0.0128)	(0.0155)	(0.0190)	(0.0210)	(0.0242)
log(ROA) $\Delta 1$ - $\Delta 5$	-0.0048***	-0.0037**	-0.0055***	-0.0056**	-0.0062**
	(0.0013)	(0.0019)	(0.0020)	(0.0024)	(0.0027)
log(Revenue) $\Delta 1$ - $\Delta 5$	-0.1114***	-0.1168***	-0.0887***	-0.0877***	-0.0856***
	(0.0173)	(0.0230)	(0.0134)	(0.0145)	(0.0160)
log(Total Debt to Equity) $\Delta 1$ - $\Delta 5$	-0.0001	0.0007	0.0007	0.0015*	0.0017*
	(0.0006)	(0.0005)	(0.0006)	(0.0008)	(0.0009)
Stock Return $\Delta 1$ - $\Delta 5$	-0.0001**	-0.0001***	-0.0002**	-0.0001	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Responsible Investor Share $\Delta 1$ - $\Delta 5$	-0.0039	0.0235	0.0043	-0.0057	-0.0298
	(0.0206)	(0.0191)	(0.0202)	(0.0228)	(0.0258)
log(Cash Holdings) $\Delta 1$ - $\Delta 5$	-0.0010	-0.0038**	-0.0042**	-0.0006	0.0011
	(0.0013)	(0.0015)	(0.0018)	(0.0020)	(0.0028)
log(Market Value) $\Delta 1$ - $\Delta 5$	0.0111*	0.0144**	0.0180***	0.0171***	0.0239***
	(0.0064)	(0.0059)	(0.0052)	(0.0054)	(0.0064)
Constant	0.0075	0.0049	0.0251	0.0345	0.0976***
	(0.0110)	(0.0204)	(0.0251)	(0.0319)	(0.0378)
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0570	0.0825	0.0746	0.0819	0.0851
F-Statistic	12.76***	14.34***	13.49***	12.99***	11.51***

This table presents the regression results for the relationship between Scope 1 emission intensity and the independent variables, showing the effects of changes over one to five years ($\Delta 1$ to $\Delta 5$). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *$p<0.1$; **$p<0.05$; ***$p<0.01$, with robust standard errors clustered at the company year level.

Decarbonization lagged dependent variable

Table B.7: ESG Rating ($\Delta 1$ - $\Delta 5$)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	0.2856***	0.4894***	0.6947***	0.8675***	1.0726***
	(0.0363)	(0.0513)	(0.0687)	(0.0880)	(0.1099)
Institutional Investor Share	-0.0268	-0.0211	-0.0376	-0.0182	-0.0968
	(0.0233)	(0.0327)	(0.0433)	(0.0555)	(0.0689)
Book to Market Ratio	-0.0009	-0.0004	-0.0023	-0.0318*	-0.0580***
	(0.0018)	(0.0034)	(0.0323)	(0.0191)	(0.0225)
European Union	0.0738***	0.1278***	0.1926***	0.2474***	0.3060***
	(0.0078)	(0.0107)	(0.0143)	(0.0176)	(0.0214)
log(ROA)	0.0082*	0.0086	0.0098	0.0067	-0.0079
	(0.0046)	(0.0069)	(0.0099)	(0.0115)	(0.0142)
log(Revenue)	-0.0006	-0.0053	-0.0146*	-0.0137	-0.0267**
	(0.0040)	(0.0058)	(0.0084)	(0.0097)	(0.0119)
log(Total Debt to Equity)	0.0027**	0.0052***	0.0086***	0.0100***	0.0094***
	(0.0011)	(0.0016)	(0.0021)	(0.0027)	(0.0036)
North America	-0.0192**	-0.0610***	-0.0796***	-0.1049***	-0.1088***
	(0.0092)	(0.0129)	(0.0172)	(0.0208)	(0.0257)
Stock Return	-0.0001	0.0001	-0.0003	-0.0004	-0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
log(Cash Holdings)	-0.0002	0.0010	-0.0006	-0.0050	-0.0076
	(0.0027)	(0.0038)	(0.0051)	(0.0063)	(0.0079)
log(Market Value)	0.0086**	0.0185***	0.0334***	0.0411***	0.0580***
	(0.0040)	(0.0059)	(0.0093)	(0.0101)	(0.0124)
ESG Rating	-0.0809***	-0.1460***	-0.2108***	-0.2641***	-0.3064***
	(0.0032)	(0.0044)	(0.0057)	(0.0069)	(0.0083)
Book to Market Ratio $\Delta 1$ - $\Delta 5$	-0.0030	-0.0016	-0.0069	-0.0172	-0.0374*
	(0.0145)	(0.0143)	(0.0198)	(0.0221)	(0.0223)
Institutional Share $\Delta 1$ - $\Delta 5$	0.0988	0.1062*	0.1390*	0.2017**	-0.0097
	(0.0606)	(0.0644)	(0.0729)	(0.0893)	(0.1004)
log(ROA) $\Delta 1$ - $\Delta 5$	0.0048	0.0139**	0.0252***	0.0117	-0.0014
	(0.0049)	(0.0063)	(0.0079)	(0.0093)	(0.0117)
log(Revenue) $\Delta 1$ - $\Delta 5$	0.0012	-0.0450**	-0.0531**	-0.0429*	-0.0470*
	(0.0185)	(0.0197)	(0.0214)	(0.0226)	(0.0241)
log(Total Debt to Equity) $\Delta 1$ - $\Delta 5$	0.0008	0.0044*	0.0042	0.0043	0.0022
	(0.0021)	(0.0024)	(0.0027)	(0.0033)	(0.0040)
Stock Return $\Delta 1$ - $\Delta 5$	-0.0001	-0.0002	-0.0003	-0.0004*	-0.0005**
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Responsible Investor Share $\Delta 1$ - $\Delta 5$	-0.0209	0.1869**	0.3064***	0.4663***	0.6611***
	(0.0792)	(0.0814)	(0.0923)	(0.1062)	(0.1206)
log(Cash Holdings) $\Delta 1$ - $\Delta 5$	0.0026	-0.0041	-0.0032	-0.0054	-0.0065
	(0.0043)	(0.0052)	(0.0062)	(0.0074)	(0.0088)
log(Market Value) $\Delta 1$ - $\Delta 5$	0.0177	0.0423***	0.0853***	0.1019***	0.1033***
	(0.0179)	(0.0160)	(0.0173)	(0.0186)	(0.0199)
Constant	-0.1066***	-0.1622***	-0.1815***	-0.2224***	-0.1180
	(0.0345)	(0.0503)	(0.0650)	(0.0801)	(0.0974)
Observations	24090	19321	15169	12012	9280
Adjusted R^2	0.0370	0.0739	0.1137	0.1446	0.1665
F-Statistic	23.32***	38.84***	49.63***	55.64***	53.50***

This table presents the regression results for the relationship between ESG ratings and the independent variables in the dependent variable model, showing the effects of changes over one to five years ($\Delta 1$ to $\Delta 5$). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Table B.8: Scope 1 Emissions (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	-0.0370	-0.0704	-0.0779	-0.0705	-0.0112
	(0.0429)	(0.0676)	(0.0903)	(0.1136)	(0.1451)
Institutional Investor Share	-0.0282	-0.0420	-0.0866	-0.0778	-0.1746*
	(0.0280)	(0.0441)	(0.0580)	(0.0729)	(0.0918)
Book to Market Ratio	0.0111	0.0479**	0.0704**	0.0984***	0.0961**
	(0.0100)	(0.0206)	(0.0286)	(0.0344)	(0.0415)
European Union	-0.0573***	-0.1087***	-0.1400***	-0.1875***	-0.2008***
	(0.0097)	(0.0147)	(0.0193)	(0.0238)	(0.0283)
log(ROA)	-0.0093	-0.0087	-0.0131	-0.0219	-0.0155
	(0.0065)	(0.0110)	(0.0142)	(0.0195)	(0.0232)
log(Revenue)	0.0368***	0.0761***	0.0963***	0.1238***	0.1235***
	(0.0075)	(0.0116)	(0.0153)	(0.0198)	(0.0223)
log(Total Debt to Equity)	0.0033*	0.0077**	0.0121***	0.0160***	0.0250***
	(0.0018)	(0.0030)	(0.0041)	(0.0052)	(0.0069)
North America	-0.0267**	-0.0488**	-0.0444*	-0.0485*	-0.0555
	(0.0129)	(0.0190)	(0.0250)	(0.0292)	(0.0351)
Stock Return	0.0002	-0.0000	0.0001	0.0006	0.0000
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0006)
log(Cash Holdings)	-0.0047	-0.0095	-0.0121	-0.0192**	-0.0080
	(0.0040)	(0.0060)	(0.0079)	(0.0096)	(0.0121)
log(Market Value)	0.0067	0.0089	0.0209*	0.0338**	0.0293*
	(0.0056)	(0.0092)	(0.0121)	(0.0152)	(0.0176)
log(Scope 1 Emissions)	-0.0392***	-0.0794***	-0.1075***	-0.1408***	-0.1537***
	(0.0035)	(0.0059)	(0.0081)	(0.0101)	(0.0119)
Book to Market Ratio Δ1 - Δ5	-0.0236	0.0050	0.0649*	0.0990**	0.1182**
	(0.0276)	(0.0339)	(0.0389)	(0.0463)	(0.0529)
Institutional Share Δ1 - Δ5	-0.0153	-0.1733*	-0.2083**	-0.0733	-0.2309*
	(0.0791)	(0.0934)	(0.1056)	(0.1081)	(0.1334)
log(ROA) Δ1 - Δ5	-0.0127*	-0.0167*	-0.0191*	-0.0356**	-0.0443***
	(0.0065)	(0.0090)	(0.0114)	(0.0143)	(0.0157)
log(Revenue) Δ1 - Δ5	0.3240***	0.3975***	0.4483***	0.5396***	0.6499***
	(0.0460)	(0.0442)	(0.0433)	(0.0533)	(0.0600)
log(Total Debt to Equity) Δ1 - Δ5	0.0090**	0.0075	0.0117**	0.0091	0.0099
	(0.0042)	(0.0052)	(0.0056)	(0.0065)	(0.0078)
Stock Return Δ1 - Δ5	-0.0001	-0.0002	-0.0001	0.0000	-0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Responsible Investor Share Δ1 - Δ5	0.0061	0.0809	-0.0325	-0.0945	0.0205
	(0.1054)	(0.1157)	(0.1322)	(0.1418)	(0.1647)
log(Cash Holdings) Δ1 - Δ5	-0.0073	-0.0068	-0.0077	-0.0081	0.0044
	(0.0067)	(0.0073)	(0.0089)	(0.0106)	(0.0132)
log(Market Value) Δ1 - Δ5	-0.0104	-0.0108	0.0293	0.0339	0.0672**
	(0.0315)	(0.0280)	(0.0282)	(0.0303)	(0.0310)
Constant	0.0213	0.0146	0.0275	0.0133	0.0535
	(0.0558)	(0.0838)	(0.1089)	(0.1436)	(0.1585)
Observations	17263	13474	10797	8730	7091
Adjusted R^2	0.0367	0.0744	0.0980	0.1356	0.1638
F-Statistic	6.96***	10.83***	12.76***	15.07***	15.82***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables in the dependent variable model, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *$p<0.1$; **$p<0.05$; ***$p<0.01$, with robust standard errors clustered at the company year level.

Table B.9: Scope 1 Intensity (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share	-0.0031	-0.0121	0.0005	0.0061	0.0152
	(0.0089)	(0.0138)	(0.0162)	(0.0208)	(0.0253)
Institutional Investor Share	0.0010	0.0016	-0.0055	-0.0043	-0.0097
	(0.0064)	(0.0097)	(0.0112)	(0.0141)	(0.0164)
Book to Market Ratio	-0.0016	-0.0015	-0.0076*	-0.0087	-0.0129*
	(0.0014)	(0.0029)	(0.0042)	(0.0058)	(0.0076)
European Union	-0.0061***	-0.0114***	-0.0213***	-0.0289***	-0.0351***
	(0.0015)	(0.0026)	(0.0030)	(0.0039)	(0.0045)
log(ROA)	-0.0023*	0.0016	-0.0040	-0.0040	-0.0047
	(0.0013)	(0.0023)	(0.0026)	(0.0031)	(0.0045)
log(Revenue)	-0.0006	-0.0007	-0.0035	-0.0053	-0.0066**
	(0.0013)	(0.0020)	(0.0026)	(0.0034)	(0.0034)
log(Total Debt to Equity)	0.0000	-0.0001	0.0000	0.0006	0.0010
	(0.0003)	(0.0004)	(0.0005)	(0.0007)	(0.0007)
North America	-0.0018	-0.0047	-0.0142***	-0.0209***	-0.0282***
	(0.0022)	(0.0044)	(0.0042)	(0.0057)	(0.0072)
Stock Return	-0.0000	-0.0000	-0.0001*	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(Cash Holdings)	-0.0011	-0.0021**	-0.0025*	-0.0018	-0.0016
	(0.0007)	(0.0011)	(0.0014)	(0.0018)	(0.0026)
log(Market Value)	0.0014	0.0016	0.0052**	0.0068**	0.0080***
	(0.0010)	(0.0016)	(0.0022)	(0.0029)	(0.0029)
log(Scope 1 Intensity)	-0.0406***	-0.0687***	-0.0917***	-0.1130***	-0.1394***
	(0.0052)	(0.0081)	(0.0099)	(0.0132)	(0.0178)
Book to Market Ratio Δ1 - Δ5	0.0056	0.0089	0.0163**	0.0193***	0.0238***
	(0.0045)	(0.0066)	(0.0064)	(0.0074)	(0.0086)
Institutional Share Δ1 - Δ5	0.0041	-0.0392**	-0.0476**	-0.0370	-0.0590**
	(0.0127)	(0.0178)	(0.0214)	(0.0231)	(0.0267)
log(ROA) Δ1 - Δ5	-0.0048***	-0.0019	-0.0063***	-0.0074***	-0.0062**
	(0.0014)	(0.0022)	(0.0021)	(0.0026)	(0.0025)
log(Revenue) Δ1 - Δ5	-0.1176***	-0.1296***	-0.0971***	-0.0885***	-0.0700***
	(0.0222)	(0.0290)	(0.0164)	(0.0183)	(0.0123)
log(Total Debt to Equity) Δ1 - Δ5	0.0005	0.0004	0.0011	0.0017*	0.0016**
	(0.0004)	(0.0005)	(0.0007)	(0.0009)	(0.0008)
Stock Return Δ1 - Δ5	-0.0000	-0.0001	-0.0001*	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Responsible Investor Share Δ1 - Δ5	-0.0062	0.0041	-0.0143	-0.0319	-0.0178
	(0.0167)	(0.0231)	(0.0217)	(0.0256)	(0.0267)
log(Cash Holdings) Δ1 - Δ5	-0.0021	-0.0032**	-0.0030*	0.0013	0.0035
	(0.0015)	(0.0016)	(0.0017)	(0.0019)	(0.0034)
log(Market Value) Δ1 - Δ5	0.0104	0.0118	0.0206***	0.0220***	0.0233***
	(0.0074)	(0.0072)	(0.0061)	(0.0064)	(0.0055)
Constant	0.0323***	0.0560***	0.0997***	0.1120***	0.1270***
	(0.0108)	(0.0213)	(0.0243)	(0.0313)	(0.0271)
Observations	17261	13473	10797	8728	7090
Adjusted R^2	0.1060	0.1444	0.1398	0.1472	0.1760
F-Statistic	13.16***	13.54***	13.69***	14.58***	15.58***

This table presents the regression results for the relationship between Scope 1 emission intensities and the independent variables in the dependent variable model, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Decarbonization without Big Three

Table B.10: Scope 1 Emissions ($\Delta 1$ - $\Delta 5$) w/o Big Three

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
Responsible Investor Share (w/o Big Three)	0.0461	0.0261	0.0864	0.1314	0.0808
	(0.0475)	(0.0715)	(0.0940)	(0.1151)	(0.1442)
Institutional Investor Share	-0.0441*	-0.0831**	-0.1533***	-0.1922***	-0.1962***
	(0.0259)	(0.0385)	(0.0512)	(0.0611)	(0.0757)
Book to Market Ratio	-0.0031	-0.0059	-0.0212	-0.0064	-0.0153
	(0.0135)	(0.0178)	(0.0245)	(0.0328)	(0.0407)
European Union	-0.0353***	-0.0761***	-0.1032***	-0.1305***	-0.1524***
	(0.0097)	(0.0144)	(0.0188)	(0.0233)	(0.0274)
log(ROA)	-0.0085	-0.0126	-0.0101	-0.0104	-0.0022
	(0.0071)	(0.0112)	(0.0142)	(0.0180)	(0.0217)
log(Revenue)	-0.0042	-0.0006	0.0024	-0.0024	-0.0197
	(0.0065)	(0.0095)	(0.0124)	(0.0159)	(0.0182)
log(Total Debt)	0.0025	0.0031	0.0037	0.0065	0.0102*
	(0.0020)	(0.0026)	(0.0036)	(0.0045)	(0.0060)
North America	-0.0218	-0.0576***	-0.0690***	-0.0690**	-0.0955***
	(0.0135)	(0.0189)	(0.0248)	(0.0288)	(0.0344)
Stock Return	-0.0002	-0.0001	-0.0002	0.0006	-0.0001
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0005)
log(Cash Holdings)	-0.0036	-0.0039	-0.0056	-0.0038	0.0129
	(0.0040)	(0.0059)	(0.0077)	(0.0092)	(0.0116)
log(Market Capitalization)	0.0064	0.0007	-0.0025	-0.0047	-0.0110
	(0.0061)	(0.0092)	(0.0121)	(0.0149)	(0.0170)
Book to Market Ratio Δ1 - Δ5	-0.0093	0.0133	0.0539*	0.1012**	0.0931*
	(0.0282)	(0.0280)	(0.0315)	(0.0441)	(0.0516)
Institutional Share Δ1 - Δ5	-0.0037	-0.2276***	-0.3282***	-0.3056***	-0.2725**
	(0.0734)	(0.0854)	(0.0965)	(0.1015)	(0.1163)
log(ROA) Δ1 - Δ5	-0.0082	-0.0281***	-0.0222**	-0.0345**	-0.0540***
	(0.0066)	(0.0100)	(0.0113)	(0.0142)	(0.0165)
log(Revenue) Δ1 - Δ5	0.3121***	0.3990***	0.4993***	0.5661***	0.6417***
	(0.0392)	(0.0410)	(0.0402)	(0.0460)	(0.0542)
log(Total Debt) Δ1 - Δ5	0.0094**	0.0068	0.0090*	0.0081	0.0052
	(0.0043)	(0.0044)	(0.0049)	(0.0055)	(0.0067)
Stock Return Δ1 - Δ5	-0.0004**	-0.0005**	-0.0006**	-0.0002	-0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Responsible Investor Share (w/o Big Three) Δ1 - Δ5	0.1401	0.4508***	0.5179***	0.4225***	0.2622
	(0.1118)	(0.1197)	(0.1384)	(0.1504)	(0.1718)
log(Cash Holdings) Δ1 - Δ5	-0.0078	-0.0112	-0.0167*	-0.0094	0.0025
	(0.0067)	(0.0077)	(0.0095)	(0.0113)	(0.0140)
log(Market Capitalization) Δ1 - Δ5	0.0320	0.0229	0.0245	0.0336	0.0628**
	(0.0301)	(0.0266)	(0.0263)	(0.0288)	(0.0311)
Constant	0.0536	0.0921	0.1137	0.1995	0.3868**
	(0.0674)	(0.0965)	(0.1224)	(0.1574)	(0.1759)
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0140	0.0285	0.0412	0.0568	0.0780
F-Statistic	4.90***	7.76***	10.19***	11.05***	11.94***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Here, we exclude the Big Three (BlackRock, State Street Global Advisors, Vanguard) from the Responsible Investor Share. Each column represents a different time horizon. The independent variable of interest is Responsible Investor Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *$p<0.1$; **$p<0.05$; ***$p<0.01$, with robust standard errors clustered at the company year level.

Robustness check CA100+

Table B.11: Regression Result for Robustness Check for High-Emitter Shunning Using CA100+ Investors

	CA100+ Ratio				Institutional Investor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1 Emissions)	-0.001***				-0.002***			
	(0.000)				(0.001)			
log(Scope 1 Intensity)		-0.014***				-0.016***		
		(0.002)				(0.005)		
Climate Policy Relevant Sector			0.005***				-0.019***	
			(0.001)				(0.003)	
Top 10% Scope 1 Emissions				-0.009***				0.006
				(0.002)				(0.005)
ESG Rating	0.009***	0.008***	0.006***	0.006***	0.029***	0.028***	0.032***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Book to Market Ratio	-0.003	-0.003	-0.002***	-0.002***	-0.046***	-0.046***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.005)	(0.001)	(0.001)
Dividend Yield	-0.003***	-0.003***	-0.003***	-0.003***	-0.009***	-0.009***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
European Union	-0.039***	-0.039***	-0.041***	-0.042***	0.102***	0.102***	0.109***	0.109***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
Historic Volatility	-0.088***	-0.088***	-0.086***	-0.085***	-0.104***	-0.104***	-0.094***	-0.098***
	(0.008)	(0.007)	(0.005)	(0.005)	(0.018)	(0.018)	(0.011)	(0.011)
log(ROA)	-0.006***	-0.006***	-0.003***	-0.004***	0.006***	0.006***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Revenue)	0.008***	0.007***	0.002***	0.002***	0.012***	0.009***	0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log(Total Debt to Equity)	-0.002***	-0.002***	-0.001***	-0.001***	-0.003***	-0.003***	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
North America	-0.043***	-0.044***	-0.048***	-0.049***	0.401***	0.401***	0.417***	0.419***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
Stock Return	0.000**	0.000**	0.000	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Cash Holdings)	0.005***	0.005***	0.007***	0.007***	-0.004***	-0.004***	-0.002*	-0.002**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
log(Market Value)	-0.008***	-0.008***	-0.007***	-0.007***	-0.018***	-0.018***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.033***	0.042***	0.070***	0.068***	0.441***	0.453***	0.244***	0.241***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.021)	(0.021)	(0.013)	(0.014)
Observations	18207	18207	38934	38934	18207	18207	38934	38934
Adjusted R^2	0.301	0.302	0.299	0.299	0.398	0.398	0.443	0.442
F Statistic	570.2***	569.6***	1007.2***	1008.5***	3134.1***	3122.0***	5165.5***	5161.1***

This table presents the regression results for high-emitter shunning, showing the relationship between various financial, ESG ratings, and climate factors on the portfolio allocation by Responsible Investors. Here, we use CA100+ Share membership as a proxy for Responsible Investor. The results are robust. The dependent variable is the level of investment in companies by the respective investor group. Independent variables are logarithmic transformations of Scope 1 emissions, Scope 1 intensity, Climate Policy Relevant Sector (that is, the company is in a climate sector), and Top 10% Scope 1 Emissions (that is, the company x year observation is among the highest 10% of absolute emissions). In addition, control variables include financial metrics, namely the book-to-market ratio, dividend yield, historic stock return volatility, return on assets (ROA) (log.), revenue (log.), total debt to equity (log.), stock return, cash holdings (log.), and market capitalization (log.), as well as year and industry fixed effects and regional dummy variables for the European Union and North America. All independent time-varying variables are lagged by 1 period. Standard errors are in parentheses below the coefficients and clustered at the company-year level. The significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01.

Table B.12: ESG Rating (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
CA100+ Share	0.1489**	0.2790***	0.3311**	0.4157	-0.0000***
	(0.0633)	(0.0981)	(0.1462)	(0.2577)	(0.0000)
Institutional Investor Share	0.0720***	0.1487***	0.2232***	0.3008***	0.3634***
	(0.0135)	(0.0198)	(0.0258)	(0.0329)	(0.0406)
Book to Market Ratio	-0.0033	-0.0045	-0.0068	-0.0130	-0.0624***
	(0.0024)	(0.0032)	(0.0048)	(0.0195)	(0.0209)
European Union	0.0243***	0.0338***	0.0625***	0.0772***	0.0996***
	(0.0069)	(0.0099)	(0.0128)	(0.0163)	(0.0198)
log(ROA)	0.0127***	0.0188***	0.0274***	0.0316***	0.0263*
	(0.0042)	(0.0066)	(0.0085)	(0.0112)	(0.0135)
log(Revenue)	-0.0015	-0.0129**	-0.0223***	-0.0258***	-0.0290**
	(0.0036)	(0.0054)	(0.0071)	(0.0094)	(0.0116)
log(Total Debt to Equity)	0.0020**	0.0052***	0.0069***	0.0090***	0.0102***
	(0.0010)	(0.0015)	(0.0019)	(0.0025)	(0.0033)
North America	-0.0074	-0.0352***	-0.0456***	-0.0617***	-0.0784***
	(0.0087)	(0.0127)	(0.0162)	(0.0204)	(0.0250)
Stock Return	-0.0002	0.0000	-0.0005**	-0.0005*	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
log(Cash Holdings)	0.0016	0.0075**	0.0079*	0.0055	0.0081
	(0.0024)	(0.0036)	(0.0047)	(0.0061)	(0.0076)
log(Market Value)	0.0018	0.0048	0.0134*	0.0183*	0.0134
	(0.0036)	(0.0055)	(0.0072)	(0.0097)	(0.0119)
Book to Market Ratio Δ1 - Δ5	0.0018	0.0105	0.0247	0.0243	0.0007
	(0.0125)	(0.0086)	(0.0161)	(0.0194)	(0.0211)
CA100+ Share Δ1 - Δ5	-0.0638	0.0081	-0.0569	-0.0774	-0.0272
	(0.1055)	(0.1054)	(0.1159)	(0.1277)	(0.1433)
Institutional Share Δ1 - Δ5	0.0465	0.1480***	0.2296***	0.3320***	0.3285***
	(0.0424)	(0.0487)	(0.0554)	(0.0654)	(0.0750)
log(ROA) Δ1 - Δ5	0.0040	0.0140**	0.0319***	0.0210**	0.0075
	(0.0044)	(0.0059)	(0.0074)	(0.0090)	(0.0112)
log(Revenue) Δ1 - Δ5	0.0124	-0.0264	-0.0390*	-0.0440**	-0.0134
	(0.0159)	(0.0178)	(0.0200)	(0.0219)	(0.0237)
log(Total Debt to Equity) Δ1 - Δ5	0.0007	0.0038*	0.0029	0.0036	0.0033
	(0.0018)	(0.0021)	(0.0025)	(0.0031)	(0.0038)
Stock Return Δ1 - Δ5	-0.0001	-0.0001	-0.0003**	-0.0005**	-0.0004
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)
log(Cash Holdings) Δ1 - Δ5	0.0033	0.0035	0.0029	-0.0011	0.0064
	(0.0040)	(0.0049)	(0.0058)	(0.0072)	(0.0086)
log(Market Value) Δ1 - Δ5	0.0220	0.0284**	0.0534***	0.0906***	0.0805***
	(0.0161)	(0.0140)	(0.0157)	(0.0176)	(0.0194)
Constant	-0.0683*	0.0430	0.1995**	0.2390**	0.3136***
	(0.0410)	(0.0629)	(0.0777)	(0.0947)	(0.1136)
Observations	29780	23934	19210	15110	11997
Adjusted R^2	0.0093	0.0144	0.0249	0.0300	0.0361
F-Statistic	7.55***	8.38***	12.41***	12.77***	13.54***

This table presents the regression results for the relationship between ESG ratings and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is CA100+ Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Table B.13: Scope 1 Emissions (Δ1 - Δ5)

	Δ 1 Year	Δ 2 Year	Δ 3 Year	Δ 4 Year	Δ 5 Year
	(1)	(2)	(3)	(4)	(5)
CA100+ Share	-0.1099	-0.1843	0.0497	0.2527	0.2994
	(0.0911)	(0.1404)	(0.1911)	(0.2563)	(0.3425)
Institutional Investor Share	-0.0140	-0.0423	-0.0935**	-0.1237***	-0.1472***
	(0.0207)	(0.0295)	(0.0397)	(0.0468)	(0.0553)
Book to Market Ratio	-0.0035	-0.0076	-0.0228	-0.0083	-0.0171
	(0.0135)	(0.0179)	(0.0245)	(0.0329)	(0.0409)
European Union	-0.0356***	-0.0787***	-0.1042***	-0.1300***	-0.1526***
	(0.0099)	(0.0147)	(0.0192)	(0.0237)	(0.0280)
log(ROA)	-0.0089	-0.0137	-0.0103	-0.0107	-0.0028
	(0.0070)	(0.0112)	(0.0142)	(0.0181)	(0.0218)
log(Revenue)	-0.0042	-0.0005	0.0026	-0.0019	-0.0191
	(0.0065)	(0.0095)	(0.0124)	(0.0159)	(0.0182)
log(Total Debt to Equity)	0.0023	0.0027	0.0032	0.0059	0.0097
	(0.0020)	(0.0027)	(0.0036)	(0.0045)	(0.0060)
North America	-0.0268*	-0.0630***	-0.0725***	-0.0716**	-0.0973***
	(0.0140)	(0.0192)	(0.0254)	(0.0293)	(0.0347)
Stock Return	-0.0002	-0.0001	-0.0002	0.0006	-0.0001
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0005)
log(Cash Holdings)	-0.0033	-0.0029	-0.0047	-0.0031	0.0137
	(0.0040)	(0.0059)	(0.0077)	(0.0092)	(0.0116)
log(Market Value)	0.0059	-0.0007	-0.0054	-0.0083	-0.0140
	(0.0061)	(0.0092)	(0.0121)	(0.0149)	(0.0170)
Book to Market Ratio Δ1 - Δ5	-0.0101	0.0146	0.0557*	0.1020**	0.0944*
	(0.0283)	(0.0280)	(0.0315)	(0.0443)	(0.0517)
CA100+ Share Δ1 - Δ5	-0.0622	-0.1139	-0.1208	-0.0985	-0.1048
	(0.1740)	(0.1815)	(0.2063)	(0.2274)	(0.2530)
Institutional Share Δ1 - Δ5	0.0602	-0.0286	-0.0978	-0.1178	-0.1464
	(0.0631)	(0.0759)	(0.0849)	(0.0876)	(0.0941)
log(ROA) Δ1 - Δ5	-0.0083	-0.0280***	-0.0211*	-0.0337**	-0.0539***
	(0.0066)	(0.0100)	(0.0113)	(0.0142)	(0.0166)
log(Revenue) Δ1 - Δ5	0.3115***	0.3977***	0.4989***	0.5681***	0.6431***
	(0.0393)	(0.0413)	(0.0406)	(0.0463)	(0.0544)
log(Total Debt to Equity) Δ1 - Δ5	0.0092**	0.0064	0.0083*	0.0074	0.0047
	(0.0043)	(0.0044)	(0.0049)	(0.0055)	(0.0067)
Stock Return Δ1 - Δ5	-0.0004**	-0.0005*	-0.0006**	-0.0002	-0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
log(Cash Holdings) Δ1 - Δ5	-0.0078	-0.0108	-0.0163*	-0.0094	0.0027
	(0.0067)	(0.0077)	(0.0095)	(0.0113)	(0.0140)
log(Market Value) Δ1 - Δ5	0.0291	0.0211	0.0226	0.0309	0.0619**
	(0.0299)	(0.0266)	(0.0263)	(0.0289)	(0.0312)
Constant	0.0487	0.0925	0.1309	0.2223	0.3961**
	(0.0673)	(0.0967)	(0.1223)	(0.1560)	(0.1747)
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0139	0.0279	0.0403	0.0563	0.0779
F-Statistic	4.93***	7.68***	9.90***	10.93***	11.96***

This table presents the regression results for the relationship between Scope 1 emissions (absolute) and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is CA100+ Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *$p<0.1$; **$p<0.05$; ***$p<0.01$, with robust standard errors clustered at the company year level.

Table B.14: Scope 1 Intensity (Δ1 - Δ5)

	Δ 1 Year (1)	Δ 2 Year (2)	Δ 3 Year (3)	Δ 4 Year (4)	Δ 5 Year (5)
CA100+ Share	0.0202	0.0206	0.0693***	0.1220***	0.1416***
	(0.0141)	(0.0231)	(0.0255)	(0.0336)	(0.0441)
Institutional Investor Share	0.0026	0.0042	0.0040	-0.0051	-0.0086
	(0.0035)	(0.0055)	(0.0066)	(0.0081)	(0.0100)
Book to Market Ratio	-0.0042***	-0.0084***	-0.0184***	-0.0208***	-0.0287***
	(0.0016)	(0.0028)	(0.0039)	(0.0055)	(0.0076)
European Union	-0.0022	-0.0065***	-0.0137***	-0.0186***	-0.0266***
	(0.0016)	(0.0023)	(0.0029)	(0.0036)	(0.0045)
log(ROA)	-0.0035***	-0.0005	-0.0044*	-0.0011	-0.0021
	(0.0013)	(0.0021)	(0.0026)	(0.0029)	(0.0041)
log(Revenue)	-0.0008	0.0014	0.0008	0.0006	-0.0051
	(0.0012)	(0.0018)	(0.0025)	(0.0032)	(0.0040)
log(Total Debt to Equity)	-0.0002	-0.0003	-0.0006	0.0001	0.0004
	(0.0002)	(0.0004)	(0.0004)	(0.0006)	(0.0007)
North America	-0.0025	-0.0078**	-0.0179***	-0.0218***	-0.0330***
	(0.0023)	(0.0037)	(0.0042)	(0.0052)	(0.0065)
Stock Return	-0.0001*	-0.0001	-0.0001*	-0.0000	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(Cash Holdings)	-0.0006	-0.0017*	-0.0024*	-0.0013	0.0010
	(0.0007)	(0.0010)	(0.0013)	(0.0016)	(0.0022)
log(Market Value)	0.0018*	-0.0001	0.0015	0.0000	0.0025
	(0.0011)	(0.0015)	(0.0022)	(0.0027)	(0.0035)
Book to Market Ratio Δ1 - Δ5	0.0038	0.0077	0.0168***	0.0172***	0.0208**
	(0.0039)	(0.0051)	(0.0049)	(0.0064)	(0.0085)
CA100+ Share Δ1 - Δ5	0.0305	0.0265	-0.0314	-0.0306	-0.0417
	(0.0277)	(0.0303)	(0.0276)	(0.0297)	(0.0313)
Institutional Share Δ1 - Δ5	-0.0014	-0.0314**	-0.0400***	-0.0485***	-0.0499***
	(0.0091)	(0.0133)	(0.0141)	(0.0152)	(0.0168)
log(ROA) Δ1 - Δ5	-0.0048***	-0.0036*	-0.0053***	-0.0054**	-0.0063**
	(0.0013)	(0.0019)	(0.0020)	(0.0024)	(0.0027)
log(Revenue) Δ1 - Δ5	-0.1115***	-0.1167***	-0.0881***	-0.0869***	-0.0853***
	(0.0173)	(0.0231)	(0.0135)	(0.0146)	(0.0161)
log(Total Debt to Equity) Δ1 - Δ5	-0.0001	0.0007	0.0006	0.0015*	0.0017*
	(0.0006)	(0.0005)	(0.0006)	(0.0008)	(0.0009)
Stock Return Δ1 - Δ5	-0.0001**	-0.0001***	-0.0002**	-0.0001	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
log(Cash Holdings) Δ1 - Δ5	-0.0010	-0.0038**	-0.0041**	-0.0006	0.0010
	(0.0013)	(0.0015)	(0.0018)	(0.0020)	(0.0028)
log(Market Value) Δ1 - Δ5	0.0112*	0.0144**	0.0177***	0.0166***	0.0235***
	(0.0063)	(0.0059)	(0.0053)	(0.0054)	(0.0064)
Constant	0.0071	0.0051	0.0257	0.0343	0.0978***
	(0.0110)	(0.0202)	(0.0252)	(0.0320)	(0.0378)
Observations	21754	17047	13706	11007	8902
Adjusted R^2	0.0570	0.0824	0.0750	0.0824	0.0853
F-Statistic	12.61***	14.13***	13.60***	13.11***	11.42***

This table presents the regression results for the relationship between Scope 1 emission intensities and the independent variables, showing the effects of changes over one to five years (Δ1 to Δ5). Each column represents a different time horizon. The independent variable of interest is CA100+ Share. Additional independent variables are Institutional Investor Share, financial metrics (Book-to-Market Ratio, Return on Assets (ROA), Revenue, Total Debt, Cash Holdings, Market Capitalization), and geographical indicators (European Union, North America). The coefficients and standard errors (in parentheses) are presented for each variable. The significance levels are marked as *p<0.1; **p<0.05; ***p<0.01, with robust standard errors clustered at the company year level.

Variable List

Table B.15: Variable Definitions

Variable	Definition
ISIN	Company Identifier
(Investor) PermID	Investor Identifier
Log Scope 1 Emissions	Natural logarithm of Scope 1 Emissions
Log Scope 1 Intensity	Natural logarithm of Scope 1 Emissions divided by revenue
Climate Policy Relevant Sector	Dummy variable indicating a company operating in a climate-relevant sector according to Battiston et al. (2017)
Top 10% Scope 1 Emissions	Dummy variable indicating the highest 10% Scope 1 Emissions
ESG Rating	MSCI IVA industry adjusted ESG rating
Responsible Investor Share	Total share of company's market value held by UN PRI Investors
Institutional Investor Share	Total share of company's market value held by institutional investors
Responsible Investor Ratio	Responsible Investor Share divided by Institutional Investor Share
CA100+ Share	Total share of company's market value held by CA100+ investors
CA100+ Ratio	CA100+ Share divided by Institutional Investor Share
log(Market Value)	Natural logarithm of market value
Book-to-Market Ratio	Book valuation divided by market valuation
Dividend Yield	Dividend per share as a percentage of the share price
Historic Volatility	Historic stock return volatility
Stock Return	Yearly stock return measures as the percentage change from total return share price in t-1 to t
log(Cash Holdings)	Natural logarithm of cash holdings
log(Revenue)	Natural logarithm of revenue
log(ROA)	Natural logarithm of return on assets
log(Total Debt to Equity)	Natural logarithm of leverage ratio defined as total debt to common equity
European Union	Dummy variable indicating a company headquartered in an European country

Continued on next page

Table B.15 – continued from previous page

Variable	Definition
North America	Dummy variable indicating a company headquartered in either the USA or Canada
Rest of the World	Dummy variable indicating company headquarter outside Europe and North America
TRBC (sector)	Company's sector classification according to TRBC level 2
Year	Dummy for the respective reporting year

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C

Appendix to Chapter 3

Publication Status

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Co-Authors

This is a single-authored paper.

Paper Abstract

Banks are the main source of external funding for small businesses. Thus, integrating sustainability considerations in small business lending can support global sustainability efforts. In surveying German banks, I show that banks are in the process of implementing sustainable small business lending. They put more emphasis on sustainability risks than on the transformation of the business model among small businesses. Sustainable relationship lending has some relevance in creating sustainability-related soft information, although respective hard information is preferred by banks. Banks and policymakers can use the findings to better apply sustainable small business lending to sustainability and resilience efforts.

Appendix A: Survey

Part	# Q	Question	Sub-elements & response options
I	1	Name of the bank	Open text field
I	2	In which department do you work?	Response options: Strategy, Risk management, Market department, Risk controlling / back-office, Regulatory affairs / compliance
I	3	In which hierarchical level do you work?	Response options: C-level, Senior management, Middle management, Technical expert, Junior management

Part	# Q	Question	Sub-elements & response options
II	1	How relevant are ESG data for the following areas of your bank?	Sub-elements: (a) Risk management, (b) Strategy, (c) Reporting, (d) Product sales, (e) Product development, (f) Client dialogue Response options: Likert scale 1 (very low) - 6 (very high) plus 'don't know' Note: The responses to Under implementation and within less than six months are shown as one in the paper as they have similar meanings, and some respondents struggled to distinguish them.
II	2	How progressed is your bank in using ESG data in the following areas?	Sub-elements: (a) Risk management, (b) Strategy, (c) Reporting, (d) Product sales, (e) Product development, (f) Client dialogue Response options: In use, Under implementation, Within less than six months, 6-24 months, >24 months, Not planned plus 'don't know' Note: The responses to Under implementation and within less than six months are shown as one in the paper as they have similar meanings, and some respondents struggled to distinguish them.

Part	# Q	Question	Sub-elements & response options
II	3	When do you plan to use ESG data for the following types of firms?	Sub-elements: (a) Listed companies, (b) Sustainability risk exposed firms, (c) Large unlisted companies, (d) Small businesses Response options: In use, Under implementation, Within less than six months, 6-24 months, >24 months, Not planned plus 'don't know' Note: The responses to Under implementation and within less than six months are shown as one in the paper as they have similar meanings, and some respondents struggled to distinguish them.
II	4	How did ESG factors affect credit supply today for the following lending types?	Sub-elements: (a) Large listed companies, (b) Small businesses, (c) Commercial real estate, (d) Mortgages Response options: No business, Changes to collateral, Pricing adjustments, Adjustment expected for the future, No adjustments expected plus 'don't know'
III	1	How do you perceive and expect ESG risks to materialize in your small business lending portfolio?	Sub-elements: (a) Today, (b) Over the next 24 months, (c) Beyond 24 months Response options: Likert scale 1 (very high) - 6 (very low) plus 'don't know'

Part	# Q	Question	Sub-elements & response options
III	2	When do you expect to use ESG aspects for the following cases in small business lending?	Sub-elements: (a) Transition risk analysis, (b) Physical risk analysis, (c) Sustainability stress tests, (d) Internal ESG ratings, (e) Manual adjustments to models, (f) Sustainability-linked client dialogue, (g) Sustainability-related management of small lending portfolios Response options: In use, Under implementation, Within less than six months, 6-24 months, >24 months, Not planned plus 'don't know' Note: The responses to Under implementation and within less than six months are shown as one in the paper as they have similar meanings, and some respondents struggled to distinguish them.
III	3	Which level of granularity of ESG data do you need for the following use cases in small business lending? (multiple choice)	Sub-elements: (a) Transition risk analysis, (b) Physical risk analysis, (c) Sustainability stress tests, (d) Internal ESG ratings, (e) Manual adjustments to models, (f) Sustainability-linked client dialogue, (g) Sustainability-related management of small lending portfolios Response options: Public industry averages, Self-calculated industry averages, Peer group assessments, External firm assessment, Unaudited firm data, Audited firm data plus 'don't know' Note: this question was designed for market research and is not discussed in this paper.

Part	# Q	Question	Sub-elements & response options
III	4	What level of challenge do you experience in obtaining ESG data on small businesses?	Sub-elements: (a) Availability, (b) Quality, (c) Comparability, (d9 Damage to client relationship, (e) Cost, (f) Materiality of data point Response options: Likert scale 1 (very low / no challenge) - 6 (very high) plus 'don't know'
III	5	How likely are you to use the following data sources to access sustainability data from small businesses?	Sub-elements: (a) Bank-internal assessment, (b) Provision by small businesses, (c) Collection by relationship manager, (d) Use of service providers, (e) Acquisition from data vendors Response options: Likert scale 1 (very likely) - 6 (very unlikely) plus 'don't know' Note: for consistency, I have inverted the scales in the paper.
III	6	How relevant are the following use cases for your bank to support small businesses in transforming business models towards more sustainability?	Sub-elements: (a) Transition plan development, (b) Scenario analysis support, (c) Bank provides advisory services, (d) Bank has a network of external advisors, (e) Provision of tools and data, (f) Research and development financing, (g) Sustainable financial products Response options: Likert scale 1 (very relevant) - 6 (not relevant) plus 'don't know' Note: for consistency, I have inverted the scales in the paper.

Table C.1: Survey instrument

The table shows the survey as distributed to German banks. It is translated into English. For some questions, sub-elements exists, that is, a question was asked for several elements. Questions are coded as Part - Question number - Sub-element (if necessary).

Appendix B: Bank Location

Figure C.1: Map of headquarters by participating banks

The map shows the location of the headquarters of the participating banks. The analysis is based on postal codes. If several banks have the same postal code, only one pin is shown.

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D

Appendix to Chapter 4

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Paper Abstract

This paper discusses the EU Taxonomy in the context of Environmental, Social, and Governance (ESG) ratings. ESG firm-level ratings tend to differ between ESG data providers, which affects investment decisions due to uncertainty about a firm's sustainability performance. We argue that the EU Taxonomy can support the reduction of this divergence. Using EU Taxonomy-related firm data in tobit regressions, we show that environmental ratings from three out of four ESG data providers are significantly related to the EU Taxonomy. However, our results suggest that the potential for reducing measurement divergence has not yet fully materialized. Our results have implications for investors, ESG data providers, and policymakers.

Variables Overview

Table D.1: Overview of Variables

Variable	Description	Source
Dependent variables		
MSCI E Rating	MSCI E rating measures a firm's environmental performance. Scores range from 0 to 10. We standardized the ratings between 0 and 100 for the purpose of our analysis.	MSCI
S&P E Rating	S&P E rating measures a firm's environmental performance. Scores range from 0 to 100.	Bloomberg
Refinitiv E Rating	Refinitiv E rating measures a firm's environmental performance. Scores range from 0 to 100.	Refinitiv
V.E E Rating	V.E E rating measures a firm's environmental performance. Scores range from 0 to 100.	Vigeo Eiris
Independent variables		
Taxonomy Exposure	Taxonomy Exposure measures a firm's share of revenue exposed to the EU Taxonomy.	ISS ESG
SC Alignment	SC Alignment measures a firm's share of revenue complying with technical screening criteria for SC to climate change mitigation.	ISS ESG
Relative SC Alignment	Relative SC Alignment is defined as a firm's SC Alignment divided by its share of revenue exposed to the EU Taxonomy. (+)	ISS ESG
Full Taxonomy Exposure	Full Taxonomy Exposure is a dummy variable based on firms' Taxonomy Exposure. It takes a value of 1 if a firm's revenue exposed to the EU Taxonomy is equal to 100%, and 0 otherwise. (-)	ISS ESG

(Continued on next page)

Variable	Description	Source
Control variables		
Domicile	We introduce three dummy variables, namely EU27, North America, and Rest of the World, indicating the firms' domicile.	Refinitiv
Industry classification	We introduce a dummy variable for each industry sector of the NACE classification system.	Refinitiv
ln(Market Capitalization)	The variable captures a firm's logarithmized market capitalization.	Refinitiv

This table provides a description and the source of the variables used. The expected directions of the regression coefficients are indicated in parentheses.

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