# Can Investor Coalitions Regulate Corporate Climate Action?∗ †

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#### Abstract

This paper investigates the effectiveness of collective investor engagement in regulating corporate climate action. Empirically, I focus on Climate Action  $100+$  (CA100+), the world's largest investor coalition on climate change. To address common measurement issues in previous research, I conduct a multidimensional assessment of companies' climate action. In particular, I collect new primary data on climate-related disclosure using a Natural Language Processing model and augment time series data on the ambition of carbon emission reduction targets. To isolate the causal impact of CA100+, I employ a binned Difference-in-differences (DiD) analysis and a combination of matching with DiD methodology. The findings suggest that CA100+ has had no significant effect on companies' disclosures, reductions in carbon emissions, or short-term targets. However, I find a heterogeneous impact on companies' medium- and long-term targets, significant only for companies potentially selected based on prior investor knowledge. Overall, this study sounds a note of caution on the effectiveness of collective engagement. It raises questions about the selectivity of investor action and highlights the risk of companies backloading their decarbonisation efforts.

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"The core message today is that the money is there, the money is there for the transition, and  $it's$  not blah blah blah." - Mark Carney, November 2021

### 1 Introduction

The transition to a low-carbon economy is a critical global challenge, necessitating substantial shifts in how entire industries operate. Financial actors play a key role in accelerating this transition by leveraging their influence over the allocation of financial resources. In particular, investors find themselves in a unique position to drive climate  $\arctan^1$  $\arctan^1$  among their investees. However, they often hold only small individual stakes in companies. To strengthen their impact, investors have formed coalitions to collectively influence corporate behaviour.

Several reviews of the sustainable finance literature note a lack of empirical evidence regarding the the role of investors in driving change (Kölbel et al., 2020; [Diener and Habisch,](#page-58-0)  $2021$ ). While recent studies have started to fill this gap [\(Azar et al., 2021;](#page-57-0) Heeb and Kölbel, [2024\)](#page-59-1), many areas of investor impact remain under-researched. Notably, the role of investor coalitions has largely been overlooked, despite their substantial growth in recent years.<sup>[2](#page-1-1)</sup> New evidence in this field is important to assess the potential of environmental governance through financial actors and to inform related policy-making.

In December 2017, Climate Action 100+ (CA100+), the world's largest investor coalition on climate change, was launched, representing the "biggest shareholder action plan ever" [\(Financial Times, 2017\)](#page-59-2). At its peak in 2023, CA100+ was supported by over 700 investors

<span id="page-1-0"></span><sup>&</sup>lt;sup>1</sup>In this study, I use the term corporate climate action to describe any measures companies can take to address climate change and reduce their climate impact. Other terms commonly used in the field include "climate performance", "carbon performance" and "environmental performance".

<span id="page-1-1"></span><sup>2</sup>To name a few examples across different themes in sustainable investing: the Net-Zero Asset Owner Alliance (NZAOA) (2019), the Investor Mining and Tailings Safety Initiative (2019), the Net-Zero Asset Manager Alliance (NZAMA) (2020), Nature Action 100 (2022), Climate Engagement Canada (2023) and the Good Work Coalition (2023).

with a combined 68 trillion<sup>[3](#page-2-0)</sup> US Dollars of assets under management  $(AUM)^4$  $(AUM)^4$  CA100+ engages with a focus group of approximately 170 large corporate polluters and aims "to ensure the world's largest corporate greenhouse gas emitters take necessary action on climate change" [\(Climate Action 100+, 2024\)](#page-58-1). Given its size and significance, CA100+ constitutes a good case study to gain broader insights into the effectiveness of collaborative investor action. Building on insights from resource dependence theory (RDT), it can be expected that companies will react to the initiative's asks.

Indeed, a few existing studies suggest that CA100+ may be effective in driving change. [Bingler et al.](#page-57-1) [\(2024\)](#page-57-1) demonstrate a correlation between CA100+ inclusion and more precise climate commitments by companies, while [\(Colesanti Senni et al., 2024\)](#page-58-2) show that CA100+ companies disclose more information on target-setting than on the implementation of their climate strategy. Focusing on investors, [Zink](#page-60-0) [\(2024\)](#page-60-0) finds that early CA100+ members support more climate-related shareholder proposals than non-signatories and late joiners. Unlike [Atta-Darkua et al.](#page-57-2) [\(2023\)](#page-57-2), [Zink](#page-60-0) [\(2024\)](#page-60-0) observes no portfolio decarbonisation among CA100+ investors. However, it's important to note that all these studies do not establish causal links, but measure associations between CA100+ and improvements in corporate or investor climate actions.

Attempting a first causal analysis, [Chang and Fang](#page-58-3) [\(2024\)](#page-58-3) find a significant negative treatment effect of CA100+ on the carbon emissions of focus companies' suppliers in China. Yet, their study has a limited geographical focus and does not interrogate whether the company selection process of CA100+ constitutes an exogenous shock. This study aims to advance the literature by providing the first comprehensive causal assessment of the effects of CA100+ on the multi-dimensional climate actions of its focus companies on a global level.

<span id="page-2-0"></span>From a causal inference point of view, isolating the true impact of CA100+ presents

<sup>&</sup>lt;sup>3</sup>In early 2024, several large asset managers from the United States left the coalition. The author estimates the current combined AUM in May 2024 as 50 trillion US Dollars by deducting the AUM of BlackRock US, State Street Global Advisors, JP Morgan Asset Management, and Invesco. The recent departures lie outside of the period analysed in this study.

<span id="page-2-1"></span><sup>4</sup>The combined AUM figures may include some instances of double counting, as CA100+ is supported by both asset owners and managers.

several endogeneity challenges. Firstly, the measurement of corporate climate action is challenging. Previous studies in the field have used uni-dimensional indicators which may induce measurement error. Secondly, CA100+ companies may have inherent differences in their climate strategies compared to other companies. There is a risk of selection bias, i.e., investors may have selected companies which they knew would strengthen their climate actions. Thirdly, CA100+ operates in a dynamic environment where multiple interventions and external factors can influence actions that companies are taking. It is crucial to control for confounding factors, such as other regulatory policies, technological advancements, and market forces.

This study aims to overcome these challenges in three steps. First, I use multidimensional and new refined metrics for corporate climate actions, focusing on climate-related disclosure, reductions in historical carbon emissions and carbon emission reduction targets. In particular, I employ the ClimateBERT-TCFD model developed by [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3) to analyse the extent to which companies report climate-related information in their Annual Reports (ARs) and how this maps onto the four categories of the Taskforce on Climate-related Financial Disclosure (TCFD). Furthermore, I collect new primary data on the carbon emission reduction targets of 296 companies from six hard-to-abate sectors (airlines, automotive, cement, electricity, oil and gas and steel) to augment an existing forward-looking dataset from the Transition Pathway Initiative  $(TPI)$ <sup>[5](#page-3-0)</sup> Second, I conduct a straightforward binned twoway fixed effects (TWFE) difference-in-differences (DiD) analysis to comment on differences in the trends of climate action between the CA100+ focus and other companies. Thirdly, I isolate the causal impact of CA100+ on its focus companies using a combination of matching and DiD methodology. I establish a control group by matching CA100+ companies to suitable non-CA100+ companies based on pre-treatment trends and conduct a set of DiD analyses, including TWFE and staggered designs.

<span id="page-3-0"></span>Overall, I find no empirical support for a statistically significant impact of CA100+ on

<sup>5</sup>TPI is an investor-led initiative with an independent research team based at the LSE which assesses companies' plans to manage climate-related risks and carbon emissions.

companies' climate-related disclosure or reductions in historical carbon intensities. The results are robust when choosing two alternative measurements of corporate climate reporting, namely corporate responses to the CDP<sup>[6](#page-4-0)</sup> and reporting of carbon intensities. The absence of an immediate effect of CA100+ on carbon emissions is not surprising, as companies may require time to adjust their operations. However, I find a significant, yet heterogeneous, treatment effect on medium- and long-term target setting.

While the effect on carbon emission reduction targets is not significant for the top 100 publicly listed corporate polluters which constituted the first addition to the CA100+ focus group (the "CA100 companies"), the negative effect is significant for companies that were added to the focus group later (the "Plus companies"). Intriguingly, endogeneity in the selection of the Plus companies cannot be ruled out. Therefore, this study raises questions about potential investor knowledge prior to engagement which may determine success. Unpacking the effect on the Plus companies' targets further, it stands out that CA100+'s impact is absent on short-term target setting. Acknowledging that climate change depends on cumulative emissions, this finding raises concerns about the backloading of corporate decarbonisation efforts, i.e. companies are relying on steeper emission reductions in the distant future. Setting long-term targets without short- and medium-term milestones against which companies can be held accountable may also constitute a form of greenwashing.

This paper contributes to the literature on investor impact. As noted above, the role of collaborative investor action is largely under-researched. An exception is the study by [Dimson et al.](#page-58-4) [\(2021\)](#page-58-4) who find that coordinated engagement through the United Nations Principles for Responsible Investing can enhance corporate sustainability outcomes, although they acknowledge potential endogeneity concerns. This is a common issue in this research area, which highlights the need for studies testing for causality.

Additionally, this study is positioned within the rapidly growing subfield of climate finance, specifically examining how investors try to mitigate climate risks among their in-

<span id="page-4-0"></span><sup>6</sup>CDP, formerly known as the Carbon Disclosure Project, is a voluntary environmental disclosure platform for companies, investors, governments and cities.

vestees. Evidence from [Ilhan et al.](#page-59-3) [\(2023\)](#page-59-3) and [Flammer et al.](#page-59-4) [\(2021\)](#page-59-4) shows that institutional investors actively seek improved climate disclosures, aligning with one of CA100+'s engagement objectives. Furthermore, [Azar et al.](#page-57-0) [\(2021\)](#page-57-0) highlight that the Big Three asset managers actively engage their investee companies to lower their carbon footprint. However, the simultaneous impact of investor action on different aspects of companies' climate action, particularly the ambition of carbon emission reduction targets, has not been extensively researched.

Furthermore, this paper aims to advance sustainable finance research regarding the measurement of corporate sustainability, specifically focusing on corporate climate action. There is a recognised inconsistency in large datasets concerning companies' sustainability and climate actions. For instance, [Berg et al.](#page-57-4) [\(2022\)](#page-57-4) illustrate the divergent results from ESG rating agencies, [Bingler et al.](#page-57-5) [\(2022b\)](#page-57-5) discuss the differences in metrics used to assess transition risks, and [Busch et al.](#page-57-6) [\(2022\)](#page-57-6) emphasise the inconsistencies in measuring Scope 3 emissions across different providers. Due to a lack of more reliable information, the existing large N literature often uses data that may induce measurement error. In contrast, this research seeks to enhance the field by using newly collected and refined metrics for corporate climate actions, albeit with a smaller sample size.

In the following section [2,](#page-6-0) I use RDT and relevant empirical studies on investor impact to derive my hypotheses. In section [3,](#page-12-0) I analyse whether the CA100+ company selection process constitutes an exogeneous shock. Section [4](#page-16-0) explains challenges in measuring corporate climate action and describes how this study tries to overcome those. Sections [5](#page-32-0) and [6](#page-37-0) present the research designs and evaluate results for the binned DiD analysis and the matched DiD. After showing a series of robustness checks in [7,](#page-45-0) I discuss my findings, highlight limitations and point towards policy implications and future areas of research in section [8.](#page-52-0)

# <span id="page-6-0"></span>2 Conceptual framework

Why would companies respond to regulatory pressure by CA100+? RDT offers valuable insights into the leverage CA100+ investors hold over companies. From an RDT perspective, organisations respond to demands from actors who possess essential resources necessary for their ongoing success [\(Pfeffer and Salancik, 1978\)](#page-60-1). In the following, I will argue that  $CA100+$ investors control significant resources for the focus companies, including financial capital and reputational influence.

Companies require continuous access to capital to fund their operations, making them financially dependent on financial actors. From a company perspective, this provides an incentive to actively engage with investors. Conversely, from an investor perspective, this dependency gives them the power to persuade or compel companies to undertake actions they might not otherwise consider. However, the extent to which resource controllers wield power depends on the scarcity and concentration of the resource [\(Pfeffer and Salancik, 1978\)](#page-60-1). On an individual level, an investor's influence over a company may be limited. While the world's largest asset managers can influence companies' carbon emissions [\(Azar et al., 2021\)](#page-57-0), smaller investors may not hold the same power. Specifically, the influence of individual investors can be expected to be negligible if they do not own a significant stake in the targeted company. The position of smaller investors may be further weakened if their specific demands significantly diverge from those of other investors. Therefore, the impact of investors is likely to depend on their total AUM and the general consensus among investors regarding the actions that companies should implement.

Investor coalitions, such as CA100+, are an opportunity for individual investors to overcome these challenges. By bundling their expectations, pooling their financial resources and collectively targeting companies, investors are significantly more powerful in a coalition than when pursuing their agendas alone. This is the fundamental idea behind  $CA100+$ .  $CA100+$ emphasises the "business case" for investors to mitigate climate change, considering the potential significant financial impact of exposure to climate risks, which in the worst case, could lead to a systemic financial crisis. Thus, "[b]y working together through Climate Action  $100+$ , investors can  $(\ldots)$  help secure stable economies that are more resilient to the risks posed by climate change" [\(Climate Action 100+, 2024\)](#page-58-1).

CA100+ aims to drive change in companies through engagement. Each investor member has signed a commitment to work with their investee companies to encourage them to take actions in line with the goals of the Paris Agreement, pursuing efforts to limit global warming to 1.5°C. Each company targeted by CA100+ is assigned a team of lead and contributing investors. While investors can only take decisions on behalf of their own AUM over which they have fiduciary duty, they engage with companies as part of CA100+ [\(Climate](#page-58-5) [Action 100+, 2023\)](#page-58-5). The significant combined AUM of  $CA100+$  investors, which translates into substantial collective ownership stakes in the focus companies, underpins the CA100+ engagement asks.

Investor engagement can be conducted through voicing or voting. Voicing relies on private engagement, conducted by investors with companies behind closed doors. Several studies provide evidence of successful outcomes from individual private investor engagement on sustainability issues [\(Barko et al., 2022;](#page-57-7) [Dimson et al., 2015;](#page-58-6) [Hoepner et al., 2024;](#page-59-5) [Bauer](#page-57-8) [et al., 2023;](#page-57-8) Heeb and Kölbel, 2024; [Aguilera et al., 2021\)](#page-57-9). This serves as suggestive evidence that collective investor action through CA100+ may drive climate actions among investee companies.

Voting constitutes a more coercive tool investors can use if companies do not comply with investors' demands. Through their voting rights, investors can file, support or oppose shareholder resolutions at companies' Annual General Meetings, trying to force them to adopt specific practices. Given that proposals are typically not filed in a vacuum, [Dyck et al.](#page-59-6) [\(2019\)](#page-59-6) suggest that institutional investors use them to support their private engagement.

Early studies on the effectiveness of shareholder resolutions in improving companies' sustainability performance did not observe a positive effect [\(David et al., 2007;](#page-58-7) [Clark et al.,](#page-58-8)

[2008\)](#page-58-8). However, the more recent literature shows tangible changes [\(Grewal et al., 2016;](#page-59-7) [Wei,](#page-60-2) [2020\)](#page-60-2), suggesting an increasing effectiveness of shareholder resolutions over time. Focusing specifically on companies' climate-related risks, [Flammer et al.](#page-59-4) [\(2021\)](#page-59-4) find that targeting firms with shareholder proposals led to significant improvements in disclosure. Similarly, [Diaz-Rainey et al.](#page-58-9) [\(2023\)](#page-58-9) show that companies targeted by climate-related proposals experience subsequent improvements in their environmental performance, although they do not observe a significant change in carbon emissions. In the context of CA100+, [Zink](#page-60-0) [\(2024\)](#page-60-0) observes that early signatories are indeed more likely to support climate-related shareholder proposals than non-signatories and late signatories. This suggests that at least some CA100+ investors may use proposals to influence the climate actions of the focus companies.

Given the complex debate around the effectiveness of investor engagement versus divestment [\(Broccardo et al., 2022\)](#page-57-10), it is important to note that CA100+ does not publicly advocate for changes in capital allocation. Yet, besides coercing companies to make certain decisions through voting, the effectiveness of private engagement may ultimately depend on the potential threat of investors to divest. If a sufficient share of investors divests from companies over sustainability concerns, this can increase their cost of capital [\(Heinkel et al.,](#page-59-8) [2001;](#page-59-8) [Rohleder et al., 2022\)](#page-60-3). Therefore, the collective financial size of CA100+ may ultimately matter in engagement work, as companies could consider the impact of displeasing CA100+ on their ability to raise capital in the future.

CA100+ investors also hold significant reputational resources. They can publicly endorse the climate actions or, in contrast, stigmatise laggards. Although there is currently no empirical evidence, both effects may indirectly influence firm behaviour (Kölbel et al., [2020\)](#page-59-0). Furthermore, CA100+ regularly publishes a Net Zero Company Benchmark which assesses the climate action of all the focus companies based on ten main indicators. [Chatterji](#page-58-10) [and Toffel](#page-58-10) [\(2010\)](#page-58-10) demonstrate that the effect of benchmarking companies' performance in sustainability ratings can induce improvement. [Sharkey and Bromley](#page-60-4) [\(2015\)](#page-60-4) show that such improvements may be even more pronounced in the presence of rated competitors.

In summary, companies can be expected to manage their dependency on financial and reputational resources by responding to engagement asks by CA100+ investors. I therefore derive the following baseline hypothesis:

# H1: Inclusion in CA100+'s focus list improves companies' climate action relative to other comparable companies.

At its launch in December 2017, the 225 initial CA100+ signatories held a combined 26 trillion US dollars in AUM [\(Financial Times, 2017\)](#page-59-2). Since then, the size of the coalition has grown considerably. At its peak in 2023, the combined AUM reached 68 trillion US dollars [\(Climate Action 100+, 2024\)](#page-58-1). As  $CA100+$  has grown, its role as a controller of financial resources over companies may have similarly increased. Furthermore, CA100+ became more vocal over time and introduced significant new measures to publicly monitor companies' climate action, most notably the Net Zero Company Benchmark in 2021. Therefore, I propose a second hypothesis:

# H2: The effectiveness of  $CA100+$  in improving the climate performance of the focus companies increases over time.

However, individual companies' dependency on CA100+ investors may vary based on their collective share of ownership which fluctuates over time. [David et al.](#page-58-7) [\(2007\)](#page-58-7) provide initial evidence that the ownership stake of investors filing shareholder resolutions impacts the responsiveness of the targeted company. Similarly, [Dyck et al.](#page-59-6) [\(2019\)](#page-59-6) demonstrate that an increasing share of company ownership by institutional investors is positively associated with improvements in corporate sustainability performance. Therefore, assuming that the intensity of the engagement through CA100+ may vary, I derive a third hypothesis:

 $H3: CA100+ focus companies with a higher share of equity owned by CA100+ investors$ improve their climate actions more significantly than companies with a lower share.

Yet, as CA100+ does not make a list of the signature dates of its investor members publicly available, this information must be obtained through screening of press releases of the 700 investor members. Collecting data on this variable is labour-intensive, which is why H<sub>3</sub> will only be evaluated in future iterations of this study.

Shifting perspectives, companies are rational actors that will carefully weigh up how to respond to CA100+ demands. While organisations need to respond to critical resource controllers, RDT posits that they will seek to manage and reduce these dependencies [\(Pfef](#page-60-1)[fer and Salancik, 1978\)](#page-60-1). In the context of environmental policies, corporates evaluate risks and costs when considering compliance with external environmental demands [\(Bansal and](#page-57-11) [Roth, 2000\)](#page-57-11). In an analysis of corporate responses to sustainability ratings, [Gauthier and](#page-59-9) [Wooldridge](#page-59-9) [\(2018\)](#page-59-9) argue that companies may use "compensating tactics", aiming to satisfy requirements from sustainability rating agencies by focusing on changes in lower-cost and -effort practices that do not affect the core business. From a cost perspective, companies may therefore prioritise less expensive climate actions over more costly measures. Indeed, previous research indicates a discrepancy between environmental disclosure and more substantial measures of environmental performance, particularly among large firms [\(Drempetic](#page-58-11) [et al., 2020;](#page-58-11) Aragón-Correa et al., 2016). Based on these observations, I derive a fourth hypothesis:

### $H_4$ :  $CA100+$  is more effective in improving companies' low-cost than high-cost climate actions.

In the above, I have argued that CA100+ is likely to improve the climate actions of its focus companies. However, its influence could go even further and potentially impact other companies. By articulating clear investor expectations on corporate climate action – such as through the Company Net Zero Benchmark – CA100+ has the potential to establish decarbonisation standards in the real economy. From an RDT perspective, CA100+ may thereby effectively alter all companies' external environment and their perception of criteria for resource allocation [\(Pfeffer and Salancik, 1978\)](#page-60-1).

In a comprehensive review, [Marti et al.](#page-60-5)  $(2023)$  refer to such indirect effects as "field building". They argue that investors can create an impact by sharing expertise with other shareholders and thereby shifting the perception of sustainability issues. With its extensive and broad membership base, CA100+ holds significant influence over discussions on climate change in the financial sector and beyond and may create such effects.

However, from an empirical point of view, it is difficult to measure "field building" through CA100+. Causal inference methods inherently rely on comparisons. Since "field building" effects could affect the whole economy, it is challenging to draw a line between treated and untreated companies. This study refrains from imprecise attempts to approximate such an effect, for example, by comparing sectors covered by CA100+ with those that are not. Instead, it focuses on assessing CA100+'s direct and indirect impacts on the focus companies, specifically through collective engagement and public benchmarking.

# <span id="page-12-0"></span>3 The CA100+ company selection process

When CA100+ was launched in December 2017, the initiative selected the 100 largest corporate greenhouse gas emitters as their focus list (the "CA100 companies"). In June 2018, the focus list was extended to include an additional 61 companies which were considered "transition enablers" (the "Plus companies"), although no clear selection criterion was disclosed. As of May 2024, the focus list comprises 170 companies from 15 sectors, reflecting later additions of smaller groups and changes due to mergers and acquisitions. This study focuses only on the CA100 and Plus companies (together the "CA100+ companies"), as these constitute the earliest and most significant additions. Figure [1](#page-13-0) shows the distribution of the CA100 and Plus companies by sector and appendices [A](#page-61-0) and [B](#page-62-0) include the full lists of companies.

In 2020, [Climate Action 100+](#page-58-1) [\(2024\)](#page-58-1) stated that the companies from the focus list accounted together for 80% of all global industrial emissions. There remain doubts about the accuracy of this calculated share due to double-counting of emissions across Scope 1, 2 and 3.[7](#page-12-1)[8](#page-12-2) Addressing double-counting in aggregating corporate carbon footprints requires detailed documentary work, such as in [Heede](#page-59-11) [\(2014\)](#page-59-10).<sup>[9](#page-12-3)</sup> In their Carbon Majors report, Heede [\(2020\)](#page-59-11) traces historical global industrial emissions from  $CO<sub>2</sub>$  and methane back to the 108 largest corporate polluters in the oil, gas, coal, and cement sectors. Thirty-six CA100+ companies are covered by their work and account collectively for approximately 22% of global cumulative emissions from  $1850$  to  $2018$ .<sup>[10](#page-12-4)</sup> This estimate covers less than one-quarter

<span id="page-12-1"></span><sup>7</sup>Scope 1 emissions refer to direct greenhouse gas emissions from a company's owned or controlled sources. Scope 2 emissions are indirect emissions from purchased electricity, steam, heating and cooling. Scope 3 emissions are indirect emissions from the company's value chain, including activities such as procurement, transportation, and product use [\(GHG Protocol Initiative, 2004\)](#page-59-12).

<span id="page-12-2"></span><sup>8</sup>Double counting of real-world emissions occurs when a company's direct emissions (Scope 1) are included in the indirect emissions of another company (Scope 2 and 3). Adding up direct and indirect carbon footprints across companies without accounting for emission overlaps in their value chains leads to an inflated total.

<span id="page-12-3"></span><sup>9</sup>[Heede](#page-59-10) [\(2014\)](#page-59-10) mitigate double-counting by incorporating only companies' emissions from production (Scope 1) and the use of produced products (Scope 3, category 11) in their calculations. Relevant production data are sourced from company disclosures and other publicly available information.

<span id="page-12-4"></span><sup>10</sup>Author's calculations based on the Carbon Major database 2020.

of all focus companies. Yet, it highlights the significant impact that CA100+ could have on the low-carbon transition, despite the relatively small group of focus companies.

<span id="page-13-0"></span>

Figure 1: This figure shows the distribution of the CA100 companies (highlighted in red) and the Plus companies (highlighted in yellow) by sector. Companies are only counted once, even if they operate in multiple sectors. The Aluminium sector, in which three Diversified Miners operate, is not listed separately.

Importantly, the focus companies could not self-select or opt-out. The initial CA100 companies were chosen solely based on their absolute carbon footprint, based on reported and estimated Scope 1, 2 and 3 emissions from the CDP database. This clear cut-off represents an exogenous shock.

The selection criterion is unlikely to have resulted in choosing companies more likely to improve their climate action. The absolute carbon footprint of a company is typically driven by sector and company size and does not clearly indicate its propensity to curb carbon emissions. From an economic perspective, a company's capability or willingness to reduce carbon emissions is inversely proportional to marginal abatement costs (MACs) [\(Gillingham](#page-59-13) [and Stock, 2018\)](#page-59-13). As MACs vary by sector, the majority of CA100 companies unsurprisingly operate in sectors that are typically considered hard to abate, such as oil and gas. However, within sectors, factors that influence companies' MACs, such as the cost-effectiveness of different mitigation options, are hard to observe and likely unknown to investors. Even if such data were available, a comparison of MACs across companies would require an intensitybased analysis to control for biases such as firm size. In section [4.2.2,](#page-21-0) I show that there are no striking differences in carbon intensities between CA100+ and other companies.

Hence, the choice of identifying CA100 companies based on absolute carbon footprints mitigates concerns regarding selection bias. While this argument holds for the propensity to reduce carbon emissions, it may not hold for other measures of climate action. Given that higher carbon footprints are typically correlated with firm size, it is possible that CA100 companies have more resources to improve their climate-related reporting.

On the other hand, there was no clear selection criterion for the Plus companies. The process could have been based on investor knowledge and political, i.e. investor members could have negotiated the outcome. In fact, investors could have selected companies which they knew would respond to investor pressure or improve their climate action in the future for other reasons. This constitutes a potential selection bias.

To identify differences between the CA100 and Plus companies, I compare them using an independent two-sample t-test. I use variables that could have been known to investors when selecting companies for the Plus list. I obtained average Scope 1, 2 and 3 emissions for the years  $2017$  and  $2018$  from Trucost<sup>[11](#page-14-0)</sup> and the remaining operational and financial metrics for the financial year 2017 from the Orbis database.

Table [1](#page-15-0) indicates that CA100 companies are nearly twice as large as the Plus companies across various variables. The results are significant at conventional levels. As explained above, this is not surprising, as companies' absolute carbon emissions strongly correlate

<span id="page-14-0"></span> $11$ To fill in gaps in the Trucost database, I use the average between 2017 and 2018.

<span id="page-15-0"></span>

with firm size. The average Tobin's Q lies below 0 for both groups, but the difference is not statist

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

Table 1: This table presents independent two-sample t-test results, comparing means across a range of variabls between the CA100 and Plus companies prior to the start of CA100+ engagement work.

Number of employees (k)  $\vert$  114.2  $\vert$  94  $\vert$  20.2  $\vert$  0.68

Tobin's Q  $\begin{array}{|c|c|c|c|c|c|c|c|} \hline \end{array}$  0.71 | 0.83 |  $\begin{array}{|c|c|c|c|c|c|} \hline \end{array}$  0.30

# <span id="page-16-0"></span>4 Data and descriptive statistics

### 4.1 Challenges in measuring corporate climate action

Naturally, researchers have turned to large off-the-shelf datasets to measure corporate sustainability and climate performance. Yet, readily available datasets face important measurement problems which can hamper the informative value of studies and may lead to limited comparability of results.

Prior research investigating investor impact on corporate environmental performance has used aggregated scores from ESG ratings [\(Dyck et al., 2019;](#page-59-6) [Barko et al., 2022\)](#page-57-7). ESG ratings typically weight responses to hundreds of individual indicators into one environmental score. Even if focusing only on a climate-specific subscore, the aggregation process may obscure evidence of impact in specific areas of corporate climate action. Moreover, the detailed methodologies of ESG ratings are rarely available and the scores of the same company can diverge significantly across different providers [\(Berg et al., 2022\)](#page-57-4). This may lead to studies coming to heterogeneous conclusions, depending on the ESG data they use.

Alternatively, some studies focus on companies' climate-related disclosures [\(Flammer](#page-59-4) [et al., 2021;](#page-59-4) [Chithambo et al., 2020;](#page-58-12) [Ilhan et al., 2023\)](#page-59-3), shedding light on investor influence over firms' transparency regarding climate-related risks. However, it is important to recognise potential discrepancies between corporate reporting and actual environmental outcomes. One significant concern pertains to greenwashing. Companies may strategically emphasise positive aspects of their environmental activities while downplaying or neglecting others [\(Lyon and Maxwell, 2011;](#page-59-14) [Callery, 2022\)](#page-57-13). This highlights the need for a multidimensional approach to assessing corporate climate action which captures changes in disclosure and other more substantial actions that directly affect companies' carbon footprints.

To assess substantial actions, several studies focus on companies' carbon intensities based on financial and operational metrics [\(Drempetic et al., 2020;](#page-58-11) [Rohleder et al., 2022;](#page-60-3) [Atta-](#page-57-2) [Darkua et al., 2023;](#page-57-2) [Bauckloh et al., 2023;](#page-57-14) [Gantchev et al., 2022;](#page-59-15) [Benlemlih et al., 2023;](#page-57-15) [Zink, 2024;](#page-60-0) [Bauer et al., 2023\)](#page-57-8). Due to data availability and reliability issues, the numerator often includes only operational Scope 1 and 2 carbon emissions. However, as several authors point out themselves [\(Bauckloh et al., 2023;](#page-57-14) [Zink, 2024\)](#page-60-0), Scope 3 emissions are of significant importance.<sup>[12](#page-17-0)</sup> For CA100+, this is particularly relevant in sectors where the majority of lifecycle emissions stem from the use of sold products, such as for oil and gas companies [\(Dietz et al., 2021a\)](#page-58-13). Yet, reported and estimated Scope 3 figures in databases from thirdparty providers are highly inconsistent [\(Busch et al., 2022\)](#page-57-6) which raises questions about their reliability.

Moreover, the metrics used in the denominator of carbon intensities can be volatile. For instance, fluctuations in financial and operational metrics, unrelated to carbon efficiency changes, can distort carbon intensities. As an illustration, the surge in energy prices in 2022 decreased the carbon intensities of oil and gas companies based on revenue, profits or market capitalisation. Financial denominators may, therefore, introduce measurement error and random variations leading to biased results.

Lastly, historical carbon intensities are inherently backwards-looking. It is possible that investors create an impact which will only manifest in the medium- and long-term. As companies take time to change their operations, an assessment solely based on current and past emissions may prematurely find a non-effect.

### 4.2 Operationalising impact through CA100+

To overcome the challenges presented in the previous section, this study measures corporate climate action through multiple dependent variables. Importantly, it collects new primary data to capture different layers of impact through CA100+. Collecting new primary data is labour-intensive. In this research context, it is possible as the sample size of treated companies is rather small. While a smaller sample size translates in lower statistical power, using

<span id="page-17-0"></span> $12$ [Drempetic et al.](#page-58-11) [\(2020\)](#page-58-11) use Scope 3 emissions from the Asset 4 database in one specification of their analysis.

more granular data which directly proxy investors' engagement asks considerably increases the accuracy of the analysis.

CA100+ defined three formal engagement goals:

- 1. Board-level accountability and oversight of climate change,
- 2. Emission reduction targets that are aligned with the Paris Agreement and
- 3. Corporate disclosure on climate change in line with the TCFD recommendations.

In the order of associated costs for companies, these three goals ask for changes in disclosure, organisational structure and commitments to reduce carbon emissions. This study evaluates the impact of CA100+ on companies' least and most cost-intensive actions, i.e., climate-related disclosure, as opposed to carbon emissions reduction targets and actual carbon emission reductions.

#### 4.2.1 TCFD disclosure on climate change

Initiated in 2015, the TCFD published a detailed set of recommendations in June 2017, aiming to enhance transparency across four main areas: governance, strategy, risk management and metrics and targets. Since the TCFD recommendations were published only six months before the launch of CA100+, obtaining pre-treatment data that precisely follow the TCFD recommendations poses a challenge. Nonetheless, an overarching assessment of corporate disclosures pertaining to these four categories, both before and after the launch of CA100+, is possible.

#### 4.2.1.1. ClimateBERT-TCFD analysis

Over the past three years, the analysis of large datasets of corporate disclosure has been significantly enhanced by the development of Natural Language Processing (NLP) models. NLP models are designed to automate text-analysis based on predefined criteria. For the analysis of climate-related information, the Climate-BERT series of models developed by [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3) is particularly useful.

ClimateBERT can distinguish between climate-related and non-climate-related paragraphs and sentences in corporate disclosures, and classify them into relevant sub-categories. Using ClimateBERT, [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3) analyse the disclosures of corporate TCFD supporters. In this study, I use their ClimateBERT-TCFD model to assess the impact of CA100+ on the disclosure practices of focus companies in line with TCFD recommendations.

#### 4.2.1.1. Descriptive Statistics – ClimateBERT-TCFD data

Isolating the causal impact of CA100+ first requires defining a baseline company universe, which includes both CA100+ companies and suitable non-CA100+ companies. Given that CA100+ focus companies are among the largest publicly listed corporate polluters, I aim to include large listed non-CA100+ companies with equally significant absolute carbon emissions to create a suitable pool of counterfactuals. Moreover, I aim to include primarily companies operating in the CA100+ sectors.

The universe of companies assessed by TPI meets these requirements. It selects companies following a top-down logic based on their total carbon emissions and market capitalisation, including all CA100+ companies. Therefore, I aim to collect data on the approximately 580 companies in the TPI universe.<sup>[13](#page-19-0)</sup> In this preliminary version of the paper, I present data already collected on the automotive and electricity sectors.

Following [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3), I focus on companies' ARs due to their mandatory nature. Investors have been found to rely more on mandatory disclosures when assessing sustainability information due to the incomparability and inconsistency of voluntary disclosures, such as Sustainability Reports [\(Ho, 2020\)](#page-59-16).

I manually download all available ARs for the period from 2014 to 2022 for all companies assessed by TPI.[14](#page-19-1) The period from 2014 to 2022 was chosen to cover at least three years for the pre-treatment period and at least four years for the post-treatment period of CA100+

<span id="page-19-1"></span><span id="page-19-0"></span><sup>13</sup>This count is as of October 2023.

<sup>&</sup>lt;sup>14</sup>As requirements for public filings vary by country, companies publish ARs in different formats. In countries where ARs were not available, I aimed to identify the most comparable annual disclosure in English, such as the Universal Registration Document in France and the Annual Integrated Report in Japan.

companies. For the CA100 companies, CA100+ engagement started in December 2017 which implies that 2018 is the first year post-treatment. On the other hand, for the Plus companies, CA100+ engagement started in June 2018. As data on corporate climate action is available on a yearly basis, it is considered that 2018 falls into the final pre-treatment year. After excluding non-listed companies and companies that did not operate over the entire period of interest (e.g. due mergers and acquisitions), I retain a sample of 103 companies from the automotive and electricity sectors, including  $19 \text{ CA}100+$ ,  $65 \text{ Plus}$ , and  $19 \text{ non-CA}100+$ companies.

I proceed by extracting the raw text from companies' ARs and split them into paragraphs. I then analyse the extracted paragraphs with the ClimateBERT-TCFD model. I follow [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3) and use the proportion of annual report content (in percentage of total paragraphs) discussing climate-related information as the main metric of analysis. Additionally, I analyse the proportion of climate-related information corresponding to each of the four TCFD categories.

Figure [2](#page-21-1) shows considerable differences across the three groups. CA100 companies reported less in both the pre- and post-treatment periods, while Plus companies reported more climate-related information in the ARs than the Non-CA100+ companies. In all groups, climate-related reporting increases in the post-treatment period, most strongly for the CA100 companies.

<span id="page-21-1"></span>

Figure 2: This figure shows the average proportions CA100, Plus and Non-CA100+ companies use of their Annual Reports to report on the four TCFD categories in the pre- and post-treatment periods.

Surprisingly, the general findings differ from the sample of TCFD supporters analysed in [Bingler et al.](#page-57-3) [\(2022a\)](#page-57-3). First, they observe considerably less reporting on climate. A potential explanation could be that the TPI universe primarily comprises large companies. Secondly, they find that companies tend to report significantly more information on governance and risk management, as opposed to the categories of strategy and metrics and targets. Despite using the same model, my results show the opposite trend. Automotive and electricity companies appear to report most extensively on climate strategy, followed by metrics and targets, and then governance and risks.

#### <span id="page-21-0"></span>4.2.2 Carbon emission reductions and targets

#### 4.2.1.1. A science-based approach to assessing corporate climate action

External stakeholders, especially investors, have shown an increased interest in science-

based methods to determine whether a company is "aligned" with achieving a global climate target, such as "Below 2 Degrees" or "1.5 Degrees". Early methods assessing companies' alignment relied on Scope 1 carbon intensities based on financial metrics. They required all companies to decarbonise at the same pace, independent from the distinct decarbonisation challenges in their sectors [\(Randers, 2012\)](#page-60-6). The Sectoral Decarbonisation Approach (SDA), created in 2015 by CDP, World Resources Institute (WRI) and the World Wide Fund for Nature (WWF), aimed to address these challenges and is today the gold standard in the field. The SDA calculates company-specific emission intensity pathways and compares them against sector-specific quantitative benchmarks representing different climate scenarios consistent with the Paris Agreement's goals [\(Krabbe et al., 2015\)](#page-59-17). By applying detailed sector-specific methodologies, the SDA overcomes the aforementioned concerns about the comprehensiveness, reliability and comparability of readily available carbon intensity data used in previous studies.

The two main organisations that employ the SDA for evaluating corporate decarbonisation efforts are the Science Based Targets Initiative (SBTi) and TPI. SBTi employs the SDA to support companies in establishing carbon emission reduction targets aligned with specific climate scenarios, subsequently certifying this alignment. However, the underlying carbon intensity data are not publicly disclosed and company assessments are not updated regularly. Moreover, companies self-select into SBTi certification. On the other hand, TPI employs the SDA in its Carbon Performance (CP) assessment to evaluate the decarbonisation efforts of the largest publicly listed polluters. They cannot self-select or opt-out and undergo a yearly assessment, rendering the TPI CP assessments the most extensive database of company assessments utilising the SDA. All CP assessments, including the company-specific carbon intensity pathways, are made publicly accessible on the [TPI](#page-60-7) [\(2023\)](#page-60-7) website. The foundation of CA100+'s engagement on carbon emission reduction targets relies on TPI's CP assessments, which are similarly employed in this study.

#### 4.2.1.2. Emission intensity data from the TPI Carbon Performance assess-

#### ment

For each sector, TPI CP analysis focuses on the most material emission categories from a life-cycle perspective. For example, in the electricity sector, TPI assesses companies' Scope 1 emissions from electricity generation [\(Dietz et al., 2021b\)](#page-58-14). In the oil and gas sector, where companies' direct and indirect climate impacts are material, TPI assesses companies' Scope 1, 2 and 3 category 11 (use of sold products) emissions [\(Dietz et al., 2023\)](#page-58-15). To address data availability and inconsistency issues in reported Scope 3 emissions, TPI calculates company-specific Scope 3 emissions in relevant sectors. Absolute emissions are then divided by a sector-specific production output that is homogeneous across companies and time, e.g., generated megawatt hour in the electricity sector and sold energy in the oil and gas sector. Using a production-based denominator reduces non-carbon-related volatility and provides a more robust measure of carbon efficiency than financial metrics. The resulting carbon intensities enable consistent comparisons of companies' carbon efficiencies within their respective sectors.

Companies' emission pathways consist of historical, current, and future carbon emission intensities. As CP assessments are exclusively disclosure-based, the length of a company's emission pathway depends on two main factors. First, the availability of historical emissions and production data. While some companies have complete carbon emission pathways with historical carbon intensities ranging from 2014 to 2022, others have shorter pathways or even no pathway at all. Second, the forward-looking part of the pathway until 2050 is calculated based on companies' carbon emission reduction targets. The carbon intensities between the year of the current intensities and the year for which a carbon emission reduction target was set, as well as between target years, are linearly interpolated. In cases where a company does not disclose a carbon emission reduction target, the most conservative assumption for how the carbon intensity is going to evolve in future years is that it remains constant.

Appendix [C](#page-63-0) shows three exemplary company pathways. The first pathway shows the past carbon intensities of a company with limited disclosure. The two following pathways illustrate how the forward-looking emission pathway of the same company, Eni, changed between 2020 and 2021. The time variable is not the calendar year shown in the company's emission intensity pathway, but the year in which TPI conducted its research (the "research cycle"). The relevant outcome variable is the ambition of a company's new carbon emission reduction target, reflected by a reduction in the forward-looking carbon intensity in a fixed target year. For example, in the TPI research cycle 2020, Eni had set a target to reduce its carbon intensity to 29.46 gCO2e/MJ by 2050. In the TPI research cycle 2021, Eni had set a target to reach a carbon intensity of 0 gCO2e/MJ by 2050. The reduction of 29.46 gCO2e/MJ for Eni's targeted 2050 carbon intensity between TPI research cycles 2020 and 2021 reflects the strengthened ambition of the company's new carbon emission reduction target. Importantly, TPI CP assessments enable the analysis of short, medium- and longterm target setting by examining future carbon intensities in different years. The CA100+ Net Zero Benchmark focuses on companies' target setting for the years 2025, 2035 and 2050. I therefore equally focus on these years in this study.

While it is unclear whether companies will achieve their carbon emission reduction targets, anecdotal evidence suggests that these pledges are not published lightly and carry significant weight. The Milieudefensie versus Shell case in the Netherlands exemplifies the heightened scrutiny and potential legal ramifications associated with climate targets. Furthermore, existing evidence suggests that ambitious climate targets are linked to reductions in carbon emissions [\(Dahlmann et al., 2019\)](#page-58-16). However, this study does not aim to evaluate the binding nature of carbon emissions reduction targets or the likelihood of companies achieving them. Instead, it utilises forward-looking carbon intensities to evaluate companies' self-declared decarbonisation ambitions.

Data reliability in CP assessments is ensured through the TPI quality assurance process. Initially, a TPI analyst prepares the CP assessment, which is subsequently reviewed by another analyst not involved in the initial drafting. The assessments are then sent to the respective companies for feedback. Following a comprehensive analysis of the feedback and an additional internal review, the assessments are published on the TPI tool.

In the main analysis, this study uses two outputs of the TPI CP assessments to proxy companies' climate action: historical carbon intensities which reflect past changes in companies' carbon efficiency until 2021 and future emission intensities which reflect the ambition of companies' carbon emission reduction targets.

# 4.2.1.3. Collecting new primary data on companies' forward-looking carbon intensities

With few exceptions [\(Dietz et al., 2021a\)](#page-58-13), academic studies have not extensively used carbon intensity data derived from the SDA. A key challenge lies in the high labour intensity needed to assess companies using the SDA, coupled with the limited availability of time series data in third-party databases like TPI and SBTi. In this study, the challenge of utilising forward-looking TPI CP data is exacerbated by the fact that TPI was established in 2017, just a few months before CA100+. Moreover, TPI's company and sector coverage expanded gradually in subsequent years. Although historical carbon intensities are available for the period from 2014 to 2022, the shape of companies' forward-looking pathways prior to their first assessment by TPI is unclear. Even for the earliest CP assessments, conducted in research cycle 2017, there are almost no pre-treatment observations of the ambitions of companies' carbon emission reduction targets before the launch of CA100+.

To enable an analysis of CA100's influence on companies' target setting, I construct novel primary data on companies' forward-looking carbon intensities, reaching back to a hypothetical research cycle 2015. In other words, I augment the existing TPI CP dataset with new "historical" CP assessments. These simulate CP assessments of companies before TPI conducted them for the first time. I begin my data collection process by identifying a relevant subset of TPI sectors. TPI CP data is currently available for 349 companies from ten sectors<sup>[15](#page-25-0)</sup>. Figure [3](#page-26-0) shows the data for CA100+ and non-CA100+ companies from TPI's research cycle 2022.

<span id="page-25-0"></span><sup>&</sup>lt;sup>15</sup>The count is as of November 2023

<span id="page-26-0"></span>

Figure 3: This figure shows the split of CA100+ and Non-CA100+ companies with available CP data by sector. CA100+ companies are highlighted in red, Non-CA100+ companies are highlighted in blue. Note that companies are counted more than once if they operate in multiple sectors.

Six CA100+ sectors, namely chemicals, coal, consumer goods, oil and gas distribution, other industrials and services, are not yet covered by TPI's assessments. Moreover, there are no more than four CA100+ companies in the aluminium, paper, and shipping sectors and the coverage of non-CA100+ companies by TPI is low in the diversified mining and the oil and gas sectors. Hence, the analysis of CA100+'s impact on companies' emission pathways can only be conducted for six sectors: airlines, automotives, cement, electricity, steel and oil and gas.[16](#page-26-1) These count among the world's highest-emitting sectors and comprise together 296 companies assessed by TPI for which I conduct "historical" assessments.

<span id="page-26-1"></span><sup>16</sup>CA100+ does not use common sector classifications (such as GICS, ICB or Fama-French industry). Instead, it follows TPI's sector rules which rely on various GICS and ICB filter settings and additional manual company research. The goal of TPI's sector allocation is to ensure that companies from the same sector face similar challenges in the low-carbon transition.

To guarantee data quality, the "historical" CP assessments adhere to the same methodology and quality assurance process as standard TPI assessments. Initial drafts were undertaken by myself and were subject to review by another analyst. While this study utilises pre-feedback data, the "historical" assessments will be sent to companies for feedback in the future. Further details on the steps taken to make the historical assessment data suitable for this study are provided in Appendix [D.](#page-65-0)

Even after conducting the "historical" assessments, the absence of data points in companies' emission pathways imposes additional constraints on the sample size. For a binned analysis of historical and forward-looking carbon intensities, all companies with at least one observation in both the pre- and posttreatment period can be used. The resulting sample size is 197. After removing companies for which no complete emission intensity pathway could be calculated, I retain the sample shown in table [2](#page-27-0) for a more sophisticated analysis which considers companies' pre-treatment trends.

<span id="page-27-0"></span>

Sector			CA100 Plus Non-CA100+	<b>Total</b>
Electricity	10	17	26	53
Autos	9		15	28
Oil and gas	19		10	34
Cement				13
<b>Steel</b>			10	17
Airlines	ΝA	5	14	19
<b>Total</b>	43	38	83	164

Table 2: This table presents the sample size for the six relevant sectors after removing companies with missing values in their historical carbon intensity pathways.

#### 4.2.1.4. Descriptive statistics – historical carbon intensities

Figure [4](#page-29-0) shows the average historical (backwards-looking) carbon intensities for the CA100, Plus and Non-CA100+ companies of the six sectors. The covered period ranges from 2014 to 2021.

I note no clear pattern in the levels of average carbon intensity in the pre-treatment period across the three groups. Plus companies have a higher average carbon intensity in the electricity and airlines, CA100 companies in the steel and oil and gas sectors, and the Non-CA100+ companies in the automotive and cement sectors

Significant reductions in carbon intensity means between the pre- and post-treatment periods are noticeable only in the electricity and automotive sectors. In contrast, the cement, steel, and oil and gas sectors exhibit nearly stable average carbon intensity. The error bars, representing standard deviations, indicate the varying degrees of carbon efficiency within each sector. Notably, the electricity sector shows the highest dispersion, illustrating differences in business models and technologies used for electricity generation. Some companies rely on renewable energy for electricity generation, leading to very low intensities, while others relying on fossil fuels exhibit very high intensities.

Notably, in the airline sector, the carbon intensity increases over the two periods. Upon inspection of the data, this is largely due to the impact of the Covid-pandemic. TPI's carbon intensity metric in this sector divides Scope 1 carbon emissions by revenue-passengerkilometers. As many airlines were required to fly empty planes in 2020 and 2021, their carbon intensity increased significantly.

<span id="page-29-0"></span>

29

#### 4.2.1.5. Descriptive statistics – forward-looking carbon intensities

Figure [5](#page-31-0) shows the average forward-looking carbon intensities for 2025, 2035 and 2050. The periods are measured in TPI research cycles, ranging from 2015 to 2022.

The targeted carbon intensities for nearly all target years are lower in the post-treatment period than in the pre-treatment period across almost all sectors. This indicates that companies' target setting has become more ambitious over time. The sole exception remains the airlines sector, which experienced a rebaselining of emissions targets post-Covid. Given that no airlines were included in the initial CA100 list, I exclude this sector from the analysis of historical and forward-looking carbon intensities to avoid a Covid-related bias which would only affect the Plus list.

Among the remaining sectors, electricity utilities stand out with the most ambitious target setting, closely followed by car manufacturers. In contrast, the oil and gas sector has established the least ambitious targets. These differences may arise from varying degrees of available technologies and decarbonisation pathways. Notably, I observe long error bars among electricity companies, suggesting significant heterogeneity within the sector. Some companies set ambitious targets to reduce their carbon intensities in the future, while others lack such goals. Conversely, performance in the oil and gas sector appears largely consistent across companies.

<span id="page-31-0"></span>

# <span id="page-32-0"></span>5 Binned DiD analysis

To provide a preliminary understanding of the impact of CA100+ on corporate climate action, I begin with a straightforward binned DiD analysis. This approach compares the differences in means between CA100+ and Non-CA100+ companies before and after the launch of the initiative. The model is estimated separately for the CA100 and the Plus companies to account for potential endogeneity in the selection of the Plus list.

### 5.1 Research design

The binned DiD analysis permits a straightforward interpretation of temporal changes within CA100+ companies compared to Non-CA100+ companies. Compared to more sophisticated approaches that require an analysis of pre-treatment trends, it leverages a larger sample size with greater statistical power. By binning companies' pre- and post-treatment observations, it allows for the inclusion of companies for which only rudimentary observations in some years are available. The model is estimated as follows:

$$
\Delta Y_i = \alpha + \beta CA100_i + \epsilon_i
$$

 $\Delta Y$  denotes the difference in the dependent variable Y of company i between the postand the pre-treatment period.  $CA100<sub>i</sub>$  is a dummy variable that takes the value of 1 for CA100+ companies. The model is estimated using a linear Ordinary Least Square (OLS) regression.

While the binned DiD analysis reveals broad trends, it does not establish causality due to unobserved heterogeneity between CA100+ and Non-CA100+ companies. For example, it is possible that CA100+ companies were already on an upward trend whereas Non-CA100+ companies' climate action was deteriorating prior to the launch of CA100+.

### 5.2 Results - binned DiD analysis

### 5.2.1 TCFD disclosure

The results in table [3](#page-33-0) and table [4](#page-33-1) suggest that  $CA100+$  had no significant impact on climaterelated reporting of the focus companies, neither on the CA100 companies nor on the Plus list. The effect is insignificant across the amount of climate-related reporting (first column) compared to reporting on other topics in Annual Reports, as well as across the four individual TCFD categories (remaining four columns on the right).

<span id="page-33-0"></span>

∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05;.p < 0.1

Table 3: This table shows the results of the binned DiD analysis on climate-related and TCFD reporting, comparing the CA100 to Non-CA100+ companies.

<span id="page-33-1"></span>

 $***p<0.001;$   $**p<0.01;$   $p<0.05; p<0.1$ 

Table 4: This table shows the results of the binned DiD analysis on climate-related and TCFD reporting, comparing the Plus to Non-CA100+ companies.

#### 5.2.2 Reductions in historical carbon intensities

Turning to more substantial climate action, I analyse the difference in the average carbon intensities between the post- and the pretreatment periods. Since carbon intensity measures vary by sector, I standardise them using z-scores. Specifically, I standardise within each sector using all companies' average historical carbon intensities and related standard deviations over the period from 2014 to 2017. The z-scores must, therefore, be interpreted as differences in standard deviations from the sector mean between 2014 and 2017. Table [5](#page-34-0) shows the results for all CA100+ and all Non-CA100+ companies with at least one carbon intensity observation available in the pre- and post-treatment periods. The effect is close to zero and insignificant for both groups.

<span id="page-34-0"></span>

	<b>CA100</b>	Plus List		
(Intercept)	$-0.18***$	$-0.18***$		
	(0.03)	(0.04)		
$CA100+$	0.04	$-0.08$		
	(0.06)	(0.08)		
Num. obs.	139	127		
$R^2$	0.00	0.01		
Adj. $\mathbb{R}^2$	$-0.00$	$-0.00$		
*** $p < 0.001$ ; ** $p < 0.01$ ; * $p < 0.05$ ; $p < 0.1$				

Table 5: This table shows the results of the binned DiD analysis on the levels of historical carbon intensities (in z-scores), comparing the CA100 and Plus to Non-CA100+ companies.

As shown in appendix [E,](#page-68-0) this holds in a within-sector analysis for the CA100 group across all sectors and for the Plus companies for all sectors apart from Oil and Gas. In Oil and Gas, Plus companies' average historical carbon intensity decreased by -2.87 tCO2e/TJ more than for Non-CA100+ companies. This effect is statistically significant at the 5% level. Yet, the sample size is very small.

#### 5.2.3 Forward-looking carbon intensities

Lastly, I analyse the difference in the forward-looking carbon intensities between the preand the post-treatment periods for different target years across all sectors. Recall that the time variable in the forward-looking analysis is TPI research cycles and the outcome variable companies' future intensities in a given target year. Again, I standardise using the z-score. Specifically, I standardise within each sector using companies' average forwardlooking carbon intensities and related standard deviation per target year from the TPI research cycle 2015. The resulting z-scores must, therefore, be interpreted as differences in standard deviations from the forward-looking sector mean from research cycle 2015. Tables [6](#page-35-0) and [7](#page-36-0) show the results for the CA100 and the Plus compared to the Non-CA100+ companies, respectively.

Interestingly, for the CA100 companies, none of the coefficients is statistically significant for any target year. On the other hand, the Plus companies reduce their forward-looking carbon intensities in the medium and long term significantly faster than Non-CA100+ companies. The effect is significant at the 1% level and stronger for target year 2050 than 2035.

<span id="page-35-0"></span>

	TY 2025	TY 2035	TY 2050
(Intercept)	$-0.35***$	$-0.65***$	$-0.97***$
	(0.05)	(0.09)	(0.16)
$CA100+$	0.06	$-0.01$	$-0.29$
	(0.09)	(0.15)	(0.27)
Num. obs.	130	130	130
$R^2$	0.00	0.00	0.01
Adj. $\mathbb{R}^2$	$-0.00$	$-0.01$	0.00

∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 6: This table shows the results of the binned DiD analysis on target-year-specific forward-looking carbon intensities (in z-scores), comparing the CA100 to Non-CA100+ companies.


∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 7: This table shows the results of the binned DiD analysis on target-year-specific forward-looking carbon intensities (in z-scores), comparing the Plus to Non-CA100+ companies.

Overall, the binned DiD analysis provides initial indications that CA100+ did not have a significant impact on the focus companies' disclosure and historical carbon intensities. Yet, the Plus companies set more ambitious medium- and long-term targets than Non-CA100+ companies in the post-treatment period. An effect which was not observed for the CA100 companies.

## 6 Matching and DiD analysis

To test for causality, I employ a more sophisticated combination of matching and DiD methodology. First, I match CA100+ companies to suitable non-CA100+ companies based on their pre-treatment trends. Then, I use different specifications of DiD models to isolate the causal impact of CA100+. This combination of matching and DiD assesses the validity of the parallel trends assumption, examines the dynamic impact of CA100+ and derives more precise estimates by considering the variation across all time periods.

#### 6.1 Research design

#### 6.1.1 Matching on pre-trends

Determining the causal impact of CA100+ requires identifying suitable counterfactuals for the focus companies. One way to identify suitable counterfactuals could be to match the CA100+ companies to Non-CA100+ companies based on a range of observable characteristics. However, this is challenging, as the CA100 companies constitute per definition the largest corporate polluters in the world and the Plus list is equally composed of companies with very large carbon footprints, such as BMW and Coca-Cola. Many of the CA100+ companies are, therefore, "unique".

The DiD analysis offers a solution to this problem. Company fixed effects in the DiD hold differences in the pollution levels and other time-invariant characteristics between CA100+ and Non-CA100+ companies constant. The most important assumption for the validity of a DiD analysis is parallel trends. Hence, the matching process in this study does not aim for balance across the treatment and control groups based on company characteristics. Nor does it match on the propensity of companies to receive the treatment (i.e., to be included in the CA100+ focus list). Instead, it matches CA100+ companies to suitable counterfactuals on the basis of pre-treatment trends in different measures of corporate climate action.

An analysis of the combined treatment effect on the CA100 and the Plus companies requires parallel trends across all three groups in the pre-treatment period [\(Goodman-Bacon,](#page-59-0) [2021\)](#page-59-0). The exact timing of the treatment requires careful consideration. Hence, the matching process aims for parallel trends across all three groups until 2017 and between the Plus List and the Non-CA100+ companies until 2018.

Importantly, companies from different sectors face heterogeneous challenges in the low carbon transition [\(Krabbe et al., 2015\)](#page-59-1). Consequently, the pace at which companies can improve their corporate climate action varies by sector. For example, in a 1.5 Degrees scenario, the electricity sector is expected to reach net zero CO2 emissions on a global level already by 2040, whereas CO2 emissions from the cement sector remain slightly net positive even by 2050 [\(International Energy Agency, 2021\)](#page-59-2). This suggests that sectoral balance is a consideration for the cross-sector analysis of the impact of CA100+.

As part of the research design, this study employs nearest-neighbour matching using the Mahalanobis distance. This technique aims to match each CA100+ company with the most similar non-CA100+ company based on a set of covariates. The covariates used in this matching process encompass various combinations of the mean, variance, average reduction and year-on-year changes in corporate climate action throughout the entire pretreatment period.

By design, the matching procedure reduces the sample size of the study. However, including only good matches reduces the risk of potential biases in the analysis. While this deliberate reduction in sample size, therefore, comes at the expense of variance, it enhances the precision of the study's outcomes.

#### 6.1.2 DiD analysis

As a baseline specification, the following non-staggered TWFE DiD regression model aims to measure the impact of CA100+ on the climate action of the focus companies compared to similar non-CA100+ companies. Again, the model is run separately for the CA100 and Plus companies:

 $Y_{it} = \alpha + \beta CA100_i * Post_t + \gamma_i + \mu_t + \epsilon_{it}$ 

Y is the climate action of company i in year t,  $CA100<sub>i</sub>$  is a dummy variable that takes the value of 1 for CA100+ companies,  $Post<sub>t</sub>$  is a time dummy that takes the value of 1 after the start of the treatment (2017 for CA100 companies and 2018 for Plus companies). Company fixed effects, denoted by  $\gamma_i$ , control for any time-invariant differences between CA100+ and non-CA100+ companies before the launch of the initiative. Year fixed effects, denoted by  $\mu_t$ , account for shocks that affect CA100+ and non-CA100+ companies alike in specific years, such as the Covid-19 crisis in 2020 and 2021. The model is estimated using a linear OLS regression.

To analyse the effect of CA100+ on the CA100 companies and the Plus List together and to explore potential temporal changes in the effectiveness of CA100+ engagement, I run a staggered DiD specification. Given the limitations of the TWFE specification in estimating heterogeneous and dynamic treatment effects in staggered models [\(Goodman-Bacon, 2021\)](#page-59-0), I use the robust estimator developed by [Callaway and Sant'Anna](#page-57-0) [\(2021\)](#page-57-0).

### 6.2 TCFD reporting

Appendix [F](#page-69-0) shows the matching and DiD results on TCFD reporting over the period from 2014 to 2022 across all sectors. Similar to the binned DiD analysis, the results suggest no significant impact. Hence, I do not discuss them further.

#### 6.3 Historical carbon intensities

Appendix [G](#page-74-0) shows the matching and DiD results on historical carbon intensities over the period from 2014 to 2021 across all sectors. The results confirm again the findings from the binned DiD analysis and do not show a significant treatment effect.

### 6.4 Forward-looking carbon intensities

#### 6.4.1 Matching

While the parallel trends assumption cannot be tested empirically, a visual inspection of the plots can indicate whether the pretreatment trends of the treatment and control groups were similar. Figure [8](#page-42-0) presents the matching specification that yields the most parallel pre-trends between the CA100, Plus and Non-CA100+ groups on forward-looking carbon intensities across all sectors.

Table [8](#page-42-0) summarises the matched sample after matching across sectors for target years 2035 and 2050. Apart from seven companies, the whole sample shown in table [2,](#page-27-0) excluding airlines, could be matched. For target year 2025, 122 companies could be matched to obtain parallel trends.

Overall, the charts indicate similar trends across all three groups over the period from research cycle 2015 to 2017 for all target years. The trends between the Plus and the Non-CA100+ companies between research cycles 2017 and 2018 are similar for target years 2035 and 2050, but diverge slightly for target year 2025. However, the event study plot for target year 2025 in figure [7](#page-44-0) confirms the absence of a significant pre-trend. The parallel trends assumption therefore appears defensible.

<span id="page-41-0"></span>

 $-CA100 - Non-CA100+ - + companies$ 

Figure 6: This figure shows the pre- and post-treatment trends across CA100, Plus and Non-CA100+ companies for each target year across all sectors after matching.

A visual inspection of figure [6](#page-41-0) suggests that CA100+ has so far, if at all, only had a minor impact on the targets of the CA100 group. However, the post-treatment trends of the Plus companies diverge considerably from the Non-CA100+ companies.

<span id="page-42-0"></span>

<b>Sector</b>			CA100 Plus Non-CA100+	Total
Electricity	9	15	26	46
Autos			15	28
Oil and gas	18	5	10	33
Cement				12
<b>Steel</b>	3			15
<b>Total</b>	39			138

Table 8: This table shows the total sample size by company group and sector after matching across sectors on pre-trends for the target years 2035 and 2050.

#### 6.4.2 DiD analysis

Tables [9](#page-42-1) and [10](#page-43-0) show the results of the TWFE DiD analysis. The CA100+ coefficient estimates the average treatment effect of CA100+ on companies' forward-looking carbon intensities, capturing the differential changes between CA100+ and Non-CA100+ companies over time. All models include company and year fixed effect. Standard errors are clustered at the company level.

<span id="page-42-1"></span>

∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 9: This table shows the results of the DiD conducted for the CA100-only analysis across all sectors using z-scores.

The results confirm the findings from the binned DiD analysis. For the CA100 companies, none of the coefficients is statistically significant at any conventional level. Across all target years, the treatment effect and the corresponding standard errors are close to zero. This may indicate that the correct interpretations of the results is indeed a non-effect, rather than the existence of an effect that is not captured by the model.

For the Plus companies, the size of the negative treatment effect grows the further the

<span id="page-43-0"></span>

	TY: 2025	TY: 2035	TY: 2050	
$CA100+$	$-0.14$	$-0.48*$	$-0.97*$	
	(0.11)	(0.22)	(0.46)	
$R^2$	0.86	0.71	0.56	
Adj. $R^2$	0.84	0.66	0.49	
Num. obs.	695	779	779	
*** $p < 0.001$ ; ** $p < 0.01$ ; * $p < 0.05$ ; $p < 0.1$				

Table 10: This table shows the results of the DiD conducted for the Plus-only analysis across all sectors using z-scores.

target year lies in the future and is significant at the 5% level for 2035 and 2050. The discrepancy with the CA100 companies is striking.

Then, I consider the heterogeneous effect of CA100+ on both the CA100 and the Plus companies using the staggered DiD specification by [Callaway and Sant'Anna](#page-57-0) [\(2021\)](#page-57-0). Figure [7](#page-44-0) shows estimates of the dynamic treatment effect of CA100+ across all sectors. For each target year, the top chart shows the dynamic treatment effect for the CA100 companies and the bottom chart for the Plus companies. The confidence intervals are set for 95%.

The event study plots confirm the absence of a significant treatment effect for CA100 companies across all target years. For the Plus list, the effect is significant at the 5% level for target year 2035 in research cycles 2020 and 2021 and for target year 2050 in research cycle 2021. Notably, the effect is consistently significant only for medium- and long-term target setting. Although not reaching statistical significance, the effect size increases over the research cycles for the Plus list.

<span id="page-44-0"></span>

 $\div$  Pre  $\div$  Post

Figure 7: This figure shows the dynamic treatment effect of CA100+ on CA100 and Plus companies' target setting using a staggered DiD specification.

## 7 Robustness checks

Given the small sample size, conducting robustness checks that further subdivide the sample is challenging, as this would compromise the statistical power of the analysis. One may worry that the lack of impact on companies' climate-related reporting in their Annual Reports may not comprehensively allow for an assessment of  $CA100+$ 's impact on companies' disclosure. Therefore, I perform additional checks on climate-related reporting using two alternative outcome variables. Additionally, I test the robustness of the results on target setting by introducing a new control variable for varying regulatory environments and employing a different matching specification.

#### 7.1 Additional proxies for companies' climate-related disclosure

#### 7.1.1 CDP disclosure

Firstly, I use companies' responses to the CDP questionnaire as a second proxy for alignment with the TCFD recommendations. CDP plays an important role in driving corporate transparency by annually sending questionnaires regarding climate change, water usage and deforestation to companies. The questionnaires allow companies to disclose relevant information which will then be made public on the CDP website. Since 2018, the CDP climate questionnaire is aligned with the TCFD recommendations. Yet, even previous versions required companies to broadly disclose information on the four TCFD categories. Therefore, I employ a binary metric indicating whether companies report to CDP as an indirect measure of their disclosures' alignment with TCFD guidelines in the pre- and post-treatment periods.

A crucial aspect of the CDP disclosure process is the choice companies have to respond or not respond. It is precisely this strategic decision to opt-in or opt-out which I exploit. If CA100+ increases the propensity of focus companies to report to CDP, this would indicate a positive impact on companies' disclosure practices.[17](#page-45-0)

<span id="page-45-0"></span><sup>&</sup>lt;sup>17</sup>A more granular analysis was tested to assess whether companies respond to specific questions that

As for the ClimateBERT-TCFD analysis, I use the approximately 580 TPI companies as my baseline universe. Since the CDP datasets prior to 2018 do not include companies that were contacted by CDP but chose not to respond, I manually collect the data on which TPI companies decided to opt-out from the CDP website for the period 2016 to 2022.[18](#page-46-0) Since CDP questionnaires usually reflect the disclosures of the previous year, this period effectively spans from 2015 to 2021.

After excluding non-listed companies and companies that were not contacted by CDP in each year, I retain a sample of 70 CA100, 44 Plus and 246 Non-CA100+ companies. Figure [8](#page-46-1) shows that treated companies were considerably more responsive to CDP before and after the launch of CA100+. Moreover, it appears that CDP reporting increased in the Non-CA100+ group but decreased slightly among the CA100 and remained largely stable among the Plus companies.

<span id="page-46-1"></span>

Figure 8: This figure shows the share of CA100, Plus and Non-CA100+ companies responding to CDP in the pre- and post-treatment periods.

address the four TCFD themes in the CDP questionnaires. However, it appears that companies that decide to participate in the CDP process largely address most or all questions. While the quality of the responses may vary, measuring companies' decision to disclose information on a question level does not add much value compared to a binary assessment of whether companies submit their CDP questionnaire or not.

<span id="page-46-0"></span><sup>18</sup>CDP's outreach to companies was considerably less extensive prior to 2016.

The results of a binned DiD analysis in table [11](#page-47-0) suggest that CA100+ had a negative impact, reducing CDP disclosures by 10% among CA100 companies, at the 1% significance level. This unexpected outcome may be explained by the fact that CA100 companies initially had the highest level of reporting across all groups, at  $90\%$ , as shown in figure [8.](#page-46-1) Given the high baseline, further improvements in reporting to CDP could be more challenging for CA100 companies than their Non-CA100+ counterparts. The effect on the Plus list is not significant. Overall, this analysis supports that CA100+ did not have a positive impact on climate-related reporting of its focus companies.

<span id="page-47-0"></span>

 $***p<0.001;$   $**p<0.01;$   $*p<0.05; p<0.1$ 

Table 11: This table shows the results of the binned DiD analysis on reporting to CDP, comparing the CA100 and Plus to Non-CA100+ companies.

#### 7.1.2 Carbon intensity disclosure

Secondly, I derive an indicator proxying the quality of companies' climate disclosure from the TPI CP assessments: the completeness of the historical carbon intensity pathway indicates companies' transparency on their climate impact. I calculate this variable using the average years with available historical carbon intensity data in the pre- and post-treatment periods. As the lengths of the periods vary between CA100, Non-CA100+ and Plus companies, I calculate the share of disclosed years over the total of years in which disclosure was possible for each group: *Carbon Intensity (CI) disclosure (%)*. Figure [9](#page-48-0) shows the average CI disclosure across the CA100, Plus and Non-CA100+ groups.

<span id="page-48-0"></span>

Figure 9: This figure shows the average carbon intensity disclosure across the CA100, Plus and Non-CA100+ groups in the pre- and post-treatment periods.

<span id="page-48-1"></span>Again, the results of a binned DiD analysis in table [12](#page-48-1) suggest that CA100+ engagement had a negative impact on companies' disclosure. The effect size is -14% at the 1% significance level for the CA100 companies and -12% at the 5% significance level for the Plus companies. However, as for CDP disclosure, CA100 and Plus companies had higher levels of disclosure to start with as illustrated in figure [9.](#page-48-0)

	CA100	Plus List		
$CA100+$	$-0.12*$ (0.05)	$-0.1$ (0.05)		
Num. obs. $R^2$	214 0.03	203 0.02		
Adj. $R^2$	0.02	0.01		
***p < 0.001; **p < 0.01; *p < 0.05; $p < 0.1$				

Table 12: This table shows the results of the binned DiD analysis on the years with reported carbon intensities in percent, comparing the CA100 and Plus to Non-CA100+ companies.

### 7.2 Varying regulatory environments

CA100+ companies represent an international sample of companies subject to varying national regulations. Company fixed effects control for different levels of climate-related regulation in their operating countries and year fixed effects for regulatory changes that affect all companies in a given year. However, changes in climate regulation over the analysed period could bias the results, especially if they primarily affect the Plus companies. To mitigate this concern, I integrate country-level data from the [Climate Change Performance Index](#page-58-0) [\(2023\)](#page-58-0) (CCPI) in the analysis. The CCPI annually rates countries' climate protection efforts based on greenhouse gas emissions, renewable energy deployment, energy use efficiency, and climate policy, serving as a proxy for climate regulation stringency evolution. Appendix [H](#page-76-0) details on how the CCPI data were used. Companies were matched to countries based on the location of their headquarter.

Tables [13](#page-50-0) and [14](#page-50-1) show the results on target setting are robust when considering changing national regulatory environments. While the treatment effect remains insignificant for the CA100 companies, it continues to show a significant effect at the 5% level on medium and long-term target setting of the Plus companies. The CCPI estimators are not statistically significant.<sup>[19](#page-49-0)</sup>

### 7.3 Within-sector matching and analysis

Lastly, it is possible that the matching procedure significantly impacts the results. Hence, I use a second matching specification to evaluate the sensitivity of the forward-looking carbon intensity results. To test for heterogeneity across sectors, I repeat the matching procedures within each sector. Table [15](#page-50-2) summarises the resulting sample, which is smaller than that for the across-sector matching.

<span id="page-49-0"></span>I repeat the analysis focusing on the two sectors with the largest sample sizes, i.e. elec-

<sup>&</sup>lt;sup>19</sup>I do not report the results for TCFD reporting and historical emission reductions for briefness. They are robust when controlling for geographical differences.

<span id="page-50-0"></span>

∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

<span id="page-50-1"></span>Table 13: This table shows the results of the DiD conducted on target setting including CCPI country scores for the CA100-only analysis across all sectors using z-scores.



∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

<span id="page-50-2"></span>Table 14: This table shows the results of the DiD conducted on target setting including CCPI country scores for the Plus-only analysis across all sectors using z-scores.

<b>Sector</b>			$CA100$ Plus Non-CA100+	<b>Total</b>
Electricity	9	15	24	48
Autos	9		13	26
Oil and gas	9	ΝA		18
Cement				
<b>Steel</b>				
Total	32	25	57	114

Table 15: This table shows the total sample size by company group and sector after matching on pre-trends within sectors.

tricity and automotive companies. As shown in appendix [I,](#page-78-0) the results indicate even more strikingly the difference between the CA100 and the Plus companies. In both sectors, the treatment effect is insignificant at any conventional level for the CA100 companies. Yet, the treatment effect becomes significant for the Plus list in 2035 and 2050. In the automotive sector, the treatment effect is significant even at the  $0.1\%$  level in 2035, despite the small sample size. In both sectors, the effect is significant at the 1% in 2050.

Using the staggered and pooled DiD, the results remain insignificant in both sectors for the CA100 companies. For the Plus companies, the negative effect is significant at the 5% level in the electricity sector for target years 2025 and 2035 in research cycle 2019 (significant at the 10% level for 2050) and for target year 2050 in research cycle 2021. In the automotive sector, the effect is only significant for medium and long-term target setting. For target year 2035, the effect is significant at the 5% level for research cycles 2020 and 2021, while for target year 2050, the effect seems to become stronger over time and reaches significance at the 5% level only in research cycle 2022.

## 8 Conclusion

#### 8.1 Discussion

This study investigates the effect of CA100+ on companies' climate-related disclosures in line with the TCFD recommendations, historical carbon emission reductions, and carbon emission reduction targets. I find no positive effect on companies' climate-related reporting or on individual TCFD categories in ARs. Using two alternative variables for robustness checks, i.e., responding to CDP and the completeness of companies' historical TPI CP pathways, shows a negative effect on CA100+ companies. However, CA100+ companies had better CDP disclosure and carbon intensity reporting levels in the pre-treatment period. Therefore, the negative effect could be interpreted as CA100+ not improving the focus companies' transparency at a faster rate than non-CA100+ companies, which are catching up.

The results also indicate no effect on reductions in companies' historical carbon intensities from the launch of CA100+ in 2017 until 2022. From a practical perspective, this finding is not surprising, as it may take time for companies to change their operations. It is possible that the treatment effect on historical carbon intensities will only show over a longer time horizon. However, this interpretation is insufficiently supported by the analysis of companies' decarbonisation commitments.

The study does find a significant effect of CA100+ on companies' carbon emission reduction targets. However, the results must be nuanced. It is striking that all specifications reveal no significant negative treatment effect of CA100+ on the CA100 companies. In contrast, there is a significant effect on the Plus list. This suggests possible endogeneity in the selection of the Plus companies and raises questions about the selectivity of investor engagement.

The heterogeneous treatment effect could be explained by prior investor knowledge about the carbon emission reduction targets the Plus companies were going to set anyway. This explanation seems particularly appealing in the electricity sector, where the negative treatment effect is strong, mostly in research cycle 2019, only one year after the Plus companies were included in the focus group. However, in the across-sector and within Autos analyses, the treatment effect appears to increase over time.

An alternative explanation could be that investors anticipated "easy wins" for Plus companies, making them more likely to adopt stringent targets. This hypothesis is again supported in the electricity sector by higher carbon intensity levels in the pre-treatment period which may indicate lower MACs. However, across all sectors, as shown in figure [4,](#page-29-0) Plus companies' levels of carbon intensities were similar or lower than those of CA100 and Non-CA100+ companies. Despite this, carbon intensities serve as an imperfect proxy for MACs, leaving room for consideration of this explanation.

An additional interpretation might be that investors chose companies for the Plus list which they thought would be more receptive to investor pressure. Factors such as ownership stakes or personal relationships with the companies could have played a role. An investigation of H3 in a future iteration of this study will evaluate this partially by assessing the impact of CA100+'s collective stake in the focus companies.

Lastly, one might argue that companies from the Plus list may have anticipated the engagement asks. However, it is important to note that the Plus list was added only six months after the launch of CA100+, making this hypothesis unlikely.

Unpacking further CA100+'s effect on Plus companies' targets, it stands out that the effect is strong and significant only on medium- and long-term target setting. The impact on target setting for 2050 becomes statistically significant only starting from research cycle 2021. This timeline aligns with the increasing prominence of "net zero" targets in the public discourse. For example, the Business Ambition for 1.5 Degrees campaign<sup>[20](#page-53-0)</sup> was launched in 2019 and closed in 2021. Given the time companies likely needed to establish relevant long-term targets, the statistically significant effect observed in research cycle 2021 appears

<span id="page-53-0"></span> $^{20}$ This campaign by a coalition of UN agencies, companies, and civil society actors, urged companies to set carbon emission reduction targets aligned with limiting global warming to 1.5°C.

plausible.

It is important to acknowledge the challenges companies face in reducing their carbon footprint in the near future, considering the time required to implement changes in operations and business models. Yet, setting medium- and long-term targets that are not underpinned by short-term milestones raises questions about their credibility. Such target setting may be indicative of strategic corporate behavior aimed at creating an appearance of climate responsibility without necessarily undertaking immediate and tangible actions. Moreover, the further carbon emission reduction targets lie in the future, the less clearly responsibility for meeting them is assigned to individuals within firms and among investors. This lack of accountability could be perceived as a form of greenwashing.

Recognising that climate change depends on cumulative emissions, achieving significant reductions in the short-term is crucial for meeting global climate targets. The less emphasis is placed on near-term abatement efforts, the steeper the decarbonisation curve will need to be in the medium- and long-term. The findings of this paper highlight a potential risk of investor engagement strategies focusing – intentionally or unintentionally – insufficiently on the near-term which may lead to backloading of corporate decarbonisation efforts.

In summary, the empirical findings do not sufficiently support the hypotheses derived from RDT. Inclusion in CA100+'s focus list has not considerably improved companies' climate actions  $(H1)$ . The absence of a significant effect, except on target-setting by the Plus list, also leads to the rejection of the hypothesis that CA100+'s impact increases over time  $(H2)$ . Regarding  $H_4$ , long-term targets could be seen as a low-cost measure, whereas shortterm targets may imply high costs. However, the complete absence of a positive effect on companies' climate-related reporting suggests the rejection of  $H_4$  as well.

Overall, contrary to previous studies measuring correlations between CA100+ and positive climate outcomes [\(Bingler et al., 2024;](#page-57-1) [Atta-Darkua et al., 2023\)](#page-57-2), I do not find strong evidence for effective collective investor engagement through CA100+. Moreover, by identifying potential endogeneity in the selection of the Plus list, I shed new light on [Chang and](#page-58-1) [Fang](#page-58-1) [\(2024\)](#page-58-1)'s finding of a positive impact of CA100+ on Chinese suppliers.

#### 8.2 Limitations

This study acknowledges several limitations and challenges. Firstly, as discussed in section [2,](#page-6-0) there could be spillover effects between CA100+ companies and Non-CA100+ companies. It is possible that CA100+ contributes to a shift in the institutional context in which companies operate [\(Matisoff, 2015\)](#page-60-0). For example, the CA100+ Net Zero Benchmark may set new decarbonisation standards for all companies to follow. In this case, collective investor action through CA100+ may have affected CA100+ and non-CA100+ companies alike. While it is difficult to control for such general equilibrium effects, we can assume that they would lead to an underestimation of the measurable treatment effect in this study.

However, while acknowledging this conceptual possibility, this study offers a key insight. Even with the potential presence of other spillover effects, only focus companies were subject to the collective and coordinated engagement efforts of CA100+. As the study reveals, there are no noticeable differences between CA100+ and Non-CA100+ companies, except for the medium- and long-term targets set by the Plus companies. This suggests that CA100+ may not directly influence corporate climate action through its engagement work.

Secondly, the current specifications estimate the average treatment effect on the treated, assuming a homogeneous treatment effect across CA100 and Plus companies, respectively. However, it is highly likely that CA100+'s "true" treatment effect is subject to heterogeneity. The heterogeneity could stem from differences in the engagement styles of investors or company-specific characteristics. Testing  $H_3$  with collective ownership data is one way to explore such potential heterogeneity within the CA100 and Plus groups.

Thirdly, it is important to acknowledge the relatively sample size. Especially, the more complex identification strategy relying on matching and DiD poses challenges in obtaining statistically significant results. The limited number of observations within each sector could affect the precision of the estimates. Although this study generally indicates a lack of impact from CA100+, these findings may be driven by low statistical power.

Moreover, as CA100+ engages with the largest publicly listed corporate polluters in the world, the external validity of the study is limited. Smaller polluters may react differently to engagement with investor coalitions. On the other hand, if the world's largest corporate polluters take action on climate change, the impact could be immense.

#### 8.3 Implications and further research

Overall, this study sounds a note of caution regarding the impact of investor coalitions on strengthening corporate climate action in the real economy. However, this should not be interpreted as a blanket conclusion on the ineffectiveness of investor coalitions. Investor coalitions such as  $CA100+$  may have effects that are difficult to quantify, such as facilitating internal company discussions about climate change. Additionally, investor coalitions may require more time to effectively drive corporate climate action, underscoring the importance of future longitudinal studies. In particular, CA100+ entered its second 5-year phase of engagement in mid-2023, which will place a stronger focus on actual reductions in companies' carbon footprints. For now, however, the present analysis suggests that collaborative engagement by investor coalitions cannot replace the need for more direct policy measures, such as the implementation and strengthening of carbon pricing mechanisms.

There are several areas for further research. Importantly, causal mechanisms through which investor coalitions drive change within corporations must be investigated further. A closer examination of specific tactics, including private engagements, the publication of benchmarks and other communication strategies could offer a more granular understanding of investor impact. Additionally, the relational aspect of investor engagement remains underresearched.

Acknowledging the inherent diversity among companies, this study also highlights the potential variability in their responses to investor pressures. Investigating the determinants of corporate responses will offer crucial insights to both investors and policymakers.

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# A Appendix - CA100 companies



Table 16: This table shows the list of CA100 companies.

# B Appendix - Plus companies



Table 17: This table shows the list of Plus companies.

## C Appendix - Exemplary TPI CP assessments



Figure 10: This figure shows an exemplary TPI CP pathway for Oil and Natural Gas from research cycle 2022.



Figure 11: This figure shows an exemplary TPI CP pathway for Eni from research cycle 2020.



Figure 12: This figure shows an exemplary TPI CP pathway for Eni from research cycle 2021.

# D Appendix - Methodological note on constructing new primary CP data

The goal of the new primary data collection is to replicate forward-looking emissions intensity pathways for companies prior to their initial assessment by TPI. However, since TPI was launched in 2017, the sectoral methodologies have undergone several revisions to enhance their robustness. Additionally, several companies experienced changes due to mergers, acquisitions, and other factors affecting how TPI assessed them. This note outlines the potential impacts of such changes on the paper's analysis and explains which further adjustments were necessary to ensure the final database remains usable for the paper's analysis. These adjustments affect both existing CP assessments and new "historical" assessments.

### Removals from the sample

I removed all unlisted companies from the analysis due to the potentially divergent pressures they face compared to listed companies in enhancing their climate action. Furthermore, I removed all companies that TPI stopped assessing during the research period from the sample. This decision primarily impacted Russian companies, as TPI discontinued assessments of Russian companies during the 2022 research cycle.

### Extending the length of company emission intensity pathways

During the early TPI research cycles from 2017 to 2019, companies' forward-looking emission intensity pathways were calculated until 2030. However, in the TPI research cycle 2020, the assessments in all sectors were expanded to cover projections until 2050. Consequently, the early TPI CP assessments from research cycles 2017 to 2019 do not allow for an evaluation of companies' carbon emission reduction targets beyond 2030. To enable this long term analysis, I prolonged the assessments for companies that had established targets reaching beyond 2030 in the early research cycles, employing the following methodology:

- 1. I identified companies with 2030 targets in research cycles 2017 to 2020.
- 2. I verified TPI internal assessments to confirm if these companies had set targets extending beyond 2030.
- 3. I adopted the targeted intensities beyond 2030 if already calculated in early TPI assessments. Otherwise, I calculated the targets myself in adherence to TPI sectoral methodologies.
- 4. I conducted all new "historical" assessments with emission intensity pathways extending until 2050.

#### Completing carbon intensity pathways from previous research cycles

In some cases, companies began reporting historical carbon intensities after their initial assessments by TPI. For example, a company may have been assessed in the 2017 research cycle as having "No or unsuitable disclosure," but then published sufficient information to calculate an emission intensity pathway from 2014 to 2019 in the 2020 research cycle. In such cases, I complete the pathways for research cycles 2017-2019 with the new carbon intensities that became available in the 2020 research cycle.

#### Automotive sector

The TPI automotive methodology uses  $gCO<sub>2</sub>/km$  as the emission intensity metric. Initially, this intensity was based on the New European Driving Cycle (NEDC) test cycle. However, with the gradual phasing out of the NEDC test cycle in the European Union and other regions, TPI transitioned to the Worldwide harmonized Light vehicles (WLTP) test cycle in a methodology update during research cycle 2022. The adoption of WLTP resulted in an upward adjustment of emission intensities for nearly all automotive companies, except for pure electric vehicle manufacturers. Since this transition affected both CA100+ and Non-CA100+ companies equally and contemporaneously, it does not introduce bias into my analysis.

Additionally, Fiat Chrysler and Groupe PSA, two CA100+ companies, merged to form Stellantis in January 2021. TPI last assessed Fiat and PSA as separate entities in research cycle 2021, after which it began assessing only Stellantis. To preserve a larger sample size, I included assessments for both Fiat Chrysler and Groupe PSA in my analysis. After research cycle 2021, I applied Stellantis' carbon emission reduction targets to both Fiat Chrysler and Groupe PSA for consistency.

#### Airlines sector

TPI's methodology for airlines underwent significant changes between RC 2018 and 2019. The emission intensity metric shifted from gCO2/Revenue-passenger-kilometer (RPK) to  $gCO<sub>2</sub>/\text{Revenue-tonne-kilometers (RTK)}$  to include cargo in the assessments. Airlines assessed in RC 2018, the inaugural year of TPI's airline assessments, initially had their assessments in  $qCO_2/RPK$  and subsequently in  $qCO_2/RTK$ .

The change in the emission intensity metric caused substantial jumps the pathways of individual companies, such as from approximately 120  $gCO_2/RPK$  to 650  $gCO_2/RTK$ . To mitigate the impact of this methodological change, I converted the  $gCO<sub>2</sub>/RPK$  pathways into  $gCO_2/RTK$  pathways using TPI's conversion factor of 150 kilograms per passenger. In RC 2020, TPI updated the conversion factor for RPK to RTK from 150kg per person to 95kg per person. Therefore, I converted all assessments from research cycles prior to 2020 again using the updated conversion factor. Starting from research cycle 2021, the airline assessments are used as available in the TPI database.

These conversions are not flawless as they overlook the impact of freight activity. However, since all airlines in the sample specialise on passenger transport, the overall impact on the assessments is minimal.

# E Appendix - Binned DiD - historical carbon intensities - within sectors



∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05;.p < 0.1

Table 18: This table shows the results of the binned DiD analysis on the average historical carbon intensities for CA100 companies compared to Non-CA100+ companies.



∗∗∗p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 19: This table shows the results of the binned DiD analysis on the average historical carbon intensities for Plus companies compared to Non-CA100+ companies.

# <span id="page-69-0"></span>F Appendix - Matching and DiD results on climaterelated and TCFD reporting



Figure 13: This figure shows the pre- and post-treatment trends on climate-related reporting across CA100, Plus and Non-CA100+ companies for each year across all sectors after matching.



 $-$  CA100 - Non-CA100+ + companies

Figure 14: This figure shows the pre- and post-treatment trends on reporting related to the four TCFD categories across CA100, Plus and Non-CA100+ companies for each year across all sectors after matching.



 $^{***}p<0.001;~^{**}p<0.01;~^{*}p<0.05;~p<0.1$ 

Table 20: This table shows the results of the DiD analysis on TCFD reporting, comparing the CA100 to Non-CA100+ companies.



 $***p<0.001;$   $**p<0.01;$   $*p<0.05;$   $p<0.1$ 

Table 21: This table shows the results of the DiD analysis on TCFD reporting, comparing the Plus to Non-CA100+ companies.


Figure 15: This figure shows the dynamic treatment effect of CA100+ on CA100 and Plus companies' climate-related reporting using a staggered DiD specification.



+ Pre + Post

Figure 16: This figure shows the dynamic treatment effect of CA100+ on CA100 and Plus companies' reporting on the four TCFD categories using a staggered DiD specification.

## G Appendix - Matching and DiD results on historical carbon intensities



Figure 17: This figure shows the pre- and post-treatment trends across CA100, Plus and Non-CA100+ companies for historical carbon emission across all sectors after matching.

	<b>CA100</b>	Plus List		
$CA100+$	0.06 (0.07)	0.05 (0.09)		
Num. obs.	798	690		
$R^2$	0.95	0.93		
Adj. $R^2$	0.94	0.92		
***p < 0.001; **p < 0.01; *p < 0.05; $p < 0.1$				

Table 22: This table shows the results of the DiD conducted on historical carbon intensities for the CA100 and Plus companies across all sectors.



Figure 18: This figure shows the dynamic treatment effect of CA100+ on the historical carbon intensities of CA100 and Plus companies across all sectors using a staggered DiD specification with confidence intervals set at 95%.

## H Appendix - Climate Change Performance Index (CCPI) data

The CCPI data were sourced from CCPI annual reports available for download on the [Climate Change Performance Index](#page-58-0) [\(2023\)](#page-58-0) website. The CCPI rating aggregates scores from four main categories: greenhouse gas emissions (40%), renewable energy deployment  $(20\%)$ , energy use efficiency  $(20\%)$ , and climate policy  $(20\%)$ . Within these categories, the CCPI assesses 14 indicators in total. The final score ranges from 0 to 100%.

The CCPI covers approximately sixty countries, with slight variations in coverage by year. To address minor data gaps for countries where included companies are headquartered but lack CCPI ratings, the following assumptions were made:

- 1. Values from China were used for Hong Kong.
- 2. For Singapore, data is available until 2016, and its index evolution post-2016 is assumed to match Malaysia's.
- 3. United Arab Emirates has no data before 2023; its index is assumed to evolve similarly to Saudi Arabia's.
- 4. Qatar's indices are assumed to mirror the UAE's.
- 5. Nigeria's evolution until 2023 mirrors South Africa's.
- 6. Chile mirrors Brazil's index evolution until 2019.
- 7. Colombia mirrors Brazil's index evolution until 2021.
- 8. The EU's evolution is assumed to be the average of all European countries in the sample until 2017.
- 9. Philippines' index evolution until 2021 mirrors Thailand's.

In the matched samples for the forward-looking analysis, these assumptions impact only one company each from Chile, Colombia, Hong Kong, and Singapore, and two companies from the European Union. For most companies, complete time series data from CCPI are available.

Table [23](#page-77-0) shows the final CCPI data used for the robustness checks.



<span id="page-77-0"></span>

## I Appendix - Forward-looking intensities - Trends in the Electricity and Autos sectors



Figure 19: This figure shows the trends across CA100, Plus and Non-CA100+ companies in the electricity sector for each target year after matching.

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	TY: 2025	TY: 2035	TY: 2050
$CA100+$	$-0.02$	$-0.01$	$-0.00$
	(0.03)	(0.04)	(0.05)
$R^2$	0.88	0.81	0.72
Adj. $R^2$	0.86	0.78	0.67
Num. obs.	275	275	275

<sup>∗∗∗</sup>p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 24: This table shows the results of the DiD conducted for the CA100-only analysis in the electricity sector.



 $***p<0.001;$   $**p<0.01;$   $^{*}p<0.05;$   $^{*}p<0.1$ 

Table 25: This table shows the results of the DiD conducted for the Plus-only analysis in the electricity sector.



+ Pre + Post

Figure 20: This figure shows the dynamic treatment effect of CA100+ on CA100 and Plus companies in the electricity sector using a staggered DiD specification with confidence intervals set at 95%.



 $-CA100 - Non-CA100+ - + companies$ 

Figure 21: This figure shows the trends across CA100, Plus and Non-CA100+ companies in the automotive sector for each target year after matching.

	TY: 2025	TY: 2035	TY: 2050
$CA100+$	6.85	$-1.43$	$-17.90$
	(4.26)	(7.21)	(11.91)
$R^2$	0.96	0.92	0.86
Adj. $R^2$	0.96	$-0.90$	0.83
Num. obs.	175	175	175

<sup>∗∗∗</sup>p < 0.001; ∗∗p < 0.01; <sup>∗</sup>p < 0.05; .p < 0.1

Table 26: This table shows the results of the DiD conducted for the CA100-only analysis in the automotive sector.



 $^{***}p<0.001;~^{**}p<0.01;~^{*}p<0.05;~^{'}p<0.1$ 

Table 27: This table shows the results of the DiD conducted for the Plus-only analysis in the automotive sector.

 $\div$  Pre  $\div$  Post



Figure 22: This figure shows the dynamic treatment effect of CA100+ on CA100 and Plus companies in the autos sector using a staggered DiD specification with confidence intervals set at 95%.