Corporate Climate Practices and Uses of Greenhouse Gas Reporting: Conceptualizing Responsibility, Filling Reporting Gaps, and Assessing Strategic Accounting

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Abstract

Corporate Climate Practices and Uses of Greenhouse Gas Reporting: Conceptualizing Responsibility, Filling Reporting Gaps, and Assessing Strategic Accounting

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This dissertation investigates the meanings and practices of corporate climate responsibility (CCR), with a special focus on greenhouse gas (GHG) accounting. Insufficient climate regulation has given rise to many fragmented options for corporate climate action. This enables inconsistent and strategic uses of climate practices, consequently impinging on effective climate mitigation and understandings of corporate climate impacts. I address these issues within the three manuscripts of this dissertation. The first manuscript improves our understanding of CCR by identifying four frames in which CCR is conceptualized and determining whether each frame aligns with a social justice perspective on responsibility. The second manuscript addresses the gap in company-level emissions data resulting from incomplete GHG reporting. We train three machine learning models to predict company-level Scope 1 emissions and use the best model to estimate global emissions from public companies. The third manuscript investigates whether companies are strategically delineating their organizational boundaries according to different consolidation approaches when conducting GHG accounting. The first manuscript demonstrates that CCR is conceptualized according to scientific, social, legal, and economic frames. We find that the scientific frame is most aligned with a social justice perspective on responsibility, while the economic frame is least aligned. According to these insights, we provide recommendations for a new and comprehensive understanding of CCR. In the second manuscript, our best model shows an improvement in prediction accuracy compared to a benchmark study. We estimate that emissions from public companies are 22% (11.4 $GtCO_2e$) of global GHG emissions in 2021. We also find that reporting companies make up 82% of global corporate emissions, implying that high emitters are already reporting their emissions. The third manuscript results suggest that companies are not using consolidation approaches strategically. However, companies are not transparent about why they choose certain consolidation approaches. Altogether, this research highlights the need for a common understanding and adoption of CCR and the climate practices which define it. In doing this, we help guide companies and policymakers to prioritize certain climate practices over others. While companies must continue to report their emissions and be more transparent about their accounting methodologies, there should be an increased focus on implementing carbon management systems that facilitate real decarbonization.

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Contribution of Authors

Chapter 2 (Manuscript 1): The study design, data collection, analysis of results and first iterations of the written manuscript were my own work. The second author, Dr. Claudine Mangen, provided early conceptual input by introducing me to the social justice theory employed in the study. In preparation for submission to the Journal of Business Ethics (submitted in December 2022), Dr. Mangen also contributed heavily to the editing of the manuscript, which included highlighting where clarification and additional evidence was needed and revising the writing to improve clarity and reduce word count. The third author, Dr. H. Damon Matthews, contributed high-level input during the early iterations of the work which included suggestions for the presentation format of the results and re-organizing parts of the paper.

Chapter 3 (Manuscript 2): This study was completed in collaboration with Dr. Elham Kheradmand and is in preparation for publication. High-level inputs were also provided by Dr. H. Damon Matthews. I directed the collaboration and overall design of the study. This included establishing the study motivations, completing the background research and literature review, designing the feature selection methodology, collecting data, pre-processing data, choosing the appropriate error metrics and output figures, analyzing the results, and completing all written work on the manuscript. Dr. Kheradmand contributed her knowledge of machine-learning to run several tree-based algorithms in Python, which encompassed uploading the data, optimizing algorithm hyperparameters, and calculating error metrics. Dr. Kheradmand provided the SHAP value figures and the model outputs (the predictions of log-Scope 1 emissions) based on input data which I provided.

Chapter 4 (Manuscript 3): This study was carried out by me. Dr. H. Damon Matthews provided suggestions to improve the analyses and discussion. Dr. Shannon Lloyd provided suggestions for restructuring the research questions and the types of analysis that could be used to test those questions. This study was originally inspired by questions that arose from the results of contract work I completed for the World Resources Institute in 2021 together with Dr. Lloyd and colleague Kian Rahimidehban. The study investigated literature on, and patterns of corporate GHG accounting and reporting.

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Chapter 1: Introduction

1.1. Climate change and the failure of governments

There is unequivocal evidence that greenhouse gas (GHG) emissions stemming from human activities are causing the warming of the earth's climate (IPCC 2021). To date, anthropogenic climate change has caused an increase of 1.2°C in global average temperature (Climate Action Tracker 2022) and we are already seeing impacts to human and ecological systems. These include irreversible losses to ecosystems, threats to food and water security, adverse effects to human health, loss and damage to infrastructure, and adverse economic effects (IPCC 2022). Disappointingly, international efforts to curb rising temperatures have largely failed (Stoddard et al. 2021). Some governments have made efforts to regulate emissions through carbon policies like cap-and-trade systems or carbon taxes (Meckling and Jenner 2016; Villoria-Sáez et al. 2016), but global emissions continue to rise (Friedlingstein et al. 2022). In 2015, countries came together to adopt the Paris Agreement which established the goal of remaining below 1.5°C of global warming to avoid dangerous climate change (UNFCCC 2015). Despite this show of solidarity between states, we remain on track for 2.7°C by the end of the century following current policies (Climate Action Tracker 2022). Such projections are extremely alarming and faith in the world's governments to mitigate climate change is waning.

1.2. What about the corporate world?

While governments have struggled to execute on their climate promises, scrutiny on the corporate world as grown. Considering they are major emitters of GHGs, stakeholders have put increasing pressure on companies to act on climate change. Some would also argue that corporate growth and profit-driven motives perpetuate consumption habits, which are incompatible with a low-carbon society (Stuart et al. 2020; Wright and Nyberg 2017) and indirectly contribute to climate change. Companies also hold great political influence which can impact climate policymaking (Brulle 2018; Streck 2020). This influence on climate policy is reflective in corporate lobbying, which, for instance, played a role in preventing the United States (U.S.) from ratifying the Kyoto Protocol in 1998 (Jones and Levy 2007). Given that companies contribute to climate change directly and indirectly, they carry a responsibility to mitigate such impacts.

The combination of government failures to implement sufficient climate regulation and the increasing pressures on companies to act have resulted in a regulatory vacuum that has been filled by voluntary measures (Southworth 2009). Various institutions and organizations–often working together with companies that fund them–have developed their own forms of climate guidance (Streck 2020; Waddock 2008). Examples include voluntary disclosure schemes such as the CDP (formerly, Carbon Disclosure Project), voluntary carbon markets, standards for GHG accounting (e.g., GHG Protocol Corporate Standard), climate-risk reporting (e.g., Task Force on Climate-related Financial Disclosures), and emissions target-setting (e.g., Science-Based Targets initiative). Companies can also choose to address climate change through sustainable investments, low-carbon technology development, renewable energy purchases, or energy efficiency improvements (Johnson et al. 2023). This myriad of climate-action options comprises a broad and incoherent framework for corporate guidance on climate change. Not only does this make it difficult for the public to discern which companies are climate-responsible, but it also results in loopholes and creates room for symbolic, rather than substantial, corporate climate strategies. In fact, a damning report by the NewClimate Institute (2022) demonstrated that companies engaging in voluntary climate practices are often exaggerating or misrepresenting their climate initiatives and progress. Academic studies have come to similar conclusions. For instance, companies wrongly use the purchase of renewable energy claims to report emissions reductions (Bjørn, Lloyd, et al. 2022) and they use language tools to mislead the public into believing that they are engaging in real climate solutions, when in fact, they are not (Jaworska 2018).

Circumventing the unconsolidated guidance on corporate climate action, academics have studied different types of practices and strategies in isolation, such as climate disclosure (LoPucki 2022; Stanny 2013), GHG accounting (Dragomir 2012; Klaaßen and Stoll 2021), and emissions target-setting (Bjørn et al. 2021; Walenta 2020). The starting point of such analyses is the climate practice in question. While this research is of value, it is failing to address questions of whether or how such practices reflect climate-responsible actions. Having a consensus on responsible corporate climate action would improve how companies are evaluated with regards to their practices and could affect which practices researchers, policymakers, and companies choose to focus on.

Corporate social responsibility (CSR) is a commonly referenced concept in organization science which begins to develop a consensus on corporate climate responsibility. CSR is a management concept that guides companies to voluntarily address their economic, social, and environmental impacts (Bondy et al. 2012; Matten and Moon 2008). However, being broad in scope, CSR is interpreted and implemented differently across companies (Bondy et al. 2012). CSR is also typically seen as a strategic or symbolic effort (Hoque et al. 2018; Wittneben et al. 2012). Consequently, CSR remains an inadequate concept for assessing corporate responsibilities for climate change specifically (Weber and Hösli 2021).

1.3. Corporate GHG accounting: a cornerstone for understanding climate impacts

A corporate practice that serves the basis for understanding the climate impact of a company is GHG accounting[1]. GHG accounting is a practice that quantifies the amount of GHGs emitted by a company and is typically reported according to three scopes: Scope 1 (direct emissions from owned or controlled sources); Scope 2 (indirect emissions from the generation of purchased electricity); and Scope 3 (all other indirect emissions resulting from sources not owned or controlled by the company) (WRI and WBSCD 2004). A GHG inventory thus provides insight into the company's direct and indirect emissions and their contributions to climate change.

GHG accounting is essential for implementing strategies that help mitigate climate change, both at the company-level and global scale (Luers et al. 2022). In fact, it is often a prerequisite for tracking the impacts of other climate practices. For example, emissions target-

[1] Also referred to as "carbon accounting" or "carbon footprinting" in the literature.

setting is only possible if the company has a GHG inventory for their base-year (Bjørn, Tilsted, et al. 2022). GHG accounting is also necessary for monitoring how operational, structural, or efficiency changes impact emissions and determining whether the company is on track to reach its targets. Having a reliable corporate emissions inventory at a global scale is also important for reconciling numbers with national and international estimates. Interoperable GHG inventories are crucial for assessing the effectiveness decarbonization policies and legitimacy of low-carbon investments (Luers et al. 2022).

At present, to gain insight into company-level emissions we rely on primarily voluntary corporate efforts to conduct GHG inventories[2]. This is a somewhat demanding task that requires collecting, at the very least, fuel, refrigerant, and electricity use data, followed by researching appropriate emissions factors (ratios relating emissions to a proxy measure of an activity releasing emissions) in order to estimate Scope 1 and 2 emissions (WRI and WBCSD 2004). Research has demonstrated that corporate GHG accounting and disclosure is not yet widespread (Hadziosmanovic et al. 2022; LoPucki 2022; Stanny 2013). Therefore, the costs of GHG accounting–which may outweigh the benefits–could be contributing to incomplete reporting among companies. This results in a gap in corporate emissions data at both the company and global levels.

The most widely used accounting standard is the GHG Protocol; a tool used for quantifying and managing GHG emissions (WRI and WBCSD, 2004). However, several issues and loopholes in the Protocol's methodology have been identified (Lopucki 2022). For instance, companies have the option to delineate the organizational boundaries of their inventory according to different consolidation approaches (WRI and WBSCD 2004). Several studies have highlighted how this methodological choice can majorly impact reported emissions (Dragomir 2012; LoPucki 2022; Smith 2016), which in turn compromises the reliability of corporate GHG accounting. Some academics have raised suspicions that companies could be using consolidation approach choices strategically (Dragomir 2012; Haslam et al. 2014). So far, there have been no analyses testing this claim, and consequently no evidence to suggest its veracity either.

Altogether, fragmented understandings and implementations of corporate climate responsibility cause confusion and stand in the way of effective corporate climate practices. Furthermore, our understanding of corporate climate impacts at both the company-level and global scale is hindered by incomplete GHG reporting among companies and discretional choices in GHG accounting methodologies, such as consolidation approach choices. These issues have led to the motivations of this research which I describe in the next section.

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[2] There are some promising regulatory developments of late that would oblige companies in the United States and Europe to publicly report their GHG emissions. In March 2022, the U.S. Securities Exchange Commission proposed a climate disclosure rule that would require many public companies to disclose their Scope 1 and 2 emissions, and in some cases Scope 3 (SEC 2022). The finalized rule is anticipated to be released in April 2023 (Kerber 2023). In Europe, the Corporate Sustainability Reporting Directive entered into force in January 2023 and will require public companies to report on their GHG emissions, among other environmental, social, and governance information, beginning in 2025 ("Corporate sustainability reporting" n.d.).

1.4. Research objectives

My research has been motivated by a desire to make it clearer to companies which climate practices are most meaningful, to help stakeholders and policymakers identify truly climate-responsible companies, to help business leaders and managers allocate their time and resources towards impactful climate practices, to provide a corporate GHG data alternative, and to clear the air about whether companies are making deliberate decisions in their GHG accounting methodologies that could be construed as misleading. Accordingly, I explore the largely unarticulated concept of corporate climate responsibility and what it *should* mean. Thereafter, I focus on the responsibility of GHG accounting: how we can gap-fill data on company-level GHG emissions and whether companies are conducting GHG inventories strategically. I now present the research objectives of the three manuscripts in this dissertation:

Manuscript 1 (Chapter 2): What does climate responsibility mean for companies and what practices should a climate-responsible company enact? The aim of this study is to propose a new conceptualization of corporate climate responsibility that is distinct from corporate *social* responsibility and that is aligned with a collective and forward-looking notion of responsibility. This research improves our understanding of corporate climate responsibilities using a frame analysis, finding that corporate climate responsibilities are understood within scientific, social, legal, and economic frames. These frames are evaluated according to principles of the responsibility for justice theory (Young 2011), from which final recommendations for a comprehensive conceptualization of corporate climate responsibility are made. This paper was submitted to the Journal of Business Ethics in December 2022.

Manuscript 2 (Chapter 3): The objective of this study is to develop a machine learning model to estimate company-level Scope 1 emissions and then employ the model to provide an estimate of global emissions from non-reporting public companies. An earlier and heavily condensed iteration of this work was presented at the NeurIPS 2022 Workshop on Tackling Climate Change with Machine Learning and is available from *https://www.climatechange.ai/papers/neurips2022/56.*

Manuscript 3 (Chapter 4): Are companies using consolidation approaches in GHG accounting strategically? And why are companies changing their consolidation approach? This study investigates the suspicion that companies are using methodological choices in GHG accounting–specifically the use of consolidation approaches which determine organizational boundaries–strategically. Thus, the aim of this study is twofold: to identify the motivations behind consolidation approach choices and to evaluate how changing them affects the emissions profile of a company.

1.5. Thesis format

This dissertation has been prepared following a manuscript-style format. Chapter 1 has introduced the research context, relevant literature, and key research objectives. Chapters 2, 3, and 4 are manuscripts, each which contain their respective introduction, literature review, and conclusion. Chapter 5 presents the overall conclusions of the research and is followed by the dissertation references and appendices.

Chapter 2: Rethinking corporate climate responsibility: a social justice approach

2.1. Abstract

Presently, many options for corporate climate action exist (e.g., disclosing climate-related information, setting emissions targets, and purchasing emissions offsets), which results in poor and conflicting understandings of corporate responsibilities for climate change and ineffective climate action. In this study, we seek to improve our understanding of corporate climate responsibilities (CCR) by asking: What does climate responsibility mean for companies and what practices should a climate-responsible company enact? We answer these questions in three steps. First, we review academic and non-academic literature on CCR. We find that it conceptualizes CCR using scientific, social, legal, and economic frames, which, as we show, shape corporate climate initiatives and assumptions about climate responsibilities. Second, we evaluate these four frames using Iris Marion Young's theory of responsibility for justice (Young 2011), discussing whether and how they align with it. Finally, we use our insights to make recommendations for a new, comprehensive CCR. Our study contributes a new conceptualization of CCR to the research field of corporate responsibility, thereby responding to calls to establish CCR as its own concept (Weber and Hösli 2021). Our CCR recommendations help guide companies and policymakers in prioritizing specific corporate climate efforts over others.

2.2. Introduction

With growing calls for corporate action on climate change, many companies respond by incorporating climate-related initiatives into their communications, operations, and supply-chains. Such initiatives are typically embedded in corporate social responsibilities (Jaworska 2018; Weber and Hösli 2021), which companies often disclose in sustainability reports (Depoers et al. 2014). Corporate social responsibility (CSR) can be understood as a management concept whereby businesses voluntarily engage in practices that contribute to improving societal good and focus on addressing and communicating their economic, social, and environmental impacts (Bondy et al. 2012; Matten and Moon 2008). Nevertheless, the meanings of CSR have been continuously debated; there remains no universal set of CSR principles or structures that companies follow (Freeman and Hasnaoui 2010; Matten and Moon 2008). A large literature shows how CSR manifests differently across companies, industries, and regions (Beschorner and Hajduk 2017; Bondy et al. 2012; Gjølberg 2009; Murillo-Avalos et al. 2021). Furthermore, CSR is routinely strategic, with goals primarily oriented toward profit-making rather than meaningful social or environmental good (Andrés et al. 2019; Bondy et al. 2012; Hoque et al. 2018). So far, there is insufficient evidence to confirm that CSR initiatives have net positive impacts on society or the environment (Barnett et al. 2020; Halme et al. 2020), and even less evidence to show any mitigating effects on climate change (Li et al. 2021).

The extensive scope and manifestations of CSR, combined with its voluntary nature and lack of climate-specific guidelines have left companies with many fragmented options for addressing climate change. A few examples include conducting greenhouse gas (GHG) inventories, setting emissions targets, offsetting emissions, making sustainable investments, seeking compliance with various standards[3], or disclosing climate initiatives to external organizations[4]. This myriad of options makes it challenging to understand the meaning of corporate climate responsibility (CCR), which obscures the requirements for mitigating climate change. Our paper seeks to improve our understanding of CCR. We ask what climate responsibility means for companies and what practices a climate-responsible company should enact.

We answer this question by proposing a new conceptualization of CCR that is different from CSR, can be understood by different actors, and is grounded in the responsibility theory developed by Young (2011). We develop our CCR conceptualization using a three-step approach. First, we review the academic and non-academic literature and show how interpretations of CCR in corporate contexts are grounded in scientific, social, legal, and economic frames. Second, we use the Social Connection Model (SCM) from (Young 2011) to evaluate the frames. Finally, we use our evaluation of the frames to develop our conceptualization of CCR.

We offer three contributions to the literature. First, we propose a new conceptualization of CCR, thereby responding to calls to establish CCR as distinct from CSR (Weber and Hösli 2021) and to provide more in-depth discussions of responsibilities (Böhm et al. 2022). Our CCR conceptualization helps us understand the divergent approaches to addressing climate change in the corporate context, facilitating more impactful and viable climate solutions. Second, we show how Young's SCM and its conceptualization of responsibility for social justice can be extended to address responsibility for environmental justice, which, in our case, focuses on climate change. By applying Young's SCM to a different phenomenon, we open the door for using the SCM to address other types of wicked problems and environmental injustices. Third, our conceptualization of CCR is of interest to actors in the corporate field (e.g., companies, regulators, and investors). It can motivate and guide companies in prioritizing their climate practices, help regulators design and implement more effective corporate climate directives, and direct investors and the public in identifying climate-responsible companies.

The paper is structured as follows: Next, we present an overview of the recent literature on ethics, responsibility, and climate change in the corporate context. We discuss the theoretical background which includes the SCM. We then present our methodology, followed by an introduction of the four CCR frames through a literature review and illustrative examples. Next, we evaluate how the CCR frames measure up against the conditions of responsibility in the SCM. Finally, we develop our conceptualization of CCR and provide our conclusions.

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[3] For example, a common standard followed for conducting GHG inventories is the GHG Protocol (WRI and WBCSD 2004) and a common standard for reporting on climate and other sustainability initiatives is the Global Reporting Initiative (GRI 2021).

[4] While many companies disclose their climate initiatives within their public reports, a growing trend is to disclose to the CDP– presently, the primary global climate disclosure organization.

2.3. Research on ethics, responsibility, and climate change

Climate change has become a salient issue in the field of business ethics (Böhm et al. 2022). A large literature has explored the role of ethics in corporate responses to climate change (Besio and Pronzini 2014; Haney 2017; Hormio 2017). Yet, compelling ethical arguments for corporate climate action have not yet provided enough direction or clarity on what effective climate action should be, nor what corporate responsibility for climate change should look like. This void is highlighted in the recent essay by Böhm et al. (2022, p. 837), wherein climate change, among other issues, is discussed as a grand ethical challenge for which "an in-depth and systematic discussion of responsibilities is not yet sufficiently developed."

Our review of the literature points to two issues that have stunted the conceptualization and development of CCR. First, a large literature attempts to define, identify, or describe activities related to CSR (Baden and Harwood 2013; Matten and Moon 2008; Sheehy 2015), yet little research attempts to do the same for corporate responsibilities specific to climate change. Instead, climate responsibilities are largely understood and discussed as a CSR (Allen and Craig 2016; Heikkurinen and Mäkinen 2018; Li et al. 2021). While this is not necessarily a false premise from which to begin, it constrains the discourse on CCR; responsibility for climate change is multifaceted and complex, so it cannot be adequately addressed through the already wide lens of CSR. In the words of Weber and Hösli (2021, p. 88), CSR is "…at risk of not being specific enough to be of actual use in the context of meaningful climate change mitigation […]." We address this issue by reviewing the literature to identify and discuss climate-specific corporate initiatives. Rather than focusing on the broad social responsibilities of companies, we zoom in on corporate climate responsibilities.

Second, the many diverse corporate climate practices imply that corporate responsibility can take on very different forms, which can also depend on how the climate change issue is framed. For example, some studies focus on climate change as a corporate ethical issue that can be dealt with via moral communications and decision-making (Besio and Pronzini 2014; Hormio 2017), whereas others discuss it as an economic issue addressed via management of business risks and opportunities (Elijido-Ten and Clarkson 2019; Nyberg and Wright 2016). Although many studies provide insights into specific climate-related corporate practices (Andrade and Oliveira 2015; Dahlmann et al. 2019; Dhanda and Malik 2020), few explore these practices concertedly, nor whether the practices actually shoulder a climate responsibility. Without a responsibility framework from which to evaluate corporate climate initiatives together, CCR will remain unclear. We tackle this issue by studying corporate climate practices jointly and evaluating them using a theoretical framework of responsibility. We thus facilitate a new and more specific conceptualization of CCR.

2.4. Theoretical background

We now discuss the theoretical underpinnings of our CCR conceptualization. We draw on the social connection model (SCM) (Young 2011) to explain how climate change can be viewed as an environmental injustice. We then explain how the SCM relates to CCR.

2.4.1. The Social Connection Model and injustices

In "Responsibility for Justice," Young (2011) proposes the SCM as a framework for thinking about responsibility in our complex and interconnected world. The SCM is anchored in the idea that human-created structures can be unjust and that responsibility for these structural injustices can only be adequately addressed in a collective and forward-looking manner. A structural injustice exists when "social processes put large groups of persons under systematic threat of domination or deprivation of the means to develop and exercise their capacities, at the same time that these processes enable others to dominate or to have a wide range of opportunities for developing and exercising capacities available to them." (Young 2011, p. 52). Injustices are produced and reproduced via the cumulative actions of many individuals acting at different times and spaces and within accepted institutional rules and societal norms (Young 2011). In the SCM, assigning fault for a structural injustice to an agent or action is consequently illogical.

Young argues that the conventional understanding of responsibility—the liability model (LM) of responsibility—is inadequate to address structural injustices. The LM assigns guilt to a perpetrator for wrongdoing in the past and focuses solely on the perpetrator's responsibility to rectify the situation while absolving others. Young (2011, p. 91) distinguishes between guilt and responsibility: guilt is attributable to those who commit a wrong, whereas responsibility is assigned to those whose "active or passive support for governments, institutions, and practices enables culprits to commit to crimes and wrongs."

The SCM has five characteristics that distinguish it from the LM (Young 2011). First, the SCM is not isolating and does not seek to pin blame on the individual. Instead, responsibility is borne by "thousands or millions of people in institutions and practices" (Young 2011, p. 106), making it difficult to establish causality between an action and an injustice. A person's behaviour may not entail criminal, legal, or moral wrongdoing at all, but is like that of many others, remaining within norms so that they avoid being causally linked to injustice. An isolating concept of responsibility, like the LM, is inadequate for handling structural injustices resulting from the participation of many actors.

Second, the SCM does not assume that the background conditions of generally accepted behaviours are morally acceptable. Instead, "[w]hen we judge that a structural injustice exists, we are saying precisely that at least some of the normal and accepted background conditions of action are not morally acceptable" (Young 2011, p. 107). Individuals are responsible for this injustice because their legitimate actions contribute to an aggregate, though sometimes far-removed, unjust outcome. By contrast, the LM identifies wrongdoing as deviance from some moral baseline of behaviour (e.g., a norm). It thus views this baseline as acceptable.

Third, the SCM is forward-looking more than backward-looking. Since structural injustice is not limited to one point in time but is ongoing and likely to persist unless social processes change, it is not helpful to turn to the past for specific wrongdoings, especially since it is difficult to identify causal links between specific actions and structural injustice. Thus, the SCM extends responsibility to all who contributed or continue to contribute to processes with unjust outcomes. Still, the SCM has a backward-looking aspect, since it is necessary to consider how structural injustices come about.

Fourth, the SCM emphasizes that responsibility is shared. A person bears responsibility but never alone because harms result from many individuals' actions. Responsibility is always individual, partial, *and* collective. Bearers of responsibility acknowledge that they belong to a collective that contributes to structural injustices through the widespread and complex interactions of many. Even the victims of the injustices may share responsibility.

Fifth, responsibility is discharged only through collective (instead of solely individual) action, because the structural "processes can be altered only if many actors from diverse positions within the social structures work together to intervene in them to try to produce other outcomes" (Young 2011, p. 111). The SCM emphasizes political responsibility (rather than a moral or legal one, like the LM), which involves organizing and encouraging collective action with many other responsible individuals through some form of public engagement. Political responsibility, thus, does not refer exclusively to government or state action, but may occur through social engagement.

2.4.2. Climate change and injustices in the Social Connection Model

The SCM is well-suited to address climate change because climate change shares three features with the SCM's injustices: it results from complex processes and structures, the causes of its harmful effects (i.e., the warming of the earth and the resulting social, economic and environmental injustices) are difficult to attribute to individuals, and individuals can simultaneously be victims and perpetrators. We now discuss each one of these three features.

These chains of causality underlying climate change are obscure and difficult to track. Scientifically speaking, climate change is caused by rising atmospheric GHGs, which, in turn, result from interwoven local and global, past and ongoing, social, economic, and political processes and structures (e.g., a consumption-based and growth economy) (Schor and Jorgenson 2019). Accordingly, climate change has been recognized as a wicked problem, which emphasizes its complex and indeterminate chains of causality and their interconnected and conflicting dynamics at many scales (Head 2022; Sun and Yang 2016).

Unsurprisingly, pinpointing and attributing blame for the harmful effects of climate change (e.g., their loss and damage) is challenging at best and impossible at worst.[5] The science of causally relating loss and damage to anthropogenic GHG emissions rather than to natural climate or weather variability, although improving, is still inadequate (James et al. 2018). It is difficult to determine the exact climate effect of an additional amount of emitted GHG because of temporal variations in GHGs, global changes to the atmosphere, and different climate tipping points (Hormio 2017). If loss and damage could be causally related to anthropogenic GHG emissions, a further challenge would consist of determining who caused the GHG emissions. To date, different frameworks have been used to attribute responsibility; they encompass different emissions accounting approaches (e.g., extraction, production, or consumption emissions), target different actors (e.g., states, organizations, individuals), and consider temporal dimensions of emissions accounting (e.g., present or past emissions). In addition to these scientific challenges, legally establishing causality in climate litigation is difficult due to varying legal rules and

[5] Loss and damage formally refer to "the actual and/or potential manifestation of impacts associated with climate change in developing countries that negatively affect human and natural systems" (UNFCCC Subsidiary Body for Implementation 2012). We extend this definition to all potentially relevant actors (i.e., communities, organizations and institutions, governments, and industrialized countries).

standards of evidence between jurisdictions and a lack of adequate legal precedence (Stuart-Smith et al. 2021). Assigning blame is further complicated when actors behave within legal bounds or accepted norms in their spaces (e.g., geographic, social, cultural, industry, or market spaces).

Finally, victims of climate change can also be perpetrators, and some perpetrators have more means than others to escape unjust climate change outcomes. For example, more than industrialized countries, developing countries are vulnerable to the environmental and economic effects of climate change (Nath and Behera 2011; Paavola and Adger 2006). Although developing countries also contribute to rising atmospheric GHGs, they often lack the economic and political means to address and adapt to climate change, compared to industrialized countries —the historical perpetrators of GHG emissions (Neumayer 2000) that have these means. Similarly, small companies may be affected by climate change outcomes more than large companies that are more resilient to market shocks and cycles (Fort et al. 2013).

2.4.3. Corporate responsibility for climate change

We now discuss how companies contribute to climate change, both directly and indirectly. Their direct contribution arises from GHGs they emit into the atmosphere. Direct emissions are categorized as Scope 1 by the GHG Protocol (GHGP); they result from burning fossil fuels, physical or chemical processing, or fugitive emissions[6] from sources that companies own or control (WRI and WBSCD 2004). Some companies produce enormous Scope 1 emissions due to the nature of their industry or operations (e.g., cement producers). In contrast, others (e.g., office-based companies) may have small Scope 1 emissions (e.g., from on-site generators).

Companies can indirectly contribute to climate change by facilitating GHG emissions in the supply chain. Notably, companies that extract and distribute fossil fuels perpetuate how global supply chains, and society at large, rely on fossil fuels (Heede 2013). Companies also indirectly contribute to climate change by producing or consuming services or products that cause emissions upstream or downstream in supply chains (e.g., by generating purchased electricity or other sources not owned or controlled by the firm), which are known as Scope 2 and Scope 3 emissions[7] (WRI and WBSCD 2004).

Even more indirectly, but no less significantly, corporate prioritization of growth and profitability contribute to climate change (Wright and Nyberg 2017). These goals legitimize a consumption ideology (i.e., the belief that we need to experience and own more) and individuality (i.e., our immediate, individual well-being associated with consumption). This legitimization normalizes a consumer society that is less concerned with the collective and long-term consequences of consumption, such as climate change. A consumer society preserves and prolongs the need for unsustainable energy production that involves GHG emissions. As companies encourage consumption and we follow suit, they grow, expanding the economy

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[6] Fugitive emissions are the result of equipment leaks or gas discharges from venting or flaring (WRI and WBSCD 2004).

[7] Scope 2 emissions are indirect emissions resulting from the consumption of purchased energy including electricity, steam, heat, or cooling. Scope 3 emissions, classified into 15 categories, are all other indirect emissions that occur upstream and downstream in the value chain of the company (WRI and WBSCD 2004).

(through increases in gross domestic product) (Burke et al. 2015; Schor and Jorgenson 2019). Yet, sustaining a growth economy is incompatible with reducing global emissions (Anderson and Peters 2016) even under economic models that depend largely on sustainable energy production (Antal and Bergh 2014; Hickel and Kallis 2019).

Companies can further delay meaningful climate progress by reinforcing ideologies like climate skepticism and denialism, particularly through funding and climate lobbying. Companies that fund organizations like grassroots lobby firms and think tanks influence the public communications of these organizations (e.g., press releases, website articles, policy statements) (Farrell 2016). These communications can seek to brush off climate change and polarize discussions around it, creating controversy and delaying climate progress (Farrell 2016). Furthermore, companies can significantly shape political processes; they invest massively in climate lobbying (Brulle 2018), especially when they risk being affected by climate legislation (Brulle 2018; Downie 2017). For example, corporate lobbying was vital in preventing the U.S. from ratifying the Kyoto Protocol (Hormio 2017; Jones and Levy 2007). In the European Union, companies from various industries influenced the GHG emissions trading scheme (Markussen and Svendsen 2005). Although most of the world's largest companies are not strategically engaged in climate policy, many fund organizations that oppose climate policy, undermining any beneficial effects they claim their own climate initiatives can generate (Influence Map 2019).

In accordance with the SCM, our discussion illustrating the direct and indirect ways companies contribute to climate change implies that all companies carry some climate responsibility, which is shared and forward-looking.[8] However, the nature and extent of this responsibility are challenging to define notably because of the temporal dimension that characterizes corporate climate contributions. For example, companies may have historically produced large quantities of emissions, but are presently reducing them significantly; or, their lobbying efforts and climate initiatives may have shifted over time with changes in their leadership. Given this evolution in their contributions to climate change, how do we attribute climate responsibility to them?

Answering this question using a conventional approach to responsibility like the liability model is difficult, if not impossible, because the LM requires a causal relationship between corporate actions and climate change outcomes, which is challenging to establish. In contrast, the SCM does not require a causal relationship but is premised on the practices of many actors that continuously contribute to outcomes, which engages their collective and ongoing responsibility. Hormio (2017) argues that even if we consider corporate activities of the recent past when science on the anthropogenic nature of climate change was established, blaming companies individually would ignore "the combined failures of nearly all of the actors in the system." (p. 324) His systems approach to corporate climate responsibility (CCR) is comparable to responsibility in the SCM, which acknowledges the complex social connections between actors that underlie collective responsibility.

[8] We extend the SCM's focus from the individual *person* to individual *companies*. Similar to how some national laws recognize companies as legal persons capable of actions (e.g., free speech in U.S.) (Schane 1986), we can recognize companies as actors capable of climate practices.

2.5. Methodology

We briefly explain our method—frame analysis—before describing our data and analysis.

2.5.1. Frame analysis

The SCM helps us conceptualize responsibility for climate change in the corporate context. However, the SCM does not point to how this responsibility—CCR—should be understood and materialized. The many ways researchers and practitioners have discussed or acted upon CCR suggest that there are multiple understandings of CCR. We explore this multitude of CCR meanings using frame analysis.

A frame describes how we construct meaning and act (Goffman 1974; Rein and Schön 1993). A frame is often shared by a cohesive group of people with similar beliefs and values (Ascui and Lovell 2011). Proponents of a frame tend to select and emphasize specific aspects of an issue (Goffman 1974), which can be conceptualized as different themes around an issue. Their work in developing a frame involves three core tasks (Snow and Benford 1988): diagnosis (i.e., defining the problem and attributing blame or causality), prognosis (i.e., suggesting solutions for the problem, including associated strategies or tactics), and motivation (i.e., inspiring and mobilizing action).

While frame analysis has been used widely in social sciences (Clune and O'dwyer 2020; Cornelissen and Werner 2014), we draw on Ascui and Lovell (2011) who employ frame analysis to explore carbon accounting. They illustrate different carbon accounting frames, explaining why and how measuring carbon has been interpreted and carried out differently by various actors over time. Similarly, we explore how there are different CCR frames, analyzing variations in how CCR is assumed and enacted.

2.5.2. Data and analysis

We conduct our frame analysis of CCR in five stages.

Stage 1: We used both academic and non-academic sources. To identify academic studies, we conducted a systematic search of peer-reviewed studies that address corporate responsibilities related to climate change published between 2007 and 2022 using the research databases Web of Science and Scopus. In our search, we used keywords including "company," "corporate," "corporation," "firm," "business," "climate change," "greenhouse gas," "ghg," "carbon," "global warming," "responsibility," "role," "duty," "accountability," "action," "practice," or "initiative."[9] To identify non-academic publications, we used our knowledge of organizations (i.e., governments, independent agencies, non-profit organizations, standard-setters, disclosure bodies, or other non-governmental bodies), references in academic studies, online news sources referencing specific documents, and Google web searches. We visited the associated websites to obtain documents related to CCR.

[9] Where applicable, keyword searches were also conducted in their plural form.

Stage 2: Using the sources identified in Stage 1, we identified practices that illustrate CCR. Examples of such practices include reducing emissions, setting emissions targets, following protocols or laws, disclosing climate-related information, engaging with stakeholders, supporting climate policy progress, reducing climate financial risks, or participating in carbon markets.

Stage 3: Based on keywords related to the practices identified in Stage 2, we conducted a second round of searches to refine our list of academic studies. Our keywords included "emission reduction," "mitigation," "target-setting," "emissions target," "disclosure," "public," "community," "social license," "justice," "lobbying," "law," "policy," "regulation," "investor," "risk," "market," "financial," "carbon price," and "carbon offset."

Stage 4; Using the studies from Stage 3, we identified any explicitly or implicitly mentioned climate actions. We then deducted goals, rationales, or motivations, as well as recurring or common themes that the studies used in their discussions around these actions. Considering how these motivations and themes were similar or different, we assigned the actions to different groups. We ended up with four groups, each reflecting a different frame (i.e., scientific, social, legal, or economic CCR). We discuss this process and the characteristics of each frame in further detail in section 2.6.

Stage 5: We considered how the frames from Stage 4 support a conceptualization of CCR consistent with the SCM. We evaluated whether and how each CCR frame aligns with the five SCM conditions. We then evaluated the actions underlying each CCR frame by considering whether they are isolating, assume background conditions that are acceptable, are shared, are forward-looking, and are discharged through collective action. Based on our evaluation, we characterized each frame as aligned, partially aligned, or not aligned with each SCM condition. We show and explain our characterization in section 2.7.

2.6. Frames of CCR

To identify frames of CCR, we first determined common themes and underlying motivations of different climate actions (henceforth distinguished as "responsibilities") discussed in the literature. To illustrate, Table 2.1 shows three examples of responsibilities we identified from the literature, their associated implicit or explicit motivations, as well as recurring or common themes around the discussions of these responsibilities. We show these three specific examples of responsibilities because they share common motivations and themes which relate to a scientific or technical understanding of what is required to address climate change in the corporate context. As such, we group these responsibilities due to their commonalities, thereby identifying the 'scientific' frame of CCR. We take the same approach for grouping all identified actions and responsibilities from the literature review, thus finally identifying four frames of CCR (scientific, social, legal, and economic). A full list of the identified responsibilities, their goals and themes, and associated frames can be found in Appendix A.

Responsibility or action	**Relevant sources**	**Underlying goals/motivations**	**Themes**
Conduct greenhouse gas inventories that reflect real impacts	Bjørn, Lloyd, et al. 2022; Brander et al. 2018; Dragomir 2012; Hertwich and Wood 2018; WRI and WBSCD 2004	Identify and evaluate reduction actions; Help set targets; Help report on progress; Strengthen global mitigation efforts	Real impacts/reductions; Global mitigation efforts; Emissions reductions; Emissions accounting
Set science-based targets (i.e., in line with global climate goals)	Bjørn, Lloyd, et al. 2022; Bjørn et al. 2021; Hadziosmanovic et al. 2022; Newell 2020; Science Based Targets 2021	Contribute to global mitigation efforts; Align business with global climate goals; Address pressure from stakeholders	Emissions reductions; Emissions targets; Global mitigation efforts
Prioritize and implement real decarbonization solutions	Brander et al. 2018; Bjørn, Lloyd, et al. 2022; IPCC 2018; IPCC 2021; Science Based Targets 2020	Ensure alignment of corporate targets with global targets; Uphold integrity of corporate targets and corporate reduction efforts; Report real progress against targets transparently to stakeholders	Real reductions; Global emissions reductions

Table 2.1: Examples of responsibilities with overlapping or similar motivations and themes, which were grouped and assigned the scientific frame.

Next, we discuss the four frames that characterize discussions around CCR in academic and non-academic literatures. Our discussion explains, for each frame, the themes and prevailing goals, the diagnosis (i.e., what is presented as the problem associated with climate change?), and the prognosis (i.e., what solutions are presented?), which are also summarized in Table 2.2.

2.6.1. Scientific CCR

Scientific CCR aims to reduce atmospheric GHG emissions and is concerned with two problems. First, how can GHG emissions be lowered quickly and effectively? Second, how can responsibilities for lowering GHG emissions be tracked and distributed? Common themes that appear in this frame include a focus on real emissions reductions, GHG accounting, and how such actions contribute to global targets and mitigation efforts.

Scientific CCR addresses the first problem via emission reduction practices, including decarbonization efforts or real emission reductions, combined with emissions-tracking and science-based emissions targets. Reports on climate change from the International Panel on Climate Change (IPCC), the leading source on comprehensive climate science, illustrate this first problem. The reports discuss climate mitigation in the context of limiting global warming to a specific global average temperature, which can be reached following different future emissions scenarios (IPCC 2018; IPCC 2021). These scenarios are based on many underlying factors, including various approaches to lowering emissions, such as energy consumption reduction, renewable energy production, and carbon removal (IPCC 2018). The academic literature evaluates these approaches, often highlighting risks to specific emission reduction strategies. For instance, a large literature has emphasized uncertainties associated with carbon removal (Anderson and Peters 2016; Girardin et al. 2021; Lenzi 2021), implying that emission reduction approaches should focus on lowering emissions in the near term, while considering carbon removal only in the long term (Holz et al. 2018).

Scientific CCR underlines the emission reduction approaches that companies should prioritize, including direct reductions (e.g., consuming less fuel or substituting non-renewable energy sources with renewables) and indirect reductions (e.g., reducing electricity and material consumption). Scientific CCR also highlights the need for companies to prioritize real or physical emission reduction practices over market-based practices. Studies show that market-based initiatives, specifically the widespread practice of purchasing of renewable energy certificates to claim emissions reductions, do not lead to real emissions reductions (Bjørn, Lloyd, et al. 2022; Brander et al. 2018). It further specifies how carbon removal measures—primarily purchased carbon offsets and, more rarely, carbon removal within corporate operations—should be used. If companies procure offsets, scientific CCR highlights that these offsets need to be credible: they must be measured accurately, have a permanent climate impact, and provide an assurance that the offset project must have not occurred without the purchase of the offset in the first place (Thamo and Pannell 2015).

The second problem that scientific CCR tackles is how responsibilities for lowering GHG emissions can be tracked and distributed. It addresses this question via different corporate target-setting methodologies, informed by corporate GHG accounting and global climate targets. GHG accounting estimates a company’s climate impact in terms of the quantity of GHGs emitted and helps calculate science-based emission targets (Bjørn et al. 2021). The gold standard for corporate GHG accounting is the GHG Protocol (WRI and WBSCD 2004), which serves as a foundation for tracking emissions over time. Responsibilities for lowering emissions can then be distributed among companies via science-based emissions targets. Targets are informed by scientifically established global climate goals, which are to remain below a global average temperature increase of 1.5°C or well below 2°C (IPCC 2018; Matthews et al. 2021) The Science-Based Targets Initiative (SBTi) is an organization that assists companies in setting science-based targets for achieving these global climate goals using methodologies that reflect different mitigation responsibilities (Science Based Targets 2021).

2.6.2. Social CCR

Social CCR seeks to uphold human rights through climate justice and considers the ethics and transparency of climate-related actions and business practices. It is concerned with two problems. Do climate solutions provide sufficient attention to climate justice? And are companies' practices and their climate-related initiatives ethical and transparent? Accordingly, common themes that appear in this frame include climate justice and human rights, ethics and morality, and transparency.

Regarding the first problem, academic research stresses that climate change action should not be simplified to the physical requirements of GHG mitigation but should also prevent the negative human rights impacts of climate change (Hormio 2017; Meikle et al. 2016; Robinson and Shine 2018). This concept—that human rights principles must be upheld and protected in the face of climate change—is understood as climate justice (OHCHR 2015). Although there is no universally accepted definition for it, The Mary Robinson Foundation–Climate Justice, for instance, states on its website that "Climate justice links human rights and development to achieve a human-centred approach, safeguarding the rights of the most vulnerable people and sharing the burdens and benefits of climate change and its impacts equitably and fairly. Climate justice is informed by science, responds to science and acknowledges the need for equitable stewardship of the world's resources," ("Principles of Climate Justice" 2022). Accordingly, academic discussions on climate justice often address issues of inequality or inequity, such as those related to the protection of vulnerable or marginalized communities, North-South disparities in historical emissions, rights to development, Indigenous rights, and reparations (Bright and Buhmann 2021; Meikle et al. 2016; Schlosberg and Collins 2014). A pressing concern is that certain climate solutions, such as those focused on purely technical solutions, will exacerbate human rights issues (Healey et al. 2021).

	Scientific CCR frame	Social CCR frame	Legal CCR frame	Economic CCR frame
Themes	• Real emissions reductions • Global mitigation efforts and targets • GHG accounting	• Climate justice and human rights • Transparency • Ethics and morality	• Soft vs. hard climate law • Fiduciary duties • Climate policy/regulation	• Climate risks • Financial impacts • Market-based solutions
Prevailing goals	• Reduce GHG emissions to the atmosphere	• Ensure climate justice and transparency are part of corporate activities	• Ensure climate laws are followed and anticipated • Ensure fiduciary duties are carried out	• Minimize climate risks to the business • Prioritize cost-effective mitigation strategies
Diagnosis	• GHG emissions are not being reduced quickly and effectively • Distribution of mitigation responsibilities is disputed	• Not all climate solutions safeguard human rights • Symbolic efforts, greenwashing • Negative corporate political or public influence (e.g., lobbying)	• Lack of international consistency in climate regulations • Fiduciary duties do not explicitly address climate risks	• Climate change can have negative financial impacts • Companies are exposed to growing climate risks
Prognosis	• Set science-based targets • Reach targets via real reductions or physical decarbonization approaches • Track emissions using GHG accounting	• Incorporate human rights into climate actions • Evade lobbying against climate actions or policy progress • Seek social licenses to operate • Increase transparency	• In absence of hard laws, follow soft laws • Support and help positively shape new climate policies • Explicitly include climate risks in fiduciary duties	• Evaluate and disclose climate risks and opportunities • Use market-based solutions (e.g., carbon pricing, market instruments to claim emissions reductions, offsets)

Table 2.2: Characteristics of climate change responsibility (CCR) frames, including their themes and prevailing goals, diagnosis (the problems), and prognosis (the solutions).

Social CCR proposes that climate justice issues can be addressed through community and stakeholder engagement, and by integrating climate justice principles in corporate risk management and due diligence frameworks. For instance, companies can seek a social license to operate, which is the "the ongoing acceptance and approval of the activities of an industry by local communities and other stakeholders," (Smits et al. 2016, p. 123). This can be done through dialogue and planning with stakeholders affected by their activities, enabling companies to address local needs and identify conflicts between organizational practices and vulnerabilities (Olawuyi 2016). Furthermore, companies can integrate human rights principles into not only their climate-related initiatives, but more broadly, their business frameworks for due diligence and risk management processes (Bright and Buhmann 2021; Macchi 2021; Olawuyi 2016). For example, a report by the International Bar Association argues that companies should develop internal policies and frameworks that align with the United Nations (UN) Guiding Principles on Business and Human Rights pertaining to climate change and justice issues (International Bar Association 2014). It highlights how human rights due diligence is significant for climate justice, enabling companies to identify, anticipate, and respond to how their practices can affect human rights (Olawuyi 2016).

The second problem that social CCR is concerned with is whether corporate practices and climate-related initiatives are ethical and transparent. The academic literature highlights the need to consider the social and moral implications of climate actions (Hormio 2017; Meikle et al. 2016; Robinson and Shine 2018). Hormio (2017), for example, demonstrates how corporate practices have moral implications. He argues that when considering the precautionary principle and scientific evidence of climate change dangers, companies should strive to not only decarbonize, but also refrain from practices that oppose climate progress. Opposition to climate progress can come in many forms. For instance, companies can carry out symbolic activities (e.g., greenwashing), which are problematic as they send confusing signals to stakeholders and society (Dahlmann et al. 2019) and produce "justifiable skepticism about the gap between what firms say and do on environmental issues" (Bowen and Aragon-Correa 2014, p. 107). Moreover, symbolic acts contribute to inaction on climate change because they mask tensions between business activities and climate mitigation requirements, making it easier for companies to evade their climate responsibilities (Ferns et al. 2019). Companies can further oppose climate progress by taking advantage of their powerful political and public spheres of influence on environmental and climate issues (Gray et al. 2020; Hormio 2017; Jones and Levy 2007). For example, fossil fuel companies can manipulate public opinion, casting doubt on climate science (Jones and Levy 2007; Oreskes and Supran 2021). Similarily, companies can delay climate progress through lobbying with goals of impeding climate legislation (Brulle 2018; Downie 2017).

2.6.3. Legal CCR

Legal CCR aims to ensure corporate compliance with soft and hard climate laws, manage corporate influence on regulation, and safeguard that fiduciary duties related to business risks are adequately addressed. It focuses on two questions: How can the lack of consistent climate regulation be dealt with? And how can the ambiguity of the managers' fiduciary duties in the context of business risks related to climate change be dealt with? Common themes in this frame include soft versus hard climate laws, fiduciary duties, and changing climate policy or regulation.

Regarding the first question, climate regulation varies across countries (e.g., climate disclosure rules, national emissions reduction targets, or emissions thresholds for industry sectors), resulting in a patchwork of corporate legal obligations. Climate laws can also vary in hardness, where hardness is determined jointly by a law's obligations, precision, and enforcement (Abbott et al. 2000). A law that is more legally binding, more precise in its requirements, and better enforced is considered a harder law. In contrast, a softer law is more non-binding, has more ambiguous wording, and is less enforced (Abbott et al. 2000; Vihma 2012). Presently, there are no hard climate laws for corporations at the international level since there is no international authority that writes or enforces laws targeting corporate climate practices. This void is due partly to international law applying to nation-states and not companies (Weber and Hösli 2021) and partly to the "nation-state oriented" design of global climate governance systems, which do not sufficiently involve corporate actors (Andrade and Oliveira 2015, p. 375).

This absence creates a regulatory vacuum (Weber and Hösli 2021, p. 86) wherein soft climate laws have emerged (e.g., norms and frameworks for corporate self-regulation and self-reporting) (Kolk and Pinkse 2007). For instance, in the U.S., market-based approaches (e.g., carbon pricing within voluntary trading schemes) have historically beat out regulatory solutions (i.e., hard climate legislation) (Bruno 2019; Jones and Levy 2007). However, recent developments, such as the U.S. Securities and Exchange Commission announcing proposed climate disclosure requirements (SEC 2022), suggest that a proliferation of soft climate laws can propel the development of hard laws (Weber and Hösli 2021; Vihma 2012).

Legal CCR addresses the question of how to deal with inconsistent climate laws by emphasizing that while voluntary climate actions can lead to positive change, regulation needs to play a more significant role in climate change mitigation (Bruno 2019; Streck 2020). In the absence of hard laws, companies should follow soft laws, while also supporting and helping positively shape the gradual hardening of soft laws (Andrade and Oliveira 2015; Bruno 2019; Streck 2020). However, some have cautioned that companies adhere to soft laws (e.g., by self-regulating) not to address climate change but to pre-empt future hard laws or to negatively influence the design of future hard laws (Jones and Levy 2007; Kolk and Pinkse 2007).

The second question underlying legal CCR asks how to deal with the ambiguity of the fiduciary duties of corporate directors and officers in the context of business risks posed by climate change. Traditionally, fiduciary duties are not explicitly concerned with climate change, but with duties of loyalty and care that relate to actions carried out lawfully and in the best interest of the company (Barker et al. 2016; Bruno 2019). Legal CCR argues for new interpretations of fiduciary duties that account for climate risks (Barker et al. 2016; Government of Canada 2019). With the growing financial risks of climate change (Sarra 2018; Weber and Hösli 2021), corporate directors risk acting negligently and disrespecting their fiduciary duties if they ignore them (Bruno 2019; Sarra 2018).

2.6.4. Economic CCR

Economic CCR is focused on the problem of reducing climate change risks to companies. Academic studies demonstrate how companies and other non-state actors conceive and discuss climate change as a business risk (Ferguson et al. 2016; Gasbarro et al. 2017; Nyberg and Wright 2016; Pattberg 2012). They draw on the practice of risk management to reshape climate change into a calculable and manageable problem (Nyberg and Wright 2016; Pattberg 2012).

Accordingly, common themes that appear in this frame include climate risk, financial impacts, and market-based initiatives or solutions to climate change.

Economic CCR argues that solving this problem requires identifying each source of risk and calculating its monetary value, which is then attributed to the risk (Nyberg and Wright 2016; Weinhofer and Busch 2012). This risk management approach to climate change is promoted by several non-state organizations, including the Task Force on Climate-related Financial Disclosures (TCFD) and the Financial Stability Oversight Council (FSOC).[10] For example, the FSOC highlights managing risks and capitalizing on opportunities presented by climate change, stating that "an individual firm is more resilient when it has sound processes for assessing risks and applies appropriate risk management practices. The disclosure of risks, and plans for managing them, can help foster the resilience of the financial system" (Financial Stability Oversight Council 2021, p. 68). The risk management approach prioritizes corporate adaptation to climate change rather than reducing emissions.[11]

Companies manage climate financial risks via voluntary market-based solutions. Pricing carbon emissions, for example, enables companies to trade carbon through established emissions trading schemes or claim emissions reductions by buying carbon offsets or renewable energy certificates (RECs) (Bebbington and Larrinaga-Gonzaléz 2008; Ferguson et al. 2016; Gillenwater 2008). Compared to state-imposed solutions (e.g., carbon taxes), market-based solutions are rationalized as being more cost-effective and providing better incentives to reduce emissions (Ferguson et al. 2016). However, the ability of market-based solutions to physically reduce emissions is doubtful at best (Bjørn, Lloyd, et al. 2022; Brander et al. 2018; Green 2021; Mason and Plantinga 2013).

Economic CCR also stresses how carbon disclosure can be used to manage climate-related risks (Kolk et al. 2008). Carbon disclosure communicates a company's climate-related information, including (but not limited to) information about its GHG emissions, climate risks, and opportunities. While mandatory national disclosure requirements have been on the rise (e.g., SEC 2022), voluntary disclosure schemes like the CDP have helped normalize and legitimate carbon disclosure (Pattberg 2012). The CDP asserts that disclosures are beneficial as they protect corporate reputation and pre-empt mandatory regulation (CDP 2023).

2.7. Alignment of CCR frames with the Social Connection Model

Now that we have shown how CCR draws on scientific, social, legal, and economic frames, we explore whether and how these frames support a conceptualization of CCR that aligns with the Social Connection Model (SCM). The five conditions of the SCM stipulate that responsibility is not isolating, it does not assume that the background conditions of generally accepted behaviours

[10] The TCFD is an industry-led organization that created a corporate climate-related risk reporting framework, which details how climate risks affect corporate profits (Task Force on Climate-related Financial Disclosures 2017).

[11] Like economic CCR, legal CCR is also concerned with risks but for different reasons. From a legal standpoint, addressing the risks that climate change imposes on companies represents a fiduciary duty. Failing to act on this duty could entail legal consequences. In contrast, economic CCR focusses on how the risks that climate change imposes on companies threaten their profitability, which requires that these risks be managed.

are morally acceptable, it is more forward-looking than backward-looking, it is shared, and it is discharged through collective (instead of solely individual) action.

We consider the responsibilities in each frame, asking whether the responsibility aligns with the conditions of the SCM. We consider three possible levels of alignment: aligned, partially aligned, and unaligned. We present the alignments of all responsibilities identified from the literature review in Table A1 (Appendix A). Since responsibilities belong to different frames, we also determine the overall level of alignment of a frame. To do this, we assign the level of alignment that is constituted by the majority of its responsibilities. When there is no clear majority, we consider the proportions of different levels of alignment to deduce the most relevant one. For example, considering the first condition (responsibility does not isolate), the legal frame constitutes five responsibilities, two of which are partially aligned with the first condition, two of which are aligned, and one of which is unaligned (see Table A1). Since it is aligned with 40% of the frame's responsibilities, partially aligned with 40%, and unaligned with the remaining 20%, we assign the legal frame a partially aligned level for the first SCM condition (also see Table 2.3).

We present the overall frame alignments in Table 2.3, which shows that scientific CCR is well aligned with the SCM, complying well with three of the five conditions underlying the SCM and partially with two conditions; social CCR complies well with two SCM conditions and partially with three conditions; legal CCR complies with one condition, and partially with four conditions; and economic CCR complies with one condition, partially with one condition, and poorly with three conditions. Next, we discuss each CCR frame and its overall alignment with each of the five SCM conditions.

SCM Conditions	Frames of CCR			
	Scientific	Social	Legal	Economic
1. Responsibility does not isolate	Aligned	Partially aligned	Partially aligned	Partially aligned
2. Responsibility questions background conditions	Partially aligned	Aligned	Partially aligned	Unaligned
3. Responsibility is forward-looking	Aligned	Aligned	Aligned	Aligned
4. Responsibility is shared	Aligned	Partially aligned	Partially aligned	Unaligned
5. Responsibility is discharged through collective action	Partially aligned	Partially aligned	Partially aligned	Unaligned

Table 2.3: Level to which each frame of corporate climate responsibility (CCR) aligns with the five conditions characterizing the Social Connection Model (SCM). Three levels of alignment are identified: Aligned, partially aligned, and unaligned.

2.7.1. Alignment of scientific CCR with the Social Connection Model

Condition 1: Scientific CCR primarily does not isolate. It sometimes isolates companies as bearing individual responsibility for certain climate change actions, but it does not absolve other actors at the same time. Solutions focus on direct and indirect corporate emissions contributions that inform emissions targets and decarbonization efforts.

Condition 2: Scientific CCR sometimes questions background conditions. Scientific CCR does not make many normative assumptions about the backdrop of climate change solutions. Although it may question whether socioeconomic systems can address climate change, it does not explicitly challenge them. Similarly, it questions whether market-based solutions, near-term reliance on carbon removal, and methods for GHG accounting and target-setting are effective but without making moral claims. However, where scientific CCR does make normative assumptions is regarding equity and equality when determining distributions of climate responsibilities.

Condition 3: Scientific CCR is primarily forward-looking. Efforts to set targets and reduce emissions are undertaken in the context of present and future corporate practices, with little or no focus on liability for past practices. Instead, the focus on emissions tracking and future global climate goals demonstrates how scientific CCR recognizes that actions contributing to climate change are recent and ongoing.

Condition 4: Scientific CCR is shared. Since it does not assign fault to an individual company for climate change, it follows that responsibility is shared among all companies. Science-based target setting, for example, is a collective effort based on the premise that most companies will set targets aligned with global goals. If only a few companies engage in target-setting, it is unlikely that global targets will be reached.

Condition 5: Scientific CCR is discharged primarily through collective action. Addressing climate change requires that many companies, especially high emitters, collectively participate in decarbonizing. While conducting GHG accounting and setting emissions targets are individual practices, global climate targets can only be reached if all companies set and reach their individual targets. Similarly, the responsibility to conduct GHG accounting may be individual, but it also involves a collective effort because it informs target-setting and is used to track mitigation efforts.

2.7.2. Alignment of social CCR with the Social Connection Model

Condition 1 : Social CCR sometimes isolates. Social CCR can isolate companies as blameworthy. A company is faulted when it fails to uphold human rights through climate justice or intentionally misleads the public regarding its climate-related practices. Thus, social CCR explicitly acknowledges a causal connection between a company and the harm (e.g., climate injustice) it causes. However, social CCR understands that global patterns of climate injustice and norms regarding symbolic corporate practices cannot be blamed on individual companies, so in that sense, it is not isolating.

Condition 2: Social CCR sometimes questions background conditions. Social CCR challenges the background conditions underlying climate change. Almost by definition, it consistently questions the moral conditions and implications of corporate practices, as highlighted by Whyte ("Experts: Why does 'climate justice' matter?" 2021), who states that "Climate justice has to begin with the assumption that there is nothing normal about the environmental conditions of today, which were shaped largely by capitalism and colonialism."

Condition 3: Social CCR is primarily forward-looking. While it may invoke a company's past emissions, decisions or practices (e.g., past lobbying or misleading communications), social CCR constitutes a largely forward-looking aspect regarding implementing human rights due diligence in future corporate policies and frameworks, improving transparency in communications, and helping shape climate legislation positively.

Condition 4: Social CCR is shared and isolated. Companies can be isolated for harmful practices and act to prevent or redress these wrongs (e.g., seeking individual social licenses to operate). However, social CCR does not absolve them from ongoing broader structural climate injustices. An individual company is responsible for how it contributes to norms and rules (or lack thereof) (e.g., via lobbying, lack of meaningful stakeholder consultations). Social CCR recognizes that other companies bear the same responsibility—the responsibility to participate collectively to change practices and processes causing climate change and its injustices.

Condition 5: Social CCR is discharged through collective and individual action. Some responsibilities are more individual (e.g., avoiding greenwashing), while others are more shared (e.g., normalizing the use of climate justice principles within corporate practices).

2.7.3. Alignment of legal CCR with the Social Connection Model

Condition 1: Legal CCR sometimes isolates. Legal CCR isolates when companies fail to follow climate-related hard laws and regulations as they are legally liable. Their directors face individual legal liability when they do not abide by their fiduciary duties. However, legal CCR can be non-isolating when it involves soft laws, where lack of compliance does not lead to legal liability or restitutional behaviour.

Condition 2: Legal CCR sometimes questions background conditions. Legal CCR may or may not assume that legal frameworks are morally justified. Legal frameworks can be influenced by companies and challenged by new precedents and changing laws, regulations, or norms—though there is no guarantee that changes result in more morally acceptable background conditions.

Condition 3: Legal CCR is primarily forward-looking. Although legal responsibilities are traditionally backward-looking, corporate efforts to influence or support new and more stringent climate laws and regulations can be anticipatory and thus forward-looking.

Condition 4: Legal CCR is shared and isolated. It is shared in that new or more stringent climate laws require collective corporate participation and isolated in that companies and their directors act independently to follow hard climate laws and avoid financial climate risks.

Condition 5: Legal CCR is discharged through collective and individual action. Specific responsibilities can be individual (i.e., non-compliance with hard laws), whereas others can be shared (i.e., shaping new soft or hard climate laws).

2.7.4. Alignment of economic CCR with the Social Connection Model

Condition 1: Economic CCR sometimes isolates. Economic CCR can isolate a company as blameworthy by identifying causal connections between its practices and the financial impacts of climate risks on its business. However, a company that participates in market-based solutions or carbon disclosure may not be explicitly isolated because it will not necessarily be found at fault for not doing so.

Condition 2: Economic CCR does not question background conditions. Economic CCR assumes that background conditions (i.e., economic systems in which companies operate) are morally acceptable.

Condition 3: Economic CCR is forward-looking. Economic CCR is primarily forward-looking since it focuses on assessing future climate risks and not on finding fault for past practices. Similarly, carbon disclosure efforts can be anticipatory (rather than restitutional) and motivated by future benefits.

Condition 4: Economic CCR is not shared. Each company is responsible for avoiding potential climate risks and participating in market-based solutions or carbon disclosure.

Condition 5: Economic CCR is discharged primarily through individual action. example, a company identifies and discloses climate information like climate risks on its own rather than cooperatively with other firms. Most market-based solutions are driven by individual action, except for participation in *voluntary* carbon markets where the collective drives demand for carbon offsets.

2.7.5. Summary

Our analysis illustrates differences and similarities between CCR frames and their alignment with the SCM. For example, scientific and economic CCR are primarily forward-looking, focusing on future actions, while largely unconcerned with past actions. They differ in the role of the individual versus the collective: scientific CCR is shared, and collective action is required to absolve companies, whereas economic CCR is primarily individual, and a company's individual actions absolve it. Overall, the scientific frame is most aligned with the social justice perspective of the SCM and the economic frame is least aligned. Social and legal CCR are partially aligned with most SCM conditions.

Importantly, our discussion shows how CCR frames are complex: no CCR frame is completely aligned or unaligned with all five SCM conditions. This frame complexity highlights that a new, more comprehensive conceptualization of CCR needs to be grounded in the SCM-aligned aspects of each frame.

2.8. Towards comprehensive CCR

Many parallels can be drawn between the wicked problem of climate change and structural injustices in the SCM. Corporate responsibility for climate change can therefore only be adequately addressed via a shared and forward-looking understanding of responsibility, whereby agents jointly, continually, directly and indirectly contribute to climate change. Since our results show that no single frame meets all the SCM conditions fully, we look at the specific responsibilities within each frame. To consolidate the four CCR frames while considering how different responsibilities of the frames align with the SCM, we derive eight recommendations for a comprehensive CCR framework, summarized in Table 2.4. Each recommendation is anchored in one or more CCR frames and highlights specific responsibilities stipulated in a frame.

We derive the recommendations by choosing and prioritizing responsibilities that are most aligned with the SCM (see Table A1), thus those that are fully aligned with at least three SCM conditions. The first four recommendations are aligned with four of five SCM conditions and partially aligned with one, the fifth and sixth recommendations are aligned with three of five conditions and partially aligned with two, the seventh recommendation is aligned with three of five conditions, partially aligned with one, and unaligned with one, and the last recommendation is aligned with three of five SCM conditions, and unaligned with two. We note, however, that the fifth responsibility combines two separate but very similar responsibilities identified in the literature: to conduct transparent and consistent GHG inventories reflecting real impacts, and to do the same including market-based impacts. We combine them because these responsibilities are encompassed in one type of practice, that is, to develop a GHG inventory.

Overall, our recommendations prioritize responsibilities according to how they align with the SCM. Thus, our first recommendations highlight responsibilities in a frame that align with the SCM. Subsequent recommendations stipulate responsibilities in a frame partially align with the SCM. On the whole, the recommendations prioritize scientific CCR, which is most closely aligned with the SCM, while placing some emphasis on social CCR and on legal CCR, followed by economic CCR. Underlying our recommendations is the recognition that a comprehensive conceptualization of CCR should be predominantly shared and forward-looking. Most recommendations benefit the collective rather than the individual company or specific stakeholders since the SCM emphasizes that collective action should alter structural processes underlying climate change. Our recommendations exclude hard climate laws as we assume companies adhere to them.

Our recommendations build on propositions suggested elsewhere. Weber and Hösli (2021) propose establishing CCR as a concept with two core aspects: transparency regarding climate risks for companies and due diligence to account for corporate impacts on human rights and the environment. The NewClimate Institute (2022) discusses corporate responsibility in the context of tracking and disclosing emissions, setting emission reduction targets, reducing emissions, providing financial support for climate action beyond the corporate value chain, and procuring credible carbon offsets. Our recommendations, especially those based on scientific CCR, are also concerned with the practices outlined by the NewClimate Institute (2022). However, we extend them in three crucial aspects. First, we stress incorporating climate justice principles into business practices (i.e., into corporate risk management and due diligence frameworks), which the NewClimate Institute (2022) report does not mention. Second, our recommendations consider corporate political influence on climate legislation, which the NewClimate Institute (2022) report also does not consider. Third, we suggest fundamental business model changes for industries and companies whose practices do not align with a low-carbon future (e.g., fossil fuel producers). Although the NewClimate Institute (2022) focuses on various decarbonization measures, these measures do not stipulate the need for some companies to implement fundamental changes to their products or services and reconstruct how profits are earned.

Our research anchors the responsibilities discussed in Weber and Hösli (2021) and the NewClimate Institute (2022) in a comprehensive approach that encompasses scientific, social, legal and economic understandings of CCR. By showing how assumptions about CCR draw on multiple and sometimes conflicting frames, we further strengthen the concept of comprehensive CCR by identifying frames that align with a theory of responsibility. Accordingly, we ground our approach in Young's SCM, applying it to climate injustices. We thus show how climate change can be conceived as a structural injustice and how Young's SCM, which encourages collective responsibility without assigning blame, can be fruitful for addressing corporate responsibility for climate change.

	CCR Recommendation	Underlying CCR frame	SCM conditions met by the CCR recommendation
1	Prioritize and implement physical decarbonization activities before market-based activities	Scientific CCR	CCR does not isolate is forward-looking is shared involves collective action
2	Set science-based targets in line with ambitious global climate goals	Scientific CCR	CCR does not isolate is forward-looking is shared involves collective action
3	Incorporate climate justice principles into corporate risk management and due diligence frameworks and implement them into business practices	Social CCR, Legal CCR	CCR does not isolate questions background conditions is forward-looking is shared
4	Support and help positively shape new climate legislation/regulations	Legal CCR, Social CCR	CCR questions background conditions is forward-looking is shared involves collective action
5	Conduct transparent and consistent greenhouse gas (GHG) inventories reflecting both real and market-based impacts	Scientific CCR, Economic CCR	CCR does not isolate is forward-looking is shared
6	Seek social license to operate and engage with stakeholders and communities	Social CCR	CCR does not isolate questions background conditions is forward-looking
7	Be transparent in communications and disclosures, and avoid symbolic disclosure	Social CCR	CCR does not isolate is forward-looking involves collective action
8	Make fundamental business model changes to reduce climate impact and align with a low-carbon future	Scientific CCR, Social CCR	CCR questions background conditions is forward-looking is shared

Table 2.4: Recommendations for a comprehensive corporate climate responsibility CCR, the CCR frame(s) in which recommendations are anchored, and the Social Connection Model (SCM) conditions met by the recommendation.

Our recommendations for a comprehensive CCR can be used as a starting point for companies looking to prioritize climate responsibilities in light of scientific, social, legal, and economic concerns related to climate change. They would benefit from using our recommendations as investors and the greater public could readily identify them as truly climate-responsible companies. Similarly, our recommendations can be used by policymakers or regulators to design and implement corporate climate directives. Based on our recommendations, future research may seek to develop a more detailed CCR framework which suggests, for example, specific standards, reporting frameworks, and other resources that would help companies adequately address each recommendation.

2.9. Conclusion

We set out to develop a comprehensive and unique conceptualization of CCR. We begin by exploring how the relationship between companies and climate change is currently understood. Our findings reveal that this understanding mobilizes four perspectives—scientific, social, legal and economic. We then mobilize the SCM from Young (2011) to evaluate how these four perspectives are consistent with promoting justice in the context of companies addressing climate change. We show how the scientific and social perspectives are most adapted for this purpose. Finally, we develop our conceptualization of CCR, which builds on the four perspectives, prioritizing those most aligned with the SCM. We highlight that climate justice requires a comprehensive CCR that is shared, forward-looking, critical of background conditions, not isolating, and enacted through collective corporate practices.

While we hope our discussions can set the stage for a more operative CCR, we note two limitations. First, our literature review has striven to be as complete and broad as possible. However, there may be other relevant CCR interpretations that we have not detected, implying that additional CCR frames could be added to the four frames we identified. Second, we recognize the inherent subjectivity in our interpretations of frames and how they align with the SCM, which could be impacted by our personal concerns about climate change. Because our recommendations for a comprehensive CCR are derived from our evaluation of the frames using the SCM, they are also subject to bias.

Chapter 3: Estimating Corporate Scope 1 Emissions Using Tree-Based Machine Learning Models

3.1. Abstract

Although corporate climate disclosure is becoming more common, there remains a gap in company-level emissions data. This data gap makes it difficult to track corporate carbon performance and to reconcile company-level emissions with global emissions. To address these issues, we train three decision-tree ensemble machine learning models to predict company-level Scope 1 emissions. Next, we estimate global emissions from public companies using our best-performing model. We select model features according to economic, agency and institutional perspectives, while considering data availability and feature importance according to Shapley Additive exPlanations. Our best model shows an 17% improvement in mean absolute error compared to a benchmark study. Our model is also of reduced complexity as it does not employ meta-learners. The features of the greatest importance are economic features and industry classification. Our model estimates that emissions from non-reporting public companies in 2021 are 2.05 $GtCO_2e$, while reporting companies' emissions are 9.35 $GtCO_2e$, which together make up 22% (11.4 $GtCO_2e$) of global GHG emissions. Fewer than 10% of publicly listed companies are responsible for 82% of our global corporate emissions estimate, implying that high-emitters are reporting emissions and low-emitters are not. To facilitate swift corporate decarbonization that would be felt at a global level, future research should shift its focus towards developing and evaluating effective carbon management systems for high emitters. While companies should continue to report their GHG emissions, they should simultaneously allocate sufficient resources to decarbonizing.

3.2. Introduction

Considering the climate crisis and the significant amounts of greenhouse gases emitted by companies worldwide, a range of stakeholders including customers, suppliers, civil society, regulators, and investors have been exerting pressure on companies to disclose their greenhouse gas (GHG) emissions (Chithambo et al. 2020; Liesen et al. 2015). Presently, companies that conduct carbon footprints typically report their emissions voluntarily, either in public reports or to disclosure organizations like the CDP (formerly Carbon Disclosure Project) (Depoers et al. 2014). While some countries and regions have mandatory reporting requirements, such as the European Union, Japan, and Australia, these schemes are often limited to certain industries or companies that emit beyond a stipulated threshold (Australian Government 2007; European Commission 2018; OECD and CDSB 2015). A recent wave of positive regulatory developments including proposals for mandatory disclosure in the United States (SEC 2022) and a climate disclosure standards directive that would serve as a global baseline for climate reporting (ISSB 2022) show promise for the future, but it could be years until a comprehensive and accessible dataset for company-level emissions is developed.

Despite such regulatory developments and voluntary initiatives, research has shown that few public companies disclose their direct (Scope 1) GHG emissions (Hadziosmanovic et al. 2022), and disclosure patterns demonstrated in other studies suggest indirect (Scope 2 and 3) emissions are reported even less frequently (Ryan and Tiller 2022)[12]. Some research highlights that large companies may be more likely to report emissions (Rankin et al. 2011), but globally we have little insight into the direct GHG emissions of most companies. This gap in corporate emissions data presents several problems. First, lack of company-level GHG data poses challenges for evaluating carbon performance and carbon risk accurately for investment portfolio construction (Gurvich and Creamer 2021), in turn impacting where investments are funneled. Second, it makes it difficult to reconcile company-level emissions with industry, national, or global level GHG estimates, which is essential for assessing decarbonization efforts accurately (Luers et al. 2022). Finally, since companies have begun announcing ambitious emissions targets and claiming emissions reductions, there is a greater need to corroborate such claims to hold companies accountable.

A proposed solution to filling the gap on corporate emissions is to use GHG estimation models. Works by both academics and non-academics have developed company-level emissions estimation models based on externally available data. However, these models are limited in a few ways. Models using statistical approaches are designed to make inferences about populations from a carefully chosen sample (Bzdok et al. 2018). These models focus on explanatory power and rely on in-sample goodness-of-fit (Nguyen et al. 2021). In contrast, machine learning (ML) models predict data based on algorithms that find patterns in complex datasets, such as those with nonlinear or high-order variable interactions, allowing for greater out-of-sample prediction accuracy (Bzdok et al. 2018; Nguyen et al. 2021). The ML models presented in the literature thus far are either of high computational cost or use too many features (predictor variables) rendering the models complex and difficult to replicate (Han et al. 2021; Nguyen et al. 2021). While complex ML models, also called "black box" models, do not offer interpretability of associations between variables and outcomes on their own (Drobnič et al. 2020), research suggests that certain tools can be used to improve model explainability (Ariza-Garzon et al. 2020). For example, Shapley Additive exPlanations (SHAP) provide an interpretation of the impact or contribution of a feature on the model's output (Ariza-Garzón et al. 2020; Marcilio and Eler 2020). Thus far, SHAP has not been used to explore feature importance in models estimating corporate emissions. In addition, studies that developed GHG estimation models have not attempted to estimate corporate emissions from non-reporting companies. Overall, research on ML techniques for estimating company-level emissions is in its early stages and there is a need for improvement and exploration of model variations and their interpretations.

Our study addresses this need by training a series of ensemble models[13] based on decision trees for the estimation of company-level Scope 1 emissions. We use a primarily economic perspective, supported by agency and institutional perspectives to select features. We also assess

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[12] A company's carbon footprint is typically calculated according to three emissions categories: Scope 1 (direct emissions from sources owned or controlled by the company), Scope 2 (indirect emissions from the generation of purchased electricity, steam, heat, or cooling); and Scope 3 (all other indirect emissions resulting from sources not owned or controlled by the company) (WRI and WBCSD, 2004).
[13] An ensemble model in machine learning is an algorithm that combines a series of base algorithms to produce an optimal or final predictive model (Dietterich 2000).

feature importance using SHAP. Lastly, we use the best performing model to estimate Scope 1 emissions from non-reporting public companies globally.

We contribute to the literature in three ways: First, in contrast to other existing ML models, our model is of reduced computational cost and complexity, as it is not built on multiple base-learners and uses features for which data is more commonly reported or available. Second, our feature importance results suggest that an economic perspective and institutional mimetic forces are overall most useful for choosing impactful features in ML models predicting corporate emissions. Third, we contribute the first estimate of global Scope 1 emissions from public companies using our model outputs.

3.3. Related works

Both academic and non-academic works have contributed to developing GHG estimation models based on externally available data, although peer-reviewed academic research on the subject is limited. Model methods can be grouped into statistical methods and machine learning methods for which we now provide an overview.

3.3.1. Statistical methods

3.3.1.1. Naïve methods

The simplest models, termed "naïve models," can rely on data availability of a company's energy figures, historical emissions, or industry-averaged data (Nguyen et al. 2021). The key limitations of naïve models are their simplified calculations and availability of input data.

Some data aggregators and providers like Morgan Stanley Capital International (MSCI) and Thomson Reuters use naïve models. MSCI's model estimates Scope 1 and Scope 2 emissions based on three underlying models: a production model, a company-specific intensity model, and an industry specific intensity model (MSCI 2016). The production model is used exclusively for power generation companies and employs fuel-mix data and total power generation per fuel type to estimate emissions. The company specific intensity model is reliant on disclosed historical emissions data and revenue of the company to estimate current emissions. In cases where historical data is not available, MSCI use the industry specific intensity model which estimates emissions based on the average emission intensity of a company's sub-industry. Thomson Reuters use a similar approach with three sub-models. The first model uses historical emissions (paired with employee and net sales figures); the second model uses energy consumption figures or energy production figures for utilities companies; and the third model uses industry-averaged emission intensity figures (Refinitiv 2021). The choice of which underlying model is used depends on what data is available, but estimates based on historical emissions are prioritized.

3.3.1.2. Regression methods

Another group of GHG estimation models are those founded in traditional statistics, namely, regression techniques. This involves relating the dependent variable (emissions) to a chosen set of independent (predictor) variables, thus assigning a quantitative measure and level of significance to each relationship. Research using regression models are evaluated "based either on 'goodness of fit' between the statistical model and the sample data or on whether the sizes and directions of certain regression coefficients match what is implied by different theoretical perspectives" (Yarkoni and Westfall 2017). Regression models are sensitive to large numbers of predictor variables, which increase model complexity and make statistical inferences less precise (Bzdok et al. 2018). They are also sensitive to multi-collinearity, which reduces our ability to identify the effects of collinear variables independently, thereby impacting the inferences that can be made about variable relationships in the model (Dormann et al. 2013).

The CDP (formerly the Carbon Disclosure Project), a global disclosure organization, uses a Gamma Generalized Linear Model (GLM) to estimate Scope 1 and 2 emissions. Scope 1 is estimated using two predictor variables: company activity (as defined by CDP) and revenue from the activity (CDP 2022). Due to large variability in energy grid mixes across regions, Scope 2 emissions are estimated using average national grid emissions factors and estimates of purchased energy consumption. In the academic literature, two studies use regression models to estimate corporate emissions (Goldhammer et al. 2017; Griffin et al. 2017). Goldhammer et al. (2017) use an ordinary least squares (OLS) regression model using five predictor variables and Scope 1 and Scope 2 emissions as the target variables. Their sample includes 93 companies in the chemicals, construction and engineering, and industrial machinery sectors. The predictor variables were chosen based on suggestions from prior studies and the authors' hypotheses of variable impacts on emissions. The predictors included company size, level of vertical integration (how much control a company has over its supply chain), capital intensity (amount of capital in fixed assets in relation to production), centrality of production (transportation required for company activities), and carbon intensity of the national energy mix (dependent on power generation sources in the region). Their study was limited by potential bias from the small sample of predominantly large firms. In contrast, Griffin et al. (2017) extracted GHG emissions data from a larger sample of companies based in the U.S. and listed in the S&P 500. They used a linear model based on several predictors including scale of operations, investment, asset composition, sector, and other financial data. However, their rationale for using these predictor variables was limited to identifying them as "emission production variables" (Griffin et al. 2017, p. 1272). Their sample was also limited to large companies.

3.3.2. Machine learning methods

ML applications in the fields of business and sustainability have grown in popularity in recent years (De Lucia et al. 2020; Torre et al. 2021; Vaio et al. 2020). ML is an approach to analyzing data which emulates human intelligence by acting autonomously, learning from data iteratively and improving predictions over time (De Lucia et al. 2020; Sarker 2021). ML is less interested in inference; rather, it is used to make predictions often based on "rich and unwieldy data" (Bzdok et al. 2018, p. 233). There are different ML learning methods, associated algorithm categories, and types of algorithms. We provide a summary chart in Figure 3.1 of ML learning types and popular algorithms that specifically depicts ML branches relevant to labeled data and continuous target variables because these are relevant to our study. [14]

[14] Figure 3.1 is not exhaustive. There are many other types of ML algorithms for regression problems (not to be confused with regression techniques in traditional statistics as described in section 3.3.1.2.). In addition, many ML

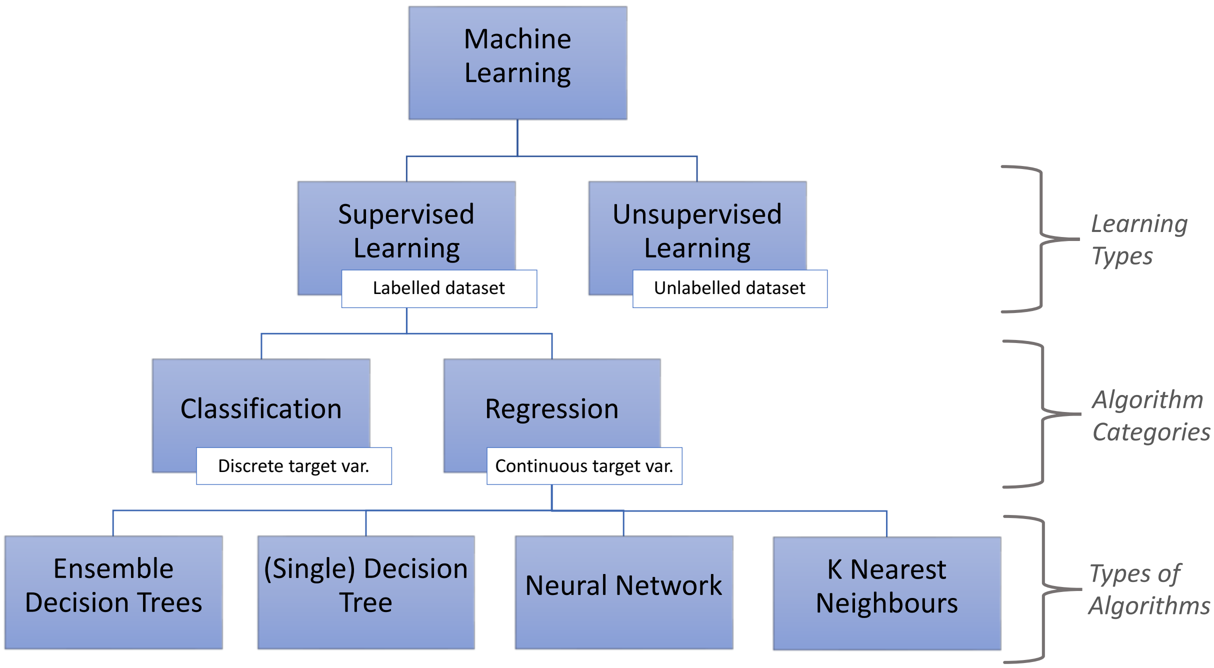

Figure 3.1 Types of machine learning and popular algorithms relevant to labeled data and continuous target variables. Adapted from Taffese and Sistonen *(2017)* and Sarker *(2021)*. Other types of linear or nonlinear regression algorithms such as generalized linear models, logistic regression, or simple linear regression are considered foundational to or outside of machine learning *(Jain et al. 2020)*. They are therefore not included in this figure.

ML can be grouped into supervised and unsupervised learning methods. Supervised learning is used when the training dataset is labeled, meaning that the data includes features (also called predictor variables)[15] that are associated to a known output value. The model is developed according to an algorithm which maps the input features to the known output, based on the sample of input-output pairs in the training dataset (De Lucia et al. 2020; Sarker 2021). For example, our training dataset of public companies is labeled because it contains company features that are mapped to log-scaled reported Scope 1 emissions (i.e., the target variable). Based on patterns observed in this training dataset, the ML algorithm builds a model that can then predict the target variable when we introduce a new, unlabeled dataset (e.g., when Scope 1 emissions are unknown). Typically, the model is validated with a labeled test dataset. The results of this validation provide the out-of-sample performance of the model after it has been trained (Nguyen et al. 2021). In contrast, unsupervised learning is used when we do not have information about what the 'correct' prediction is, thus the target variable is not labeled.

Two common branches of supervised learning are classification and regression. Classification techniques are used when the output is a categorical (discrete) variable, whereas regression techniques are used for predicting continuous variables (Sarker 2021). There exist

algorithms can be used in both regression and classification problems. For example, the algorithms depicted in Figure 3.1 may also be used in classification problems.

[15] The terms "predictor variable" and "feature" are used interchangeably.

many different algorithms for regression models. Next, we describe ensemble decision trees algorithms, as they have been used in prior studies modelling corporate emissions.

3.3.2.1. Ensemble decision trees

Decision trees represent data as series of choices, or 'nodes' on a tree. Each datapoint is associated to a root node and a decision test, after which the data is split by two or more branches (De Lucia et al. 2020). A node represents an attribute, while a branch is the corresponding value the node can take (Maimon and Rokach 2015). When an end node, or 'leaf' node is reached, then a prediction is made based on the values of datapoints at that node (De Lucia et al. 2020). Effectively, a decision tree is a series of if-then-else rules (Jain et al. 2020). We provide a visual example of a decision tree in Figure C1 in Appendix C.

Ensemble decision trees, based on the concept of ensemble learning, are the aggregation of several decision tree models to make a final prediction (Nguyen et al. 2021). Ensemble learning is highly effective because it represents the "wisdom of the crowd," rather than relying on a single model's prediction (Sagi and Rokach 2018). Predictive performance is significantly improved with ensemble learners compared to single learners (Sagi and Rokach 2018). There are several ways to combine decision trees into an ensemble, including methods called boosting and bagging.

3.3.2.1.1. Bagging

Bootstrap aggregating (Breiman 1996), also known as bagging, is a method that trains several individual models (e.g., a decision tree) in *parallel*, based on a random subset of the original training dataset (with no single subset of the data being the same) (Che et al. 2011). The result of each of these models are then aggregated based on a majority vote, which becomes the prediction of the bagging ensemble model. A common bagging algorithm is Random Forest.

3.3.2.1.2. Boosting

Boosting is a method which trains individual models *sequentially*, rather than in parallel. Thus, each sequential model is an improvement on the errors of the previous one (Che et al. 2011; Jain et al. 2020), hence 'boosting' the model's performance at each iteration. Each boosting algorithm handles the model's errors differently. For example, Gradient Boosting Machine (GBM) aims to minimize the loss function (mean squared error for decision trees), so that each new tree is fitted to the residuals (prediction errors) of the previous tree (Touzani et al. 2018). Extreme Gradient Boosting (XGBoost) and LightGBM are different improvements on GBM. XGBoost adds several refinements and optimizations to GBM which make it better suited to handling sparse data (Sagi and Rokach 2018). XGBoost does not develop trees fully (i.e., trees are developed horizontally rather than vertically), meaning that decision splits happen at all leaves in the same layer or level of the tree (Liang et al. 2020). In contrast, LightGBM develops trees fully (i.e., vertically), meaning that decision splits are made at the leaf where the best fit is found (Liang et al. 2020). Other popular boosting algorithms include Adaptive Boosting (AdaBoost) and Categorical Boosting (CatBoost).

3.3.2.2. Existing machine learning models for predicting corporate emissions

To our best knowledge, the academic research on predicting company-level emissions using machine learning methods is limited to two non-peer reviewed studies (Han et al. 2021; Serafeim and Caicedo 2022) and one peer-reviewed study (Nguyen et al. 2021).

The ML model constructed by Han et al. (2021) predicts Scope 1 and Scope 2 emissions using a multi-step model development methodology. First, they use LightGBM to make initial predictions. Then, the distribution of the training dataset is recalibrated using a validation dataset. Finally, because of a large quantity of missing data–a consequence of choosing over 1,000 features–they use a self-designed technique called patterned dropout to address this issue. This technique applies the missing data patterns in the unlabeled dataset to the labeled (training) dataset to improve the model's predictive performance. This multi-step methodology for constructing the prediction output, combined with the large number of features, renders the model computationally complex and difficult to replicate. Additionally, the study does not compare the performance of different algorithms.

Serafeim and Caicedo (2022) compared OLS, generalized linear, k-nearest neighbours (kNN), Random Forest, and AdaBoost models to estimate Scope 3 emissions per category.[16] Overall, AdaBoost showed the highest prediction accuracy, with an average mean absolute percentage error (MAPE) of 27% across all Scope 3 categories. This was followed by Random Forest which had an average MAPE of 33%. Features were chosen manually, reflecting "financially relevant as well as commonly used features" in estimation regression models used by data providers (Serafeim and Caicedo 2022, p. 25). To eliminate features with little predictive value, they used recursive feature elimination, which is a technique that fits data to different models and ranks features according to the quality of their predictions. Those with the lowest weights (i.e., least predictive value) were eliminated. Missing financial indicator data was imputed using the k-nearest neighbours algorithm.

The study by Nguyen et al. (2021) (henceforth, the benchmark study) is to our knowledge the only peer-reviewed ML model that estimates corporate GHG emissions. Their study tests a range of different regression and ML models including ordinary OLS, Elastic Net, kNN, Neural Network, Random Forest, and XGBoost, to predict Scope 1, Scope 2, and total (Scope 1 and 2) emissions. They set up their final model as a two-step framework: a set of base models, called base-learners, make predictions which are then aggregated using a meta-learner. Meta-learning refers to learning from knowledge or experience from other learning tasks (Chan and Stolfo 1993). In this case, the meta-learner learns how to optimize the best predictions from the base-learners. The best performing base-learners was XGBoost with a mean absolute error (MAE) of 1.031 for Scope 1 estimation and the best meta-learner was the meta-Elastic Net with a MAE of 0.994. They used a sample of over 2,000 company-year observations and selected initial features according to features used in prior regression models and naïve models. The final set of features was chosen based on the results of OLS regressions on all combinations of the initial set of features. While this is a common method used for feature selection, it assumes linearity between the features and the target variable. Missing feature data was imputed using the mean values

[16] The GHG Protocol groups Scope 3 emissions into 15 different categories (WRI and WBSCD 2004).

from the same industry groups. Overall, the model in Nguyen et al. (2021) is characterized by complexity and high computational cost due to the use of a meta-learner and several base-learners.

Here, we attempt to address several shortcomings of models developed in prior studies. First, we aim to develop a model that has an improved predictive performance (in comparison to the benchmark study), but with lower complexity and computational cost. We ensure to test more than one algorithm but focus on comparing tree-based models because these have resulted in the best performances in Nguyen et al. (2021) and Serafeim and Caicedo (2022). We also introduce a more organized approach to choosing features, providing theoretical foundations to our feature choices and using feature importance rankings (rather than linear regression) to reduce the number of features necessary for the model, while retaining the model's level of predictive performance. We also avoid imputation of missing values to reduce bias in the trained models, when possible. Finally, we apply our ML model to estimate 2021 emissions from non-reporting public companies globally.

3.4. Data and methods

3.4.1. Building the prediction model

In the following sections, we describe our methods and rationale for choosing the target and predictor variables, and their sources of data. A flow chart of our overall methodology for building the model can be found in Appendix C, Figure C2.

3.4.1.1. Target variable: Scope 1 emissions

We focus on predicting Scope 1 emissions of companies, in contrast to prior studies which modelled other scopes, or a combination of scopes (Han et al. 2021; Nguyen et al. 2021; Serafeim and Caicedo 2022). We decide on Scope 1 as the target variable for two reasons. First, of companies that report emissions, Scope 1 is the most reported of the scopes (Datt et al. 2021), thus providing us with a larger and broader dataset with which to train our models. Second, since part of our research objective is to estimate global emissions from companies and compare these results to global emissions estimates, we avoid double-counting by focusing on Scope 1.

We obtain Scope 1 emissions data for public companies for the years 2018-2021[17] from the database of the Bloomberg Terminal (henceforth, Bloomberg) (Bloomberg L.P. 2022). Bloomberg provides a platform with real-time and archived data and analytics on global financial markets (Bloomberg Finance L.P. 2023). At the time of data collection, there were 18,292 company-year observations for which Scope 1 emissions were reported.

3.4.1.2. Feature selection and data collection

We choose our features based on possible explanations or drivers of company-level emissions which we derive from concepts in economic theory, supported by perspectives from agency and

[17] Since companies often report alongside their financial reporting timelines, we collect data on a fiscal year basis.

institutional theories. In addition, we consider data availability in our choice of features, including only those that had greater than 50% available data from our initial sample of companies between 2018-2021.

We collect data on carbon regulations from the Climate Change Laws of the World database (GRICCE and SCCCL 2022), countries that are Paris signatories from the United Nations (UN) Treaty Collection (2022), and subregion classifications from the UN (UN Statistics Division 2022). The remainder of feature data was collected from Bloomberg. A summary of the features and their sources is provided in Table 3.1, while a detailed list of feature definitions can be found in Table B1, Appendix B. We also provide summary statistics for each numerical feature in Table B2, Appendix B. In the next section, we expand on the theoretical foundations of our initial feature choices.

3.4.1.3. Theoretical foundations for feature selection

We first consider economic theory which posits that climate change, caused by anthropogenic GHG emissions, is a negative externality of business activities. Externalities can be understood as market failures or by-products resulting from the inefficiency of production and consumption of goods and services (Ayres and Kneese 1969). Indicators that reflect a company's level of production or consumption include company size (measured in revenue or number of employees) (Nguyen et al. 2021), physical production units, such as volume or weight for homogenous sectors (Krabbe et al. 2015), and energy consumption (Olsthoorn et al. 2001). We collect data for company *revenue*, *number of employees*, and *energy consumption*, leaving out measures of physical production because this is only available for specific subsets of companies and because the physical units used vary between or within industries.

Since the social cost of pollution is not accounted for in the market economy, economic theory points to internalizing these costs. Two approaches to internalizing the costs include the creation of price incentives such as taxes imposed on consumers or producers (Pigou 1920) and the allocation of rights to emit (Endres 1994). In the absence of external institutional pressures, companies can set their own internal carbon prices or can set limits to their emissions through emissions-target setting. Accordingly, we collect data on whether a company has set an internal *carbon price* and *emissions target*.

Studies have also suggested that a company's capacity to address CSR issues – such as addressing the company's impact on climate change – can be linked to its economic health (Beliveau et al. 1994). While a company may have interest in climate mitigation, if it does not possess enough resources or capital to invest in mitigation activities, it may not engage in such activities. Measures of financial performance can indicate a company's capacity to internalize or mitigate emissions. For example, common measures of profitability include return on assets (*ROA*), return on equity (*ROE*), and earnings before interest, taxes, depreciation, and amortization margin (EBITDA) (Kludacz-Alessandri and Cygańska 2021). We collect data for *ROA* and *ROE*, but to improve comparability between companies of different sizes, we use *EBITDA margin (*relative profitability calculated by dividing EBITDA by revenue) instead of EBITDA. We also opted to include measures of cash flow because cash flow is necessary for making purchases on business assets that could impact emissions. We use cash flow from operations (*CFO*), which is money generated from regular business activities. This could represent a company's capacity to invest in asset upgrades or more efficient equipment or technologies, consequently impacting emissions. We also collect data for free cash flow (*FCF*) which is the money generated from operating activities *after* accounting for the cash needed to maintain or expand assets. Greater *FCF* may also lead to further reinvestments in new or upgraded assets. Finally, we include cash flow per share (*CFPS*) as an alternative cash flow metric that represents a company's overall financial health.

Similarly, a company's investments in its physical assets overtime can reflect its efforts to internalize emissions. For example, companies with greater property, plant, and equipment are likely to be more carbon intensive (Goldhammer et al. 2017) since more assets require more energy inputs. Companies with older, less efficient equipment (which can be measured by the average age of physical assets) could lead to greater emissions as well (Nguyen et al. 2021). Greater investments in physical assets, represented by a company's capital expenditures could lead to reduced emissions as a result of newer, more efficient technologies (Nguyen et al. 2021). Therefore, we collect company data for gross property, plant, and equipment (*GPPE*), average asset age (*Asset age*), and capital expenditures (*CAPEX*).

Institutional and agency theories may also contribute to explaining company-level emissions, as they have been discussed as internal and external drivers of corporate social responsibility actions (Frynas and Yamahaki 2016).[18] Institutional theory suggests that companies are driven by the need for organizational legitimacy (rather than economic efficiency), and consequently conform to institutional pressures and social norms (Dubey et al. 2016; Frynas and Yamahaki 2016). These pressures can be in the form of rules or regulations imposed by governments (coercive forces), social or cultural norms of a region or environment (normative forces), or uncertainties in an organization which lead to mimicking competitor behaviours (mimetic forces) (Damert and Baumgartner 2018). We include features that represent these institutional forces.

First, we consider company locations and characteristics of these locations as both coercive and normative forces, since regulations across regions differ, as do norms and institutional settings (Damert and Baumgartner 2018). Since company headquarters are not always where most of the company's operations occur, we consider both the company's country of domicile (location of management) and country of risk. The country of risk largely depends on where the company holds the largest portion of its operations, or, when this information is not available, where it generates its highest revenues (Bloomberg L.P. 2022). We also include whether the company's country of domicile and country of risk are signatories to the Paris Agreement to account for normative forces. We consolidate Paris signatory country data at a subregion level to minimize the number of categorical variables used in our prediction model. We also include the presence of carbon taxes and emissions trading schemes in the company's country of domicile and country of risk as coercive forces. Another feature that could represent coercive and normative forces is a company's multi-nationality, measured as percent of revenue from foreign sources (*Percent Foreign Revenue)*. Multi-nationality can indicate different

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[18] We note that many predictor variables that may align with agency and institutional theories, such as belief systems or leadership perspectives of directors or CEOs (agency theory) or historic initiatives or historic emissions (institutional theory) are data that are not widely available nor easily accessible. We chose to focus on predictor variables that are likely to be available for most public companies.

regulatory exposures (Grauel and Gotthardt 2016) while also representing varying institutional settings in foreign markets (Damert and Baumgartner 2018). Finally, to account for mimetic forces, we include the industry of the company according to the International Classification Benchmark (ICB) system.

Agency theory accounts for internal forces, providing a way to assess the relationships between principals (shareholders) and agents (managers) (Adegbite 2015). An agency perspective suggests that "managers as agents have distinct incentives…" compared to their principals (Frynas and Yamahaki 2016, p. 264). Consequently, individual decisions by managers can have an impact on a company's sustainability practices (Dubey et al. 2016). To account for this, we include the highest level at which climate change is managed in a company as a feature (*CC management*) and whether there is a climate change policy at the company (*CC policy*). Research has shown that women can have an impact on sustainability activities, such as GHG disclosures (Hollindale et al. 2019), hence we also include the percent of women on the board of directors (*Percent women on board*) as a feature.

Economic theory's interpretation of externalities, institutional theory's account of external forces, and agency theory's account of internal forces provide the basis for our initial selection of features that may impact corporate GHG emissions.

Category	**Supporting perspective**	**Feature (*feature abbreviation*)**	**Source of data**
Voluntary climate initiatives	Economic	Whether an internal price of carbon is set (*Use of carbon price*); Whether an emissions target is set (*Emissions target*)	Bloomberg
Profitability & cash flow	Economic	Return on assets (*ROA*); Return on equity (*ROE*); Earnings before interest, taxes, depreciation, and amortization margin (*EBITDA margin*); Free cash flow (*FCF*) Cash flow per share (*CFPS*); Cash flow from operations (*CFO*)	Bloomberg
Company size	Economic	Revenue; Number of employees (*Employees*)	Bloomberg
Energy consumption	Economic	Energy consumption in megawatt hours (*Energy consumption*)	Bloomberg

Table 3.1 Initial feature selection: feature category, supporting perspective, features names, and sources of data

Category	**Supporting perspective**	**Feature (*feature abbreviation*)**	**Source of data**
Physical assets	Economic	Gross property, plant, & equipment (*GPPE*); Average age of assets (*Asset age*); Capital expenditure (*CAPEX*)	Bloomberg
Presence of carbon regulations	Institutional	Presence of carbon tax in country of domicile (*Carbon tax (country)*); Presence of carbon tax in country of risk (*Carbon tax (country of risk)*); Presence of emissions trading scheme in country of domicile (*ETS (country)*); Presence of emissions trading scheme in country of risk (*ETS (country of risk)*)	Climate Change Laws of the World Database
Company location	Institutional	Subregion according to country of domicile (*Subregion*); Subregion according to country of risk (*Subregion of risk*); Paris signatory according to country of domicile (*Paris* (*country)*); Paris signatory according to country of risk (*Paris (country of risk)*)	Bloomberg; UN Treaty Collection Depositary
Multi-nationality	Institutional	Percent of revenue from foreign sources (*Percent foreign revenue*)	Bloomberg
Industry	Institutional	Industry according to International Classification Benchmark categories	Bloomberg
Climate change management	Agency	Presence of a climate change policy (*CC policy*); Highest level at which climate change is managed (*CC management*)	Bloomberg
Influence of the board of directors	Agency	Percent of women on the board of directors (*Percent women on board*)	Bloomberg

Table 3.1 (Continued): Initial feature selection: feature category, supporting perspective, features names, and sources of data.

3.4.1.4. Data pre-processing

We pre-processed data by removing outliers, and transforming and scaling certain numerical features. Our final data set after preprocessing included 17,824 company-year GHG observations. We detail this process in the next sections.

3.4.1.4.1. Outliers

Following initial data collection, we removed the 1st and 99th percentiles of reported Scope 1 emissions, the target variable. Of the feature data, we only removed outliers if they were several orders of magnitude outside of the 25-75 percentile range and isolated (i.e., points which were not observed in clusters). If observations were outside of the 25-75 percentile range but appeared in clusters, we did not remove these as we endeavored to retain as much real data as possible. In addition, we removed company-year observations where Scope 1 emissions were reported as zero, following the approach of prior studies (Nguyen et al. 2021; Serafeim and Caicedo 2022).

3.4.1.4.2. Logarithmic transformations and scaling

Following the approaches of Serafeim and Caicedo (2022) and Nguyen et al. (2021), we applied a natural logarithmic transformation to the target variable (Scope 1 emissions), and a transformation such that $z' = \log(z+1)$ to the numerical predictor variables *GPPE*, *EnergyConsumption*, *Employees*, and *AssetAge*. For the predictor variables *FCF*, *CFO*, and *CAPEX*, we applied a logarithmic transformation such that $z' = \log(z + |\min(z+1)|)$ to handle negative values. We did not apply logarithmic transformations on ratios or percentage predictor variables. These include *CFPS*, *ROA*, *ROE*, *percent foreign revenue*, *percent women on board,* and *EBITDA margin*.

3.4.1.4.3. Categorical variables

Since our chosen algorithms do not have a predetermined encoding methodology for handling categorical data, we used one-hot encoding on categorical variables, except for *CC management* where ordinal encoding is more intuitive. One-hot encoding creates a binary variable for each category (denoting 1 or 0 for whether the category applies or not). Ordinal encoding assigns a discrete value to each variable in a specific ranked order.

3.4.1.5. Training decision-tree ensembles

We train decision tree ensemble models because our dataset is best suited to this type of model and because they have shown the greatest predictive power in prior relevant studies (Han et al. 2021; Nguyen et al. 2021; Serafeim and Caicedo, 2022). Decision tree ensembles can detect non-linear relationships and are robust to multi-collinearity between features (Friedman and Popescu 2008) and to noisy data (Serafeim and Caicedo 2022). Specifically, we use XGBoost, LightGBM, and Random Forest on our dataset of company-year observations of emissions reported from 2018-2021.[19] We use the XGBoost, LightGBM, and Sklearn libraries in Python to build each model, respectively.

Of the original labeled dataset after pre-processing (17,824 company-year observations), we used 80% as the training dataset and we tested the prediction performance of the models on 20% of the dataset (the test dataset). Each model contains defined hyperparameters which control the learning process. We used grid search with tenfold cross validation to tune the hyperparameters according to the optimal (minimum) value of RMSE for each model. (See Table B3 in Appendix B for hyperparameters).

Since the predictive power of an ML model is dependent on the training dataset, we note that using a different training dataset could lead to changes in the model's performance as well as the output predictions when unlabeled data is presented. In this study, our training dataset is characterized by companies that report emissions. Thus, this sample of data may carry different characteristics compared to non-reporting companies (the group for which we predict Scope 1 emissions using the trained model). Although this is not a unique limitation to our model but a limitation to all predictive ML models, we provide some additional information about these two sets of data to substantiate that they carry similar characteristics. We compare the top three important numerical features between reporting companies (used in the training dataset) and non-reporting companies (used to predict Scope 1 emissions) by showing their descriptive statistics in Table B5 (Appendix B). We focus on the most important features as they have the greatest impact on the model's predictions. Figure C3 (Appendix C) shows bar plots representing the mean values of the top four numerical features (logEnergyConsumption, logGPPE, and logEmployees) including standard deviation error bars for reporting and non-reporting companies. The error ranges show an overlap for almost all industries across all three features. Overall, this suggests that the data from reporting companies which we used to train our model is similar to that of data from non-reporting companies.

We evaluate each model's prediction accuracy according to several metrics to demonstrate the robustness of our model. We calculate the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and adjusted R^2 of model predictions. MAE is the average absolute error between actual and predicted values (i.e., residuals), providing a value in terms of the target variable. MAPE represents the same error but measured as a percentage difference rather than in absolute terms. MAPE is useful for comparing across models with different target variables. Low MAE and MAPE values suggest good model predictions; a value of zero would suggest a perfect prediction of the target variable. RMSE, calculated as the square root of the mean squared error of residuals, penalizes large prediction errors more than MAE or MAPE, and is thus sensitive to outliers. It is also easily interpreted as it is given in the same units as the target variable. Adjusted R^2 modifies the R^2 metric – which measures how well features can predict the target variable – by taking into account the number of

[19] In earlier iterations of this work, we also trained models using Catboost and Adaboost with a smaller sample of company-year observations (reported emissions from 2018-2020). We found that these models performed poorly compared to XGBoost, Random Forest, and Light GBM. Hence, we decided to use the latter three algorithms in this version of the study. Still, we provide the performance results of these earlier models in Table B4 in Appendix B.

features present in the model. It is given as a value between 0 and 1, where 1 indicates that 100% of the variation in the predictions can be explained by the features.

3.4.1.5.1. Missing data

An advantage of using XGBoost and LightGBM is that they can handle missing data without the need for imputation, thus avoiding the creation of potential bias in the training dataset. On the other hand, Random Forest is unable to handle missing data. Consequently, for this model, we imputed missing values by using the kNN algorithm. kNN is based on the concept that an unknown value can be predicted according to similar data points that are within some specified close range (Jain et al. 2020). The similarity of data points is calculated according to the lowest metric distance (usually Euclidian distance) between k neighbouring data points (De Lucia et al. 2020). An optimal K can be determined according to error rate calculations of a range of k values.[20]

3.4.1.5.2. Feature pruning and assessing according to SHAP

We use SHAP (Lundberg and Lee 2017) to evaluate the impact of features on the model's target variable. SHAP is a unique tool used to improve the interpretability of ML models. Specifically, a feature's SHAP value associated with a specific prediction represents the difference between the actual prediction (for that row of data) and the mean prediction (of the entire dataset) (Marcilio and Eler 2020). This provides *local* interpretability since it explains individual predictions (Ascher et al. 2022). A feature's *global* impact on model predictions is represented as the mean of all absolute SHAP values of a specific feature for the entire dataset (Ariza-Garzon et al. 2020).

In addition to evaluating feature importance according to SHAP, we also use it to further simplify our best performing model (one of XGBoost, LightGBM, and Random Forest). We do this by removing features of negligible importance (i.e., those with SHAP values of zero) since they are considered redundant and add noise to the model (Kumar and Boulanger 2020).

3.4.2. Estimating global corporate emissions

We used our best performing model to estimate emissions from all non-reporting public companies globally in 2021. At the time of data collection, there were 50,155 companies listed in Bloomberg that had not reported Scope 1 emissions. We collected data on the features used in the model for these companies (using the same data collection methods as outlined in section 3.4.1). This data was used as the input to the model. Since our target variable, Scope 1 emissions,

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[20]We calculated the root mean-squared error (RMSE) of different k values. We chose k=19 to impute the missing data, which had a relatively low error (1.38). Higher values of k had lower errors, but since a high k is associated with underfitting of the model, we opted for a lower value of k. We imputed missing values for all numerical features (*EBITDA margin, ROA, ROE, logRevenue, logGPPE, logCAPEX, logEnergyConsumption, logEmployees, logFCF, logCFO, CFPS, logAssetAge, Percent foreign revenue*), except for the *percent of women on the board*, which we assumed to be 0% if a company did not report this metric. We excluded Scope 1 emissions from the imputation calculations because this is the predicted variable.

is predicted on a logarithmic scale, we calculated the inverse logarithm of the model outputs to estimate the absolute Scope 1 emissions of non-reporting companies in metric tonnes of CO_2e.

3.5. Results and Discussion

3.5.1. Predictive performance of the models

We present the prediction performance results of our models in Table 3.2, including the results from the benchmark study for comparison. Specifically, we compare our results to the best meta-learner for the prediction of Scope 1 emissions from Nguyen et al. (2021).[21]

All measures of performance (MAE, RMSE, adjusted R^2) for each model showed an improvement compared to the benchmark study's best Scope 1 meta-learner. Overall, our best performing model is XGBoost, followed by LightGBM and Random Forest. XGBoost showed an improvement of 21.21 % in MAE, 17.33% in RMSE, and 21.13% in adjusted R^2 compared to the best Scope 1 meta-learner of the benchmark study. Since the adjusted R^2 for XGBoost, LightGBM, and Random Forest are higher than the best-meta learner in the benchmark study, this indicates that our choice of predictor variables may better explain the variation in log-scaled Scope 1 emissions. The MAPE for XGBoost is 0.17, which demonstrates that the model predictions are within ±0.17% accuracy of actual (reported) Scope 1 emissions on a logarithmic scale. MAPE was not reported in the benchmark study.

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[21] We compare our results to the benchmark study's best meta-learner namely because the error metrics for MAE, RMSE, and adjusted R^2 are not provided for the XGBoost base-learner. We note, however, that the benchmark study's XGBoost and Random Forest base-learners both resulted in a MAE of 1.03, which is also a greater error than that of our XGBoost model.

Model	MAE	MAPE	RMSE	Adjusted R^2	MAE improvement (%)	RMSE improvement (%)	Adjusted R^2 improvement (%)
XGBoost[a]	0.78	0.17	1.24	0.86	21.21%	17.33%	21.13%
LightGBM	0.78	0.17	1.25	0.86	21.21%	16.67%	21.13%
Random Forest	0.91	0.20	1.37	0.84	8.08%	8.67%	18.31%
Benchmark study (best Scope 1 meta-learner)	0.99	n/a	1.50	0.71	n/a	n/a	n/a

Table 3.2: Out-of-sample prediction performance measured as mean absolute error, mean absolute percentage error, root mean squared error, and adjusted R^2 for our tree-based ensemble models and the benchmark study's best meta-learner, meta-Elastic Net. [a]Error results for XGBoost represent the errors calculated once features of low importance were removed from the model. However, because these features had practically no impact on the model, removing them did not change the error results.

Overall, the predictive performances of our ensemble tree-based models show a notable improvement over the benchmark study's best meta-learner, meta-Elastic Net, as well as its XGBoost base-learner. Our study solidifies the performative ability of ensemble tree models to estimate corporate emissions, specifically, Scope 1 emissions. Our models are of lower complexity and computational cost compared to the benchmark study as we do not employ meta-learners.

We also differentiate our study by our feature selection approach. Prior studies have used a large number of features at random (Han et al. 2021) or features commonly used in regression or naïve models of earlier studies (Nguyen et al. 2021; Serafeim and Caicedo 2022). While prior evidence supporting the use of certain features is informative, having some theoretical framework(s) to guide initial feature choices helps organize the selection process and contributes to the interpretability of the model. Accordingly, we take an economic, institutional, and agency perspective on the impacts of company characteristics and actions on GHG emissions in our feature selection process. We further differentiate our feature selection approach by considering data availability and SHAP importance: we leave out features with <50% of available data in our original training dataset and we remove features with zero SHAP importance from the final model (XGBoost). In contrast, the benchmark study selects its final set of features based on the results of OLS regressions on all combinations of the initial set of features. One disadvantage of this approach is the assumption that features are linearly associated with the target variable and may thus discount variables that have non-linear relationships with the target variable. We endeavored to retain all features contributing to the model (i.e., those with >0 SHAP values) and did not rely on the assumption of linearity between features and the target variable. We provide more detail on feature SHAP values in the next sections.

3.5.2. Feature importance with SHAP

SHAP values help explain the impact of a feature on a model's predictions (Marcilio and Eler 2020). First, we use SHAP to prune the number of features in our best performing model (XGBoost). Then, we assess feature importance using SHAP. We provide a global feature importance (SHAP) ranking of all final features in Appendix C, Figure C4.

3.5.2.1. Features with zero SHAP

To simplify our model, we removed features of no importance (those where SHAP=0), which included *Paris (country), ETS (country), Carbon tax (country)*, and all individual *Subregion* features (as these were one-hot encoded binary categorical variables). Notably, each of these features are related to the country of domicile (location of management), and not the country of risk (location of company operations). This may indicate that a company is more affected by carbon regulations and institutional norms in the locations where it operates, rather than where it is managed or headquartered. Alternatively, if country of domicile and country of risk were highly correlated, SHAP would assign a lower value to the feature that is less predictive.

After the removal of these features, we were left with 23 features (accounting for ICB *Industry* variables and *Subregion of Risk* variables as single features which had been one-hot encoded) in our final XGBoost model.

3.5.2.2. Interpreting model features with SHAP

Next, we assess the global impact of features to help explain the entire dataset. Figure 3.2 displays the top 20 features by overall feature importance in the final XGBoost model based on mean absolute SHAP values. The rankings of all features can be found in Appendix C, Figure C4. The most important feature in the XGBoost model is *logEnergyConsumption*, and its SHAP value indicates that it has an average absolute impact on log-scaled Scope 1 emissions of 1.61. This is followed by *logGPPE* (SHAP = |0.72|), *Subregion of Risk (Eastern Asia)* (SHAP = |0.20|), and *logEmployees* (SHAP=|0.14|) Prior studies have similarly demonstrated the importance of energy consumption and physical assets in predicting corporate emissions (Nguyen et al. 2021; Serafeim and Caicedo 2022).

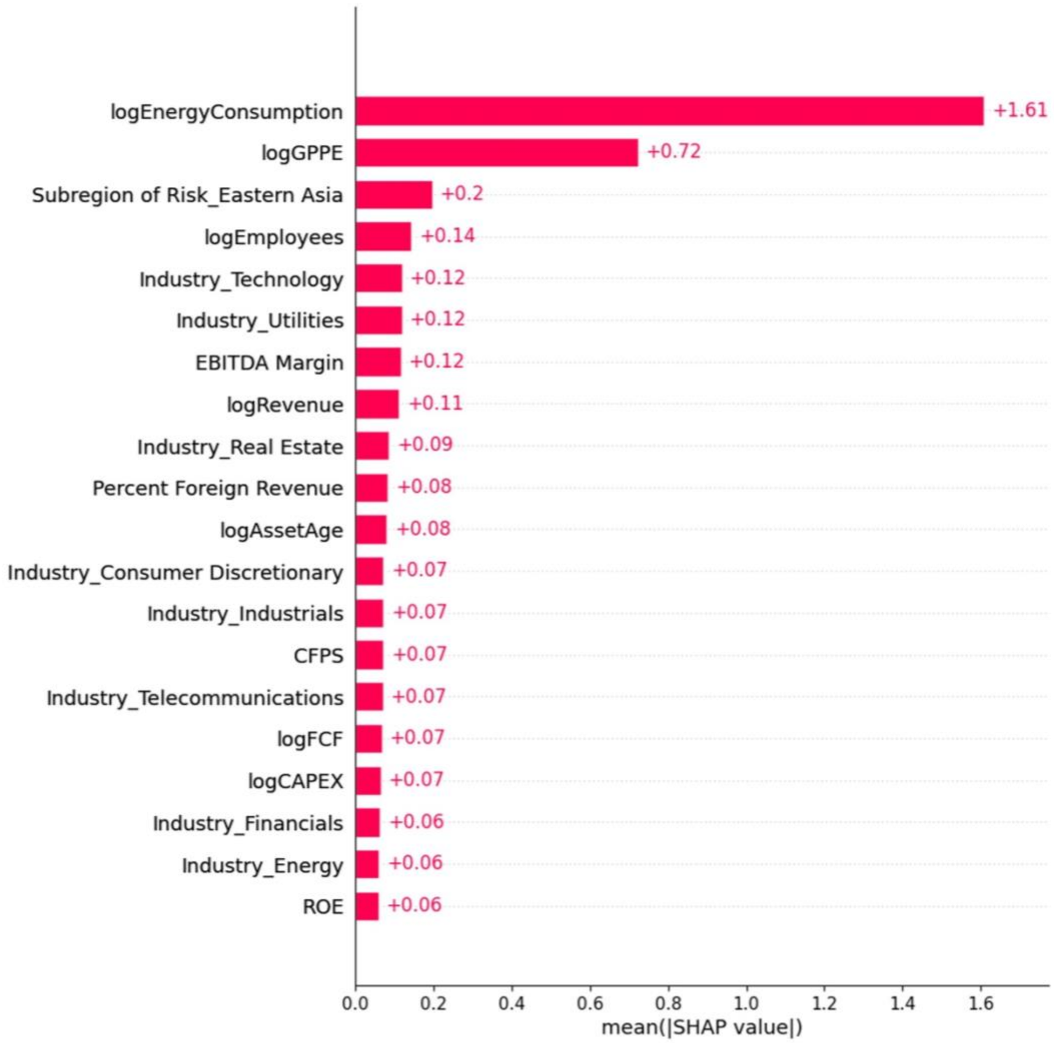

Figure 3.2 Bar plot displaying average absolute SHAP values for the top 20 XGBoost model features. Features are ranked according to their contribution to the model's predicted Scope 1 emissions on a logarithmic scale.

It is notable that the climate management features, derived from agency theory, scored low in mean absolute SHAP values (<0.05), including *CC management* and *CC policy* (see Figure B3). These results suggest that company efforts to internalize or mitigate emissions via internal management systems do not significantly contribute to predicting emissions. This deduction is similar to that of Doda et al. (2016) who found that corporate policies, strategies, and management responsibilities related to climate change did not have an effect on reducing emissions. Reasons for this could be that climate management is not well reported or that management practices are not oriented towards emissions reductions (Doda et al. 2016).

Voluntary climate initiatives *(Emissions target* and *Carbon Price)* also had low SHAP values (<0.05). This suggests that corporate climate commitments and the use of carbon pricing, a market-based approach to climate change, may not lead to changes in emissions. This is unsurprising, since other studies have made similar deductions (Bjørn, Lloyd, et al. 2022; Doda et al. 2016; NewClimate Institute 2022). Most features for the presence of carbon regulations and company location including *ETS (country of risk), carbon tax (country of risk), Paris (country of* *risk),* and *Subregion of Risk* (except for *Eastern Asia*) also had low SHAP values (<0.05), suggesting that coercive and normative institutional forces may not play a significant role in predicting emissions. This is an important finding for policy makers, as it may indicate that carbon regulations are not stringent enough to be making an impact on company-level emissions.

To assess the directional effects (positive or negative contributions) of features on the model predictions, we present beeswarm plots (Figure 3.3) which include *Subregion of Risk* features (Figure 3.3a), *Industry* features (Figure 3.3b), and all remaining features (Figure 3.3c). A beeswarm plot not only shows the ranked global importance of features, but it also depicts the relationship between individual feature values and their predictions. Each dot represents one datapoint in a row of data. In other words, a dot represents a feature value that is associated to one company of a particular year. The dots are distributed horizontally according to their SHAP value, where similar SHAP values result in a higher density of points. A negative SHAP value means that the feature of that company-year observation negatively contributes to the prediction of that observation. Conversely, a positive SHAP value means that the feature of that company-year observation positively contributes to the prediction of that observation. The dot colour represents the relative raw value of the datapoint, where red represents a high value and blue represents a low value. Since the features in Figures 3.3a and 3.3b are binary categorical variables, a high value (1) indicates that the company belongs to that category, and a low value (0) indicates that the company does not belong to that category. This is also the case for all binary categorical variables in Figure 3.3c.

Figure 3.3b shows the impacts of a company's industry on predictions. Companies in the *Technology, Real Estate, Consumer Discretionary, Telecommunications, and Financials* industries have overall negative contributions to predictions, for example, up to -2.4 units (-11 tCO_2e) for the *Real Estate* sector. Companies in these sectors are typically office-based or have the majority of their emissions in Scope 2 and Scope 3 categories. In contrast, companies in the *Utilities, Industrials,* and *Energy* industries have positive contributions to predictions, for example, up to +4.1 units (60.3 tCO_2e) for the *Utilities* sector. These are high-emitting sectors, known for their high reported Scope 1 emissions due to intensive on-site operations (Hadziosmanovic et al. 2022). The overall importance of a company's industry for estimating carbon footprints has been established in prior studies as well (Griffin et al. 2017; Nguyen et al. 2021; Serafeim and Caicedo 2022). While these results may highlight that companies mimic competitor behaviour (reflecting mimetic institutional forces at play), the effect of industry could also be related to the type and level of goods or services produced by the company. We discuss such effects next, as they relate to economic drivers of corporate emissions.

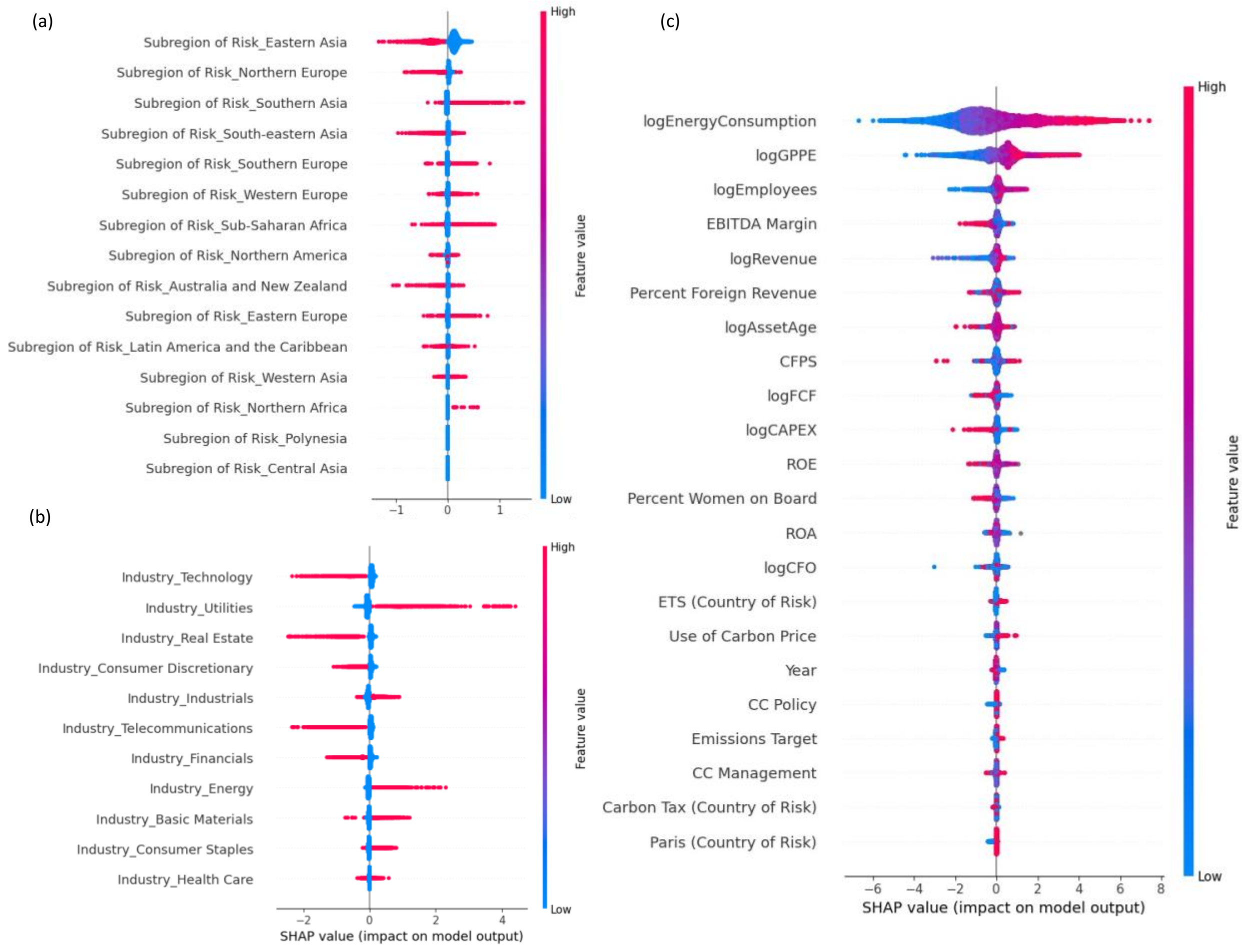

Figure 3.3 Beeswarm plots of features ranked by mean absolute SHAP values showing the distribution of the impacts of each feature. Each dot represents one data point of the dataset related to a specific feature. The dots are distributed horizontally according to the SHAP value of the datapoint, where many equal or similar SHAP values result in a high density of points. The colour of the dot represents the relative raw value (high or low) of the datapoint. (a) displays Subregion of Risk features, (b) displays Industry features, (c) displays all other features. Note that x-axes scales vary between (a), (b), and (c).

Several predictor variables in Figure 3.3c show clear patterns for the effect of low to high feature values on model predictions. *logEnergyConsumption*, *logGPPE*, and *logEmployees* show that low feature values have a negative impact on predictions, while high values have a positive impact on predictions. This is also evident from the individual feature plots (discussed in the next section) that are supplied in Appendix C. Notably, *logEnergyConsumption* can impact predictions up to ±7 units, equivalent to ±1096 tCO_2e. These results align with past regression studies that have found significant relationships between corporate emissions, and metrics for energy consumption, company size, or physical assets (Goldhammer et al. 2017; Griffin et al. 2017).

EBITDA margin, *logCAPEX* and *Percent Women on Board* have the opposite effect: low feature values have a positive impact on predictions, and high feature values have a negative impact on predictions. High *EBITDA margin* reflects greater operational efficiency and higher cash flows (Tsai et al. 2006). Our results align with this notion, since high EBITDA margin values have a negative impact on predicted emissions, suggesting greater operational efficiencies within a company.

CAPEX is capital used to invest in physical assets, whether to acquire new assets, or upgrade or maintain existing assets. High CAPEX could thus indicate that a company is investing in more efficient, low carbon technologies, which can contribute to mitigating emissions. A similar rationale was posited by Goldhammer et al. (2017). However, because they used capital intensity (ratio of GPPE to turnover), they found the opposite effect. Consequently, our results indicate that investments in new and efficient technologies would be better measured using CAPEX rather than capital intensity, and that ownership of physical assets are better measured using GPPE.

Other features show less clarity with respect to the direction of contributions to the model's predictions. For example, *Percent Foreign Revenue* (SHAP=|0.08|), *logFCF* (SHAP=|0.07|), *CFPS* (SHAP=|0.07|), and *logAssetAge* (SHAP=|0.08|) show that both high and low feature values can lead to both positive and negative prediction contributions. However, non-linear relationships and high-order variable interactions could be present, since these features still contribute to the model predictions both locally and globally (see Figure C4, Appendix C).

3.5.2.3. Individual feature analysis

Here, we discuss results from a sample of individual features, visualized as dependence plots in Figures 3.4 and 3.5. (All other individual feature plots can be found in Appendix C). Dependence plots exhibit the relationship between feature values and SHAP values, effectively acting as a "zoomed-in" look at individual features from the beeswarm plot (Figure 3.3). Dependence plots also exhibit the distribution of data (shown by the grey inset histogram) and possible interaction effects between predictor variables. Interaction effects are shown by the vertical distribution of points: when the same feature value has a range of different SHAP values, this suggests that the values of other features in the same row of data (company-year observation) have an effect on the SHAP value of the observed feature.

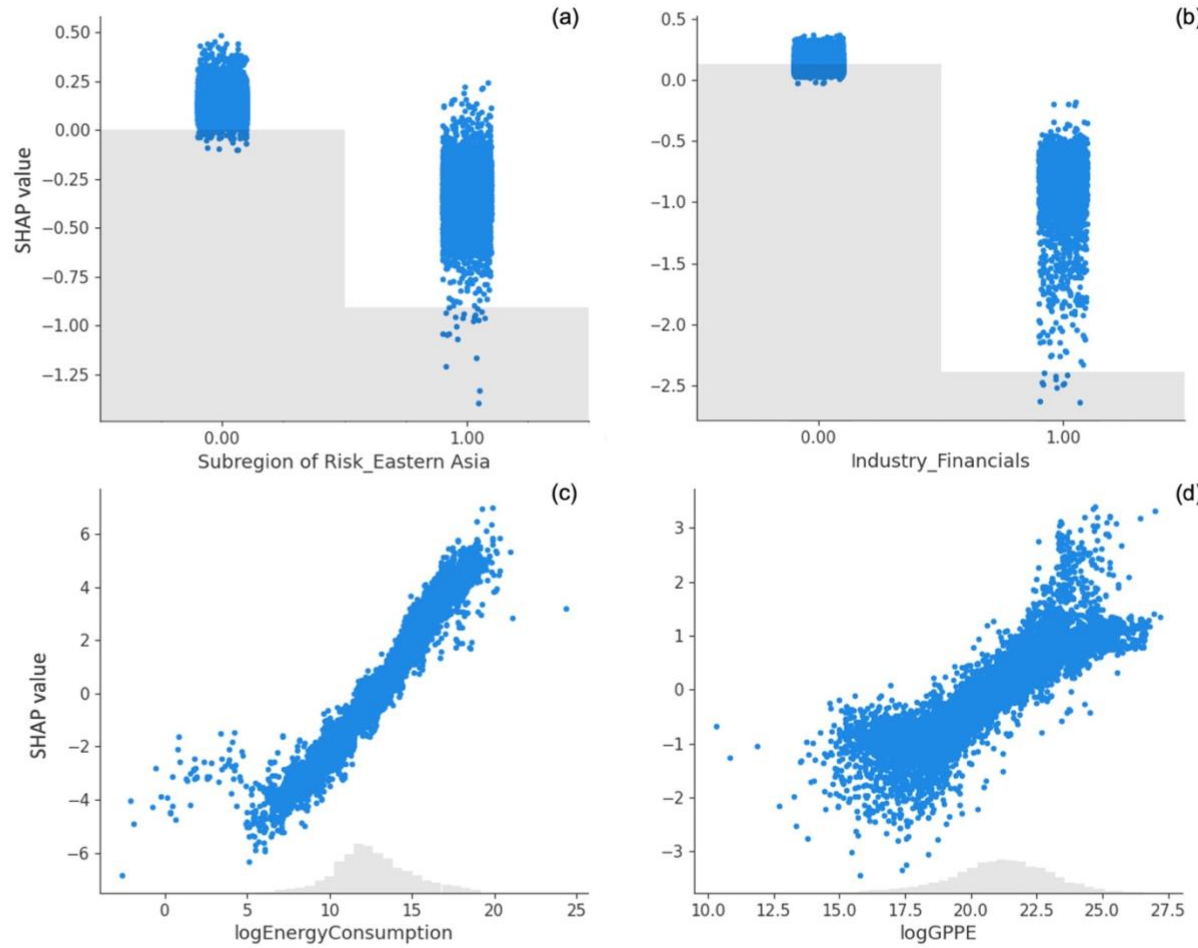

Figure 3.4 Individual feature dependence plots showing the relationship between individual feature values and SHAP values. We show four features ranking in the top 20 features: Subregion of Risk (Eastern Asia) (a), the Financials industry (b), log-scaled energy consumption (c) and log-scaled GPPE (d).

Figure 3.4 depicts four features of the top 20 important features. Figures 3.4a and 3.4b show that predicted emissions will be impacted negatively when companies that have operations in Eastern Asia and when they are in the Financials industry. Figures 3.4c and 3.4d show that energy consumption and GPPE are positively associated with predicted emissions, meaning that higher values of these features have positive impacts on predicted emissions. These same conclusions can be drawn from observing the patterns of these features in the beeswarm plot (Figure 3.3).

Figure 3.5 depicts four features which were not in the top 20 important features and were difficult to analyze visually in the beeswarm plots due to their SHAP values being close to zero. Figure 3.5a presents the relationship between SHAP and different levels at which climate change is managed in a company. Bloomberg classifies four levels of management, and we added a fifth for when no information was available. The ordered levels are:

(0) Board
(1) Subset of Board/Committee appointed by Board
(2) Manager/Officer
(3) No individual or committee
(4) Unknown

Each level of CC management ranges from negative to positive prediction contributions, but cluster close to zero. This reaffirms the results from Figure 3.5 indicating a low overall importance of this feature, but it also shows that the *individual* levels of CC management have a small impact on emissions predictions. The vertical distributions of data (from positive to negative SHAP values), demonstrate that there are interaction effects with other features.

The presence of a carbon tax in the country of risk (Figure 3.5b) has an overall more negative impact on predictions compared to when there is no carbon tax (although the vertical distribution of the SHAP values indicate positive effects for individual predictions as well). This finding is informative for two reasons: the presence of a carbon tax in countries where companies operate shows potential for having a mitigating impact on direct emissions, but carbon taxes may not be stringent enough to ensure this effect since SHAP values are close to zero (mean|0.01|).

For companies that set an emissions target (Figure 3.5c), this appears to have a more positive impact on emissions predictions. At first, this seems counterintuitive. Companies voluntarily limiting their GHG emissions via target-setting suggests a motivation for addressing climate change, and accordingly, reducing emissions. Our results show an opposite effect, and we conjecture that companies setting targets are larger in size and operations and are thus more exposed to stakeholder pressures to set emissions targets. A similar argument is made by Liu and Anbumozhi (2009) who posit that large companies are under more public scrutiny and are thus more likely to engage in environmental disclosure. While the overall contribution of the *Emissions target* feature is low (mean|0.02)|, it still highlights that setting emissions targets may not lead to lower emissions.

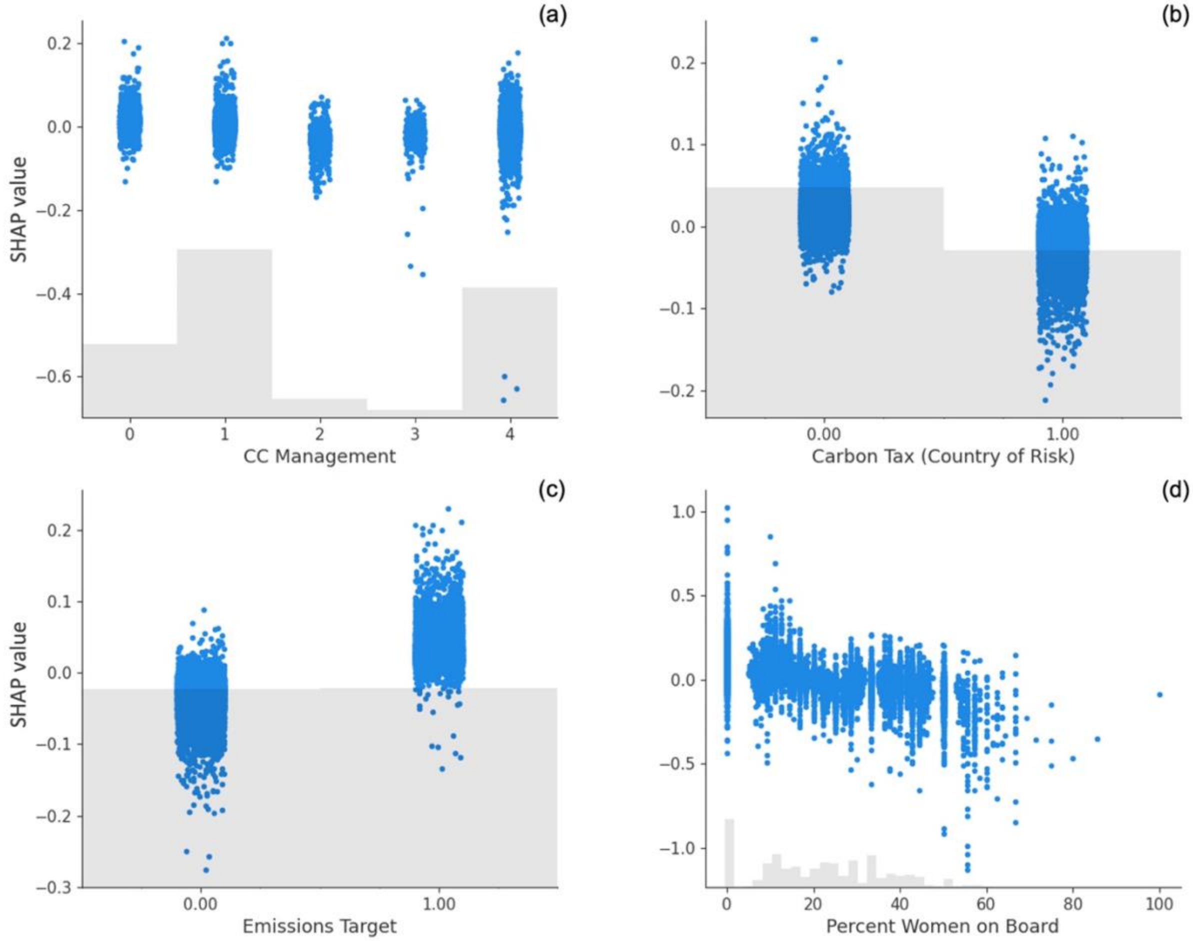

Figure 3.5 Individual feature dependence plots showing the relationship between individual feature values and SHAP values. We show four features ranking below the top 20 features: CC management (a), Carbon tax (b), Emissions target (c) and Percent of women on the board (d).

The SHAP values observed for changes in the percent of women on the board (Figure 3.5d) show an interesting pattern. As percent of women on the board increases, up to around 40%, SHAP values are close to zero but show a slow decline. Once the percent of women on the board surpasses 40%, the downward trend in SHAP values is more noticeable, and SHAP values become more negative. Although there are fewer observations with >40% women on the board (as shown by the inset histogram), these results suggest that having a majority of women on the board of directors reduces predicted emissions. While some studies provide evidence that more women on the board of directors have a positive effect on climate-related initiatives (Hollindale et al. 2019), a counterargument could be made that organizations with lower emissions might already have a progressive approach regarding their social impacts and governance, which could be the driver for greater diversity of their board of directors. We also note the increase in vertical distribution of data after 40%, implying that are more interaction effects with other features on the SHAP values of *Percent women on the board*.

3.5.3. Model estimates of global corporate emissions

At the time of data collection (October 2022), there were 4,847 publicly listed companies in Bloomberg that reported Scope 1 emissions (reporting companies) and 50,155 that had not reported Scope 1 emissions (non-reporting companies) for 2021. Adjusting for the log-scaled output, our XGBoost model estimates that non-reporting companies account for 2.05 $GtCO_2e$. Reporting companies accounted for 9.35 $GtCO_2e$. Therefore, we estimate the global total for public companies in 2021 to be 11.4 $GtCO_2e$. Considering non-CO_2 gases, this is approximately 22% of total global GHG emissions which were estimated to be 52.8 $GtCO_2e$ in 2021 (UNEP 2022).

What is immediately striking is that the emissions estimate for non-reporting companies (which make up 91% of publicly listed companies) is significantly smaller than the emissions of reporting companies (which make up 9% of publicly listed companies). Non-reporting companies contribute 18% of emissions to the 11.4 $GtCO_2e$ global estimate, while reporting companies contribute 82% of emissions. This implies that high-emitters are the companies reporting emissions and low-emitters are not. This is significant because it suggests that we may have a decent estimate of emissions globally from public companies based on already reported data.

Much of academic discussion on corporate GHG accounting up until now has stressed the importance of complete, accurate, and transparent accounting (Gillenwater 2022; Klaaßen and Stoll 2021; Schaltegger and Csutora 2012). While we also consider these principles valuable, the results of our study compel us to shift our attention elsewhere. Since our findings indicate that we have a decent estimate of corporate emissions, we argue that both academic and corporate attention should be shifted towards developing processes and systems that actually decarbonize company operations, and away from pouring resources into more meticulous, complete, or even verified GHG accounting. A recent survey by a major sustainability consulting company, ERM, suggests that on average, companies invest almost $90,000 (USD) more in GHG accounting and disclosure efforts compared to their investments in integrating climate management processes, annually (Lee et al. 2022). Considering the critical need for immediate climate mitigation action, this distribution of resources seems flawed. Furthermore, on average companies spend another $82,000 (USD) on assurance and verification processes (Lee et al. 2022). Yet, studies have cast doubt on whether verification practices can guarantee the reliability of GHG inventories (Datt et al. 2021; Talbot and Boiral 2015), suggesting that investments in these practices could be better placed towards climate mitigation efforts.

Our recommendation to shift the focus towards impactful climate mitigation action aligns with that in the recent review on climate accounting by Gulluscio et al. (2020) They suggest that research should concentrate on the extent to which climate management practices impact corporate sustainability and how to better develop them so that their climate impacts are real, while focusing less on climate reporting or accounting issues. Afterall, improving GHG reporting alone will not solve the climate crisis, a consideration echoed almost three decades ago by Gibson (1996) in her review on reporting pollution allowances.

Importantly, we are not suggesting companies should not account for and report their GHG emissions. We are also not suggesting that machine learning should *replace* emissions accounting, but that in the interim, it can be used to fill a data gap which would otherwise be better filled by companies themselves. Here, we posit that fixations on GHG accounting accuracies at the company-level may not have consequential effects at the global level. For a company already reporting its emissions, the time and resources committed to further improving accounting accuracies could be better applied to implementing effective climate management systems and decarbonization initiatives.

3.5.4. Limitations

We note a few limitations to our study. First, our model is trained to predict only Scope 1 emissions, which accounts for direct on-site emissions. According to the GHG Protocol, companies should also report Scope 2 and Scope 3 indirect emissions. Since one of our objectives was to estimate global emissions from public companies, include indirect emissions in the model would have led to double counting. For the purpose of filling the gap in data on corporate indirect emissions, future research may look to improving on past models estimating Scope 2 and Scope 3 emissions, namely those by Nguyen et al. (2021) and Serafeim and Caicedo (2022).

Second, most of our features were obtained using the Bloomberg database, which requires a license to access. However, most company financial metrics which we use as features can be obtained from other public sources. Other features including CC management and CC policy are derived by Bloomberg from corporate responses to the CDP disclosure program, so data for these features can be collected from the CDP as well. A similar or equivalent predictor variable to the Bloomberg unique identifier, country of risk, can be sourced from other financial databases or devised from company annual filings.

Lastly, although we endeavored to improve the interpretability of our model by providing theoretical underpinnings for our feature selection process and using SHAP to interpret feature importance, the explanatory power of ensemble tree models remains weaker than simpler models such as regression models. Since our focus in this study was on predictive power rather than explanatory power, we suggest that future research explore ways to improve the interpretability of ensemble tree models or to develop ways to balance predictive and explanatory power more methodically.

3.6. Conclusion

Our study uses ML methods to estimate company-level Scope 1 emissions and can be used as a gap-filling approach for non-reporting companies until GHG accounting and reporting is widespread. We establish the usefulness of decision tree ensemble models for estimating corporate emissions, showing an improved performance in prediction accuracy of each of our trained models compared to the benchmark model. Also, our models are of reduced complexity because they do not employ meta-learners.

We have shown that a model could be improved with a feature selection methodology that uses theoretical frameworks as a basis and SHAP values to remove unnecessary features. Overall, our feature importance results demonstrate that corporate emissions predictions are most associated with economic and mimetic institutional forces more so than agency forces or coercive and normative institutional forces. This is informative to managers as it implies that internal company efforts like setting climate policies or assigning climate issues to certain levels of management are efforts that are not substantially impacting corporate emissions. It also indicates to policymakers that existing carbon regulations are not having a notable effect on corporate emissions.

This research is the first to estimate global Scope 1 emissions from public companies, which we quantify using our XGBoost model outputs. We estimate that public companies account for 11.4 $GtCO_2e$ globally in 2021, which is about 22% of global GHG emissions. Future studies may seek to validate our estimate by developing different machine learning models, or by determining emissions from non-corporate sources and corroborating these with global GHG estimates.

Our finding that 82% of global emissions from public companies come from reporting companies suggests that high-emitters are reporting more than low-emitters. This should encourage companies already reporting to commit their resources to better climate management systems and decarbonization efforts. Similarly, future academic research could analyze the effectiveness of such climate management systems and other corporate climate initiatives. This would benefit companies, their stakeholders, and society at large–perhaps more than deep dives into the minutiae of GHG accounting.

Chapter 4: Motivations and effects of consolidation approach changes in corporate greenhouse gas accounting

4.1. Abstract

Companies conducting GHG accounting must first delineate their organizational boundaries. These boundaries are set according to a chosen consolidation approach, typically one of operational control, financial control, or equity share, as defined by the Greenhouse Gas (GHG) Protocol Corporate Standard. Researchers have voiced concern that companies are using these consolidation approaches strategically to reshape their boundaries and alter their GHG inventories to their benefit. This study investigates this concern. First, I look for motivations driving companies to choose certain consolidation approaches and change them from year to year in public corporate reports. Second, I investigate how changing a consolidation approach impacts the emissions profile of a company. I compare annual emissions intensity changes of companies that altered their consolidation approach and those that did not, as well as comparing the change in emissions intensity before and after a company changes its approach. The findings indicate that changes to a consolidation approach are not correlated with lower emissions intensity compared to when consolidation approaches were consistent. While this result provides some initial insight that suggests companies may not be using consolidation approaches strategically, other factors that impact emissions profiles such as company structure, emissions reduction measures, and operational activity changes should be considered in future analyses in order to support this claim. Furthermore, I find that a failure of transparency on consolidation approach choices sows doubt on the true motivations of companies for changing their GHG accounting methodology or for selecting a particular approach in the first place. Going forward, I recommend that climate disclosure organizations such as the CDP require this information, and that companies report their choices and rationales in their public-facing reports.

4.2. Introduction

An important way in which companies determine their climate impacts is through greenhouse gas (GHG) accounting. The GHG Protocol, the gold standard for GHG accounting, sets guidelines for how GHG inventory boundaries should be set (WRI and WBSCD 2004). First, it establishes operational boundaries which relate to how emissions are categorized. Emissions are grouped in one of three categories: Scope 1 represents direct emissions from sources owned or controlled by the company; Scope 2 represents indirect emissions from purchased energy; and Scope 3 represents all other indirect emissions, namely those in the company's value chain (WRI and WBSCD 2004). However, whether emissions in any scopes are accounted for is determined by how a company sets its organizational boundaries. An organizational boundary is set according to varying legal and economic corporate ownership structures (WRI and WBSCD 2004). The emissions that are consolidated within different perimeters of these structures is determined by a selected consolidation approach.

The GHG Protocol defines two types of consolidation approaches: the control approach and the equity share approach. The control approach refers to operations which the company controls, which is further split into financial control and operational control. The operational control approach accounts for emissions sources where the company has full authority to introduce and implement operating policies (WRI and WBSCD 2004), so this is typically "assessed on a "case-by-case basis," (Dragomir 2012, p. 226). In contrast, the financial control approach accounts for emissions sources where the company has authority to change both financial and operating polices while standing to gain an economic benefit from those operations (WRI and WBSCD 2004). Financial control is established when a company has more than 50% economic interest in an operation, although this rule can be overridden by unique contractual agreements (Dragomir 2012). The equity share approach accounts for emissions based on the company's share of ownership (or percentage of equity/shareholdings) in an operation (WRI and WBSCD 2004).

The choice of consolidation approach can have major implications for a GHG inventory. To provide a simple example, let us consider a company that has a minority stake of 40% in an operation. Under the equity share approach, it would account for 40% of emissions from that operation. However, since a minority stake is typically associated with no controlling interests in an operation (Corporate Finance Institute 2022), no emissions would be accounted for according to the financial control approach (unless there is a contractual agreement that stipulates a controlling status).[22] However, corporate ownership structures can be much more complex, making it unclear how the choice of one approach over another would impact reported emissions. While limited evidence has suggested that the choice of one approach versus another may not have an impact on emissions in any particular or consistent direction (Smith 2016), research on the subject is scant and more conclusive evidence is needed to show whether one approach is more likely to result in lower or greater reported emissions compared to another approach.

Companies are also able to change their chosen consolidation approach between reporting years. Although the GHG Protocol stipulates that GHG accounting must be based on the principles of consistency and transparency (among others), consistency between reporting years and transparency about accounting choices remains obscure (Dragomir 2012; NewClimate Institute 2022). Companies may be motivated differently to change their consolidation approach. Potential motivations may be to align with international financial report standards (Smith 2016; WRI and WBSCD 2004). Both financial control and equity share align with financial reporting standards because the economic substance of the relationship between a company and an operation takes precedence over the legal relationship status under both approaches. Another potential motivation is to align with the requirements of relevant government regulations. For example, the operational control approach is often the expected reporting approach for complying with relevant government regulations, such as emissions trading schemes (WRI and WBSCD 2004). Yet, few studies tell us whether these, or other motivations are the reasons for which companies change their consolidation approach. Furthermore, while authors have voiced concerns over the possible strategic use of organizational boundary choices in GHG accounting (Dragomir 2012; Haslam et al. 2014), there is not enough research to substantiate the claim that

[22] More examples of how emissions are accounted for differently according to different consolidation approaches are provided in Table 1 of the GHG Protocol Corporate Standard (WRI and WBSCD 2004, p. 19).

this is happening. I aim to address this and the void in understanding why companies change their consolidation approach.

Specifically, this study investigates two questions: What is the motivation for changing the GHG accounting consolidation approach? And how does changing the consolidation approach impact the emissions profile of companies? To address the first research question, I look for explanations provided by public companies for their consolidation approach change within their annual financial, sustainability, and GHG assurance reports. To address the second question, I take a two-step approach: First, I compare companies that altered their consolidation approach and those that did not by assessing annual emissions intensity changes in the two groups. Second, by considering only companies that altered their consolidation approach, I compare their annual change in emissions intensity before they changed their approach and after they changed their approach. I contribute a novel analysis of motives taken from public reports and emissions profile changes of companies that changed their consolidation approach.

4.3. Literature review and hypothesis development

There has always been some concern that companies engaging in GHG reporting are doing so symbolically (Hrasky 2011). Accordingly, studies have investigated corporate motives for GHG reporting, finding some evidence to support the notion that it is a greenwashing tactic (Hrasky 2012; Tang & Demeritt). However, the motives and impacts of specific GHG accounting choices have received much less attention. Namely, literature investigating consolidation approach choices in GHG accounting is sparse. One group of studies has investigated trends in the choice of consolidation approach (Lopucki 2022; Ryan and Tiller 2022). LoPucki (2022) randomly sampled 200 S&P 500 companies and evaluated their emissions reporting in publicly available corporate social responsibility reports. The study found that only 60% reported a consolidation approach. Of these companies, 88% used operational control, 5% used financial control, 4% used equity share, and the remaining 3% delineated their organizational boundaries according to something other than the GHG Protocol's suggested approaches. Ryan and Tiller (2022) evaluated 237 New Zealand companies subject to mandatory disclosure, looking at various company reports. They found that only 14% of their sample reported a consolidation approach. Of this sample, the majority (97%) used operational control, 3% used financial control, and 0% used equity share or another consolidation approach. Overall, the trends imply that operational control is the most popular approach, followed by financial control, and equity share.

Another group of studies have addressed the design and use of the GHG Protocol's consolidation approaches (Dragomir 2012, Haslam et al. 2014; Smith 2016). Smith (2016) identified and interviewed 18 North American companies which used two different consolidation approaches to report Scope 1 emissions, evaluating the impact of these choices on the company's reported emissions. The results indicated that the choice of consolidation approach can significantly impact reported emissions. For example, the companies that reported GHG emissions according to both the operational control and equity share approaches had operational control emissions that ranged from -73% (lower) to +57% (higher) compared to equity share emissions. Those that reported under equity share and financial control reported identical emissions. However, the authors acknowledged that this result may not reflect general patterns outside of their sample of companies. Due to the small and localized sampling of companies in the study, conclusions about how different consolidation approaches impact emissions could not be made for the wider population of companies.

In the interviews, Smith (2016) inquired about the reasons for, and challenges of reporting according to different consolidation approaches. Reasons for the choice of consolidation approach varied: some companies preferred to report on emissions over which they had operational influence (operational control), others preferred to report on emissions in order to align with their financial accounting boundaries (financial control), and some wanted to provide greater insight to investors about their important company segments, which could be outside of operational control but still carry economic importance (equity share) (Smith 2016). Several companies also cited data collection challenges as playing a part in the choice of consolidation approach, namely, that GHG accounting using the equity share approach was more challenging than the other approaches because of difficulties in obtaining data from entities not operated by the reporting company or from entities under joint ownership. In addition, the equity share approach often requires more data estimation techniques because of missing or incomplete data. The interviews expose several motivations for using different consolidation approaches, but the small sample size limits the analysis.

Two other studies have scrutinized the GHG Protocol's consolidation approach design for GHG accounting (Dragomir 2012; Haslam et al. 2014). Haslam et al. (2014) explored changes in emissions disclosures of firms in the United Kingdom, while also discussing challenges with reporting according to different organizational boundaries. They stressed that setting organizational boundaries according to the operational and financial control approaches are subject to discretionary decisions within the company. Such decisions are influenced by issues about ownership, or physical and contractual relations where significant managerial discretion and judgement exist. Haslam et al. (2014, p. 208) stress that the choices for setting organizational boundaries are "malleable and capable of manipulation" and are further complicated due to corporate structural changes, like acquisitions and divestments.

Dragomir (2012) evaluated sustainability reports from five large European oil and gas companies published between 1998 and 2010. As part of the analysis, he noted several deficiencies in the design of the GHG Protocol's consolidation approaches. First, the equity share approach does not encourage the introduction of emission reduction measures since such measures rely on operational control of emissions sources. Second, both control approaches absolve organizations from any responsibilities tied to economic interests in operations where economic interest is significant but where full control is not established. Since one company in the analysis reported a large difference in emissions following two consolidation approaches, Dragomir (2012, p. 236) underscored that "as long as companies can choose their consolidation method for emissions reporting, they can reshape the organizational boundaries by silently dismissing undesirable polluting facilities…".

For my second research question, which asks how changing the consolidation approach can impact the emissions profile of company, I provide two hypotheses:

Hypothesis 1a (*H1a*): *There is a difference in emissions intensity change between years when a company changes its consolidation approach compared to when a company does not change its consolidation approach.*

Hypothesis 1b (*H1b*): *When a company changes its consolidation approach, its relative change in emissions intensity will decrease more than when a company does not change its consolidation approach.*

Given past evidence for corporate greenwashing behaviour, and the more specific concerns put forward in the literature about the strategic use of consolidation approaches, I rationalize that if companies can manipulate organizational boundaries to their benefit, this would be done in order to report a lower climate impact. Specifically, I use emissions intensity (tonnes of CO_2e per unit of revenue) as the measure of a company's emissions profile. Using this measure, rather than absolute emissions, improves comparability between companies and industries. Also, since revenue is a proxy for company size, it allows us to take annual company structure changes into account. Overall, the hypotheses test the concern over the strategic use of consolidation approaches raised in the literature.

4.4. Research design

4.4.1. Data collection and categorization

I collected GHG disclosure data from corporate responses to the CDP (formerly Carbon Disclosure Project). The CDP is a global disclosure organization that collects environmental information from organizations on an annual basis. I collected company data including reported Scope 1 and Scope 2 (location-based)[23] emissions, consolidation approach, and revenue for the CDP response years 2017-2020. A CDP response year is typically indicative of a company's prior fiscal year's activities. For example, the 2017 response year will reflect a company's fiscal year (FY) 2016 activities.[24] I include both Scope 1 and 2 emissions because these are more completely and consistently reported compared to Scope 3 emissions (Lopucki 2022; Ryan and Tiller 2022). Since some companies may not disclose revenue to the CDP, I collected revenue (local currency in 2022) for the relevant fiscal years that were missing from the CDP responses from the Bloomberg database (Bloomberg L.P. 2022). I collected missing revenue figures for CDP-responding companies that were uniquely identified by company tickers. These tickers are required for the Bloomberg database search.

Companies reported their consolidation approaches as one of the three defined by the GHG Protocol, something else, not applicable, or had left the CDP field blank. I categorized the responses as *financial control, operational control, equity share* or *other.* Responses which I categorized as *other* were unique organizational boundaries described by a company and were thus not one of the three approaches established by the GHG Protocol. This category also included companies that reported emissions and yet indicated the question as not applicable or

[23] Location-based accounting represent emissions resulting from the electricity mix used by the company. In contrast, market-based accounting allows companies to purchase contracts that claim renewable energy attributes which are typically associated with low, or zero emissions (Bjørn, Lloyd, et al. 2022). We chose to focus on location-based because they better reflect a company's true consumption of energy and the emissions associated with that consumption.

[24] Companies can also report for other past years, but our data collection was limited to companies reporting for the most recent fiscal year.

left the field blank. In these instances, I assume that there is some organizational boundary chosen because emissions were reported.

I address the first research question by looking at company reports. I first ranked companies that reported a change in consolidation approach according to reported Scope 1 + Scope 2 emissions across the 2017-2020 CDP response years. I chose the top 50 emitting reporting companies as the focused sample for this analysis. I conducted an internet search for each company's public annual financial, sustainability[25], and GHG assurance reports (in cases when companies assured their GHG inventories) for the two consecutive years that reflected a change in consolidation approach. For example, if a company reported a consolidation approach change between the CDP response years 2018 and 2019, I searched for company reports that reflected FY2017 and FY2018 activities. I were able to find reports using the search engines Google, ResponsibilityReports.com (2022), AnnualReports.com (2022), or directly from company websites. If a company assured its GHG inventory, assurance reports or statements were typically found within the company's sustainability report.

I address the second research question by looking at company emissions intensity changes. I used revenue to estimate emissions intensity of a company (Scope 1 + 2 tCO_2e/unit of revenue). In cases where emissions data was not reported, revenue data was not available or was reported as negative, or Scope 1 and 2 emissions were reported as zero, I did not calculate emissions intensity. Consolidation approach information was taken from CDP questions CC8.1 in 2017, and question C0.5 in 2018, 2019, and 2020.[26]

4.4.2. Identifying motivations for consolidation approach changes

My first analysis aims to address the first research objective, which is to identify motivations of public companies for changing their consolidation approach. I looked at company annual financial, sustainability, and GHG assurance reports. I searched for any mention of the consolidation approach used for the company's GHG inventory, any acknowledgement of the change in consolidation approach, and any explanation provided for the choice of consolidation approach. To do this, I used the following keywords to search each document:[27] "operational control," "financial control," "equity share," "consolidation," "boundary," "greenhouse gas," "GHG," "carbon," and "emission". From there, I reviewed the surrounding text of each keyword found to determine whether the company provides any reason for choosing their consolidation approach or changing it from the prior year–that is, if the consolidation approach was mentioned at all.

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[25] Includes reports that cover non-financial information, sometimes referred to as corporate social responsibility reports, environmental reports, sustainability reports, or similar. Sometimes companies report sustainability together with their annual financial reporting, which is referred to as an integrated report.
[26] The format of CDP questionnaires can change annually, so specific data or information may be contained in different questions from year to year.
[27] The plural form of keywords was used when applicable.

4.4.3. Assessing company emissions profile changes

The methods in this section aim to address the second research objective, which is to determine how changing the consolidation approach impacts the emissions profile of a company. I test the hypotheses, *H1a* and *H1b*, by running two separate analyses (outlined in 4.4.3.1. and 4.4.3.2.). Each analysis tests both *H1a* and *H1b*.

4.4.3.1. Assessing differences between groups: companies that changed their consolidation approach and companies that did not

First, I compare emissions intensity changes of two different groups: companies that altered their consolidation approach and companies that did not. To do this, I identified companies that changed their consolidation approach and companies that did not between two consecutive reporting years of the CDP response years 2017-2020. I then calculated the percentage change in emissions intensity between the two consecutive years for each company. I considered percentage changes greater than +1,000% as extreme values that were likely a result of misreporting or miscalculation, so I removed these observations from the dataset.[28] The final sample included 4,513 observations of emissions intensity change between two years when companies did not change consolidation approach, and 395 observations of emissions intensity change between two years when companies changed their consolidation approach. Having determined that the dataset reflected non-parametric characteristics and unequal variance (see Appendix D), I were limited to a few choices of statistical tests. While the Wilcoxon-Mann-Whitney (WMW) test is commonly used as a non-parametric test for testing differences between groups, many academics have stressed that it is not appropriate when the assumption of equal variance is violated (Divine et al. 2018; Kasuya 2001; Nachar 2008). Instead, I use Welch's t-test at the suggestions of Karch (2021) and Zimmerman (1993). Although Welch's t-test is a parametric test, it is shown to be superior to the WMW test when the assumption of equal variance is violated (Karch 2021). To further validate the results, I opted to also apply the Brunner-Munzel test for stochastic equality–a nonparametric test with no assumption of equal variance–at the suggestion of Karch (2021) and Divine et al. (2018). I apply two-tailed tests to assess *H1a* (that there is a difference in emissions intensity changes between two groups) and one-tailed tests to assess *H1b* (that changes in consolidation approach result in greater decreases in emissions intensity changes compared to when there is no change in consolidation approach).

4.4.3.2. Assessing differences in the same group: impacts before and after a company changed its consolidation approach

Next, I compare emissions intensity changes within the same group of companies. In other words, I compare the annual change in emissions intensity between two consecutive years when a company changed its consolidation approach to the annual change in emissions intensity in two prior consecutive years when the same company's consolidation approach did not change. To illustrate, if a company reported using operational control in the CDP response years 2017 and 2018, but then changed their approach to equity share in 2019, I compare the emissions intensity change between 2018 and 2019, to the emissions intensity change between 2017 and 2018. The

[28] 71 observations from the sample showing >1,000% change in emissions intensity were removed.

resulting sample included 79 observations.[29] This data did not carry the assumption of normality but did present homogeneity of variance (see Appendix D for these tests). Accordingly, I use a two-tailed WMW test to assess whether emissions intensity changes between the groups are different (*H1a*), and a one-tailed WMW test to assess whether there are greater decreases in emissions intensity when a company changes its consolidation approach compared to when it does not (*H1b*).

4.5. Results

4.5.1. Trends in consolidation approach changes

I first present overall trends in consolidation approach changes. I found a total of 740 cases when companies changed their consolidation approach between CDP response years 2017 and 2020. However, 345 of the 740 did not report emissions or revenue associated to one or both years of the reported consolidation approach. Figure 4.1 displays the transitions from one approach to another between consecutive years. It shows that the most frequent approach was operational control both before (37%) and after (47%) a change in approach. Equity share was the least frequent before (4%) and after (3%) a change in approach. Companies with an original approach categorized as *other* made up a large portion (36%) of cases. However, the flows show that the use of the three GHG Protocol approaches were more frequent (76% altogether) after a change in consolidation approach than before (64% altogether). Overall, more companies switch to operational control compared to any of the other approaches.

[29] This sample size was small because both emissions and revenue data across three consecutive years (rather than only two) were required in order to be included in this analysis.

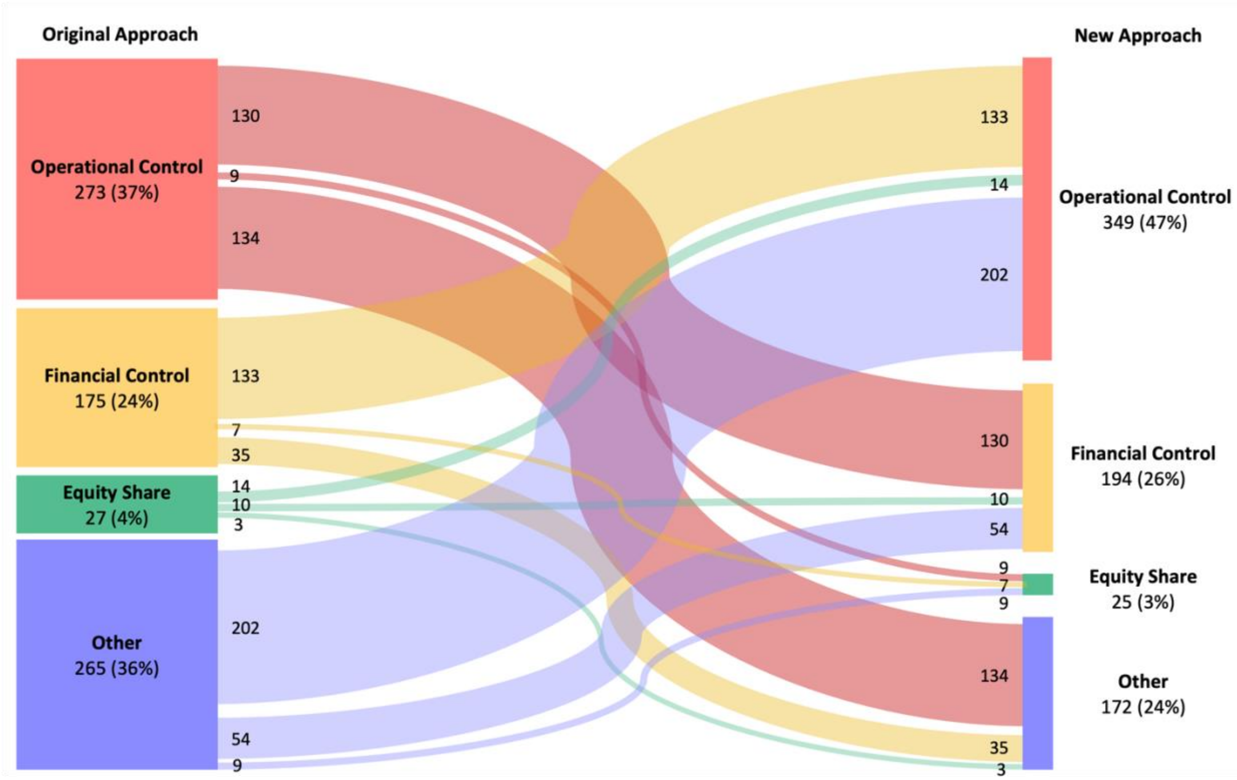

Figure 4.1 Flows of consolidation approach changes reported between CDP response years 2017 and 2020. Shown is the original approach (on the left) and the new approach (on the right) between two consecutive years.

4.5.2. Motivations for consolidation approaches in company reports

I reviewed public reports from the top 50 emitting companies from the CDP dataset. The reports I reviewed were relevant to the fiscal years between which companies reported a change in consolidation approach. I provide a detailed list of these companies and the reports for which I found consolidation approach information in Appendix D. For ease of interpretation, I henceforth refer to one 'public report' as encompassing one or more of the different types of reports (i.e., financial, sustainability, or GHG assurance report) published for a given year.

Of the 50 companies evaluated, 47 companies reported a change between two consecutive years, thus reports from two years were evaluated; 2 companies reported a change between three consecutive years, thus reports from three years were evaluated; and 1 company resulted as a merger of two other companies, so I reviewed reports of the two older companies in the year prior to a consolidation approach change and reports of the merged company in the year when the consolidation approach was changed. The resulting number of company-year observations for which I reviewed public reports was 104.

Table 4.1 is a summary of consolidation approach information provided by companies in their public reports. Of 104 public reports, the majority (74%) did not mention the consolidation approach used for their GHG inventory. 29 (28%) public reports mention the consolidation approach used, but 11 of these reports did not align with the consolidation approach identified by the company in their CDP response. Only 2 public reports acknowledged that the company changed their consolidation approach from the previous year, and only one of these reports described why there was a change in consolidation approach.

	Number of public reports	**Percentage of public reports reviewed**
Consolidation approach not mentioned	75	72%
Consolidation approach mentioned and aligned with CDP response	18	17%
Consolidation approach mentioned, but conflicts with CDP response	11	11%
Consolidation approach change acknowledged	2	2%
Motivation for choice of consolidation approach provided	1	1%
Number of public reports reviewed*	104	

Table 4.1 GHG inventory consolidation approach information provided by companies in their public reports (including annual financial, sustainability, and GHG assurance reports). *A public report encompasses one or multiple types of reports of a given year, which may include the company's annual financial, sustainability, and/or GHG assurance report.

The one company that acknowledged and explained its change in consolidation approach was LafargeHolcim Ltd. This company changed their consolidation approach from operational control (FY2017) to financial control (FY2018). In their 2018 sustainability report (LafargeHolcim 2018, p. 69), they state:

> *"To align with Group financial reporting, and in preparation for a transition to integrated reporting, we have changed our consolidation scope to include the entities covered in the Group consolidated financial statements"*

Although they do not explicitly refer to their approach as "financial control", I interpret this approach from the fact that the GHG inventory covers entities within the company's consolidated financial statements. Their motivation, however, is clearly stated: they want to align with financial reporting.

The one other company that acknowledged its change in consolidation approach, but did not provide a sufficient motivation, was Sumitomo Chemical Co., Ltd. This company also changed their consolidation approach from operational control (FY2017) to financial control (FY2018). In their 2018 sustainability report (Sumitomo Chemical 2018, p. 106), they state:

> *"...Sumitomo Chemical changed its approach to financial control consolidation for disclosure purposes from fiscal 2017..."*

Although they clearly state their new consolidation approach and acknowledge that it was changed, the reasoning for doing so (i.e., “for disclosure purposes”) is vague and can be interpreted varyingly.

4.5.3. Emissions intensity changes between different groups of companies

I present two violin plots with embedded scatter in Figure 4.2 to depict the distribution of changes in emissions intensity (measured as a percent change between two consecutive years) when companies changed their consolidation approach (upper violin) and when they did not change their approach (bottom violin). For visual purposes, I limited the range to ±100% change in emissions intensity. However, the interquartile range and maximum values (shown in Table 4.2) reveal that both samples are actually highly positively skewed with extreme positive values of emissions intensity changes. Consequently, the mean values are positive and are larger than the median values. Both the mean and median of companies that did not change their consolidation approach were lower than the mean and median of companies that did change their approach. However, the median is a better measure of central tendency for skewed data as it is less sensitive to extreme values as compared to the mean. The distributions of each sample are different: the upper violin (companies that changed their approach) has a lower kurtosis and thicker left tail than the lower violin (companies that did not change their approach). The statistical tests confirm unequal variance between the two groups (see Appendix D and E).

Table 4.2 shows the descriptive statistics of emissions intensity changes for when companies changed their consolidation approach and when they did not, and the statistical test results comparing the two groups. Both the Welch’s t-test and Brunner Munzel two-tailed tests indicate a weakly significant difference ($p < 0.10$) in emissions intensity changes between consecutive years when companies changed their consolidation approach and when they did not. This finding thus supports the first hypothesis (*H1a*) to a limited degree. However, I find insignificant results for the one-tailed tests, providing no support for the second hypothesis (*H1b*). Altogether, the results suggest that although there is a weakly significant difference between the groups, changing consolidation approach may be associated with a smaller decrease in emissions intensity change –the opposite effect to what was hypothesized.

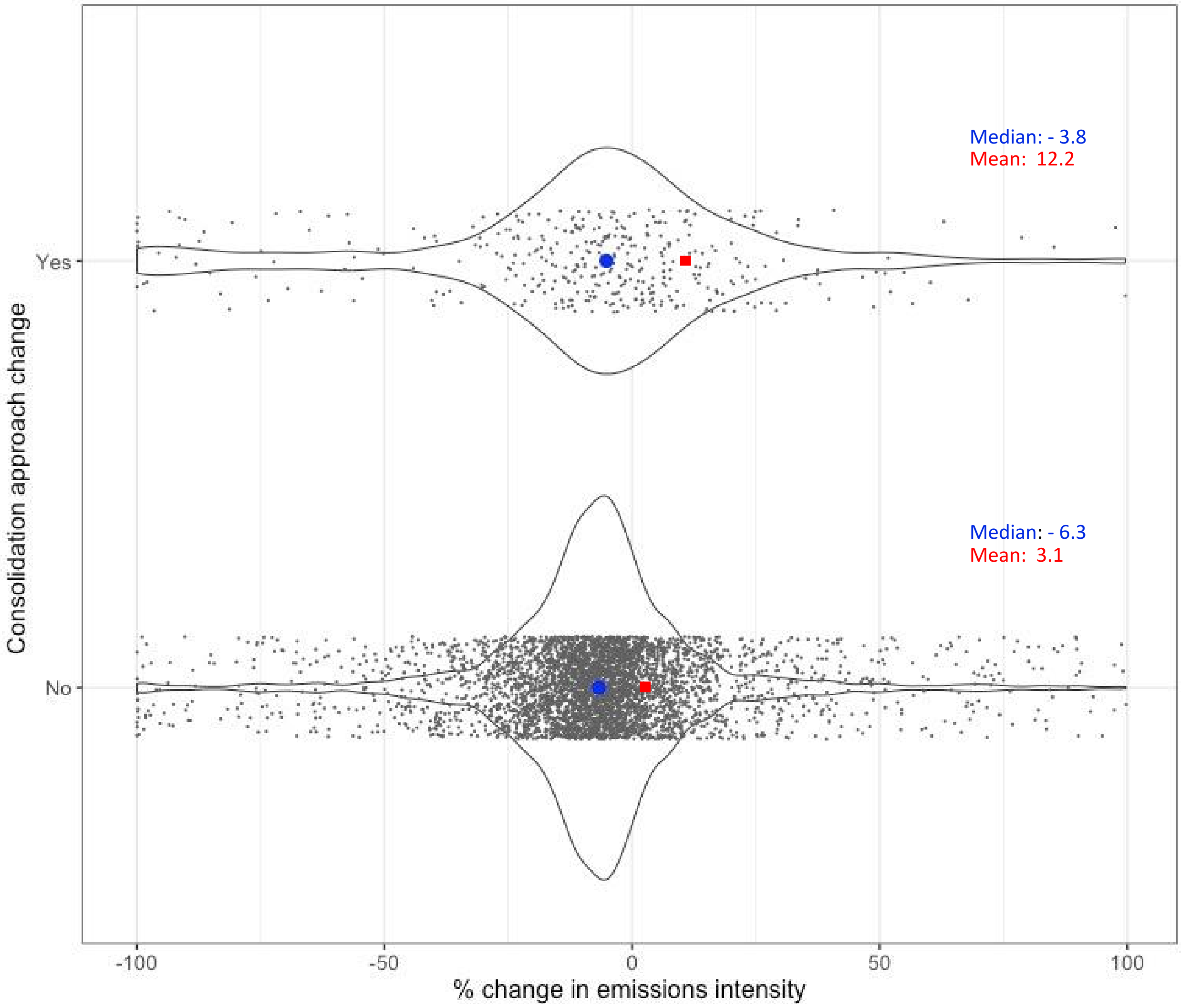

Figure 4.2 Violin plots showing the distribution of percentage changes in emissions intensity between two years, for companies that changed their consolidation approach (top violin) and companies that did not change their consolidation approach (bottom violin). Medians and means represent the entire dataset, which includes extreme values which are greater than +100% and are not displayed in these plots.

Consolidation approach	N	Mean (SD)	Median (Q1,Q3)	Min (Max)	Welch's t-test (two-tailed)	Brunner-Munzel (two-tailed)	Welch's t-test (one-tailed)	Brunner-Munzel (one-tailed)
Changed	395	12.0 (105.1)	-3.8 (-17.9, 11.2)	-99.9 (863.3)	1.695* (0.091)	1.872* (0.062)	1.695 (0.955)	1.873 (0.969)
Did not change	4513	3.1 (70.9)	-6.3 (-14.6, 2.2)	-99.9 (988.9)				

Table 4.2 Descriptive statistics of emissions intensity changes and results from two-tailed and one-tailed Welch's t-test and Brunner-Munzel tests, shown as the test statistic (p-value). *, ** and *** indicate significant test statistics at 10, 5 and 1 %, respectively. SD—Standard Deviation; Q1—first quartile; Q3—third quartile.

I further investigate the sample of 395 companies that changed their approach by visualizing the individual effect of different types of consolidation approach changes on emissions intensity change (shown in Figure 4.3). Each violin represents a different consolidation approach change and each point represents one instance of a company changing its approach. For example, a large number of companies change their approach from operational to financial control, and the distribution of percentage change in emissions intensity is wide compared to other types of changes. However, for some types of changes such as other to equity share, operational control to equity share, and equity share to other, the sample sizes were very small, so any patterns should be interpreted with caution. The central tendency (medians) of most types of consolidation approach changes is negative, indicating a reduction in emissions intensity, except for changes from other to operational control, equity share to operational control, and equity share to financial control. However, companies that did not change consolidation approach also showed a negative central tendency in emissions intensity change (Figure 4.2), suggesting that consolidation approach changes were not associated with larger decreases in emissions intensity compared to other companies.

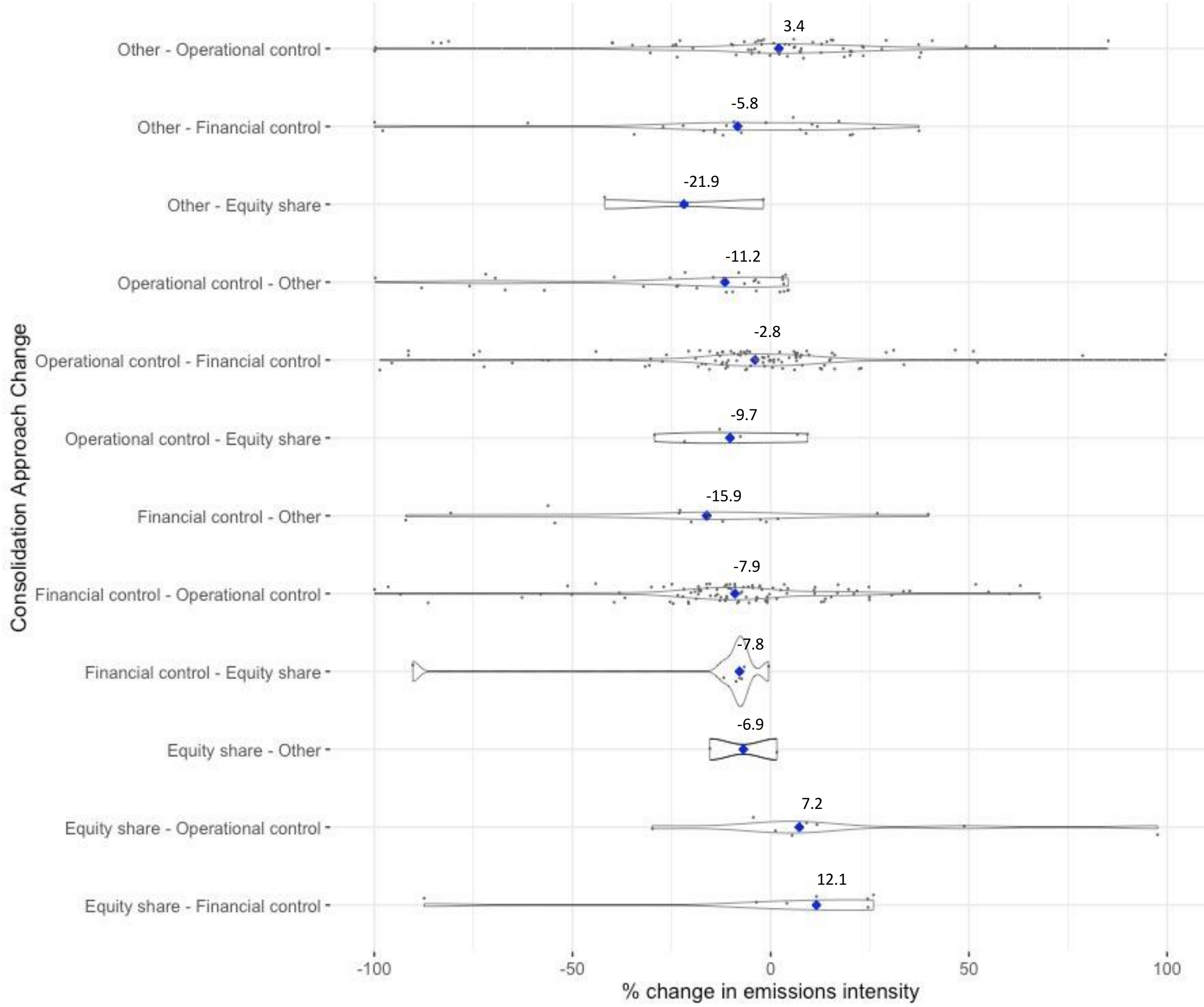

Figure 4.3 Violin plots showing percentage changes in emissions intensity for companies that changed their consolidation approach. Each violin represents a different consolidation approach change as indicated on the y-axis. The medians are marked by a blue point, and represent the full datasets of each sample, which includes extreme values which are greater than +100%, but not displayed in these plots.

4.5.4. Emissions intensity changes before and after a company changes its consolidation approach

I further test the hypotheses, *H1a* and *H1b*, by conducting a second analysis that tests differences within the same group of companies. I test whether the annual change in emissions intensity is significantly different after a company changes its consolidation approach compared to before it changes its approach. Figure 4.4 shows the distribution of emissions intensity changes between the two years when a company had the same approach (bottom violin) and the two subsequent years when a company changed its approach (upper violin). Notably, the distributions show slightly different patterns compared to those of the larger sample of different companies shown in Figure 4.2 from the previous analysis. In Figure 4.4, the upper violin (emissions intensity changes after companies changed their approach) has a higher kurtosis and thinner tails than the lower violin (before the same companies changed their approach).

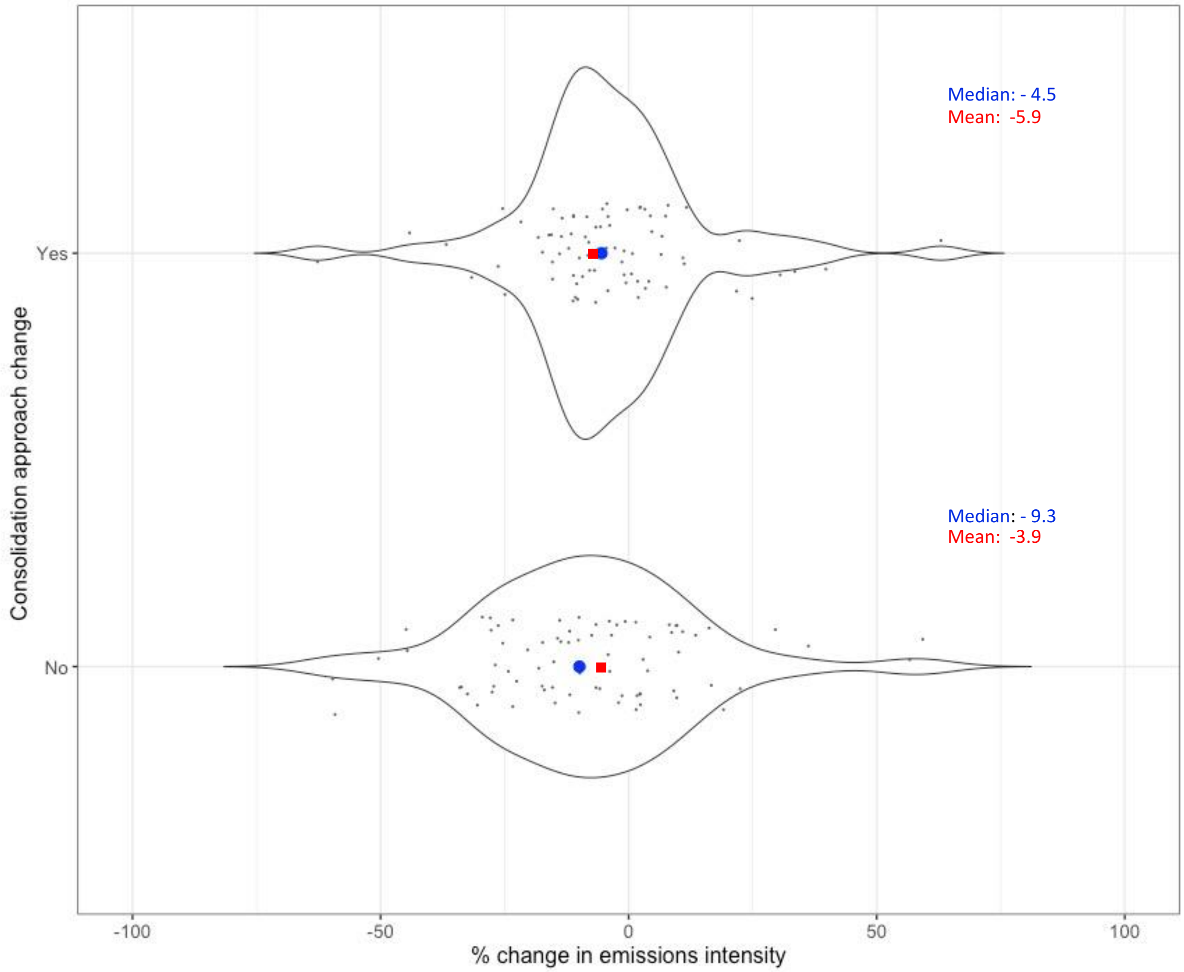

Figure 4.4 Violin plots showing the distribution of percentage changes in emissions intensity between two years after a company changed its approach (top violin) and before it changed its approach (bottom violin). Medians and means represent the entire dataset, which includes extreme values which are greater than +100% and are not displayed in these plots.

The summary statistics in Table 4.3 indicate that the mean and median percentage change in emissions intensity is higher (5.9% and -3.9%, respectively) after companies changed their approach, compared to before they changed their approach (-4.5% and -9.3%, respectively). The WMW two-tailed test suggests that there is no significant difference between emissions intensity change before and after a company changes its consolidation approach ($p > 0.10$), which leads us to reject the first hypothesis (*H1a*). The one-tailed test indicates that a change in consolidation approach does not lead to lower emissions intensity changes. I thus also reject the second hypothesis (*H1b*).

Consolidation approach	Mean (SD)	Median (Q1,Q3)	Min (Max)	WMW (two-tailed) Test statistic (*p*-value)	WMW (one-tailed) Test statistic (*p*-value)
Before change	-3.9 (44.0)	-9.3 (-22.9, -9.8)	-59.7 (333.2)	1893 (0.127)	1893 (0.937)
After change	5.9 (66.1)	-4.5 (-11.4, -4.5)	-62.7 (537.2)		

Table 4.3 Descriptive statistics and results from two-tailed and one-tailed Wilcoxon-Mann-Whitney (WMW) tests on emissions intensity changes before and after companies change their consolidation approach. *N*=79. SD—Standard Deviation; Q1—first quartile; Q3—third quartile. *, ** and *** indicate significant test statistics at 10, 5 and 1 %, respectively.

4.6. Discussion

4.6.1. Transparency issues in consolidation approach choices

Findings from our analysis of public reports suggest a lack of transparency regarding both corporate consolidation approach choices and rationales for changing consolidation approaches. The majority of companies in the sample did not mention a consolidation approach in any of their public reports, let alone provide a rationale for their choice or change in approach. Although information on the consolidation approach used by a company can be obtained from the CDP, the finding that some companies' CDP-reported consolidation approach conflicted with the approach stipulated in their public reports makes it difficult to rely on either avenue of disclosure. This inconsistency adds to information asymmetry, which in turn can damage a company's legitimacy in the eyes of stakeholders like investors, as well as the wider public (Ching and Gerab 2017). In addition, considering the high impact of using different approaches on emissions inventories (Smith 2016), consolidation approach information is consequential and should be included by default when a company reports its GHG inventory in public-facing reports. This aligns with the GHG Protocol's consistency principle, which stipulates that companies claiming to be in line with the GHG Protocol's accounting standard must "[t]ransparently document any changes to the data, inventory boundary, methods, or any other relevant factors in the time series." (WRI and WBSCD 2004, p. 7). It also aligns with the transparency principle which states that companies must "[d]isclose any relevant assumptions and make appropriate references to the accounting and calculation methodologies and data sources used" (WRI and WBSCD 2004, p. 7). Not providing information on the choice of consolidation approach is nontransparent and makes a company appear unreliable in their climate reporting efforts.

Another area of concern is the lack of rationales provided for choosing and changing consolidation approaches. Only one public report provided a clear motivation for the choice and change in approach, which was that the company wished to align with financial reporting. This motivation has also been noted in the study by Smith (2016), in which a company expressed interest in aligning its GHG emissions boundary with its financial accounting boundaries.

Although the analysis of company reports shows limited information about corporate motivations, companies choosing financial control may indeed be driven by a desire to align their GHG inventories with financial reporting. Aligning these boundaries satisfies reporting needs of either financial regulatory bodies or investors as they better reflect the financial risks and opportunities associated with climate change compared to using operational control boundaries (Smith 2016). Companies may be similarly motivated when choosing the equity share approach but could be further driven by the desire to provide investors insight into the operations in which they have any economic interest (Smith 2016). However, the small proportion of companies using equity share in comparison to operational or financial control (Figure 4.1) highlights that something else could be driving this difference. For example, data collection challenges could play a part in the choice of consolidation approach. GHG accounting using the equity share approach has been noted as more challenging than the other approaches because of the difficulties in obtaining or estimating data from entities not operated by the reporting company or from entities under joint ownership (Smith 2016). In contrast, the majority of companies in the analysis used the operational control approach, demonstrating a greater preference for this approach. This could be a result of multiple factors, including easier access to and collection of data (since reporting is on emissions over which the company has operational influence), compliance with government regulations such as emissions trading schemes (WRI and WBSCD 2004), or simply following the most commonly used approach among company peers and competitors to allow for greater comparability between inventories.

Overall, while a company is unlikely to admit their choice of approach is strategic about reporting their climate impacts, if companies provided some description of their rationales, it would at least alleviate worries that they *are* being strategic.

4.6.2. Changing consolidation approaches: is it strategic?

Overall, the analyses suggest that there is a weak difference in corporate emissions profiles between years when a company changes its consolidation approach and when it does not. Importantly, however, the *direction* of this significance is opposite to what was expected (*H1b*). Namely, I found that years when companies did not change their consolidation approach were associated with larger decreases in emissions intensity compared to years when companies changed their approach. This was both the case between groups of different companies (analysis in section 4.5.3), and within the same group of companies (analysis in section 4.5.4). In addition, the lower kurtosis in the distribution of emissions intensity changes (Figure 4.2) suggests that changing the approach may have a more wide-ranging effect on emissions intensity compared to keeping the same consolidation approach. This implies that the comparability of annual GHG inventories may be compromised. In other words, changing consolidation approach, without at least a valid motivation for doing so, violates the GHG Protocol's consistency principle, which requires that companies use consistent methodologies over time to enable comparability (WRI and WBSCD 2004).

The results of the analyses, if taken at face value, might suggest that companies are not using consolidation approaches strategically. However, other factors outside the scope of this study may also play a role in changing the emissions profile of a company, thus obscuring any causal effects that may exist between a change in consolidation approach and the associated change in emissions intensity. For example, emissions intensity may be impacted by major structural changes in a company, including mergers, acquisitions, and divestitures. Such structural changes can affect both absolute emissions and revenue, used to calculate emission intensity. Other variables that can also lead to changes in emissions intensity include emissions reductions measures and operational activity changes. For example, a company switching to onsite renewable energy use would report reduced Scope 2 emissions, while another company may report lower Scope 1 or 2 emissions as a result of reduced operational activities impacted by low demand in the market. Thus, while our results may provide initial insight about the effect of consolidation approach changes on emissions intensity, future research may explore the effect of other independent variables as well.

The design and results of this study build on those of Smith (2016), which included interviews with a small sample of companies and an analysis focused on absolute reported emissions. Their study showed that absolute emissions can be impacted positively or negatively by any consolidation approach, meaning that no specific consolidation approach reflects a consistent one-directional change in absolute emissions. This study, which uses a large sample of companies and assesses emissions intensity (allowing for comparability between companies as it accounts for company size) provides further support for this finding. It is thus evident that different consolidation approaches will impact companies differently. This could be due to varying organizational structures and discretional decisions about how organizational boundaries are set (Dragomir 2012).

4.7. Limitations

There are a few limitations to this study. First, due to the characteristics of the dataset, I used non-parametric tests in part of the analyses. Non-parametric tests are known to be less reliable than parametric tests and are more prone to type II errors (false negatives). However, because the *p*-values for the one-tailed tests were so high, I believe the results are robust. Second, I acknowledge that using emissions intensity measured as tCO_2e/unit of revenue may not accurately represent the emissions profiles of all companies, especially those in homogenous industries. A more appropriate measure would be tCO_2e/unit of product for such companies. For the purposes of this study, however, I required a metric that could be used and compared across companies in different industries. Third, since I grouped all responses with something other than operational control, financial control, or equity share into one category, *other*, I did not assess changes within the *other* category more granularly. Consequently, if the consolidation approach in back-to-back years was categorized as *other,* this was not considered to be a change in consolidation approach. However, if the description provided by the company indicated a change in the organizational boundaries used to conduct the GHG inventory, I did not capture this in the analysis. Finally, I assume that a percentage change decrease in emissions intensity reflects a relative reduction in a company's GHG impact. This assumption may be flawed in cases where a company experiences major structural or operational changes that would otherwise cause a large increase in emissions intensity (e.g., +50%), but by changing the consolidation approach, that increase is curtailed (e.g., +20%). Consequently, the real impact of the consolidation approach change on emissions intensity change is obscured.

4.8. Conclusions and recommendations

This study responds to calls to better understand the use and effects of different consolidation approaches in GHG accounting (Dragomir 2012; Smith 2016). I present two key findings. First, there is a concerning lack of transparency pertaining to consolidation approaches used by companies and their motivations for choosing and changing them between reporting years. Second, I find a greater decrease in the emissions intensity of companies that keep the same consolidation approach compared to companies that change their approach. Counter-intuitively, these results suggest that lower climate impacts are reported when companies are consistent in their choice of consolidation approach. While the results provide some insight into the question of whether companies are using consolidation approaches strategically, future analyses should assess the impact of other variables such as corporate structural changes and emission reduction initiatives when aiming to answer this question. Nevertheless, the failure in transparent reporting of consolidation approach choices and changes sows a level of doubt and distrust in these companies' methodological choices.

Going forward, in order to reduce information asymmetry and improve overall transparency of GHG accounting, I suggest that the CDP make changes to its climate change questionnaire. Specifically, I strongly recommend that the CDP request that companies explain their motivations for choosing a certain consolidation approach and explain why, if applicable, a change in consolidation approach occurs. Furthermore, these companies, and even companies not disclosing to the CDP but completing GHG inventories should stipulate their consolidation approach choice and provide their rationale for the choice in their public reports. I also propose that verifiers or assurers of GHG inventories provide explanations in their assurance reports for the choice (and change) of a company's consolidation approach. Finally, I encourage companies to follow the principles set out by the GHG Protocol, including reporting consistently and transparently. In this context, this translates to a) consistent use of consolidation approaches when reporting GHG emissions or, if the approach must be changed, that prior year inventories are recalculated and disclosed according to the new organizational boundaries, and b) transparent reporting of the methodology used to set the company's organizational boundary.

Chapter 5: Conclusion

In this dissertation, I have explored how we interpret corporate climate responsibility, while further examining the specific responsibility of corporate greenhouse gas accounting.

The first manuscript sought to advance our understanding of how corporate responsibility for climate change is interpreted among actors, and to investigate whether the climate practices associated with those interpretations align with a social justice perspective on climate responsibility. We determined that CCR is understood according to scientific, social, legal, and economic frames. Considering the parallels between social injustice and the consequences of climate change, we established that a comprehensive conceptualization of CCR should reflect a forward-looking and collective form of responsibility. Our recommendations for such a conceptualization of CCR reflect elements from all the frames. However, the scientific and social frames demonstrated the greatest alignment with a social justice perspective on CCR. Accordingly, our top four recommendations were derived from the scientific and social frames. Although parts of our CCR recommendations may seem like common sense to some, I doubt there are many companies that have followed through on all of them consistently. Plenty of companies still favour market-based approaches, either because these approaches are deemed more economically friendly or because companies believe them to be credible climate actions. Plenty of companies continue to lobby against climate regulation. Plenty of companies are simply interested in showcasing their environmental metrics to investors and customers. And plenty of companies mimic current trends in corporate climate practices without much thought given to what it really means to be climate-responsible nor what it really looks like to decarbonize. By introducing explicit recommendations that are anchored in a collective and forward-looking understanding of CCR, we enable more meaningful and effective corporate climate action. I recognize that some of the CCR recommendations presented may require further specification in order to be properly implemented. It would be beneficial, for example, to identify specific standards or protocols, reporting frameworks, or decarbonization measures that have been vetted through our conceptualization of CCR. While this was beyond the scope of the study, I hope that researchers, and established organizations in the field will use our recommendations as a stepping-stone for developing a detailed and full-fledged framework that properly institutes CCR.

The second manuscript addressed the gap in corporate emissions data using machine learning to predict direct emissions from companies globally. We trained three decision-tree ensemble models finding that XGBoost performed most optimally. Model features were selected according to economic, agency and institutional perspectives, but we also considered data availability and feature importance according to SHAP. Our XGBoost model showed an improvement relative to previous prediction models in the literature. We found that economic features and industry classification features, overall, contributed the most to emissions predictions. We used our model to contribute the first academic estimate of global emissions from public companies in 2021, which was 11.4 $GtCO_2e$ or 22% of total global GHG emissions. Interestingly, we found that less than 10% of publicly listed companies were responsible for 82% of the estimated 11.4 $GtCO_2e$ of global corporate emissions. These results led us to believe that high-emitting companies are already reporting their emissions and that we have good enough information about corporate (direct) emissions to proceed with other avenues of research and climate initiatives. Although it is perhaps daring to conclude that research and corporate efforts should be shifted away from more accurate GHG accounting, our suggestion to shift the attention towards decarbonization through effective carbon management systems and processes is rooted in the primary goal of decarbonizing society to avoid dangerous climate change. We have only 9 years before reaching 1.5°C in global warming (see https://climateclock.net/). If today companies are having to choose between committing resources to better GHG accounting or to replacing on-site energy systems with renewables, then I would argue the latter should be prioritized. Thus, a question I posit for future research is, will improving corporate GHG accounting significantly contribute to decarbonizing the corporate sector? Or is it distracting from the real work of climate mitigation?

The third manuscript investigated company motivations for choosing and changing their consolidation approaches in GHG accounting, and whether these methodological choices were strategic. Namely, I looked at whether changing a consolidation approach changed the emissions profile of a company. The quantitative evidence demonstrated that the emissions intensity of companies that changed their approach did not decrease more than when companies did not change their approach, suggesting that companies may not be using consolidation approaches strategically to report lower climate impacts. However, the analysis of public reports revealed that companies are not being transparent regarding their motives for choosing and changing their consolidation approaches. Such findings offset any certainty we have that companies are *not* using consolidation approaches strategically. Key climate disclosure organizations like the CDP should require information about motivations for consolidation approach choices, and companies must integrate their rationales in their public-facing reports. As for discretional decisions around setting organizational boundaries, I stress that consistency is key. Ideally, companies should retain the same consolidation approach between reporting years, but if a change is deemed necessary, the rationale should be disclosed, and all prior year inventories should be recalculated according to the new boundaries.

I concede that GHG accounting is a necessary effort that companies must undertake to not only track and disclose emissions, but also help identify emissions sources that could be decarbonized. Yet, as evidenced in this dissertation, GHG accounting is not the only necessary CCR nor is it a full proof practice on its own. With the climate clock ticking, we must look to other ways of estimating corporate emissions that would help us understand the global climate impacts of companies. We must also reconsider whether the amount of time, money, and research spent on GHG accounting and its methodologies are warranted, considering the short period of time we have left to decarbonize society before reaching dangerous levels of global warming. I stress again that companies and researchers should weigh their interests in improving GHG accounting methodologies with their efforts in developing and implementing climate mitigation measures that truly decarbonize corporate activities.

Altogether, I hope that the works presented herein help clarify the meaning of corporate climate responsibility and help business leaders allocate their time and resources towards meaningful practices that lead to climate mitigation. GHG accounting remains a crucial corporate climate practice, but in the end, it is not accounting that will save us from a climate disaster.

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Appendix A: Chapter 2 Tables

Table A1 List of responsibilities identified in the literature. Includes example literature sources, underlying goals, themes, assigned frame, and levels of alignment with the five Social Connection Model conditions.

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Conduct greenhouse gas inventories that reflect real impacts	Bjørn, Lloyd, et al. 2022; Brander et al. 2018; Dragomir 2012; Hertwich and Wood 2018; WRI and WBSCD 2004	Identify and evaluate reduction actions, help set targets, help report on progress, strengthen global mitigation efforts	Real impacts/reductions, global mitigation efforts, emissions reductions, emissions accounting	Scientific	Aligned	Partially aligned	Aligned	Aligned	Partially aligned
Conduct greenhouse gas inventories that reflect all impacts (i.e., includes market-based accounting)	WRI and WBSCD 2015	Identify and evaluate reduction actions, help report on progress, portray individual corporate procurement actions, convey risks or opportunities through contractual relationships	Emissions reductions, emissions accounting, market solutions, electricity market, climate risks/opportunities,	Scientific, Economic	Aligned	Unaligned	Aligned	Aligned	Unaligned
Disclose climate information: climate data, targets, risks, strategies, and actions	Hrasky 2012; Lopucki 2022; Villiers 2022	Address pressure from shareholders and stakeholders, comply with local regulations, increase transparency, increase legitimacy, increase trust	Stakeholder/shareholder pressure, transparency, legitimacy, substantive vs. symbolic	Social, Economic	Unaligned	Aligned	Partially aligned	Unaligned	Unaligned

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Set science-based targets (i.e., in line with global climate goals)	Bjørn, Lloyd, et al. 2022; Bjørn et al. 2021; Hadziosmanovic et al. 2022; Newell 2020; Science Based Targets 2021	Contribute to global mitigation efforts, align business with global climate goals, address pressure from stakeholders	Emissions reductions, emissions targets, global mitigation efforts	Scientific	Aligned	Partially aligned	Aligned	Aligned	Aligned
Set other carbon reduction targets (can be non-science based)	Giesekam et al. 2018; Gouldson and Sullivan 2013	Address external stakeholder pressure, comply with local regulations	Emissions reductions, emissions targets, global mitigation efforts, stakeholder pressure	Scientific, Social	Partially aligned	Partially aligned	Aligned	Partially aligned	Partially aligned
Prioritize and implement real decarbonization activities before market-based activities*	Brander et al. 2018; Bjørn, Lloyd, et al. 2022; IPCC 2018; IPCC 2021; Science Based Targets 2020	Ensure alignment of corporate targets with global targets, uphold integrity of corporate targets and corporate reduction efforts, show real progress against targets to stakeholders, reduce emissions	Real reductions, global emissions reductions	Scientific	Aligned	Partially aligned	Aligned	Aligned	Aligned
Make fundamental business model changes to reduce climate impact and align with a low-carbon future	Grasso and Vladimirova 2020; Jaworska 2018 Newell 2020	Ensure alignment of corporate actions with global targets, contribute to rapid transition, adapt to changing market conditions, moral duties to decarbonize	Energy/sustainability/just transitions, climate targets, global emissions, decarbonizing, moral management/responsibility	Scientific, Social	Unaligned	Aligned	Aligned	Aligned	Unaligned

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Be transparent in communications and disclosures and avoid symbolic disclosure	Dahlmann et al. 2019; Ferns et al 2019; Hrasky 2012; Hormio 2017	Address stakeholder pressure, increase pragmatic and moral legitimacy, improve management of climate issues	Stakeholder pressure, transparency, legitimacy, substantive vs. symbolic	Social	Aligned	Partially aligned	Aligned	Unaligned	Aligned
Seek social license to operate and engage with stakeholders and communities	Hormio 2017; Olawuyi 2016; Smits et al 2016;	Increase legitimacy, increase trust, address stakeholder pressure	Climate justice, human rights, ethics, transparency, communities, society	Social	Partially aligned	Aligned	Aligned	Partially aligned	Partially aligned
Incorporate climate justice principles into corporate risk management and due diligence frameworks	Bright and Buhmann 2021; International Bar Association 2014; Macchi 2021; Olawuyi 2016	Protect human rights, provide a way to address adverse climate-related human rights impacts, avoid lawsuits on violating duties	Human rights law, climate justice, due diligence, litigation	Social, Legal	Aligned	Aligned	Aligned	Aligned	Partially aligned
Support and help positively shape new climate legislation/regulations	Brulle 2018; Downie 2017; Hormio 2017	Quicken climate legislation development, determine possible or desirable legislation	Climate legislation/regulation, moral responsibility, lobbying	Legal, Social	Partially aligned	Aligned	Aligned	Aligned	Aligned
Participate in voluntary climate disclosure schemes	Hahn et al. 2015; Weber and Hösli 2021	Increase legitimacy, improve carbon management, reduce costs, manage climate risks, increase competitiveness	Carbon/climate management, climate risks, soft law, voluntary reporting	Legal, Economic	Partially aligned	Unaligned	Aligned	Unaligned	Unaligned

Responsibility	**Example sources**	**Underlying goals/motivations**	**Themes**	**Frame**	**Does not isolate**	**Questions background**	**Forward-looking**	**Shared**	**Collective action**
Participate in voluntary carbon trading markets	Cadez and Czerny 2016; Gillenwater 2008; Kolk et al. 2008	Anticipate mandatory trading, shape future trading systems, gain competitive advantage	Voluntary vs. mandatory mechanisms, governance, markets	Legal, Economic	Aligned	Unaligned	Aligned	Partially aligned	Partially aligned
Use market-based instruments to claim reductions	Gillenwater 2008; Jaworska 2018; WRI and WBSCD 2015	Influence the electricity market, portray individual corporate procurement actions, convey risks or opportunities through contractual relationships	Neoliberalism, free market, business opportunity, economic risk	Economic	Partially aligned	Unaligned	Aligned	Unaligned	Unaligned
Purchase carbon offsets to claim reductions or removals	Dhanda and Malik 2020; NewClimate Institute 2022; WRI and WBSCD 2004	Reduce emissions, reach targets, show progress to stakeholders, reduce climate risks	Emissions reductions, carbon management	Scientific, Economic	Partially aligned	Partially aligned	Aligned	Partially aligned	Partially aligned
Comply with carbon/climate regulation, including mandatory trading schemes	Bruno 2019; Kolk et al. 2008; Streck 2020; Weber and Hösli 2021	Avoid legal or economoic consequences	Hard law, climate regulation	Legal	Unaligned	Partially aligned	Unaligned	Aligned	Unaligned
Disclose climate information: climate data, targets, risks, strategies, and actions	Lopucki 2022; Villiers 2022; Hrasky 2012	Address pressure from shareholders and stakeholders, comply with local regulations, increase transparency, increase legitimacy, increase trust	Stakeholder/shareholder pressure, transparency, legitimacy, substantive vs. symbolic	Social, Economic	Unaligned	Aligned	Partially aligned	Unaligned	Unaligned

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Set science-based targets (i.e., in line with global climate goals)	Bjørn, Lloyd, et al. 2022; Bjørn et al. 2021; Hadziosmanovic et al. 2022; Newell 2020; Science Based Targets 2021	Contribute to global mitigation efforts, align business with global climate goals, address pressure from stakeholders	Emissions reductions, emissions targets, global mitigation efforts	Scientific	Aligned	Partially aligned	Aligned	Aligned	Aligned
Set other carbon reduction targets (can be non-science based)	Gouldson and Sullivan 2013; Giesekam et al. 2018	Address external stakeholder pressure, comply with local regulations	Emissions reductions, emissions targets, global mitigation efforts, stakeholder pressure	Scientific, Social	Partially aligned	Partially aligned	Aligned	Partially aligned	Partially aligned
Prioritize and implement real decarbonization activities before market-based activities*	Brander et al. 2018; Bjørn, Lloyd, et al. 2022; IPCC 2018; IPCC 2021; Science Based Targets 2020	Ensure alignment of corporate targets with global targets, uphold integrity of corporate targets and corporate reduction efforts, show real progress against targets to stakeholders, reduce emissions	Real reductions, global emissions reductions	Scientific	Aligned	Partially aligned	Aligned	Aligned	Aligned
Fundamental business model changes to reduce climate impact and align with a low-carbon future	Grasso and Vladimirova 2020; Newell 2020; Jaworska 2018	Ensure alignment of corporate actions with global targets, contribute to rapid transition, adapt to changing market conditions, moral duties to decarbonize	Energy/sustainability/just transitions, climate targets, global emissions, decarbonizing, moral management/responsibility	Scientific, Social	Unaligned	Aligned	Aligned	Aligned	Unaligned

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Be transparent in communications/disclosures and avoid symbolic disclosure	Hormio 2017; Dahlmann et al. 2019; Ferns et al 2019; Hrasky 2012	Address stakeholder pressure, increase pragmatic and moral legitimacy, improve management of climate issues	Stakeholder pressure, transparency, legitimacy, substantive vs. symbolic	Social	Aligned	Partially aligned	Aligned	Unaligned	Aligned
Seek social license to operate/community and stakeholder engagement	Smits et al 2016; Olawuyi 2016; Hormio 2017	Increase legitimacy, increase trust, address stakholder pressure	Climate justice, human rights, ethics, transparency, communities, society	Social	Partially aligned	Aligned	Aligned	Partially aligned	Partially aligned
Incorporate climate justice principles into corporate risk management and due diligence frameworks	Bright and Buhmann 2021; International Bar Association 2014; Macchi 2021; Olawuyi 2016	Protect human rights, provide a way to address adverse climate-related human rights impacts, avoid lawsuits on violating duties	Human rights law, climate justice, due diligence, litigation	Social, Legal	Aligned	Aligned	Aligned	Aligned	Partially aligned
Support and help positively shape new climate legislation/regulations	Hormio 2017; Brulle 2018; Downie 2017	Quicken climate legislation development, determine possible or desirable legislation	Climate legislation/regulation, moral responsibility, lobbying	Legal, Social	Partially aligned	Aligned	Aligned	Aligned	Aligned
Participate in voluntary climate disclosure schemes	Hahn et al. 2015; Weber and Hösli 2021	Increase legitimacy, improve carbon management, reduce costs, manage climate risks, increase competitiveness	Carbon/climate management, climate risks, soft law, voluntary reporting	Legal, Economic	Partially aligned	Unaligned	Aligned	Unaligned	Unaligned

Responsibility	Example sources	Underlying goals/motivations	Themes	Frame	Does not isolate	Questions background	Forward-looking	Shared	Collective action
Participate in voluntary carbon trading markets	Cadez and Czerny 2016; Gillenwater 2008; Kolk et al. 2008	Anticipate mandatory trading, shape future trading systems, gain competitive advantage	Voluntary vs. mandatory mechanisms, governance, markets	Legal, Economic	Aligned	Unaligned	Aligned	Partially aligned	Partially aligned
Use market-based instruments to claim reductions	Gillenwater 2008; Jaworska 2018; WRI and WBSCD 2015	Influence the electricity market, portray individual corporate procurement actions, convey risks or opportunities through contractual relationships	Neoliberalism, free market, business opportunity, economic risk	Economic	Partially aligned	Unaligned	Aligned	Unaligned	Unaligned
Purchase carbon offsets to claim reductions or removals	Dhanda and Malik 2020; NewClimate Institute 2022; WRI and WBSCD 2004	Reduce emissions, reach targets, show progress to stakeholders, reduce climate risks	Emissions reductions, carbon management	Scientific, Economic	Partially aligned	Partially aligned	Aligned	Partially aligned	Partially aligned
Comply with carbon/climate regulation, including mandatory trading schemes	Bruno 2019; Streck 2020; Kolk et al. 2008; Weber and Hösli 2021	Avoid legal or economoic consequences	Hard law, climate regulation	Legal	Unaligned	Partially aligned	Unaligned	Aligned	Unaligned

Appendix B: Chapter 3 Tables

Table B1 Feature names, definitions, data manipulation, and source of data.

Feature name & abbreviation	**Definition**	**Additional data manipulation (before preprocessing)**	**Source of data**
Average asset age (Asset Age)	Measure calculates the age in years of capital facilities and the potential need for future investment. Calculated as: Accumulated Depreciation / Depreciation Expense	Although Bloomberg provides this variable, we downloaded data for accumulated depreciation and depreciation expense to calculate Asset Age because this resulted in more datapoints for this feature. Where one of these variables was not available, average asset age was not calculated. Where one of accumulated depreciation or depreciation expense is not available, then no estimate for Asset Age was made.	Bloomberg
Carbon tax (country or country of risk)	Presence of a carbon tax in the country or country of risk.	Field is assigned 1 (Yes) or 0 (No).	Climate Change Laws of the World Database, Bloomberg
Capital expenditure (CAPEX)	Amount the company spent on purchases of tangible fixed assets. May include intangible assets when not disclosed separately. The value is always negative. Figure is reported in millions.	None.	Bloomberg
Cash flow from operations (CFO)	Total amount of cash a company generates from its operation. The effect of Changes in Non-cash Working Capital on Cash from Operations can be either positive or negative. Decrease in current assets or increase in current liabilities, increases Cash from Operations; while an increase in current assets or decrease in current liabilities, decreases Cash from Operations. Generally calculated as: Net Income + Depreciation & Amortization + Other Noncash Adjustments + Changes in Non-cash Working Capital	None.	Bloomberg
Cash flow per share (CFPS)	Measure of a firm's financial strength which represents the net cash a firm produces on a per share basis. Units: Actual Calculated as: Cash from Operations / Weighted Number of Shares Outstanding	None.	Bloomberg
Climate change policy (CC policy)	Indicates whether the company has outlined its intention to help reduce global emissions of the Greenhouse Gases that cause climate change through its ongoing operations and/or the use of its products and services.	Fields were converted to the following ordinal scale: 0 (No), 0.5 (Unknown), 1 (Yes).	Bloomberg

Feature name & abbreviation	Definition	Additional data manipulation (before preprocessing)	Source of data
	Examples might include efforts to reduce Greenhouse Gas (GHG) emissions, efforts to improve energy efficiency, efforts to derive energy from cleaner fuel sources, investment in product development to reduce emissions generated or energy consumed in the use of the company's products etc. "N" indicates that the company has not explicitly disclosed any such efforts in its most recent Annual or Company Responsibility reports. When accessing historical data, field will return a '1' - Yes or '0' - No.W		
Country of Domicile - Subregion	Location of management/headquarters.	ISO country codes were converted to country names. The subregion of the country was then assigned according to the United Nations subregion categories. Subregions were used instead of countries to reduce the cardinality of this categorical variable.	Bloomberg, United Nations Statistics Division
Country of Risk - Subregion	This evaluation is used when the company identifies itself as a holding company with the majority of its revenue generating operations being derived from subsidiaries or other equity investments. In these cases, the country or territory which holds the largest portion of operations, defined by criteria consisting of Earnings Before Interest and Taxes/Earnings Before Interest, Taxes, Depreciation and Amortization (EBIT/EBITDA) by geography, revenue by origin, or long-term operational assets, should be used. When this information cannot be sourced, the country which the company generates the highest amount of revenue from should be used.	ISO country codes were converted to country names. The subregion of the country was then assigned according to the United Nations subregion categories. Subregions were used instead of countries to reduce the cardinality of this categorical variable.	Bloomberg, United Nations Statistics Division
Earnings before interest, taxes, depreciation, and amortization margin (EBITDA margin)	Measure, in percentage, calculates the relation of Earnings Before Interest, Taxes, Depreciation and Amortization to Revenue. Calculated as: (EBITDA / Revenue) * 100	None.	Bloomberg
Emissions target	Two fields in the Bloomberg terminal were used to determine whether an emissions target was set: Scope 1 GHG target: Target year by which the company plans to achieve its Scope 1 emissions reduction target. Target Year for GHG Emissions Target: Target year by which the	This field was denoted as 1 (Yes) or 0 (No) based on information provided from the two Bloomberg fields.	Bloomberg

Feature name & abbreviation	Definition	Additional data manipulation (before preprocessing)	Source of data
	company plans to achieve its total GHG emissions reduction target.		
Emissions trading scheme (ETS) (country or country of risk)	Presence of an emissions trading scheme in the country or country of risk.	Field is assigned 1 (Yes) or 0 (No).	Climate Change Laws of the World Database, Bloomberg
Employees	Number of people employed by the company, based on the number of full-time equivalents. If unavailable, then the number of full-time employees is used, excluding part time employees.	None.	Bloomberg
Energy consumption	Total energy consumption in thousands of megawatt hours (MWh). This includes energy directly consumed through combustion in owned or controlled boilers, furnaces, vehicles, or through chemical production in owned or controlled process equipment. It also includes energy consumed as electricity.	None.	Bloomberg
Free cash flow (FCF)	Measure of financial performance calculated as operating cash flow minus capital expenditures. Free cash flow represents the cash that a company is able to generate after laying out the money required to maintain or expand its asset base. Figure is reported in millions.	None.	Bloomberg
Gross Property, Plant, & Equipment (GPPE)	Gross Fixed Assets: This field includes depreciable and non-depreciable (tangible) fixed assets held for own use, capitalized fixed assets, and rental properties. Field is gross of accumulated depreciation expenses on fixed assets and real estate assets. Includes capitalized exploration and development costs for mining companies. Some countries allow companies to value their tangible fixed assets at replacement cost. A revaluation reserve in Retained Earnings accumulates the difference from historic cost. May include intangible fixed assets such as easements and land rights. (Definition may differ slightly per industry or per country according to Bloomberg)	None.	Bloomberg
Industry	Industry is according to the International Classification Benchmark (ICB) system. Denotes 1 of 11 industries: Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Financials, Healthcare, Industrials, Real Estate,	None.	Bloomberg

Feature name & abbreviation	Definition	Additional data manipulation (before preprocessing)	Source of data
	Technology, Telecommunications, Utilities		
Highest level at which climate change is managed (CC management)	Explains how the overall responsibility for climate change is managed and indicates the highest level of management related to climate change. The information is directly from the company's response to the CDP climate change information request. This feature typically returns one of four categories: i. Board/Subset of Board/Committee appointed by Board ii. Subset of Board/Committee appointed by Board iii. Manager/Officer iv. No individual or committee v. Blank/unknown	Fields were converted to the following ordinal scale: 0 (Unknown/blank field), 1 (No individual or committee), 2 (Manager/Officer), 3 (Subset of Board/Committee appointed by Board), 4 (Board/Subset of Board/Committee appointed by Board) Some fields did not stipulate one of the four categories but included bespoke text. We thus manually coded these answers to match one of the four typical categories. For example, the following text was assessed as belonging to the category *Subset of Board/Committee appointed by Board:* *"Whilst climate change is not considered at Board level, the Legal Director is responsible for monitoring emerging regulations including climate change and the Finance Director is responsible for monitoring energy and business travel costs. Both are IG Group Board members."*	Bloomberg
Internal price of carbon	Specifies whether the company uses an internal price of carbon. The information is directly from the company's response to the CDP climate change information request.	Fields were converted to the following ordinal scale: 0 (No), 0.5 (Unknown), 1 (Yes).	Bloomberg
Percent of revenue from foreign sources (Percent foreign revenue)	Revenue from foreign sources as a percentage of total revenues. Revenues from foreign sources are calculated as total revenues minus revenues from the country of domicile.	In cases where the field returned >100%, this was adjusted to 100%.	Bloomberg
Percent of women on the board of directors (Percent women on board)	Percentage of women on the board of directors, as reported by the company. Data collected from company's Environmental, Social and Governance (ESG) annual filings. Europe: Where the company has a supervisory board and a management board, this is the percentage of women on the supervisory board. Field is part of the ESG group of fields.	If no percentage was reported, we assumed 0%.	Bloomberg
Return on assets (ROA)	Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings.	None.	Bloomberg

Feature name & abbreviation	Definition	Additional data manipulation (before preprocessing)	Source of data
	For Industrials, Banks, Financials, Utilities, & REITS, calculated as: (Trailing 12 Month Net Income / Average Total Assets) * 100 For Insurance, calculated as: ((Trailing 12 Month Net Income + Trailing 12 Month Policyholders' Surplus) / Average Total Assets) * 100		
Return on common equity (ROE)	Measure of a corporation's profitability by revealing how much profit a company generates with the money shareholders have invested, in percentage. Calculated as: (T12 Net Income Available for Common Shareholders / Average Total Common Equity) * 100	None.	Bloomberg
Revenue	Gross revenues from operating activities. (Definition may differ slightly per industry or per country according to Bloomberg)	None.	Bloomberg

Variable	*N*	Mean	Median	St. Dev.	Min	Max
Asset age	14,379	12.53	7.41	88.51	0.00	5,776.65
CAPEX	17,931	(524,203,249.06)	(100,106,000.00)	1,787,276,830.22	(61,053,001,728.00)	0.00
CFO	17,946	36,163,912,592.87	357,000,000.00	1,041,619,879,218.36	(13,331,600,000,000.00)	83,800,500,000,000.00
CFPS	18,238	44.34	0.97	4,000.16	(308.33)	491,986.91
Employees	15,490	25,557.17	7,389.50	63,008.86	2.00	2,300,000.00
FCF	18,202	866,999,852.66	108,261,194.77	5,809,892,948.01	(79,910,002,688.00)	211,524,171,889.17
EBITDA margin	16,697	(192.78)	16.44	21,760.83	(2,671,260.00)	23,225.00
Energy consumption	14,479	13,705,043.08	354,948.00	370,167,121.40	0.07	37,364,301,824.00
GPPE	15,385	9,437,284,331.51	1,814,031,442.00	30,199,197,287.48	0.00	634,780,000,000.00
% Foreign revenue	13,553	36.89	28.71	34.91	0.00	100.00
% Women on board	17,969	21.62	21.43	14.60	0.00	100.00
Revenue	18,275	9,090,394,339.83	2,241,039,607.21	24,418,892,887.40	(8,958,397,768.59)	559,151,000,000.00
ROA	18,254	4.08	3.50	9.92	(306.95)	236.78
ROE	17,842	11.06	9.98	37.77	(417.87)	2,674.81
Scope 1 emissions	18,292	2,242,445.58	20,984.00	14,715,203.25	0.00	1,000,000,000.00

Table B2 Descriptive statistics of numerical data from the original *labeled* dataset (companies reporting emissions) before pre-processing.

Parameter	Search Range	Optimal Parameter Value
n_estimators	(200, 800, 1400, 2000)	2000
max_depth	(10, 30, 50)	10
min_child_weight	(1, 3, 6)	6
learning_rate	(0.05, 0.1, 0.16)	0.05

Table B3 Tuning range and optimal values for hyperparameters using grid search for the XGBoost prediction model.

Model	RMSE	MSE	MAE	MAPE	Adjusted R^2
Catboost-1	1.43	2.03	0.96	0.32	0.81
Catboost-2	1.41	1.99	0.96	0.29	0.82
XGBoost	1.30	1.69	0.83	0.29	0.84
Random Forest	1.32	1.74	0.87	0.3	0.84
Adaboost	1.94	3.77	1.38	0.36	0.66
LightGBM	1.32	1.73	0.86	0.30	0.84

Table B4 Performance results of five ensemble tree model from earlier iterations of this work in which we used a sample of company-year observations spanning 2018-2020. Catboost-1 was trained with the original encoding solution provided for categorical data in CatBoost on the variables industry, subregion of domicile, and subregion of risk. Catboost-2 was trained with one-hot encoding on these categorical variables. Overall, Adaboost and Catboost performed poorly compared to XGBoost, Random Forest, and LightGBM.

Feature	Mean		Median		St. Dev.		Min		Max		*N*	
	Reporting	Non-reporting	Reporting	Non-reporting	Reporting	Non-reporting	Reporting	Non-reporting	Reporting	Non-reporting	Reporting	Non-reporting
logEnergy Consump-tion	12.83	11.43	12.78	11.51	2.66	3.06	-2.60	-2.14	24.34	20.25	14157	821
log GPPE	21.27	17.37	21.33	17.71	1.92	2.90	10.33	0.00	27.18	26.59	15039	31357
log Employees	8.81	6.11	8.91	6.28	1.78	2.05	0.69	0.00	14.65	15.31	15126	24629

Table B5 Descriptive statistics of the top three important numerical features (according to SHAP) for the labeled dataset (reporting companies) and unlabeled dataset (non-reporting companies).

Appendix C: Chapter 3 Figures

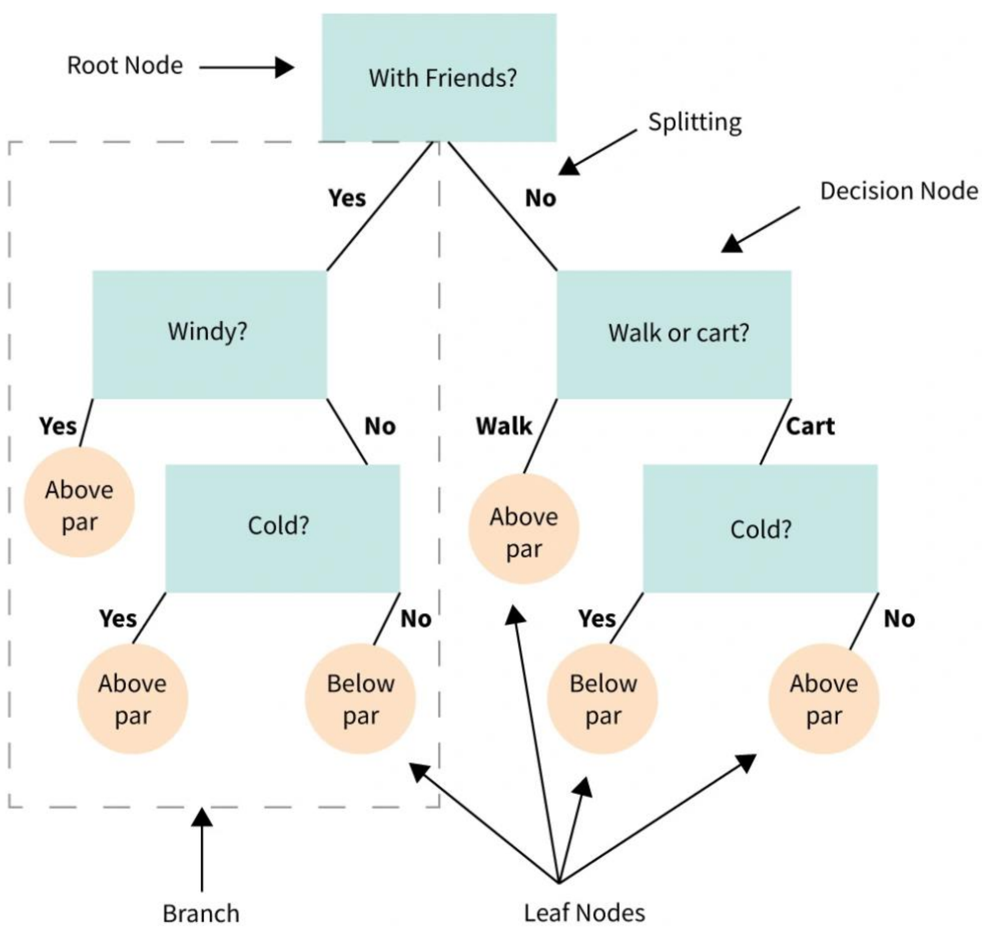

Figure C1 An example of a single decision tree: a prediction of whether a golfer's score will be below par or above par, based on various predictor variables such as being with friends or strangers, wind speed, walking or taking a cart, and temperature (Master's in Data Science 2023).

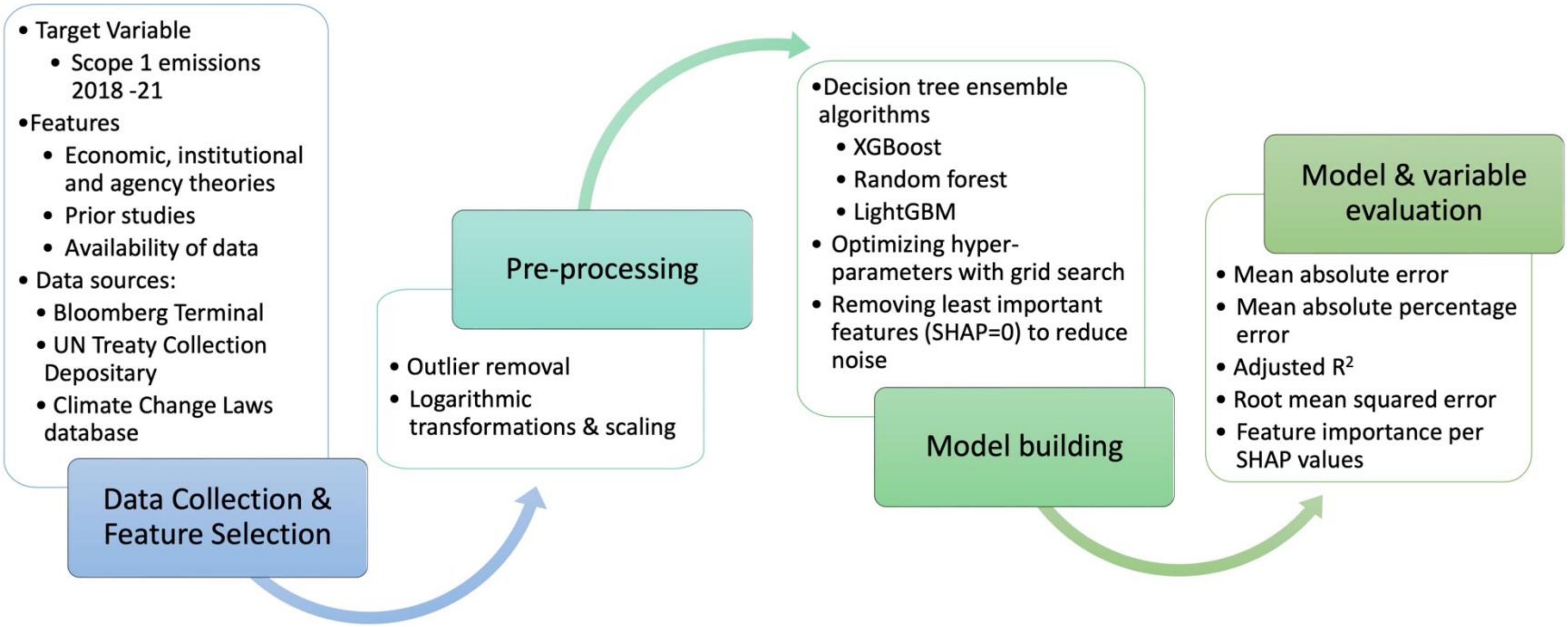

Figure C2 Flow chart depicting the overall methodology for building the emissions prediction model.

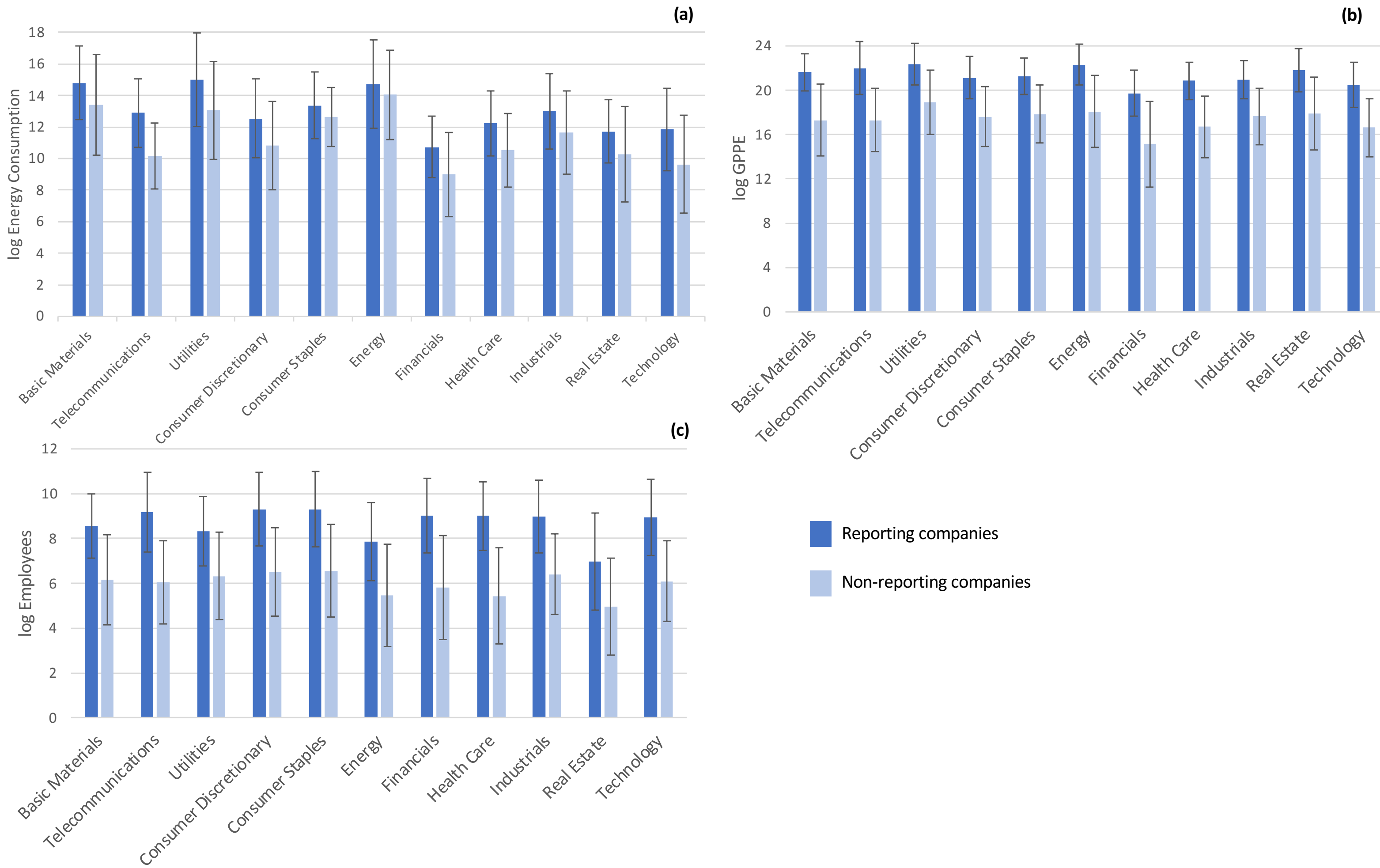

Figure C3 Bar plots representing the mean values of the top three important numerical features per industry for reporting companies (dark blue bar) and non-reporting companies (light blue bar). Standard deviation error bars shown. (a) logEnergyConsumption, (b) logGPPE, and (c) logEmployees.

Figure C4 Bar plot displaying average absolute SHAP values for all features used in the final XGBoost model. Features are ranked according to their contribution to the model's predicted Scope 1 emissions on a logarithmic scale.

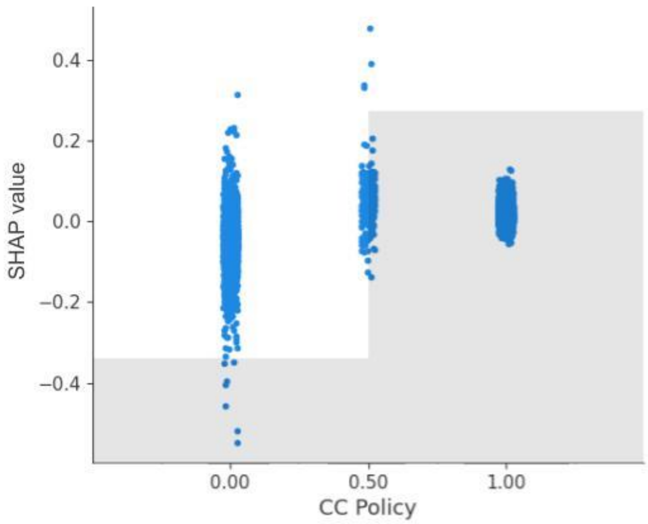

Figure C5: SHAP plot for climate change policy

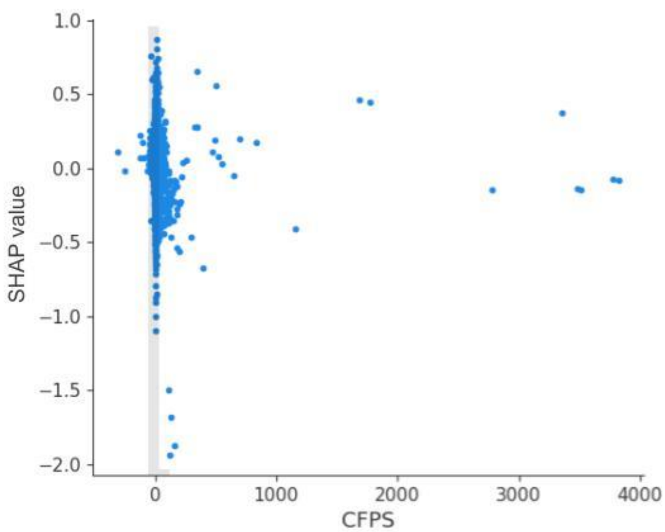

Figure C6: SHAP plot for cash flow per share (CFPS)

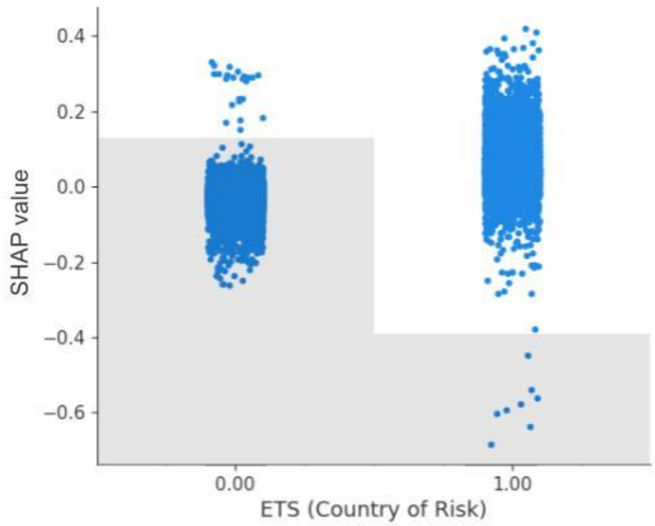

Figure C7: SHAP plot for emissions trading scheme in the country of risk

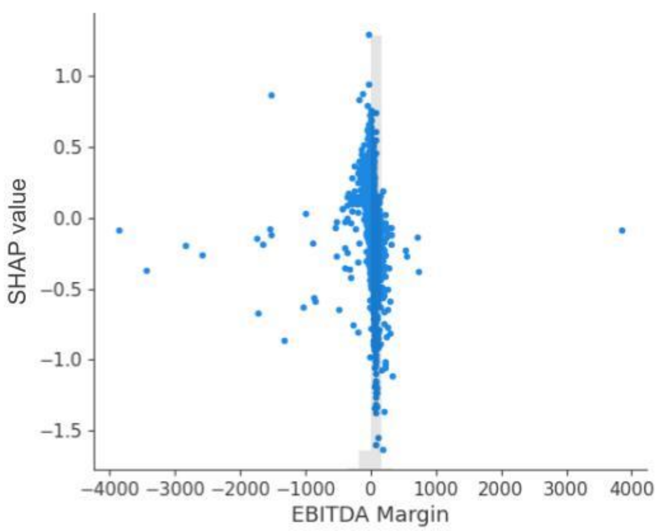

Figure C8: SHAP plot for EBITDA margin

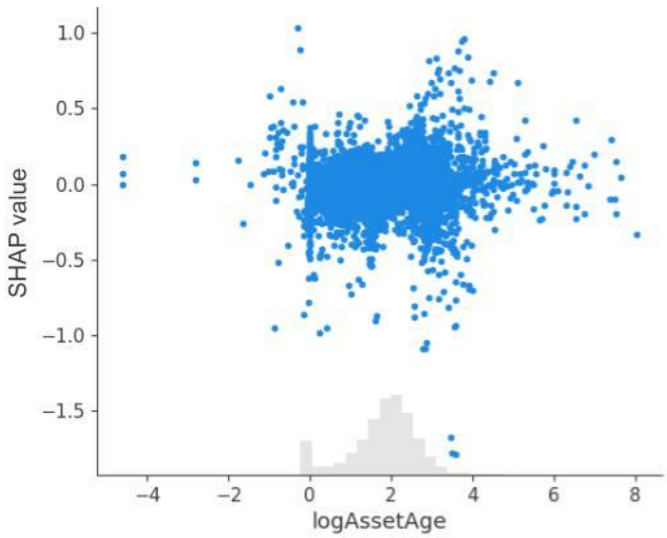

Figure C9: SHAP plot for log of average asset age

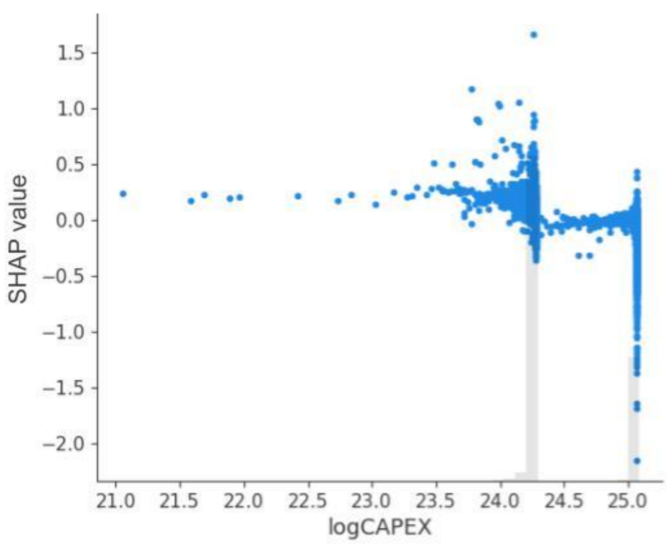

Figure C10: SHAP plot for log of capital expenditure

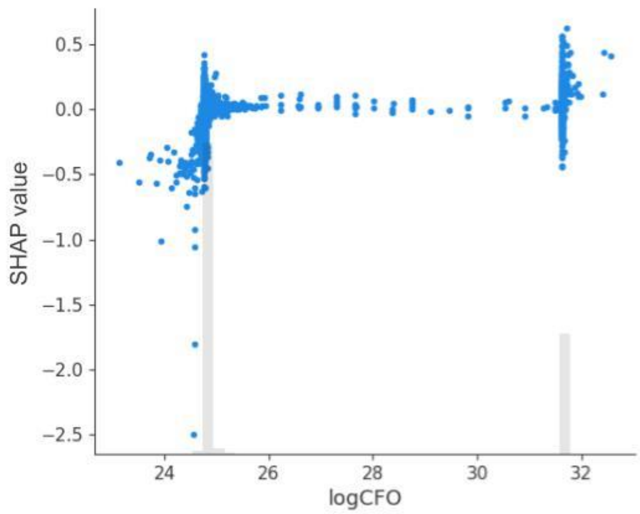

Figure C11: SHAP plot for log of cash flow from operations

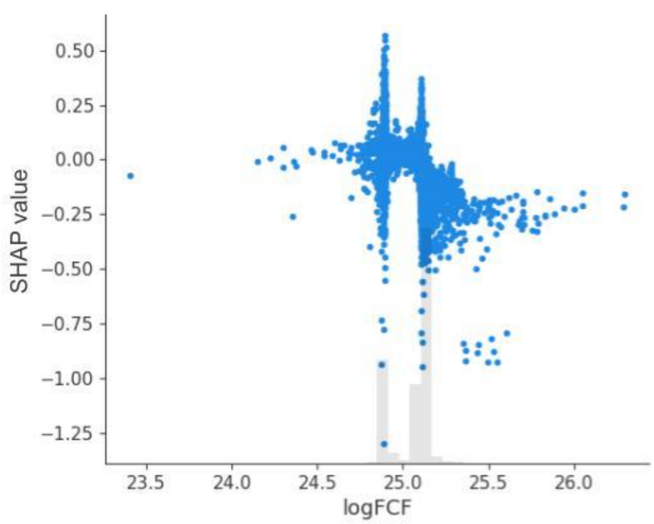

Figure C12: SHAP plot for Climate Change Policy

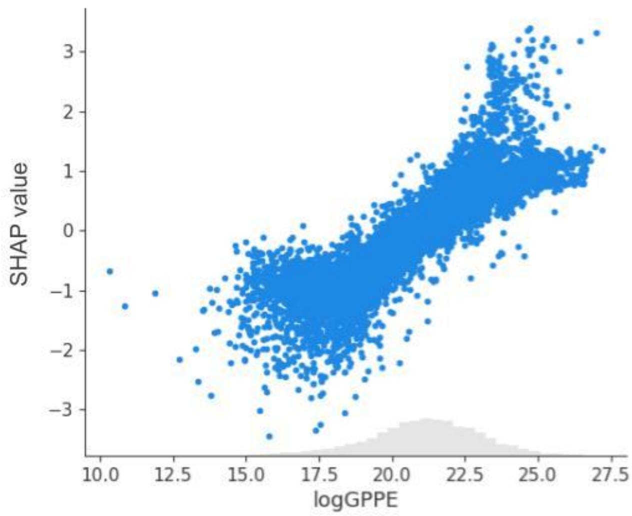

Figure C13: SHAP plot for gross property, plant, and equipment

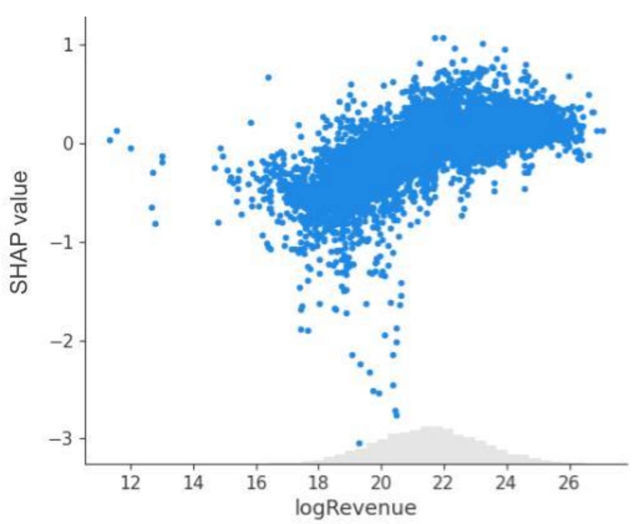

Figure C14: SHAP plot for log of revenue

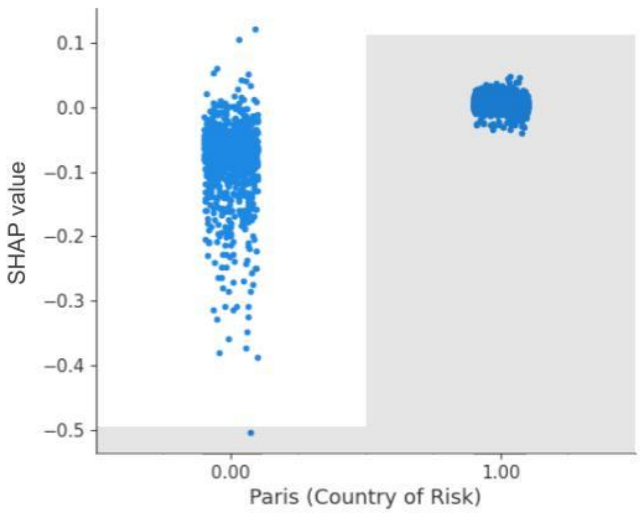

Figure C15: SHAP plot for Paris signatory in the country of risk

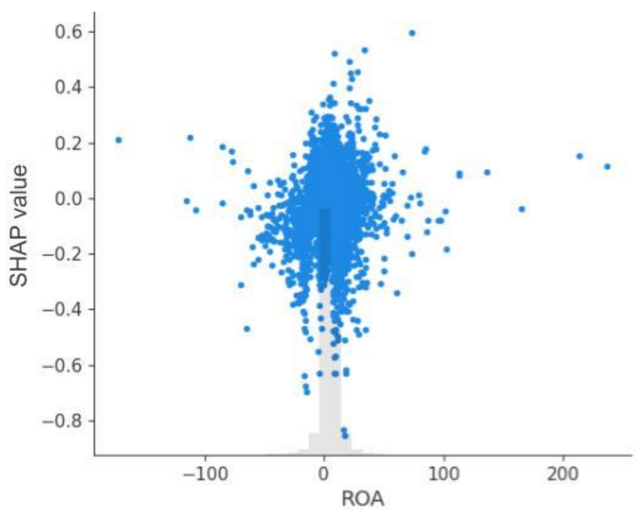

Figure C16: SHAP plot for return on assets

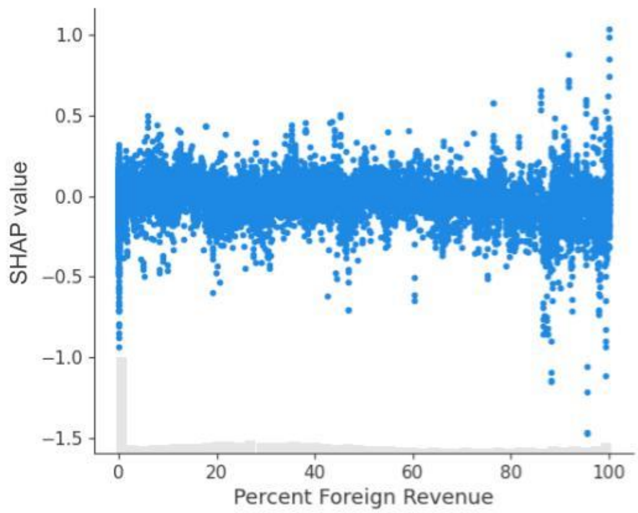

Figure C17: SHAP plot for percent of revenue from foreign sources

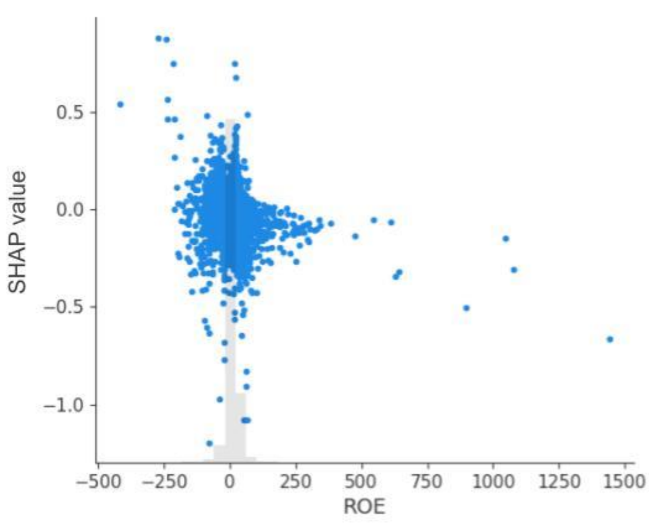

Figure C18: SHAP plot for return on equity

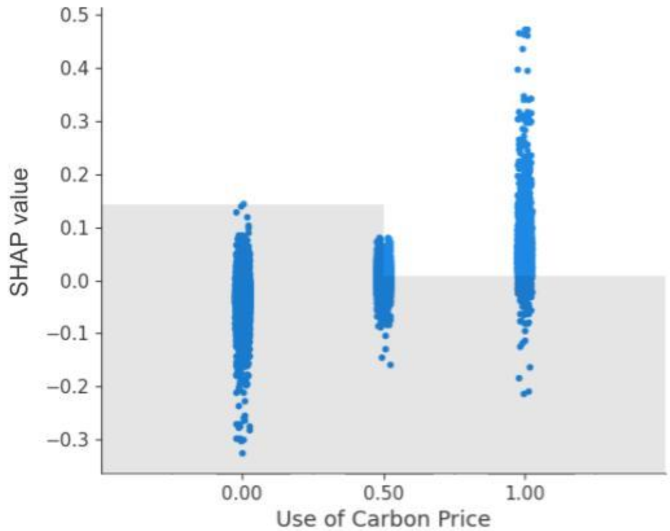

Figure C19: SHAP plot for use of carbon price

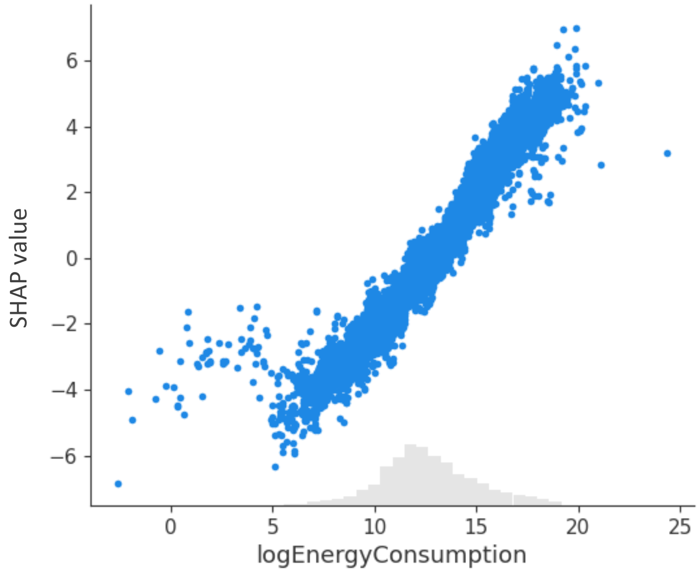

Figure C20: SHAP plot for log of energy consumption

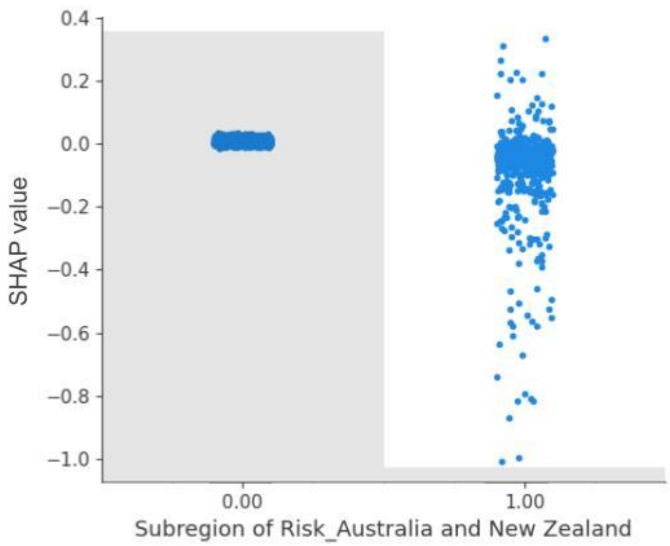

Figure C21: SHAP plot for subregion of risk Australia and New Zealand

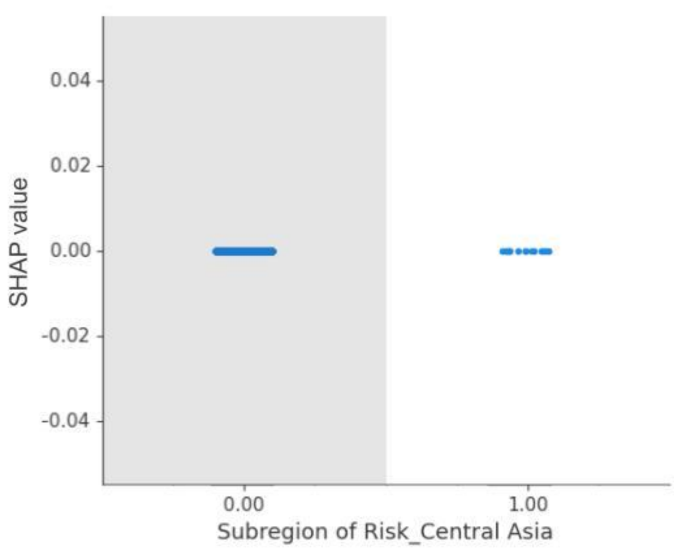

Figure C22: SHAP plot for subregion of risk Central Asia

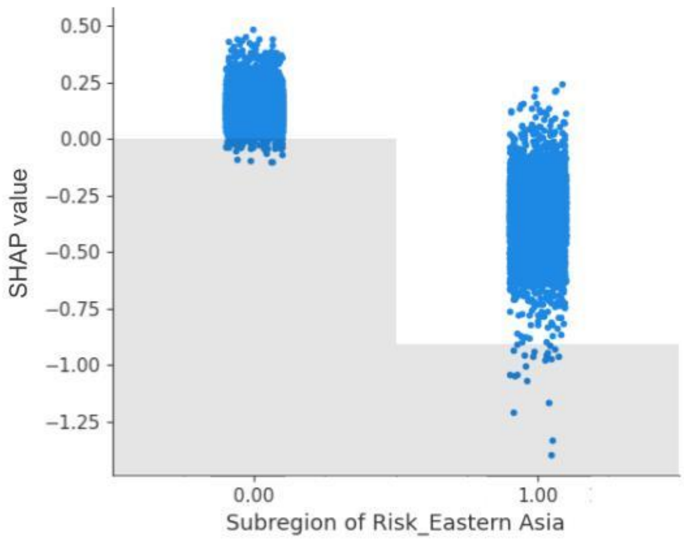

Figure C23: SHAP plot for subregion of risk Eastern Asia

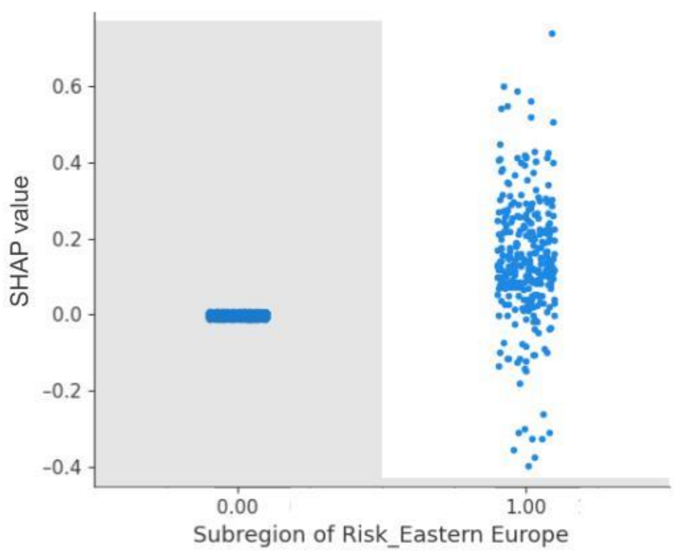

Figure C24: SHAP plot for subregion of risk Eastern Europe

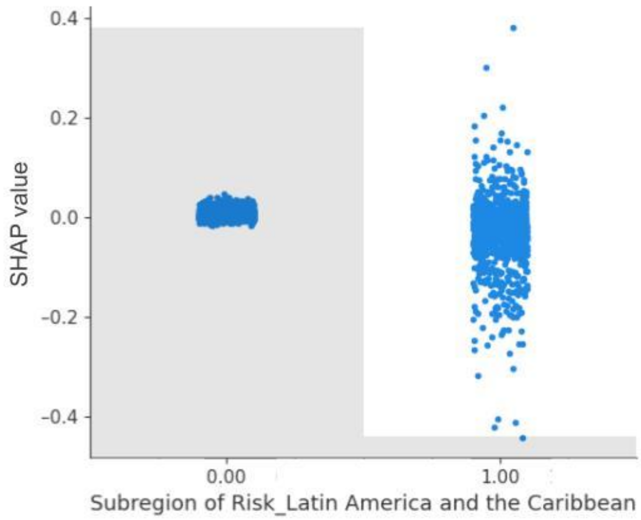

Figure C25: SHAP plot for subregion of risk Latin America and the Caribbean

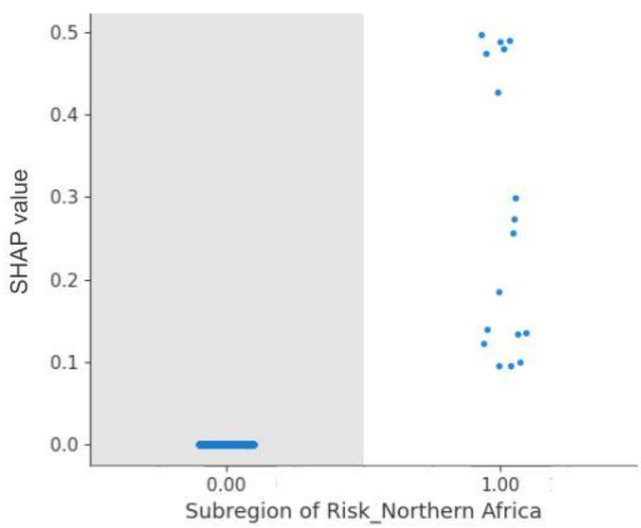

Figure C26: SHAP plot for subregion of risk Northern Africa

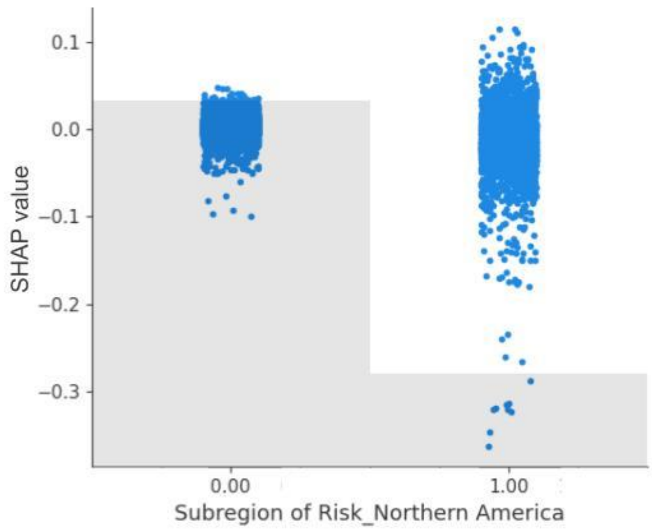

Figure C27: SHAP plot for subregion of risk Northern America

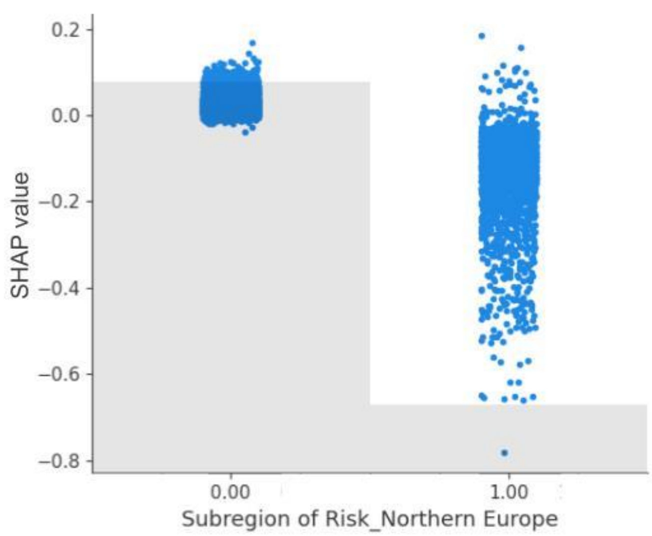

Figure C28: SHAP plot for subregion of risk Northern Europe

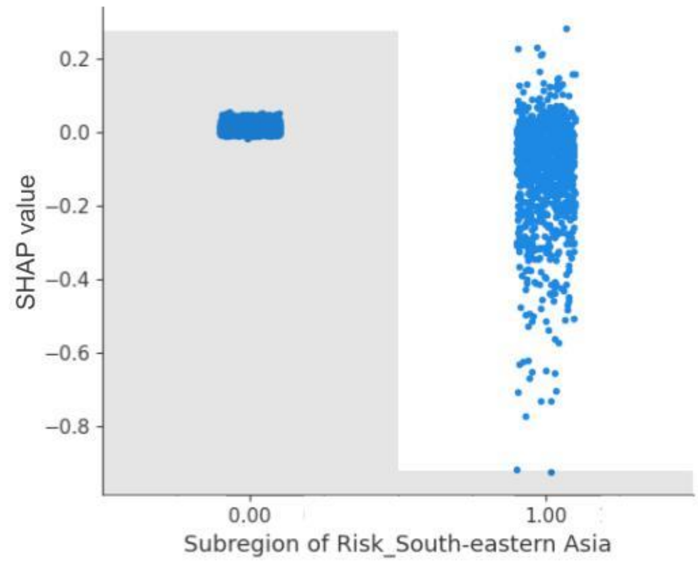

Figure C29: SHAP plot for subregion of risk South-eastern Asia

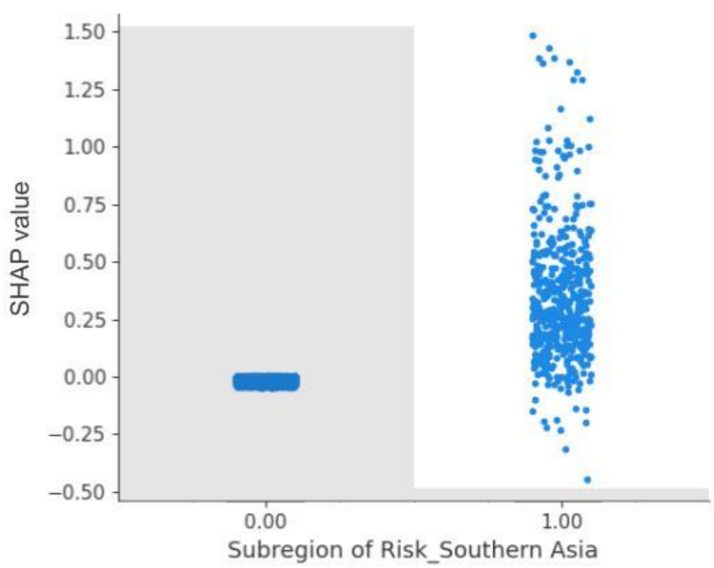

Figure C30: SHAP plot for subregion of risk Southern Asia

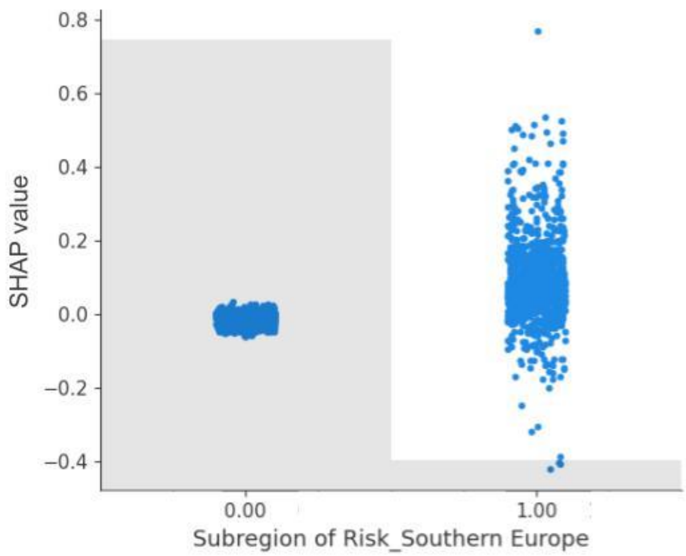

Figure C31: SHAP plot for subregion of risk Southern Europe

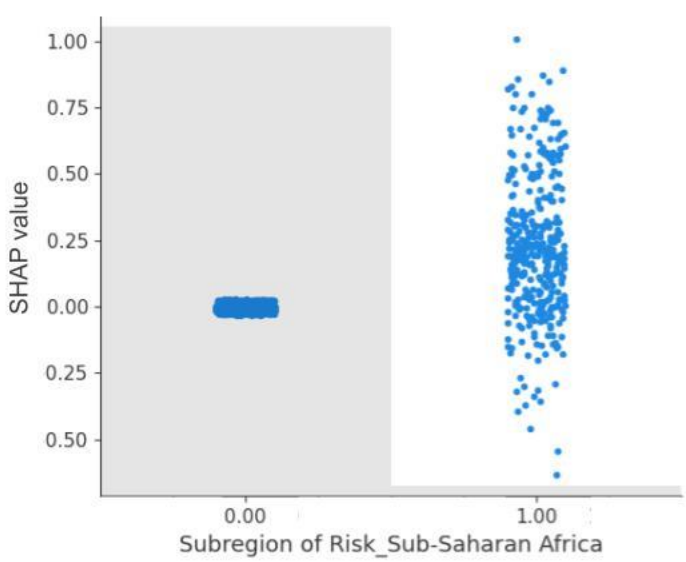

Figure C32: SHAP plot for subregion of risk Sub-Saharan Africa

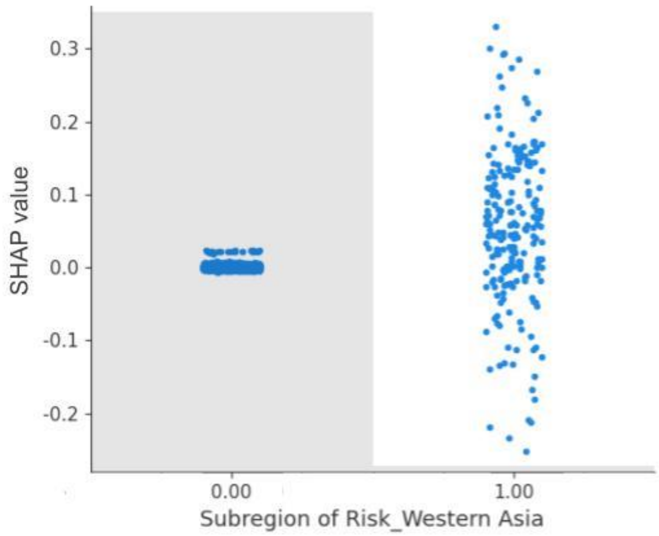

Figure C33: SHAP plot for subregion of risk Western Asia

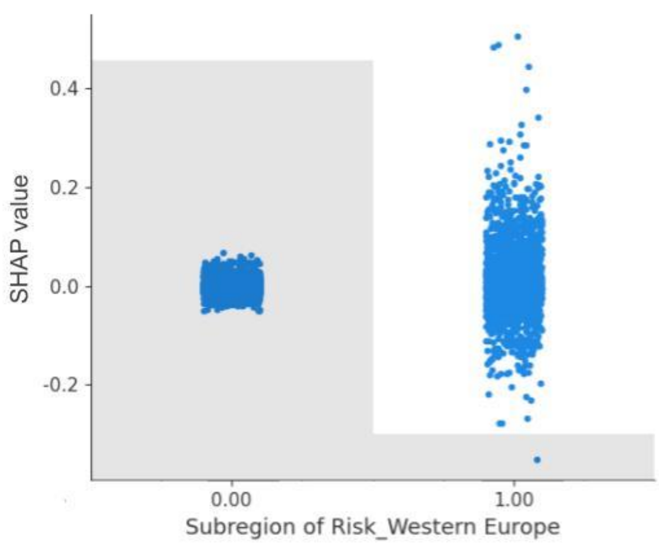

Figure C34: SHAP plot for subregion of risk Western Europe

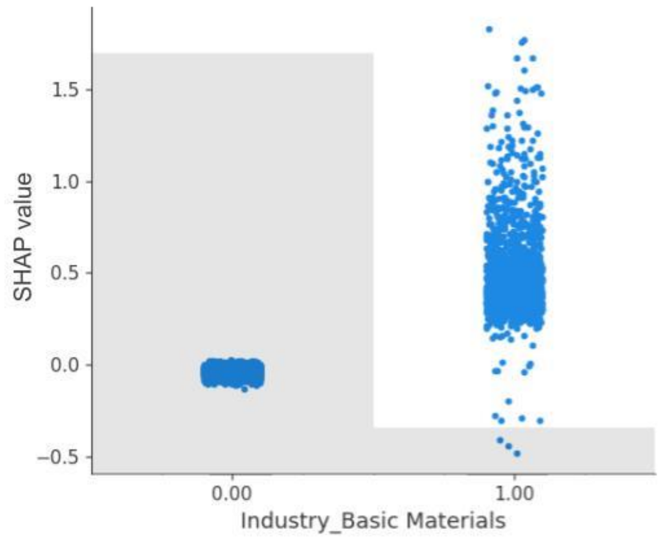

Figure C35: SHAP plot for Basic Materials industry

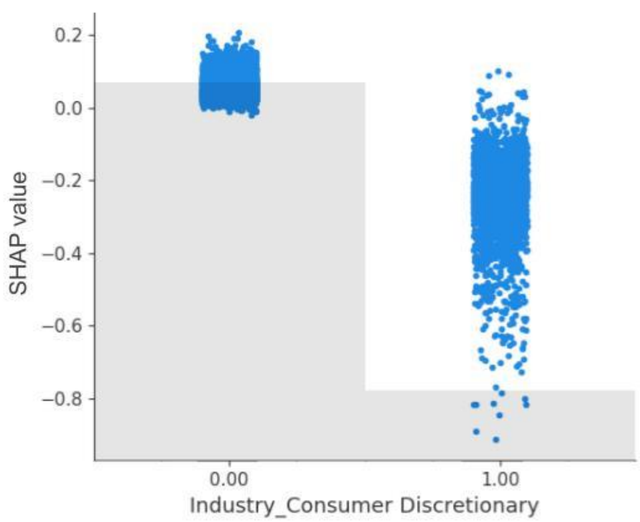

Figure C36: SHAP plot for Consumer Discretionary industry

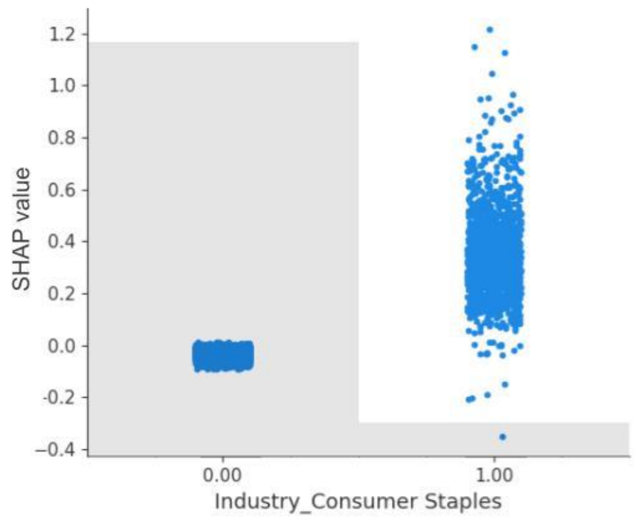

Figure C37: SHAP plot for Consumer Staples industry

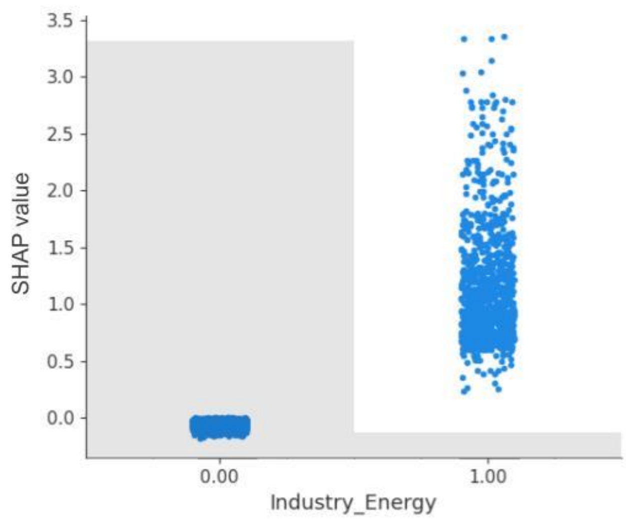

Figure C38: SHAP plot for Energy industry

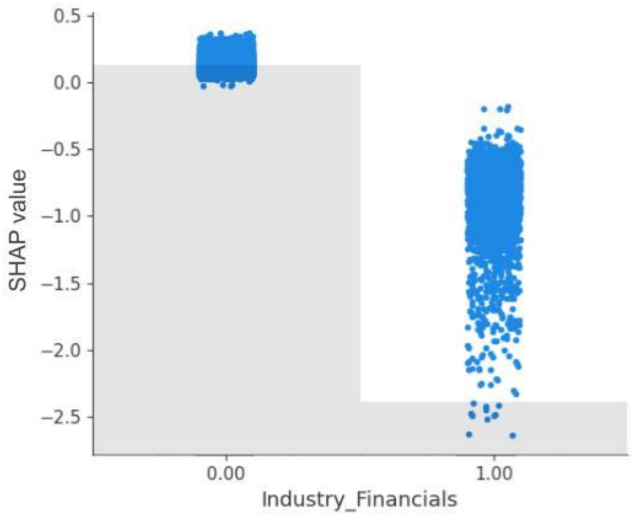

Figure C39: SHAP plot for Financials industry

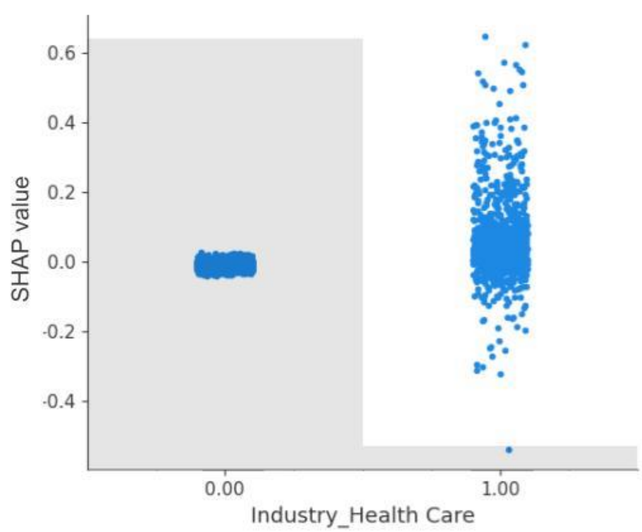

Figure C40: SHAP plot for Health Care industry

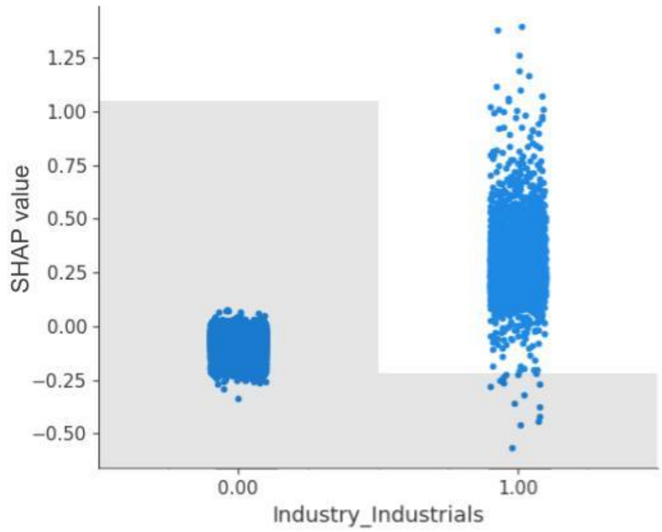

Figure C41: SHAP plot for Industrials industry

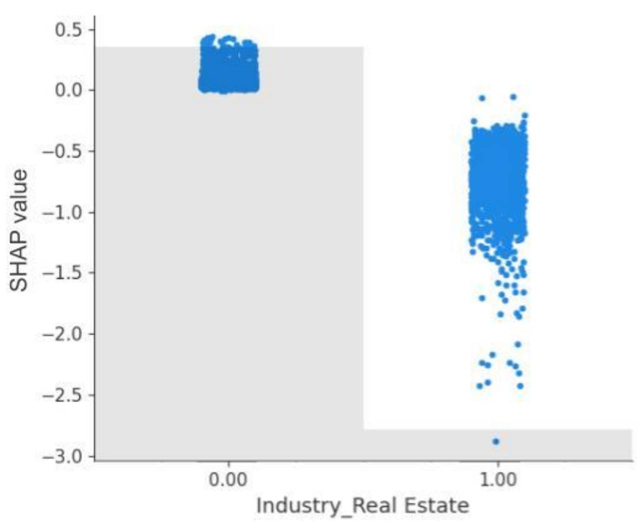

Figure C42: SHAP plot for Real Estate industry

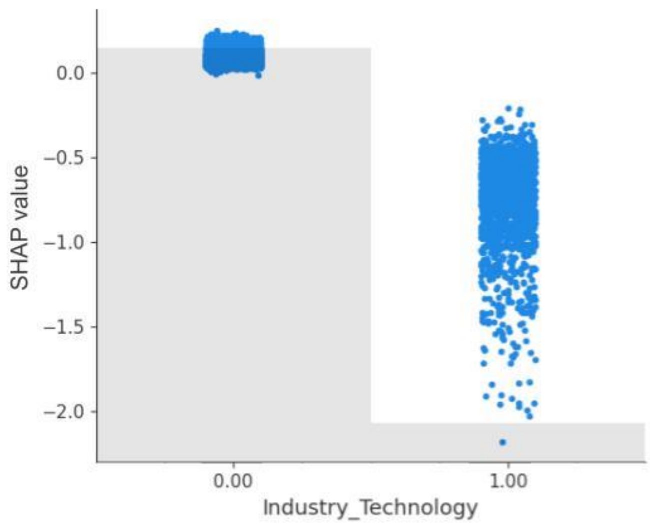

Figure C43: SHAP plot for Technology industry

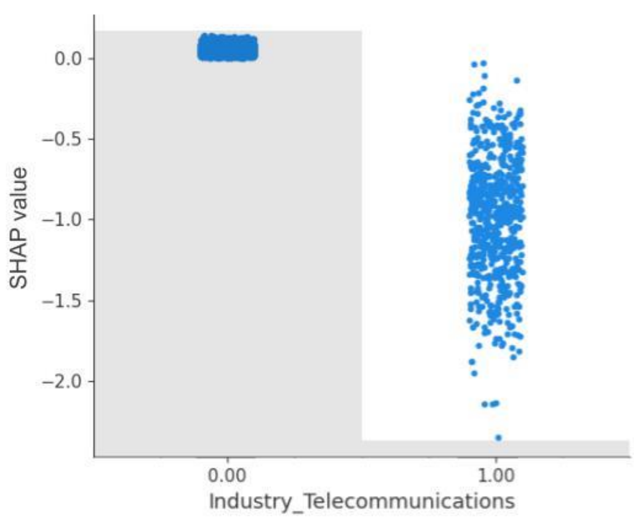

Figure C44: SHAP plot for Telecommunications industry

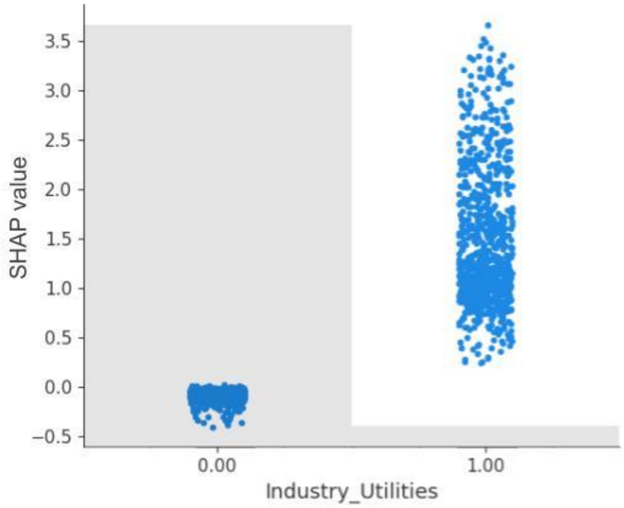

Figure C45: SHAP plot for Utilities industry

Appendix D: Chapter 4 Tables

	No change in consolidation approach	**Change in consolidation approach**
Shapiro-Wilk W statistic (*p*-value)	0.374*** (<0.001)	0.476*** (<0.001)
Fligner-Killeen Chi-squared statistic (*p*-value)	64.369*** (<0.001)	

Table D1 Results for Shapiro-Wilk normality test and Fligner Killeen homogeneity of variance test on emissions intensity changes of companies that did not change their consolidation approach (N=4513) and companies that changed their approach (N=395). Results suggest non-normal distributions and unequal variance.

	Before change in consolidation approach	**After change in consolidation approach**
Shapiro-Wilk W statistic (*p*-value)	0.514*** (<0.001)	0.353*** (<0.001)
Fligner-Killeen Chi-squared statistic (*p*-value)	0.879 (0.348)	

Table D2 Results for Shapiro-Wilk normality test and Fligner Killeen homogeneity of variance test on emissions intensity changes of companies before changing consolidation approach (N=79) and after changing consolidation approach (N=79). Results suggest non-normal distributions and equal variance.

Table D3 List of companies and the reports analyzed for consolidation approach information. Reports listed in *italics* indicate that the consolidation approach mentioned does not align with the approach reported to CDP that year.

Company name	CDP response year	Fiscal year end date	Consolidation approach	Consolidation approach information in this report	Motivation explained?
The Southern Company	2019	2018-12-31	Financial control	CSR Report 2018, p. 52 & 56	No
The Southern Company	2020	2019-12-31	Equity share	n/a	No
Tata Steel	2017	2017-03-31	Operational control	n/a	No
Tata Steel	2018	2018-03-31	Equity share	n/a	No
LafargeHolcim Ltd	2018	2017-12-31	Operational control	Sustainability Report 2017, p.54	No
LafargeHolcim Ltd	2019	2018-12-31	Financial control	Sustainability Report 2018, p.69	Yes
Uniper SE	2018	2017-12-31	Financial control	*Sustainability Report 2017, p.12*	No
Uniper SE	2019	2018-12-31	Operational control	Sustainability Report 2018, p.30	No
SABIC	2019	2018-12-31	Financial control	Sustainability Report 2018, p.90	No
SABIC	2020	2019-12-31	Operational control	*Sustainability Report 2019, p.82*	No
JSW Steel	2017	2017-03-31	Operational control	n/a	No
JSW Steel	2018	2018-03-31	Financial control	*Integrated Report 2018, p.1*	No
DTE Energy Company	2018	2017-12-31	Equity share	*n/a*	No
DTE Energy Company	2019	2018-12-31	Operational control	*n/a*	No
SeverStal PAO	2019	2018-12-31	Operational control	*n/a*	No
SeverStal PAO	2020	2019-12-31	Financial control	*n/a*	No
Nippon Yusen Kaisha Line	2017	2017-03-31	Operational control	*n/a*	No
Nippon Yusen Kaisha Line	2018	2018-03-31	Financial control	*n/a*	No
JSW Energy	2017	2017-03-31	Operational control	*n/a*	No
JSW Energy	2018	2018-03-31	Financial control	*n/a*	No
JSW Energy	2019	2019-03-31	Financial control	*n/a*	No
JSW Energy	2020	2020-03-31	Operational control	*n/a*	No
EnBW Energie Baden-Württemberg AG	2017	2016-12-31	Operational control	*Integrated Report 2016, p.69*	No
EnBW Energie Baden-Württemberg AG	2018	2017-12-31	Financial control	*Integrated Report 2017, p.79*	No
WestRock Company	2017	2016-09-30	Financial control	*n/a*	No
WestRock Company	2018	2017-09-30	Operational control	*n/a*	No

Company name	**CDP response year**	**Fiscal year end date**	**Consolidation approach**	**Consolidation approach information in this report**	**Motivation explained?**
Toyota Motor Corporation	2017	2017-03-31	Operational control	*Environmental Report 2017, p.44*	No
Toyota Motor Corporation	2018	2018-03-31	Financial control	*Environmental Report 2018, p.29*	No
DSV A/S	2017	2016-12-31	Operational control	*n/a*	No
DSV A/S	2018	2017-12-31	Financial control	*n/a*	No
Norfolk Southern Corp.	2019	2018-12-31	Financial control	*n/a*	No
Norfolk Southern Corp.	2020	2019-12-31	Operational control	*n/a*	No
Kuraray Co., Ltd.	2017	2016-12-31	Financial control	*n/a*	No
Kuraray Co., Ltd.	2018	2017-12-31	Operational control	*n/a*	No
Ahold Delhaize	2017	2016-12-31	Operational control	*n/a*	No
Ahold Delhaize	2018	2017-12-31	Financial control	*n/a*	No
Reliance Jio Infocomm Limited	2019	2019-03-31	Operational control	*Integrated Report 2018, p.115*	No
Reliance Jio Infocomm Limited	2020	2020-03-31	Financial control	*Integrated Report 2019, p.118*	No
Smurfit Kappa Group PLC	2017	2016-12-31	Operational control	*n/a*	No
Smurfit Kappa Group PLC	2018	2017-12-31	Financial control	*n/a*	No
Algonquin Power & Utilities Corporation	2017	2016-12-31	Financial control	*n/a*	No
Algonquin Power & Utilities Corporation	2018	2017-12-31	Operational control	*n/a*	No
Aisin Seiki Co., Ltd.	2017	2017-03-31	Financial control	*Sustainability Report 2017, p.5*	No
Aisin Seiki Co., Ltd.	2018	2018-03-31	Operational control	*Sustainability Report 2018, p.1*	No
Fletcher Building	2019	2018-06-30	Financial control	*n/a*	No
Fletcher Building	2020	2019-06-30	Operational control	*n/a*	No
Walgreens Boots Alliance	2019	2019-08-31	Financial control	*n/a*	No
Walgreens Boots Alliance	2020	2020-08-31	Operational control	*n/a*	No
Outokumpu Oyj	2017	2016-12-31	Financial control	*Sustainability Review 2016, p.26*	No
Outokumpu Oyj	2018	2017-12-31	Operational control	*Sustainability Review 201, p.23*	No
African Rainbow Minerals	2017	2017-06-30	Equity share	*Integrated report 2017, p.2*	No
African Rainbow Minerals	2018	2018-06-30	Operational control	*Sustainability Report 2018, p.1*	No
EDF	2017	2016-12-31	Operational control	n/a	No
EDF	2018	2017-12-31	Financial control	n/a	No

Company name	CDP response year	Fiscal year end date	Consolidation approach	Consolidation approach information in this report	Motivation explained?
Linde PLC (Praxair)	2018	2017-12-31	#N/A	n/a	No
Linde PLC (Linde AG)	2018	2017-12-31	Operational control	CSR Report, 2017, p. 93	No
Linde PLC	2019	2018-12-31	Financial control	Sustainable Development Report 2018, p.50	No
Iberdrola SA	2017	2016-12-31	Equity share	Sustainability Report 2016, p.142	No
Iberdrola SA	2018	2017-12-31	Operational control	n/a	No
China Everbright International	2019	2018-12-31	Operational control	Sustainabilty Report 2018, p. 3	No
China Everbright International	2020	2019-12-31	Financial control	n/a	No
Fortum Oyj	2017	2016-12-31	Financial control	n/a	No
Fortum Oyj	2018	2017-12-31	Operational control	Annual Report 2017, p.20	No
Mitsui O.S.K. Lines Ltd	2017	2017-03-31	Financial control	n/a	No
Mitsui O.S.K. Lines Ltd	2018	2018-03-31	Operational control	n/a	No
ANA Holdings Inc.	2017	2017-03-31	Operational control	n/a	No
ANA Holdings Inc.	2018	2018-03-31	Financial control	n/a	No
Sumitomo Chemical Co., Ltd.	2017	2017-03-31	Operational control	n/a	No
Sumitomo Chemical Co., Ltd.	2018	2018-03-31	Financial control	Sustainability Report 2018, p.106	No
Oneok Inc.	2017	2016-12-31	Operational control	n/a	No
Oneok Inc.	2018	2017-12-31	Financial control	n/a	No
Oneok Inc.	2019	2018-12-31	Operational control	n/a	No
Wilmar International Limited	2019	2018-12-31	Operational control	Sustainability Report 2018, p.1	No
Wilmar International Limited	2020	2019-12-31	Financial control	n/a	No
Halliburton Company	2017	2016-12-31	Financial control	n/a	No
Halliburton Company	2018	2017-12-31	Operational control	n/a	No
Thomas Cook Group	2017	2017-03-31	Financial control	n/a	No
Thomas Cook Group	2018	2018-03-31	Operational control	n/a	No
AngloGold Ashanti	2018	2017-12-31	Operational control	n/a	No
AngloGold Ashanti	2019	2018-12-31	Financial control	n/a	No
Arconic	2017	2016-12-31	Operational control	n/a	No
Arconic	2018	2017-12-31	Financial control	n/a	No

Company name	CDP response year	Fiscal year end date	Consolidation approach	Consolidation approach information in this report	Motivation explained?
Canadian Pacific Railway	2017	2016-12-31	Financial control	n/a	No
Canadian Pacific Railway	2018	2017-12-31	Operational control	n/a	No
Carrefour	2017	2016-12-31	Financial control	n/a	No
Carrefour	2018	2017-12-31	Operational control	n/a	No
Panasonic Corporation	2018	2018-03-31	Financial control	n/a	No
Panasonic Corporation	2019	2019-03-31	Operational control	n/a	No
Pennon Group	2017	2017-03-31	Equity share	Annual Report 2017, p.101	No
Pennon Group	2018	2018-03-31	Financial control	Annual Report 2018, p.103	No
Avangrid Inc	2017	2016-12-31	Equity share	n/a	No
Avangrid Inc	2018	2017-12-31	Operational control	n/a	No
Mitsubishi Gas Chemical Company, Inc.	2017	2017-03-31	Operational control	n/a	No
Mitsubishi Gas Chemical Company, Inc.	2018	2018-03-31	Financial control	n/a	No
Teijin Ltd.	2019	2019-03-31	Financial control	n/a	No
Teijin Ltd.	2020	2020-03-31	Operational control	n/a	No
Sumitomo Electric Industries, Ltd.	2017	2016-03-31	Operational control	n/a	No
Sumitomo Electric Industries, Ltd.	2018	2017-03-31	Financial control	n/a	No
McDonald's Corporation	2019	2018-12-31	Financial control	n/a	No
McDonald's Corporation	2020	2019-12-31	Operational control	n/a	No
JSW Cement Limited	2019	2019-03-31	Financial control	n/a	No
JSW Cement Limited	2020	2020-03-31	Operational control	n/a	No
Jabil Inc.	2017	2017-08-31	Operational control	n/a	No
Jabil Inc.	2018	2018-08-31	Financial control	n/a	No

Appendix E: Chapter 4 Figures

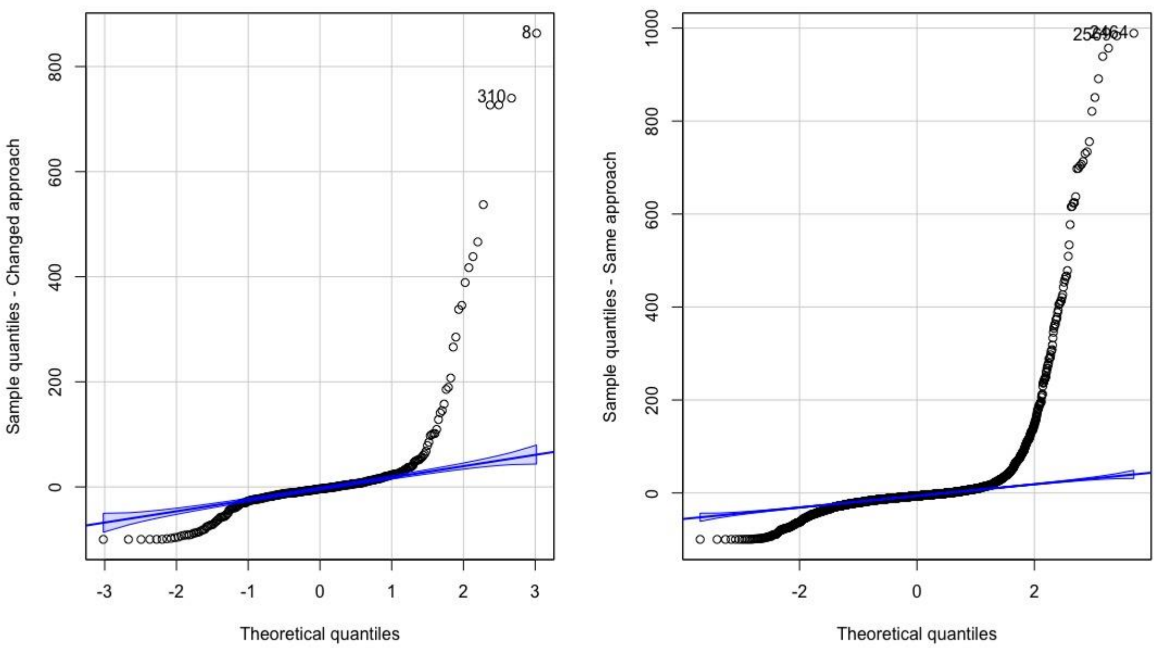

Figure E1 Q-Q plots for emissions intensity changes of companies that changed their consolidation approach (left) and companies that did not change their approach (right). Results suggest non-normal distributions and positive skew.