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Working Paper 21-108

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Funding for this research was provided in part by Harvard Business School.

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Abstract

We examine the effect of voluntarily adopting a standard for setting science-based carbon emissions targets on target difficulty and investments to achieve those targets. We find that firms with a track record of setting and achieving ambitious carbon targets are more likely to set science-based targets. Firms are also more likely to set science-based targets if they perceive climate change-related risks and have carbon-intensive operations. Using a difference-in-differences research design that compares the science and non-science targets of a firm, we find that targets become more difficult when firms adopt the science-based standard for the target, consistent with the standard increasing target difficulty and inconsistent with firms relabeling their existing targets. The increase in target difficulty is accompanied by more investment in carbon-reduction projects and higher expected emissions and monetary savings from these projects. Given that the science-based standard is determined externally of the adopting organization, our results suggest that external standards for target setting could have both target and investment effects.

Keywords: *climate change, environment, target setting, management control systems*

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1. Introduction

It is well understood that targets should be challenging yet attainable, but the role of internal performance standards (e.g., prior year performance, internal budgets) versus external performance standards (e.g., thresholds prescribed by experts and regulators) in setting optimal targets is less understood. Although internal standards may allow managers to retain control and influence over their targets, external standards can resolve optimal-target uncertainty, bolster credibility and signal ambitiousness. In the context of environmental performance, where cheap-talk could be rampant, "best-in-class" external standards have emerged, notably among them standards for setting carbon emissions reduction targets that are based on climate science. Although many firms have voluntarily adopted these standards, it is unclear whether and how external standards influence target difficulty and effort relative to internal standards. In this paper, we study whether the emergence of an external standard that aligns a firm's carbon reduction target with climate science is associated with target difficulty and investments to achieve the target.

Targets adopted by companies to reduce carbon emissions are considered "science-based" if they are in line with the level of decarbonization required to keep global temperature increases below 2 degrees Celsius compared to pre-industrial temperatures, as described in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). By the end of 2019 nearly 900 large multinational firms, including Walmart, McDonalds, BMW, and Nike, had already released or committed to release science-based targets (SBTs) based on the work of the Science Based Targets initiative (SBTi).[1] The SBTi, a non-profit organization, independently assesses and approves companies' targets based on climate science.[2] We use the emergence of the initiative and its creation of a standard for SBTs as our setting to study target setting and real effects.

Using an international sample of firms that set carbon reduction targets from 2011-2019, we first analyze why firms adopt external science-based standards, as opposed to keeping their targets aligned with

[1] See: https://sciencebasedtargets.org/companies-taking-action/

[2] However, the SBTi does not guide or advise firms on how to reduce emissions or achieve science-based targets (see page 5 of the SBT manual: https://sciencebasedtargets.org/wp-content/uploads/2017/04/SBTi-manual.pdf)

internal standards. We find that firms with a track record of setting ambitious targets and achieving their targets are more likely to adopt the external standards. We also find that firms that perceive climate change-related risks and that have carbon-intensive operations, are more likely to set SBTs. These findings suggest that lower expected costs (i.e., greater ability) and higher expected benefits (i.e., economic incentives) are determinants of SBT adoption.

Next, we analyze how target difficulty changes following the adoption of science-based standards. Ex ante it is unclear what the effect will be. If firms relabel their existing targets as science-based, then we should not observe targets becoming more difficult after adopting science standards. In this case, firms relabel their targets as science-based to add legitimacy to their extant efforts and to signal ambitiousness. Alternatively, if firms are uncertain about whether their targets are optimal and external standards help to resolve this uncertainty, targets may become more difficult after adopting science standards. Implementing a difference-in-differences research design that compares a firm's science and non-science targets, we document that targets for which firms adopt science standards become more difficult. This suggests that SBT-adoption yields more challenging targets than when internal standards are used.

Furthermore, we examine if firms that set SBTs change behaviors to reduce emissions. Even if targets become more difficult after adopting science standards, firms may not change their actions, such that there will be a disconnect between the targets and the efforts needed to achieve them. In effect, the targets could be 'cheap talk'. Alternatively, adopting science-aligned targets could inspire greater effort and investment by the firm to achieve the targets, consistent with SBT-adoption having real effects. We find support for the latter explanation. Specifically, we document that the required investment in carbon-reduction projects, and the expected emissions and monetary savings from these projects, increases for firms that adopt SBTs.

Our findings suggest that SBT adoption has real effects, but it is possible that similar effects arise for difficult targets adopted in the absence of science standards. In other words, does the adoption of external standards have incremental real effects over that of the adoption of difficult targets using internal standards? We conduct two tests to examine this. First, we identify firms that have targets that are equally ambitious as science targets, but do not use science standards. If target difficulty drives real effects, then we expect to observe similar real effects for these firms as for the firms that adopt science standards. Alternatively, adopting science standards could increase external pressure and accountability over targets, or result in stronger commitment and motivation to achieve a target that is part of a collective effort to limit global warming. Using a difference-in-differences specification, we find that firms with equally-ambitious (but not science-based) targets do *not* increase investment in, expected carbon savings from, or expected monetary savings from projects to reduce emissions after the SBT standards were released. Second, when we model the relation between target difficulty and these outcomes, we find that target difficulty is positively related to each of them; however, the association is *stronger* for firms that adopt SBTs. Therefore, the results suggest that external standards have incremental real effects over the real effects from target difficulty.

We acknowledge that firms are not randomly assigned to SBT adoption, and therefore we cannot completely rule-out endogeneity concerns. However, our results are robust to several identification strategies, which mitigates these concerns. First, we include firm fixed effects in our models which allows us to estimate changes in difficulty for targets that adopt science standards, relative to changes in difficulty for targets of the same firm that do not adopt science standards. Second, our results are robust to propensity-score matching, where firms that set SBTs and firms that do not set SBTs are matched on observable characteristics that, according to the results of our determinants model, are related to the decision to adopt SBTs. If firms endogenously select into SBT adoption based on observable factors, these estimations should mitigate the selection effects. Third, we validate the key assumption behind our difference-in-differences research design, namely that the trends in target difficulty are similar between the science and non-science targets of a firm, and the trends in emission-reduction efforts are similar between science and non-science firms, prior to adopting science-based standards.

With these caveats in mind, we contribute to two streams of literature. First, we contribute to the literature on corporate sustainability and climate change. Prior literature finds that firms setting more ambitious carbon reduction targets complete a higher proportion of their targets especially in settings where innovative activities are needed (Ioannou, Li and Serafeim 2016) and that mandatory disclosure regulations are effective at incentivizing companies to reduce carbon emissions (Grewal 2019; Tomar 2019). We add to this literature by studying how an external standard for setting carbon targets relates to target difficulty and carbon reduction efforts.

Second, we contribute to the literature on how firms set targets and the actions they take to achieve them. Extant research examines the role that supervisor incentives and managerial discretion (Bol, Keune, Matsumura and Shin 2010) or that different types of rewards (Presslee, Vance and Webb 2013) play in setting targets. We build on this research by documenting effects of an external (to the organization) standard for setting targets on target difficulty and investments to achieve targets. Apart from research on incentive compensation (e.g., Murphy 2000), little is known about the role of internal versus external standards in motivating and guiding performance. We fill this gap by examining factors influencing firms' choice to use external versus internal standards for target setting, and how this choice is related to target difficulty and efforts to achieve those targets.

2. Literature Review

2.1 Target setting and standards

Understanding how targets are set is important because targets play a key role in many aspects of management accounting and control. For instance, targets help with selecting action plans and investments, and evaluating performance. In the budgeting literature, the focus of many studies is budgetary slack. A robust finding from this literature is that employees use their information advantage to obtain easier targets (Schiff and Lewin 1968; Merchant 1985; Lukka 1988) and employees expend greater efforts to create slack when the returns from such effort are higher (Anderson et al. 2010). Research examining target setting from the manager's side mainly focuses on the relationship between target achievability and subordinates' effort or performance. Although this research suggests that difficult goals motivate better performance than easier goals (e.g., Locke and Latham 1990), Merchant and Manzoni (1989) document that budget targets are more attainable than the goal-setting literature would predict. Interviews that Merchant and Manzoni (1989) conduct with managers suggest that targets are attainable because employee performance is not their only concern; target setting decisions are also affected by factors such as increasing the predictability of budgets and discouraging earnings management.

Nevertheless, the standard prescription from the vast literature on target setting is that targets should be set at levels that are both difficult and attainable (e.g., Locke and Latham 1990, 2002), and prior research shows that many types of information and methods are used in determining such thresholds. These include the use of historical results (targets based on year-to-year growth or improvement), budgetary plans (targets based on the company's annual budget goals), peer-benchmarking (targets based on performance of other companies in the market or industry), timeless standards (targets of a fixed standard, such as pre-specified return on assets), discretionary standards (targets are set subjectively by the board of directors or managers), local information of employees (in the case of participative target setting), and cost of capital (targets based on the company's cost of capital) (Ittner and Larcker 2001; Murphy 2000; Bol et. al. 2010; Anderson et. al. 2010). In executive incentive plans, Murphy (2000) categorizes these methods into "internal standards" (e.g., budgets, historical performance) versus "external standards" (e.g., timeless standards, cost of capital) and theorizes that performance standards used to set targets generate important incentives when employees can influence the standards. He shows that companies are more likely to choose external standards (which are less easily affected by management actions) when prior year performance is a noisy estimate of contemporaneous performance.

Apart from the research on the use of external versus internal standards to filter-out noise and provide a more precise performance signal, little is known about how firms choose between internal versus external standards, and their role in target setting. Outside of incentive compensation, managers routinely face decisions about whether to set targets using internal standards (over which managers retain a higher degree of influence and control) versus external standards (over which they retain a lower degree of influence and control). For example, setting a target for revenue based on the prior year (where prior year's revenue is an *internal* standard) is more controllable by employees than an external revenue threshold set by a regulator or stock exchange because the firm is unlikely to have much, if any, influence over the regulator's standard.

Although firms may be unwilling to relinquish control over target standards, there are other considerations. For instance, firms may choose to use external target standards to bolster credibility and signal ambitiousness. This is particularly relevant in the context of environmental performance, where firms often face pressure from activists, investors, and customers to improve their environmental outcomes (e.g., Hawn and Ioannou 2016). Accordingly, adopting external standards for carbon reduction targets could send a credible signal of commitment, enhance reputation, and placate concerned stakeholders.[3] Moreover, if adopting external standards leads to more ambitious targets and engenders greater accountability to achieve them, firms may increase their efforts. However, it is uncertain whether external standards will increase target difficulty and effort relative to internal standards, given that firms could strategically choose external standards that produce easier targets relative to internal standards. Despite these unresolved matters, there is little empirical evidence on how firms choose between internal versus external standards and the implications for target setting and achievement arising from these choices.

2.2 Environmental performance and target setting

A vast prior literature examines the relation between a firm's corporate social performance and financial performance (see Margolis, Elfenbein, and Walsh (2009) for a review). Environmental initiatives and environmental performance are typically studied as a pillar of a firm's overall sustainability strategy. While some researchers argue for a causal link between financial and environmental performance due to the cost savings from improved process efficiency and the avoidance or reduction of future liabilities from regulations (e.g., Porter and Van der Linde 1995), others have cast doubt on the causal claims by controlling for a firm's fixed characteristics and strategy (e.g., King and Lenox 2001). Prior research in this area documents a $34 million increase in market value for a 10% reduction in toxic chemical emissions (Konar and Cohen 2001) and a penalty to firm value of $212,000 for every additional thousand metric tons of carbon emissions (Matsumura et al. 2014).

[3] External standards for environmental, social and governance (ESG) performance have emerged in recent years, for example United Nations' Sustainable Development Goals, Business Roundtable Principles of Corporate Governance, CEO Action for Diversity, Pay Equality Pledge, and Science-Based Targets (the focus of our study).

A related stream of literature studies firms' decisions to disclose information on environmental performance and the consequences from doing so. This literature points to firm, industry and country-level characteristics that influence the decision to disclose environmental data (e.g., Barth, McNichols and Wilson 1997; Clarkson et al. 2007). Moreover, prior research shows that markets penalize firms that do not disclose emissions information (Matsumura et al. 2014) and that mandatory disclosure regulations improve subsequent environmental performance (e.g., Grewal 2019; Tomar 2019).

Relatively less explored is *what* firms do to achieve better environmental performance and *how* environmental targets are determined. In terms of the first question, three notable exceptions are Dahlmann et al. (2019), Dahlmann et al. (2013) and Ioannou et al. (2016). Dahlmann et al. (2019) finds that targets characterized by a commitment to more ambitious reductions, a longer target time frame, and absolute reductions, are associated with higher reductions in firms' emissions. Dahlmann et al. (2013) document that firms offering monetary and non-monetary incentives relating to environmental performance reduced their carbon emissions intensity, but assigning responsibility to an independent director only yielded reductions for energy-intensive firms. Ioannou et al. (2016) document that firms setting more difficult carbon emissions targets completed a higher percentage of their targets. However, in terms of the second question, the literature to date is silent on the methods and standards that companies use to set environmental targets and how these choices are associated with target difficulty and achievement.

3. Hypothesis Development

The extent to which adopting external standards affects target difficulty and real efforts to achieve targets, depends on both the information and incentives surrounding existing target setting practices prior to the adoption of these standards. Both the breadth of information and the variety of target setting practices highlighted in the previous section demonstrate the challenges inherent in setting difficult yet attainable targets, even on well-understood dimensions of performance such as sales or earnings. These challenges are likely exacerbated in the context of determining appropriate emissions reduction goals which requires scientific expertise in addition to the requisite knowledge of underlying business strategy and operations.

In this context, the effect of external standard adoption is an open empirical question with several different possibilities depending on the nature of the incentives, information, and expertise available to firms prior to adoption. Below, we develop interrelated hypotheses that collectively allow us to explore determinants and consequences of adopting external standards for target setting.

3.1 Determinants of adopting external standards for target setting

Faced with increasing investor and non-equity stakeholder pressure to report on and manage environmental outputs (Cheng et al. 2014; Eccles et al. 2011; Delmas and Toffel 2008), thousands of publicly-traded firms set carbon emissions targets and disclose these targets publicly (Dahlmann et al. 2019). In the absence of external standards, firms use *internal* standards, such as setting targets based on what peer firms are doing, or on what is achievable given the organization's past performance and internal carbon budgets.

The introduction of external standards to align carbon reduction targets with what climate science says is needed to limit global warming to well-below pre-industrial levels, allows us to study the determinants and consequences of adopting external standards for target setting.[4] It is unclear whether companies will choose external standards to set targets. Firms spend considerable time and resources setting carbon targets using internal standards, and changing these targets may be difficult, costly and disruptive to the organization.[5] Although the SBT initiative guides firms on how to set science-aligned targets, it does *not* guide companies on how to achieve their targets (SBT 2020, p. 5); as a result, firms may be reluctant to adopt SBTs without a plan to achieve them. Moreover, adopting external standards allocates decision rights and control over targets to the external standard-setting organization. If standards change over time and require increasingly difficult targets to be adopted, firms risk losing control over the target setting process and committing to targets that are sub-optimal or unattainable. In this setting, it is possible that

[4] According to the Science Based Target Initiative, "targets adopted by companies to reduce greenhouse gas (GHG) emissions are considered "science-based" if they are in line with what the latest climate science says is necessary to meet the goals of the Paris Agreement – to limit global warming to well-below 2°C above pre-industrial levels and pursue efforts to limit warming to 1.5°C." See: https://sciencebasedtargets.org/what-is-a-science-based-target/
[5] See: https://www.c2es.org/site/assets/uploads/2001/11/ghg_targets.pdf

what constitutes a SBT may change to reflect advances in scientific modelling and climate science (SBT 2020, p. 4). Given that one of the benefits of using external standards is that firms obtain certification that their targets are aligned with climate science, it may not be costless (from a reputational or brand value standpoint) to lose this certification. However, if firms anticipate benefits from adopting external standards for target setting – such as strengthening their credibility and reputation among stakeholders and resolving uncertainty about what constitutes "tough but achievable" emissions targets – firms may forgo internal standards in favor of external ones.

We hypothesize that past target difficulty and past target completion are positively associated with the adoption of external standards for target setting. Firms with a track record of difficult and successful target completion may already have the intention and ability to achieve targets in line with science-based standards and opt for external standards simply to confer legitimacy on their existing efforts – in effect, "adopting a label". Under this scenario, firms know whether they are at the "tough but achievable" threshold on their targets; those that are at this threshold adopt science standards, and those that are not at this threshold do not adopt science standards.

Another possibility is that firms face uncertainty regarding whether they are setting optimal carbon targets, and external standards help to resolve this uncertainty. Specifically, because SBTs are grounded in an objective scientific evaluation of what is needed to mitigate climate change, science-based standards provide firms with information about what constitutes a credible and rigorous target according to climate science. Upon learning that their existing targets fall short of external standards, firms align their targets with external standards – in effect, "adopting through learning". For instance, according to a manager of a company that adopted a science-based target: "Ultimately, the science brings meaning and grounds our ambition in reality…[the] targets are no longer numbers pulled from thin air, they are goals linked to a real issue. Science-based targets commit us to what is required, not just what is achievable." (SBT 2020, p. 12). Again, under this scenario, firms that set more difficult targets are more willing to adopt external standards and firms that have a track record of achieving past targets are more confident in their ability to achieve targets set using external standards. Therefore, under both the "adopt a label" and "adopt through learning" scenarios, we conjecture that the likelihood of adopting external standards for setting targets is increasing in (1) past target difficulty, and (2) past target completion or success. Our first hypothesis is as follows:

H1a: Firms with more difficult past targets and achievement of past targets are more likely to adopt external standards for target setting.

We also hypothesize that firms will be driven to adopt external standards if they anticipate economic incentives from doing so. For instance, firms perceiving regulatory risks in the form of policies and legislation to limit emissions may set SBTs to stay ahead of, and prepare for, future regulation (Delmas et al. 2008). In addition, companies that set SBTs and signal their leadership on climate change will be better positioned to influence policymakers and shape legislation (Porter and Van der Linde 1995). Firms may also anticipate significant cost savings from aligning their targets with climate science, because more ambitious targets could drive leaner, more efficient operations (Tomar 2019). Moreover, firms that perceive business opportunities from climate change – for example, new business models, products, revenue sources and markets – will set SBTs to create the internal conditions needed to spur large-scale innovation and investments, which both address carbon reductions and are of value to the firm's broader financial performance and strategic aspirations (Sharma 2000). Our second hypothesis is as follows:

H1b: Firms with greater economic incentives to address climate change are more likely to adopt external standards for target setting.

We note, however, that the extent to which economic incentives predict adoption of external standards depends whether firms (on average) adopt standards to confer legitimacy on their existing efforts ("adopt a label") versus to resolve uncertainty about optimal target setting for carbon emissions ("adopt through learning"). If firms are, on average, knowledgeable and experienced at determining the tough but achievable threshold for emissions targets, firms with economic incentives to reduce emissions will already set difficult targets and will be more likely to adopt the label. In this case, past target difficulty and completion (as hypothesized under *H1a*) will be sufficient for predicting who adopts external standards. Alternatively, if firms face uncertainty about optimal target setting for emissions and determining achievability is challenging in this context, then firms with incentives to reduce emissions may adopt external standards upon learning that their existing targets fall short of science standards. In this case, the risks and opportunities from climate change faced by the firm will predict who adopts external standards, incremental to past target difficulty and completion. However, even if the "adopt through learning" explanation prevails, firms may align targets with external standards in a symbolic attempt to manage stakeholder perceptions, rather than a substantive commitment by the firm to reduce emissions (Dahlmann et al. 2019); we examine this in our fourth hypothesis, *H3*.

3.2 The relation between external standards and target difficulty

In our setting, external standards developed for corporate carbon reduction targets are intended to create challenging and accelerated targets that "…ensure the transformational action [companies] take is aligned with current climate science".[6] However, if firms only adopt external standards when they know that their existing targets are *already* aligned with the standards, firms may reclassify their targets as being externally-aligned or "adopt a label" without increasing target difficulty. This will allow firms to bolster credibility and reputation as responsible corporate citizens that use external standards to set targets, without enhancing target difficulty.[7] Alternatively, if external standards resolve uncertainty about target optimality – and reveal to firms that their existing targets fall short of science standards – firms that adopt the standards upon learning what is needed to align with climate science (i.e., "adopt through learning"), will increase target difficulty. Therefore, our third hypothesis is:

H2: Adopting external standards for target setting is related to increased target difficulty.

3.3 Real effects of external standards for target setting

[6] See: https://sciencebasedtargets.org/what-is-a-science-based-target/

[7] Moreover, as discussed in section 4.2, firms choose between three approaches to calculate science-based targets; this further increases the possibility that firms will choose the approach that produces the easiest targets.

Firms may adopt external standards as a symbolic act without intending to pursue or achieve those targets. The notion that companies set environment targets they are unable – or do not intend – to achieve is an issue that has been framed as a "decoupling" of policy and practice (Dahlmann et al. 2019; Crilly et al. 2012; Crilly et al. 2016). In line with these findings that cast doubts on corporate benevolence in taking action on environmental and climate change challenges, Trexler and Schendler (2015) criticizes SBTs as "green fluff" and a "distraction" that can delay important regulation for which SBTs are not a substitute. Although firms can lose their SBT certification if they are not on track to achieve the certified targets, it may take time (i.e., a few years) for this to become apparent to the external standard-setting organization (i.e., the Science-Based Targets Initiative) and for the firm to be disciplined, both in terms of losing their certification and any resulting brand and reputational consequences. Thus, firms could adopt external standards and increase target difficulty without changing behaviors that enable target achievement.

On the other hand, firms that adopt external standards may change their 'real' behaviors, such investing in projects and technologies that yield carbon reductions. If science standards yield more ambitious targets, firms may need to think beyond efforts that result in incremental carbon reductions, and focus instead on investments and approaches that transform business operations to yield more substantive reductions. For instance, more ambitious science-based targets could create the internal conditions needed to spur large-scale innovation and unleash creativity and urgency among employees with the purpose of collaborating and deviating from existing practices to drive significant carbon reductions (Dahlmann et al. 2019). It is also possible that adopting external standards increases the external visibility of firms' targets, given that firms with approved SBTs are showcased on the SBTi website, firms use the SBT logo in promoting their environmental efforts, and media and news articles bring attention to firms that set SBTs (Trexler et al. 2015). This, in turn, may result in additional stakeholder pressure on firms, and a greater sense of accountability by firms, to achieve these targets. Finally, aligning carbon targets with a goal that extends beyond the firm – to limit global warming to 2°C – may increase target commitment and motivation if firms attach meaning and significance to their role in the collective effort. For instance, a representative from Sony's Quality & Environmental Department stated: "By being part of the global [Science-Based Targets] Initiative, we know we are part of a bigger movement".[8] Our fourth hypothesis is:

H3: Adopting external standards for target setting is related to increased efforts to reduce carbon emissions.

4. Institutional Background

4.1 Science Based Targets initiative (SBTi)

SBTi is a collaboration between the Carbon Disclosure Project, the United Nations Global Compact, World Resources Institute, World Wide Fund for Nature and the We Mean Business Coalition. The initiative's aim is for science-based target setting to become standard business practice. To this end, the SBTi defines and promotes best practices in setting science-based targets with the support of a Technical Advisory Group and Scientific Advisory Group. However, the SBTi does not provide guidance on implementing carbon reduction measures or achieving science-based targets.[9] Rather, SBTi independently assesses and approves companies' targets through a validation process. Targets adopted by companies to reduce carbon emissions are considered "science-based" if they are in line with what climate science says is necessary to meet the goals of the Paris Agreement – to limit global warming to well-below 2°C above pre-industrial levels and pursue efforts to limit warming to 1.5°C.

4.2 Science-Based Targets (SBT)

To set a science-based target, a firm must first sign a commitment letter indicating that it will work to set a science-based target. If the firm already has an emissions reduction target, the letter confirms the firm's interest in having the existing target independently verified against a set of criteria developed by the SBTi. Once the firm has signed the commitment letter, it has up to two years to develop and submit its target for official validation. Target validation costs $4,950 USD and subsequent resubmissions cost $2,490 USD if

[8] See: https://sciencebasedtargets.org/why-set-a-science-based-target/

[9] See page 5 of the SBT manual (https://sciencebasedtargets.org/wp-content/uploads/2017/04/SBTi-manual.pdf).

the company does not initially pass the validation process. On confirmation that the target meets the SBTi criteria, the firm can use the SBT logo on its website and promotional materials.

There are three approaches developed by the SBTi to set science-based targets. The first is the sector-based approach where the global carbon budget is divided by sector and emission reductions are allocated to individual companies based on its sector's budget. The second is the absolute-based approach where the percent reduction in absolute emissions required by a given scenario is applied to all companies equally. The third is the economic-based approach where a carbon budget is equated to global GDP and a company's share of emissions is determined by its gross profit.

The SBTi recommends the sector-based approach and absolute-based approach.[10] Per our discussions with a senior member of the SBTi, by far the most frequently adopted approach was the sector-based approach. The SBTi recommends companies to screen the approaches and choose the one that best drives emissions reductions to demonstrate sector leadership. The SBTi also urges companies not to default to the target that is easiest to meet, but instead to use the most ambitious decarbonization scenarios and methods that lead to the earliest reductions and the least cumulative emissions. However, given that firms ultimately choose their approach, we discuss the implications of this for our results in section 7.2.

5. Data

We obtain information on firms' carbon targets and climate change initiatives through the investor survey of the Carbon Disclosure Project (CDP) for the years 2011 to 2019. CDP is an international, not-for-profit organization that provides a system for companies to measure and share information on a wide set of environmental metrics. We note that CDP serves as the primary data source for data providers that aggregate and disseminate information on the environmental performance of firms, namely Bloomberg, MSCI KLD, Thomson Reuters and Sustainalytics.[11] Moreover, a lead analyst at Bloomberg informed us that her team's research had not identified companies that report carbon emissions, targets, and initiatives in other channels

[10] See: https://sciencebasedtargets.org/faq/

[11] For each of these data providers, definitions for climate change data fields specify that the information comes directly from responses to the Carbon Disclosure Project (CDP) survey.

(e.g., CSR reports) without also responding to the CDP survey. This suggests (and is consistent with prior research, e.g., Ioannou et al. 2016) that the annual CDP survey is the most comprehensive source of direct, large-scale, cross-sectional data on the details of carbon targets set by firms. Importantly, firms that do not set carbon targets are not part of our analyses; accordingly, we cannot generalize our findings to these firms. However, our focus on firms that *do* set carbon targets is appropriate, given our interest in why firms adopt external standards for their targets (as opposed to keeping targets aligned with internal standards) and how the adoption of external standards relates to target difficulty and efforts to reduce carbon emissions.[12]

We merge CDP survey response data with accounting data from Bloomberg. Our final sample includes 1,752 unique firms that set 7,557 carbon emissions targets (around 4.3 targets per firm) and have 14,143 climate initiatives (around 8 initiatives per firm). Table 1a presents the frequency of science and non-science targets across countries: we note that many countries are represented in our sample while a significant number of target observations originate from the US, Japan and the UK. Table 1a presents the frequency distribution across sectors: companies in the industrials, financials and information technology sectors set the highest number of targets.

5.1 The Climate Disclosure Project[13]

The annual CDP survey requests information on the risks from climate change from the world's largest companies (by market capitalization) on behalf of institutional investor signatories (in 2019, there were over 800 institutional investor signatories with a combined $100 trillion in assets under management). The survey is sent to the largest companies in each country that are members of the major local stock market index. Response rates are typically very high with most companies providing data to CDP. For example, in 2019, 94 percent of the Global 500 – the largest 500 companies in the world – responded to the CDP survey. We acknowledge that, by construction, the sample is biased towards larger companies, yet it is also a sample

[12] It is unclear whether and how a firm's decision *not* to set carbon targets would systematically relate to a firm's decision to adopt science standards, or would otherwise bias our results. Moreover, we assess the likelihood that firms set targets but do not disclose them as low, given the effort that firms expend to set targets; the pressure on firms to report climate change efforts; and the benefits from doing so. See, for example, Delmas et al. (2008).
[13] For more information about CDP see: https://www.cdp.net/en/info/about-us.

with a diverse representation both in terms of countries (Table 1a) and in terms of sectors (Table 1b). It is also important to note that in the context of climate change and attempts to reduce global carbon emissions, public policy and civil society pressures are predominantly placed on the world's largest companies given that carbon emissions are proportional to firm size. Moreover, following the Paris Climate Agreement, many of the world's largest companies have publically acknowledged the risks of climate change and have taken action to mitigate its effects. Consequently, the largest companies are in fact the most relevant sample for studying our research question.

The data collection effort by CDP proceeds as follows. Companies are asked to respond to the questions that are included in the survey through the CDP website for direct data entry (and only send the answers via email if absolutely necessary). Drop-down options and tables are included in the Online Response System (ORS) for ease of response. Surveys are typically sent to companies by the end of the previous year (i.e., the 2019 survey was sent out by the end of 2018). Survey guidance is available starting in January of the survey year, which details all the options available and provides screen shots of the ORS to aid companies in completing the request. CDP requests a reply by the end of May of the same year. The survey explicitly asks companies to "answer the questions as comprehensively as possible. Where you do not have all the information requested, please respond with what you have as this is more valuable to us than no response." In most cases, the individuals who complete the survey hold positions in sustainability departments and are typically supervised by the Chief Sustainability Officer (or equivalent). Upon completion of the responses, a senior officer signs on the accuracy and completeness of the data that is reported therein; most frequently this is a member of the firm's executive committee.

CDP survey questions are designed to solicit answers on the existence of a particular management practice (e.g., yes/no answers), as opposed to answers based on cognitive or affective assessment (e.g., open-ended questions). These types of questions are useful for generating objective responses and consequently, they are less subject to certain biases of survey studies, such as scaling effects.[14]

[14] Scale design and anchor choice will influence respondents' ratings, rendering comparisons across respondents difficult.

5.1.1 Reliability of CDP Survey Responses

As with all surveys, data accuracy is a potential threat to the validity of the estimates. To address this concern, we assess whether our results hold after we restrict our sample to firms that have received an outside audit of their carbon emission data, since third-party auditing (or assurance) of the disclosed information increases our confidence in their accuracy and reliability. To identify such firms, we use the response to a question in the CDP survey that asks: "Please indicate the verification/assurance status that applies to your … emissions". Firms can choose a response from the following options: a) "No third party verification or assurance", b) "Third party verification or assurance complete", or c) "Third party verification or assurance underway". When we restrict our sample to firms that respond that a third party assurance or verification has been completed, untabulated results show that the inferences from our main results (reported in Tables 3, 5a and 7a) remain unchanged.

5.2 Emissions Reduction Targets

We obtain data from responses to questions in the CDP investor survey that require structured answers (through the drop-down options and tables). The primary question of interest we utilize is stated as follows: "*Did you have an emissions reduction target that was active in the reporting year?*" Firms can indicate if they set one or more targets and are then asked a series of follow-up questions about their target(s).

Emissions reductions targets are described as a percent reduction in emissions with respect to a base year, to be achieved by a target year. We quantify an emissions reduction target from the following set of variables from the CDP investor survey: *target difficulty*, *horizon*, *scope*, *coverage* and *base year emissions*. The percent reduction in emissions is the *target difficulty*. However, the ambitiousness of a target cannot be accurately assessed without accounting for the base year and target year of the target in question. For example, if two targets have the same nominal *target difficulty* and the same target year, the target with the earliest base year emissions will represent the greater (more difficult) absolute reduction in emissions.[15]

[15] Targets are usually set with respect to a base year that is not the same year in which that target was set. As emissions are increasing for most firms, an earlier base year represents a more ambitious target, all else equal.

Similarly, a later target year reflects a less challenging target as the annualized reduction in emissions is smaller. We define *horizon* as the difference between the target year and base year.

A company can have multiple emissions reductions targets that refer to different portions of their business, denoted by the *scope* of a target. There are three main types of *scope*. Scope 1 emissions are direct emissions from sources owned or controlled by the company (e.g., on-site fuel combustion and fleet fuel consumption). Scope 2 emissions are indirect emissions from the generation of purchased energy (e.g., emissions generated by a utility to produce energy purchased by the company). Scope 3 emissions are indirect emissions that occur in the reporting company's value chain (both upstream and downstream). Scope 3 emissions can come from a variety of sources including purchased goods and services, capital goods, waste generated in operations, business travel, employee commuting, investments and more. *Scope* is defined for four categories: Scope 1, Scope 2, Scope 1+2, and Scope 1+2+3.

Targets are further described by their *coverage*, which refers to the percentage of base year emissions accounted for in the target. A target with a *coverage* less than 100 percent does not apply to all a firm's emissions, decreasing the real reduction in net emissions. For example, a target with a *target difficulty* of 10 with a *coverage* of 50 is comparable in net emissions reduction to a target with a *target difficulty* of 5 with a *coverage* of 100, all else equal.

Finally, *base year emissions* impact the implicit ambitiousness of a target. Targets with greater *base year emissions* are generally more ambitious given they represent a greater reduction in absolute emissions. While many firm-specific characteristics influence a firm's ability to reduce emissions, firms with greater *base year emissions* have more carbon intensive operations, therefore requiring more fundamental organizational changes to achieve targets.

Starting in 2016, a new field was added to the CDP survey that allows us to identify emissions reduction targets as science-based. This new field asked "*Is this a science-based target?*" and permitted the following responses: "Yes"; "No, but we are reporting another target that is science-based"; "No, but we anticipate setting one in the next two years"; "No, and we do not anticipate setting one in the next two years"; and "Don't know". Although it is possible that a firm could identify a target as being science-based in its CDP response when it is not, we cross-checked the CDP responses with a listing of firms with approved science-based targets from the SBTi and noted only nine discrepancies that were due to mismatched company names or identifiers.

5.3 Economic Incentives of Climate Change

We measure economic incentives to reduce emissions using response data from the CDP. Firms are asked to assess the risks to their business created by climate change and, for each risk reported, firms use a numeric scale to assess the likelihood of occurrence, the magnitude of impact and the timeframe in which the risk will manifest. Each risk corresponds to one of three categories: regulatory impact, physical impact, or other impact. Firms may report multiple risks for each category, or none. CDP also asks companies to report the percentage of total revenues from products and/or services that the firm generates from products that enable a third party to avoid greenhouse gas emissions. We name this variable *low carbon revenue*.

5.4 Emissions reduction initiatives

CDP collects data on the initiatives that companies undertake to reduce emissions, by asking companies to: "*Provide details on the initiatives implemented in the reporting year.*" Companies are asked to report the activity-type of each initiative, where the primary activity-types include energy efficiency improvements, process emissions reductions, fugitive emissions reductions, behavioral changes, low carbon energy installations, low carbon energy purchases, product design changes and transportation changes. We obtain data on the investment required, monetary savings and CO_2 savings for each initiative implemented in a firm-year.

6. Determinants of Science-Based Target Adoption

6.1 Model, Variables and Summary Statistics

To study the determinants of adopting SBTs, we use the CDP data and identify 1,752 unique firms that set carbon targets. Within this sample of firms that set carbon targets, we assess which firms are more likely to adopt external standards, as opposed to continuing to use internal standards, for their targets. We specify a firm-level cross-sectional logit model to assess firm characteristics associated with the adoption of SBTs. Equation 1 defines our model:

$$
\begin{aligned}
\Pr(Science\ Firm_i = 1) \\
&= \beta_1(Past\ Target\ Ambition_i) + \beta_2(Past\ Target\ Completed_i) \\
&+ \beta_3(\ln(Low\ Carbon\ Revenue_i)) + \beta_3(\ln(Emissions/Sales_i)) \\
&+ \beta_4(\ln(Likelihood\ Risks_i)) + \beta_5(\ln(Timeframe\ Risks_i)) \\
&+ \beta_6(\ln(Magnitude\ Risks_i)) + \alpha_1(\ln(CAPEX/Sales_i)) + \alpha_2(\ln(Total\ Assets_i)) \\
&+ \alpha_3(ROA_i) + \alpha_4(\ln(Price - to - Book_i)) + \alpha_5(\ln(Volatility_i)) + \theta_s + \delta_c + \varepsilon_i
\end{aligned}
$$

Our dependent variable is *science firm*, a time-invariant indicator equal to 1 if a firm adopted at least one SBT over the sample period (2011-2019), and 0 otherwise (note that the SBT standards were released in 2015, and the earliest SBTs were set in 2016). Hypothesis 1a predicts that the decision to adopt a SBT is influenced by past target setting behavior. We model past target setting behavior using two variables, *past target ambition* and *past target completed*. Since the earliest SBTs were set in 2016, we calculate *past target ambition* as the natural logarithm of the average *target difficulty* divided by *horizon* multiplied by *coverage* (i.e., 100% *coverage* scales the value by 1, while 90% *coverage* scales the value by 0.9) for all of the targets set by a firm before 2016; *past target completed* is an indicator that takes the value of one if a firm has ever completed a carbon reduction target prior to 2016, independent of the difficulty of that target. Table 2a reports summary statistics of our sample. The mean of *science firm* is 0.22, indicating that 22% of the firms in our sample adopted a SBT. The mean of *past target ambition* is 0.94, and the standard deviation is 0.49. *Past target completed* has a mean of 0.75, which reveals that 75% of the sample firms have completed a previous target. We predict both variables will be positively associated with a firm's decision to adopt a SBT.

Hypothesis 1b conjectures that the decision to adopt a SBT is influenced by the firm's economic incentives to address climate change. The first variable we employ to measure economic incentives is *low carbon revenue*, calculated as the percent of a firm's revenue generated from products and/or services that enable customers to avoid greenhouse gas emissions. Using response data from the CDP, we find that the average firm identifies 15.2% of their revenues as *low carbon revenues* (see Table 2a). The second variable, *emissions/sales*, represents the carbon intensity of a firm measured as metric tons of CO2 equivalent per million USD of sales revenue. The mean (median) *emission/sales* is 1,208 (29.3) metric tons of CO2 equivalent per million USD of revenue. A low carbon economy poses high risk to carbon-intensive firms, as the transformation required of these firms is significant; thus, managers of carbon-intensive firms could adopt SBTs as a mechanism to accelerate organizational change.[16]

We also measure economic incentives using the variables *likelihood risk*, *timeframe risk* and *magnitude risk*, which reflect managers' assessments of the risks facing their business owing to climate change (see Appendix 1 for variable definitions). Specifically, we utilize firm responses to CDP survey questions about the risks they perceive that relate to regulatory, physical, and other impacts of climate change. Firms use numeric scales to assess the likelihood/timeframe/magnitude of a particular risk. Firms measure *likelihood risk* on a scale between 1 and 8, with higher values corresponding to a higher perceived likelihood that a given risk will materialize. *Timeframe risk* is measured between 1 and 4, with lower values corresponding to perceptions that a given risk will materialize sooner rather than later. *Magnitude risk* is measured between 1 and 5, with higher values corresponding to perceptions that the impact of the risk will be greater. As shown in Table 2a, firms (on average) perceive a high likelihood that risks relating to climate change will affect their business (mean of *likelihood risk* is 5.44). The mean *timeframe risk* (2.30) suggest that firms assess these risks to materialize in the medium-term. The mean of *magnitude risk* (2.91) indicate that firms assess moderate impacts of risks relating to climate change on their organization. Since most firms reports multiple risks, we average the likelihood/timeframe/magnitude scores across reported risks to create a composite likelihood/timeframe/magnitude score (see Appendix 1).

We refer to prior literature for guidance on the set of controls to include in our model to account for observed heterogeneity that could influence firms' propensity to adopt external standards for setting

[16] However, we acknowledge that the tension between developing low carbon assets (or organizational capabilities to achieve SBTs) and exploiting current carbon intensive assets, would be high for carbon-intensive firms. Firm ambidexterity – exploiting current assets while contemporaneously developing new assets which inherently decrease the value of current assets – is a challenging issue and can create internal firm disruptions (O'Reilly and Tushman 2013). It is therefore plausible that carbon-intensive firms would avoid SBTs to avoid issues of firm ambidexterity.

emissions targets. We control for carbon intensity (*CAPEX/Sales*), size (*total assets*), profitability (*ROA*), market-to-book ratio (*price-to-book*) and price volatility (*volatility*) because prior research suggests that these factors relate to the difficulty of firms' carbon emission reduction targets (e.g., Ioannou et al. 2016). These control variables are also at the firm-level and measured in 2016. We include sector fixed effects (θ_s) and country fixed effects (δ_c) given that multiple dimensions of firms' carbon reduction targets (e.g., incentives, target ambition, etc.) likely differ depending on sector membership (Ioannou et al. 2016) and where firms are headquartered (Matsumura et al. 2014). Table 2a reports that the average size of the firms in our sample (as measured by total assets) is relatively large due to the inclusion criterion (i.e., largest firms by market capitalization) in the investor CDP survey. On average, sample firms have $58 billion in assets (*total assets*), their average price-to-book ratio (*price-to-book*) stands at 2.68, return on assets (*ROA*) is 4.77%, capital intensity (*CAPEX/sales*) is 4% and average stock price volatility (*volatility*) is 29.7%.

Tables 2b displays the univariate correlation of our variables of interest. *Science firm* is most correlated with *emissions/sales* (0.10) and with *target ambition* (0.06), both at the 1% significance level, but shows no major correlations otherwise. *Emissions/Sales* is positively correlated with *low carbon revenue* at 0.08 (1% significance level), suggestive of carbon intensive firms innovating to create products that reduce carbon emissions. *Emissions/sales* is also positively associated with *magnitude risk* at 0.07 and *timeframe risk* at 0.08 (1% significance level), which is unsurprising given that firms with carbon-intensive operations likely perceive a higher impact of the regulatory and physical impacts of climate change. The correlations between the financial accounting variables are in-line with our expectations.

6.2 Results: Determinants of Science-Based Target Adoption

Table 3 presents the results of our determinants model. The 1,752 observations represent unique firms, and standard errors are clustered at the firm level.[17] The odds-ratio on *past target ambition* exceeds 1 and is significant at the 1% level, suggesting that the difficulty of past targets increases the likelihood of adopting a SBT, relative to keeping targets aligned with internal standards. The odds-ratio on *past target*

[17] Our inferences are unchanged if we cluster standard errors at the sector or industry level.

completed is also in excess of 1 and is statistically significant at the 5% level, consistent with past target completion increasing the odds of setting a SBT. In terms of economic magnitudes, the estimates indicate that a one-standard deviation increase in *target ambition* from its mean (holding other covariates at their means) is associated with an increased likelihood of SBT adoption of 34%. For otherwise average firms, the predicted probability of adopting a SBT is 30% greater for firms that have completed a target in the past than for firms that have not.

With respect to economic incentives, the odds-ratio on *emissions/sales* exceeds 1 (significant at the 1% level), consistent with more carbon intensive firms being more likely to adopt SBTs. At the means of other covariates, the estimates suggest that a one-standard deviation increase in *emissions/sales* from its mean is associated with an increased likelihood of setting a SBT of 35%. However, we do not find evidence that higher revenues from low-carbon products (*low carbon revenue*) increases the probability of setting a SBT. This is consistent with SBTs relating principally to scope 1 and 2 emissions in our sample while low carbon revenues come from the sale of products, which reduce scope 3 emissions. We also find that firms perceiving more imminent climate change risks to their business, and firms perceiving a greater magnitude of impact from these risks, are more likely to set a SBT. Increasing *timeframe risk* (*magnitude risk*) by one standard deviation from its mean increases the likelihood of adopting a SBT by 26% (30%).

To summarize, our results suggest that past target ambition and completion, as well as economic incentives to reduce carbon emissions, predict who adopts external standards versus not adopting the science standards for their targets. Since economic incentives provide incremental predictive ability for SBT adoption, this suggests that firms (on average) set SBTs upon learning about optimal target setting from the science standards, rather than to adopt a label and legitimize their existing efforts.

7. Target Setting Difficulty

7.1 Model, Variables and Summary Statistics

Next, we assess whether the adoption of external standards increases target difficulty. Because firms set multiple targets (on average, firms set 4.3 targets) that differ by *scope*, *horizon* and SBT denotation, we conduct our analysis at the target level and follow specific targets over time through the adoption (or non-adoption) of science-based standards. To do so, we create a target-level panel dataset from 2014 to 2019; data are fairly evenly distributed across years.[18] While data are available prior to 2014, our analysis occurs at the target level and requires target identifiers. Before 2014, these identifiers were reported inconsistently and we are therefore unable to create a target-level panel dataset prior to 2014. From 2014 onwards, each emissions reduction target is given a target identifier from the CDP that distinguishes it from all other targets.[19]

To identify changes (if any) associated with SBT adoption, we define a target-level, time-variant dummy variable called *science target*. *Science target* takes the value of one in the year a target becomes a SBT and for every year after, zero otherwise. Our model estimates the effect of our independent variable, *science target,* on our dependent variable, *target difficulty*, after controlling for a series of target and firm characteristics. Equation 2 defines our estimation model:

$$\begin{aligned}\ln(Target\ difficulty)_{t,a} &= \beta_1\left(Science\ target_{t,a}\right) + \alpha_1\left(\ln\left(Horizon_{t,a}\right)\right) + \alpha_2\left(\ln(Coverage)_{t,a}\right) \\ &+ \alpha_3\left(\ln(Base\ year\ emissions)_{t,a}\right) + \theta_{t,f} + \delta_{a,s} + \gamma_t + \mu_f + \varepsilon_{t,a}\end{aligned}$$

Target characteristic controls include the natural logarithm of *horizon* in year *t* for target *a*, the natural logarithm of *coverage* in year *t* for target *a* and the natural logarithm of *base year emissions* in year *t* for target *a*. θ refers to a vector of financial controls in year *t* for firm *f*, which includes *ROA* and the natural logarithm of *total assets*, *Price-to-Book* and *CAPEX* scaled by total assets. δ represent scope fixed effects, γ represent year fixed effects and μ represent firm fixed effects. The inclusion of scope fixed effects allows

[18]Approximately 14% of our 7,557 target observations occur in 2014, 16% in 2015, 17% in 2016, 18% in 2017, 17% in 2018 and 18% in 2019.

[19] We expect targets that are adjusted to align with the SBT methodology to be predominantly altered by their *target difficulty*. Slight adjustments in *horizon* are expected to be minimal given that the SBTi instructs firms to choose base years that do not cover progress-to-date (in emissions reduction) in order to protect the integrity of the target. Therefore, we predict tracked targets to have similar, if not identical, *horizon* values across our sample. To confirm this, we compare each target's *horizon* in year *t* with its *horizon* in year *t+1*. A summary tabulation of the difference between $horizon_t$ and $horizon_{t+1}$ produces a mean value of 0.45 years and a median of 0 years. The 5th percentile is -1 years and the 95th percentile is 5 years. For robustness, we drop values at the 5th and 95th percentile (targets that may have been incorrectly matched) and observe virtually no effect on our results.

us to control for the effect of target scope on target setting.[20] Firm fixed effects absorb all observed and unobserved time-invariant firm characteristics, while the inclusion of year fixed effects controls for common macroeconomic shocks that affect all firms. The error term is denoted by ε for target *a* in year *t*.

Equation (2) uses a difference-in-differences framework where science and non-science targets of the same firm are benchmarked against each other. The key assumption of this model is that the mean outcome changes in the non-science targets are a valid estimate of the counterfactual mean outcome changes in the science targets. To test this, we plot the coefficient estimates in event time in Figure 1 to test if pre-period trends in *Target difficulty* are similar between the science and non-science targets of a firm. We find that the coefficients are close to zero and statistically insignificant in the time periods leading up to the adoption of science standards, suggesting that the parallel trends assumption is not violated.

Table 4a summarizes statistics for our sample of 7,557 target-year observations. The average *target difficulty* for our sample is 28.04, meaning that, on average firms target a 28% reduction in emissions over the time horizon of their targets. The standard deviation of this mean is 27.7%. Ioannou et al. (2016) utilize CDP for years 2011-2013 and find an average *target difficulty* of 20%, suggesting that target difficulty is increasing over time. The average *horizon* is 11 years (average base year is 2011 and average target year is 2022). Average *base year emissions* is 63 million metric tons of CO_2 equivalent. Across the entire sample, 52% of our targets are SBTs.

Table 4b presents the correlation matrix for the variables used in our analysis. The matrix shows a positive correlation between the natural logarithm of *target difficulty*, *horizon,* and *coverage* with whether the target is science-based (*science target*); correlations are 0.21, 0.22 and 0.12, respectively. Target difficulty and horizon show the strongest positive correlation at 0.48 (significant at the 1% level) consistent with longer targets allowing for smaller incremental (i.e., annual) emissions reductions over a longer time period, resulting in higher *target difficulty*.

7.2 Results: Target Setting Difficulty

[20] Our analysis includes targets that address scope 1 or scope 2 emissions. Included scopes are 1, 1+2, 1+2+3 and 2.

Table 5a presents the results of the estimation. The columns differ by the level of required *coverage*. Column 1 employs no restriction on *coverage*, column 2 restricts the sample to targets with at least 75% *coverage*, column 3 restricts *coverage* to 90% and column 4 requires full *coverage*. Due to these restrictions, observations decrease across the columns. The natural logarithm of *coverage* is included as a control in all columns, except column 4. The coefficients on *science target* are positive and significant across all specifications. The coefficient estimates suggest that targets that become align with science standards increase in magnitude between 20.9% and 25.6% on average, depending on target coverage.[21] We cluster standard errors at the firm level.[22]

The inclusion of firm fixed effects allows us to estimate changes in difficulty of targets that adopt science-based standards relative to changes in difficulty of targets *for the same firm that do not* adopt science-based standards. Although all of the firms in our sample set targets, some firms adopt science-based standards and other firms do not. Therefore, it is possible that differences across adopting and non-adopting firms introduce bias into our coefficient estimates. To help mitigate this concern, we use propensity scores to match firms that adopt science-based standards (*science firms*) and firms that do not (*non-science firms*) across a set of exogenous covariates that are likely to influence a firm's decision to adopt science-based standards. In particular, we match on *past target ambition*, *past target completed*, *ln(emissions/sales*), *ln(timeframe risk)* and *ln(magnitude risk)* because the estimates in Table 3 suggest that these covariates are associated with *science adoption*. We also match on factor variables for GICS sector and country of domicile. Matching covariates are measured in 2015, the year before firms start to adopt science-based standards. Panel A of Appendix 2 shows the matched sample of 330 *science* and *non-science* firm-pairs attained by employing single nearest-neighbor propensity score matching without replacement. Panel B of Appendix 2 illustrates how matching improves balance in the means of the covariates across the *science* and *non-science* samples. Each row in the table reports the means for the *science* and *non-science* firms and a *t*-statistic from the difference of means; matching produces balance across all covariates.

[21] For instance, the coefficient estimate on *Science Target* in column 1 is 0.19, therefore (exp(0.19)-1)*100 = 20.9%.
[22] Our inferences are unchanged if we cluster standard errors at the sector or industry level.

Table 5b presents results from estimating Equation 2 for our matched sample. Consistent with the results reported in Table 5a for the full (unmatched) sample, the coefficients on *science target* in Table 5b are positive and significant across all specifications. Moreover, matching produces larger, more economically significant estimates; the results suggest that targets of *science firms* that adopt SBT standards increase in difficulty between around 23.1% and 27.8% on average, depending on target coverage, relative to the targets of *science firms* that do not adopt SBT standards, and relative to the targets of matched *non-science firms*.

These results are consistent with firms, on average, increasing target difficulty after adopting science-based standards for those targets, rather than taking already-ambitious targets and relabeling them as science-based with no change in target difficulty. We note that this is in-line with our results from the determinants model, where we do not find supporting evidence for the "adopting a label" explanation behind why firms adopt SBT. However, given the voluntary nature of adopting SBTs, we caution against the interpretation that adopting SBTs *causes* firms to increase target difficulty. For instance, if firms were already planning to increase target difficulty and adopt SBTs (1) upon learning what constitutes difficult yet achievable targets according to science-based standards, (2) to add legitimacy to their target-setting efforts by obtaining the SBT certification, or (3) both, this could also be consistent with our findings. Our results in this section are therefore limited to the interpretation that target difficulty increases subsequent to adopting science-based targets as opposed to no change in target difficulty due to relabeling of already-difficult targets as science-based.

A limitation of our analyses is that we are unable to observe (and therefore unable to control for) the approach used by firms to set science-based targets. As discussed in section 4.2, the SBTi allows firms to choose one of three approaches to calculate carbon reduction targets based on science standards. Unfortunately, our data do not provide information on which approach firms have chosen among the sector-based approach, the economics-based approach, or the absolute-based approach. This creates an omitted variable concern because target difficulty and the adoption of science-based standards may be related to the approach selected by firms. However, we believe this omitted variable biases *against* our finding of increased target difficulty following the adoption of science-based standards, given our expectation that firms will choose the approach that yields the easiest science-based emissions target. Therefore, failing to control for the (unobservable) method should bias the coefficient on *science target* downwards, attenuating the positive relation we document between *science target* and *target difficulty.* Another concern is that firms "game" the SBT process by using false or misleading information as inputs to obtain easier targets that are approved by the SBTi. Although the SBTi assesses the validity of data provided by firms as inputs to their science-based targets (e.g., projected growth rates) and requires most inputs to be third-party verified (e.g., base year emissions and financial information), successful attempts to manipulate the process should also downward bias the positive association between SBT adoption and target difficulty.

8. Real Effects of External Standards for Target Setting

8.1 Model, Variables and Summary Statistics

Our results suggest that target difficulty increases after adopting science-based standards. However, prior literature suggests that companies often set targets they are unable, or do not intend, to achieve (e.g., Crilly et al. 2012; Crilly et al. 2016; Trexler and Schendler 2015). Although brand and reputation could suffer from failing to achieve publicly-disclosed targets, the long lag (i.e., ten years on average in our sample) between when a target is set and when it is meant to be achieved suggests that it may take several years before firms are penalized. Therefore, it is conceivable that firms adopt external standards and set more difficult targets without adjusting their behavior to enable target achievement. On the other hand, higher target difficulty resulting from the adoption of science standards could motivate firms to think beyond incremental efforts and adopt new, transformational approaches to reduce emissions. This would be consistent with the insights we obtained from semi-structured interviews we conducted with companies that adopted SBTs. Several interviewees highlighted how the adoption of science-based standards inspired collaboration between different functions (e.g., operations, sustainability, finance etc.) and increased information exchange, and joint efforts, projects and investments across teams to reduce emissions.

To test whether firms that adopt external standards increase their efforts to reduce carbon emissions, we create a firm-level panel dataset using CDP data on emissions reduction initiatives from 2011-2019 (not all dependent variables are available for the full panel). Equation 3 defines our model:

$$
\begin{aligned}
&Emissions\ Reduction\ Effort_{f,t} \\
&\quad = \beta_1(Science\ Firm_f) + \alpha_1(Post\ Science_{f,t}) + \alpha_2(\ln(Base\ year\ emissions)_{f,t}) \\
&\quad + \theta_{f,t} + \gamma_t + \mu_f + \varepsilon_{f,t}
\end{aligned}
$$

We measure firms' efforts to reduce carbon emissions using three variables: *investment required*, *monetary savings* and *CO_2 savings*. *Investment required* measures the total investment in USD ($) made by firm *f* in year *t* to fund emissions reduction initiatives implemented in the year. *Monetary savings* and *CO_2 savings* refer to annual savings in USD ($) and in metric tons of CO_2 equivalent, respectively, that firm *f* estimates will be saved from the initiatives implemented in year *t*. *Investment required*, *monetary savings* and *CO_2 savings* are the summations of all emissions reduction initiatives reported by a firm each year. *Science firm*, defined previously, takes the value of one if a firm ever sets a SBT, and 0 otherwise. *Post science* is our primary independent variable of interest and takes the value of one in the first year a firm sets a SBT and for every year thereafter, 0 otherwise. A positive coefficient on *post science* indicates that after adopting science-based standards, firms increase their efforts to reduce carbon emissions. θ refers to a vector of financial controls in year *t* for firm *f*, which includes *ROA* and the natural logarithm of *base year emissions, total assets*, *Price-to-Book* and *CAPEX* scaled by total assets. γ represent year fixed effects and μ represent firm fixed effects.

Table 6a summarizes statistics and Table 6b presents the correlation matrix for our climate change initiatives analysis. The average firm reports annual savings of $5.52 million from its emission reduction initiatives implemented in the year, $37.9 million in investments in climate change initiatives and 300 thousand metric tons of CO2 equivalent saved from climate change initiatives.[23] *Science firm* (*Post science*)

[23] *Monetary savings* and *investment required* are disclosed in currencies indicated by the reporting company; when reporting in currencies other than USD, we convert financial numbers using the exchange rate at the end of the year for which the data are reported. *CO_2 savings* are reported in metric tons of CO_2 equivalent.

is moderately positively associated with *monetary savings* at 0.12 (0.11), *investment required* at 0.14 (0.13) and *CO2 savings* at 0.08 (0.05). *Base year emissions* are strongly positively correlated with *monetary savings* (0.17), *investment required* (0.15) and *CO2 savings* (0.20), indicating that firms with higher base year emissions undertake climate change initiatives that have higher monetary savings, investment required and CO2 savings. The required investment in climate change initiatives is highly, positively associated with monetary savings from the initiatives at 0.68 and CO2 savings from the initiatives at 0.41.

In Figures 2-4, we plot the coefficient estimates in event time for *monetary savings, investment required* and *CO2 savings*, respectively, to assess whether, prior to adopting SBTs, the required investment, monetary saving and CO2 savings are similar between firms that eventually adopt SBTs and firms that do not. We find that the coefficients are statistically insignificant in the time periods leading up to the adoption of science standards, indicating that the parallel trends assumption is not violated.

8.2 Results: Real Effects of External Standards for Target Setting

Table 7a presents the results of OLS specifications for each of our dependent variables of interest, which are natural logarithm transformed: *investment required*, *CO_2 savings* and *monetary savings*. The specifications in columns 1, 4 and 7 include *science firm* as the independent variable of interest and provide baseline estimates of how the climate change initiatives of science firms compare to non-science firms, on average. Specifications in columns 2, 5 and 8 introduce *post science* in addition to *science firm*, allowing us to estimate the relation between adopting a SBT and climate change initiatives, controlling for the effect of being a science firm. All these specifications employ sector, country and year fixed effects, while the final specifications in columns 3, 6 and 9 use firm fixed effects instead of sector and country effects (but continue to employ year fixed effects). This allows us to perform *within-firm* analyses and assess whether, following the adoption of SBT, firms change their climate change initiatives.

In terms of science versus non-science firms, the estimates in columns 1, 4 and 7 suggest that the climate change initiatives for science firms have approximately 113% more *investment required*, 25% more *CO_2*

savings and result in 79% more *monetary savings* relative to non-science firms.[24] The ratio of the coefficients between *investment required* and *CO_2 savings* indicates that a 3.35% increase in *investment required* is associated with about a 1% reduction in annual CO_2 production.

In terms of climate change initiatives following SBT adoption, regardless of the use of country and sector versus firm fixed effects, the coefficients on *post science* are positive and statistically significant (at the 5% level or better) for the *investment required*, *CO_2 savings* and *monetary savings* dependent variables. In particular, the results in Columns 2 and 3 suggest that setting SBTs is associated with increased expenditures on climate change initiatives between 60% and 64%, resulting in annual *CO_2 savings* between 17% and 19% (Columns 5 and 6) and annual *monetary savings* between 22% and 33%. Given these estimates, we expect the percent change in *investment required* to be 3.35 times greater than the percent change in *CO_2 savings* if the internal rate of return for *CO_2 savings* remains constant following the adoption of SBTs. However, the coefficient estimates indicate that the percent increase in *investment required* is between 3.1 and 2.7 times greater than the percent increase in *CO_2 savings*, suggesting that investments are becoming more efficient in reducing annual CO_2 production.[25]

Table 7b replicates the analysis for a sample of matched science and non-science firms, to help address the concern that differences across these two groups bias the coefficients reported in Table 7a (see Section 7.2 for a description of our matching approach). The results for the matched sample are consistent with the results for the full sample, but some of economic magnitudes are smaller. For instance, climate change initiatives for science firms have approximately 63% more investment required and result in 19% more emissions savings and 56% more monetary savings, relative to matched non-science firms. Moreover, SBT-adoption is related to increased investment of 49%, and emissions and monetary savings of 29% and 23%, respectively (Columns 3, 6 and 9).

[24] For instance, the estimate on *Science firm* in Column 1 is 0.759, therefore (exp(0.759)-1)*100 = 112.9%.
[25] In untabulated analyses, we examine the association between science-based targets and payback periods from climate change initiatives. The relation is insignificant across all specifications suggesting that the initiatives that are undertaken by a firm after adopting SBTs do not have different payback periods.

Taken together, our findings suggest that relative to non-science firms, firms that set SBTs have higher investment in, and higher expected emissions and monetary savings from, their emissions reduction initiatives. After setting SBTs, firms increase the expected monetary and emissions savings from their initiatives and require greater up-front investment in these initiatives.

8.3 Robustness: Real Effects of External Standards for Target Setting

8.3.1 Disentangling target difficulty from SBT adoption

Tables 7a and 7b suggest that adopting SBTs is associated with increasing target difficulty and undertaking real efforts and investments to reduce emissions. However, the results reported in Table 5 suggest that firms that set SBTs have more difficult carbon emissions reduction targets relative to firms that do not set SBTs. Consequently, our results do not distinguish whether the changes in climate change initiatives are attributable to SBT-adoption, rather than being due to firms with more ambitious targets adopting different climate change initiatives than firms with less ambitious targets. For instance, since the SBTi showcases firms with approved SBTs on its website and firms use the SBT logo in promoting their environmental efforts, certification from the SBTi may increase the external visibility of firms' carbon targets which could result in greater stakeholder pressure on firms to change internal behaviors to achieve the targets. It is also possible that aligning targets with a goal that has importance beyond the firm (i.e., to mitigate climate change and global warming) increases effort if firms are motivated to achieve a goal that they perceive as meaningful. The experimental ideal would randomly assign firms to set (or not set) SBT and assess the effect of setting SBT on climate change initiatives; given that this is infeasible, we control for target difficulty and assess whether setting science-based targets is related to firms' real behaviors.

To do this, we conduct two tests. For the first test, we repeat our Table 7a analyses for firms that set ambitious targets but do not identify them as being science-based in the CDP survey response, which we presume to mean that the targets are not certified by the SBTi. We label such firms as *ambitious firm* and their targets as *ambitious targets*. *Ambitious firm* is a firm-specific, time-invariant indicator, which we identify by estimating separate annual cross-sectional models for 2016-2019 as in Equation 2 but omitting the *Science target* indicator. We take the residuals and calculate, for each firm-year, the difference between its residual and the average residual for all science-based targets in the firm's sector in that year. *Ambitious firm* takes the value of one if a firm's residual in any of 2016-2019 is greater than or equal to the average residual for all science-based targets in the firm's sector in that year, as long as the firm does not ever set a science-based target; effectively, these firms set targets that are at least as ambitious as those of the science-based targets of its sectoral peers. We also define *Ambitious target* which takes the value of one in the year that a firm is first identified as an *ambitious firm* and every year thereafter, 0 otherwise.

The results in Table 8 show that the coefficient estimate on *ambitious firm* is only positive and significant for *monetary savings* (column 8). Unlike the analogous results in Table 7a for science firms, ambitious firms have not been investing more in climate change initiatives or saving relatively more CO_2. More importantly, however, is that the coefficient estimate on *ambitious target* is insignificant across all specifications. This stands in contrast to the positive and significant coefficient estimates on *post science* in Table 7a. These results are consistent with firms undertaking real efforts and investments to reduce emissions following the adoption of SBT, as opposed to firms with ambitious targets – that are not certified by the SBTi – changing behaviors following the release of the SBT standards.

The second way we address this concern is by explicitly control for target ambition in our real effects models. We measure *target ambition* as the natural logarithm of the *target difficulty* divided by *horizon* multiplied by *coverage* (i.e., 100% *coverage* scales the value by 1, while 90% *coverage* scale the value by 0.9), averaged over the firm's targets in a year. If setting a SBT has an incremental effect on organizational initiatives and investment, we expect the interaction between *post science* and *target ambition* to be positive and significant even when controlling for *target ambition*. Table 9 presents the results, which support our expectation. Specifically, firms with more ambitious targets save more money and CO_2 annually, and invest more in their climate change initiatives. In addition, the estimates on the interaction terms are positive and significant across all specifications, consistent with the relation between target ambition and investments, monetary savings, CO_2 savings being stronger for firms that set SBTs.

Overall, our tests provide evidence consistent with SBT-adoption having an incremental effect on investments and behaviors to reduce carbon emissions, after accounting for the effect of target ambition.

9. Conclusion

In this paper, we study the determinants and consequences of adopting external standards for target setting. Our setting is the development of an external "science-based" standard for setting carbon emissions reduction targets, where the targets adopted by firms are considered science-based if they are in line with what climate science says is necessary to meet the goals of the Paris Agreement – to limit global warming to well-below 2°C above pre-industrial levels and pursue efforts to limit warming to 1.5°C.

Using a novel dataset compiled by the CDP that includes over 1,752 unique firms from around the world, we find that firms with a track record of ambitious and successful target completion are more likely to adopt external standards for setting carbon targets as opposed to keeping targets aligned with internal standards. While this result alone does not allow us to distinguish whether firms opt for external standards to confer legitimacy on their existing efforts (i.e., adopt a label) or whether firms adopt science-based standards to resolve uncertainty about optimal emissions targets (i.e., adopting from learning), we also find that economic incentives predict adoption of external standards. Given that firms with economic incentives to reduce emissions are more likely to *already* set ambitious targets and therefore adopt the label, our results imply that firms face uncertainty about optimal target setting for emissions and, in the presence of economic incentives to reduce emissions, firms adopt external standards upon learning what constitutes tough but achievable targets according to science standards, or to create external pressure to reduce their emissions.

Next, we examine whether the adoption of external standards to set targets is positively related to target difficulty. Because firms set multiple carbon emissions targets, we conduct our analysis at the target level and follow specific targets through the adoption (or non-adoption) of external standards. Our results suggest that targets that become aligned with the science-based standard (relative to targets set by the same firm that do *not* become aligned with the external standard) increase in magnitude between 21% and 25% on average, depending on target coverage. This is consistent with firms, on average, increasing target difficulty subsequent to adopting science-based standards for those targets, rather than taking already-ambitious targets and relabeling them as science-based with no change to target difficulty.

We also document that SBT-adopting firms change investments and behaviors in ways that are likely to reduce emissions. Specifically, we find that the required investment in and expected monetary and carbon emissions savings from emissions reduction initiatives increases after firms adopt SBTs (our results are robust to the inclusion of firm fixed effects). This is consistent with real effects from the adoption of external standards for target setting, as opposed to firms adopting external standards as a marketing ploy, a symbolic act, or “cheap talk”.

Given that science targets are more ambitious than non-science targets, we assess whether the adoption of science standards has an incremental effect on firm behavior over the effect of target difficulty. To do this, we examine a sample of firms that set targets that are as (or more) difficult than the science-based targets in the firm’s sector, but these firms do not identify their targets as science-based in their CDP response. If target difficulty drives our results, we expect to find similar real effects for these ambitious, but not science, firms. Following the introduction of SBT standards, we do not find that these ambitions firms change their efforts to reduce emissions. We also explicitly control for target difficulty in our specifications and find that the science standard has incremental real effects over the target’s difficulty. This suggests that there are incremental real effects of adopting SBTs over the effects of target difficulty, such as additional external pressure on firms to achieve targets that become more visible after certification, or greater motivation to achieve targets that are part of a collaborative effort to limit global warming.

Our study contributes to two streams of literature. First, we contribute to the literature on how firms set targets and the actions they take to achieve them. The vast literature on target setting prescribes that targets should be set at levels that are both difficult and attainable, but there is a dearth evidence on how firms choose between internal versus external standards and the performance implications arising from these choices. We address this gap by examining the factors influencing firms’ decisions to use external versus internal standards for target setting, and the implications for target setting and real behaviors. Second, we contribute to the literature on corporate sustainability and specifically, climate change. We add to this literature by analyzing the effect that an external standard for setting carbon emissions targets has on target difficulty and the investments that organizations make to reduce carbon emissions.

Although we find that target difficulty increases and real behaviors change following the adoption of external standards, a limitation of our study is that it is too early (at the time of this manuscript's writing) to assess the overall impact of the SBTi on corporate carbon emissions; undoubtedly, this is an important question for future study. The impact on the innovation process could be another fruitful avenue for future research; because science-based targets are harder to achieve, how do organizations innovate to achieve the targets in an economically efficient way? These, and other related questions, could further our understanding of the process through which firms set targets and the actions taken to achieve them.

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Figures

Figures 1-4 report the coefficients in event time of OLS regressions estimating the association between adopting science-based standards and various outcomes (defined in Appendix 1). For Figure 1 (Figures 2-4), we estimate Equation 2 (3) but replace *Science target* (*Post science*) with time indicators marking time periods relative to when science standards are adopted (t=0). The indicator for year t=0 serves as the benchmark period with an OLS coefficient and standard error of zero. Vertical lines represent 95% confidence intervals for the point estimates in each time period.

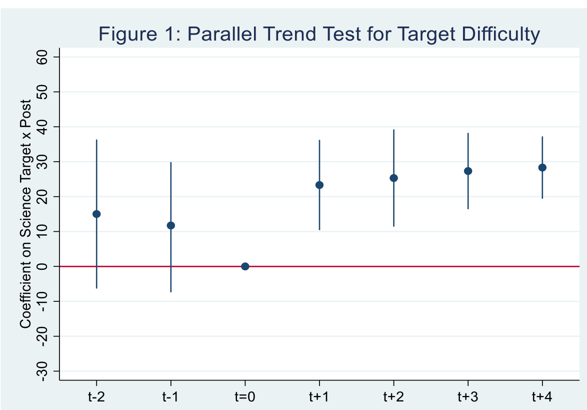

Figure 1: Parallel Trend Test for Target Difficulty

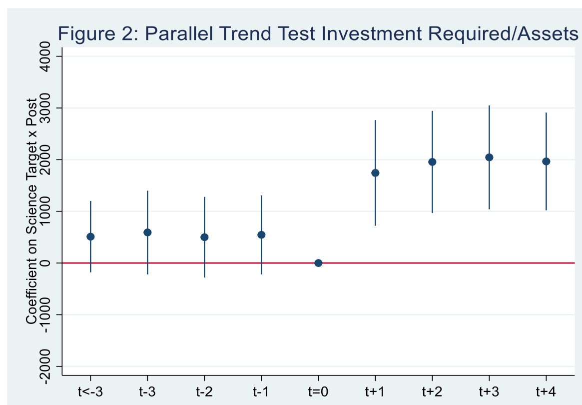

Figure 2: Parallel Trend Test Investment Required/Assets

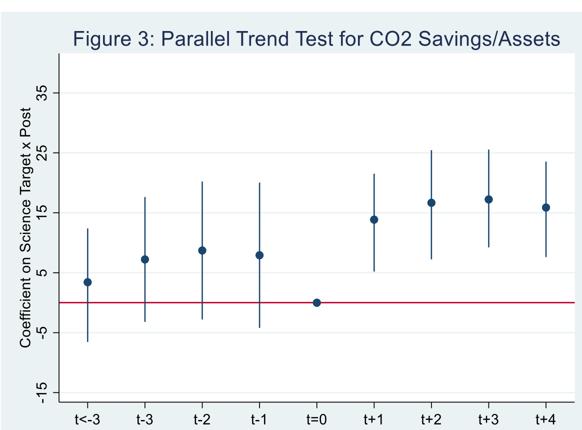

Figure 3: Parallel Trend Test for CO2 Savings/Assets

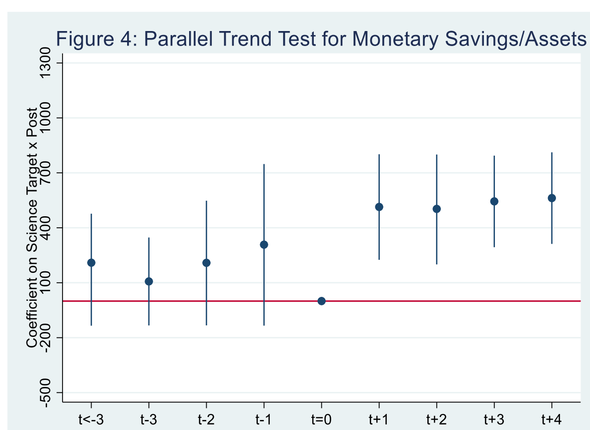

Figure 4: Parallel Trend Test for Monetary Savings/Assets

Table 1a. Target Setting by Country

	Science Based Targets					Non-Science Based Targets				
Country	Obs.	Target Difficulty	Horizon	Coverage	Base Year Emissions	Obs.	Target Difficulty	Horizon	Coverage	Base Year Emissions
Australia	131	28.3	7.4	84.2	311,423	73	30.3	10.0	70.6	5,890,395
Austria	49	53.0	21.5	91.6	2,191,758	13	12.4	2.9	33.6	2,435,113
Belgium	46	36.3	11.2	94.3	93,863	12	43.1	6.9	91.6	3,388,570
Bermuda						1	3.0	4.0	100.0	45,725
Brazil	59	12.3	6.7	86.3	4,465,046	122	10.1	4.1	70.7	908,387
Canada	41	31.2	16.2	66.0	14,000,000	217	32.4	9.5	69.2	1,340,226
Chile	1	40.0	13.0	100.0	71,886	2	16.5	3.0	93.0	39,707
China	3	4.3	1.0	33.7	22,700	34	28.3	10.0	90.4	6,377,396
Colombia	20	20.8	8.1	84.0	11,368	9	7.5	3.1	82.6	2,578,501
Cyprus	5	10.0	3.8	100.0	111,689					
Czech Republic						2	35.0	4.0	100.0	12,662
Denmark	34	40.4	9.9	99.4	478,411	19	36.1	9.2	94.6	921,796
Finland	72	33.9	12.8	89.7	162,948	92	22.1	8.8	84.3	788,537
France	211	30.4	12.6	76.4	7,373,073	77	16.2	4.9	60.2	2,595,088
Germany	121	40.1	12.2	79.7	2,269,051	124	33.6	10.4	84.4	4,767,783
Greece						16	9.5	6.1	100.0	169,430
Hong Kong	26	20.5	7.1	88.4	5,083,134	18	15.3	8.7	60.8	80,283
Hungary	8	27.6	8.5	100.0	117,395	2	13.0	6.0	55.0	4,129,901
India	59	35.0	11.8	95.6	445,260	26	45.3	6.4	94.2	3,789,720
Indonesia						2	2.0	1.0	100.0	4,401,610
Ireland	48	63.4	11.0	73.4	288,719	7	7.8	5.1	99.1	55,699
Israel						17	15.8	5.5	87.0	1,357,934
Italy	60	42.0	8.7	82.8	2,410,071	194	21.9	7.2	67.2	1,638,497
Japan	741	32.2	18.1	86.7	3,146,437	583	18.1	14.3	75.9	3,457,193
Mexico	16	34.9	16.7	95.6	584,007	11	20.0	5.2	82.7	192,710
Netherlands	101	48.6	12.6	92.0	523,118	41	25.6	4.8	75.8	608,220

New Zealand	28	28.1	11.7	86.9	210,546	10	14.6	6.2	92.1	502,010
Norway	84	42.1	14.3	71.7	117,798	57	21.1	6.1	89.7	2,644,455
Philippines						2	2.6	7.5	100.0	41,193
Poland						2	12.5	1.0	100.0	31,197
Portugal	40	28.2	8.8	96.9	4,520,878	22	21.7	7.5	46.0	37,403
Russia	9	18.2	6.3	73.5	60,800,000					
Singapore	7	16.3	7.3	86.7	280,674	7	69.8	7.7	56.6	831,417
South Africa	115	21.7	10.8	85.3	1,724,517	143	16.0	7.1	74.2	3,591,436
South Korea	106	19.0	11.6	92.5	1,326,393	235	20.9	11.9	94.1	1,704,031
Spain	206	32.3	13.9	83.5	9,437,504	193	25.9	6.2	72.2	821,679
Sweden	47	51.9	14.5	87.0	1,097,460	77	36.8	7.8	72.6	795,642
Switzerland	88	29.3	9.9	89.1	1,106,382	110	18.7	8.8	70.6	185,628
Taiwan	92	14.7	7.7	86.1	1,458,039	58	15.0	9.4	87.3	682,419
Thailand						21	9.4	6.3	97.9	9,585,202
Turkey	24	17.9	5.5	69.9	70,405	94	21.6	5.3	66.9	111,608
USA	837	35.8	13.2	90.5	546,000,000	567	23.6	8.4	82.6	4,472,915
United Kingdom	395	36.3	13.4	84.0	3,520,315	315	19.9	7.3	76.7	1,532,910
	Total	Mean	Mean	Mean	Mean	Total	Mean	Mean	Mean	Mean
	3,930	33.4	13.3	86.2	119,000,000	3,627	22.2	9.0	77.3	2,513,411

This tables presents the frequency of science-based and non-science based targets by country, along with the associated averages for *target difficulty*, *horizon*, *coverage* and *base year emissions* by country and science/non-science targets. Variables are defined in Appendix 1. Missing data indicates that data are unavailable for the respective target category.

Table 1b. Target Setting by Sector

	Science Based Targets					Non-Science Based Targets				
Country	Obs.	Target Difficulty	Horizon	Coverage	Base Year Emissions	Obs.	Target Difficulty	Horizon	Coverage	Base Year Emissions
Consumer Discretionary	445	33.7	12.7	87.2	6,014,650	389	25.0	11.5	76.4	3,294,823
Consumer Staples	318	34.5	15.7	90.4	2,110,099	244	24.5	10.2	67.6	618,734
Energy	91	28.6	8.3	73.5	11,100,000	164	19.7	6.7	68.6	7,780,937
Financials	540	34.8	12.0	91.5	322,948	700	28.4	8.5	82.4	235,308
Health Care	237	32.9	12.6	92.3	1,006,859	176	19.2	5.4	69.8	203,702
Industrials	707	33.8	14.5	79.8	1,270,149	728	17.4	8.4	77.9	1,068,108
Information Technology	467	33.8	12.9	89.5	966,000,000	311	21.2	8.0	85.8	657,722
Materials	282	24.7	13.9	88.1	4,621,305	398	17.8	11.7	82.3	6,695,017
Real Estate	220	29.8	10.6	89.3	254,912	147	18.1	6.5	79.0	269,264
Telecommunication Services	219	40.2	12.9	86.8	635,435	140	25.9	9.0	89.9	2,036,195
Utilities	404	35.0	14.9	78.3	22,700,000	230	25.1	8.8	55.5	9,719,328
	Total	Mean	Mean	Mean	Mean	Total	Mean	Mean	Mean	Mean
	3,930	33.4	13.3	86.2	119,000,000	3,627	22.2	9.0	77.3	2,513,411

This tables presents the frequency of science-based and non-science based targets by sector, along with the associated averages for *target difficulty*, *horizon*, *coverage* and *base year emissions* by sector and science/non-science targets. Variables are defined in Appendix 1. Missing data indicates that data are unavailable for the respective target category.

Table 2a. Summary Statistics – Science Target Adoption Determinants Model

Variable	Obs.	Mean	P50	Std. Dev.	Min	Max
Science Firm	1,752	0.22	0	0.41	0	1
Past Target Ambition	1,752	0.94	0.91	0.49	0	4.62
Past Target Completed	1,752	0.75	1	0.44	0	1
Low Carbon Revenue	1,752	15.22	0	29.26	0	100
Emissions/Sales	1,752	1208.13	29.29	36,203	0.00	1,513,446
Likelihood Risks	1,752	5.44	5.50	1.19	1	8
Timeframe Risks	1,752	2.30	2.27	0.81	1	4
Magnitude Risk	1,752	2.91	3.00	1.03	1	5
CAPEX/Total Assets	1,752	0.04	0.03	0.04	0	0.20
Total Assets	1,752	58,021	9,858	180,798	315	1,531,100
Price-to-Book	1,752	2.68	1.78	2.85	0.21	20.09
ROA	1,752	4.77	4.05	5.54	-9.25	20.16
Volatility	1,752	29.67	27.09	10.47	13.63	69.81

All variables are defined in Appendix 1. Financial variables are winsorized at 1- and 99-percent levels.

Table 2b. Correlation Matrix – Science Target Adoption Determinants Model

	Science Firm	Past Target Ambition	Past Target Completed	ln(Low Carbon Revenue)	ln(Emissions/ Sales)	ln(Likelihood Risks)	ln(Timeframe Risks)	ln(Magnitude Risk)	ln(CAPEX/ Total Assets)	ln(Total Assets)	ln(Price-to-Book)	ROA
Science Firm	1											
Past Target Ambition	**0.06**	1										
Past Target Completed	-0.05	**-0.07**	1									
ln(Low Carbon Revenue)	0.01	0	**0.05**	1								
ln(Emissions/Sales)	**0.1**	**-0.12**	-0.01	**0.08**	1							
ln(Likelihood Risks)	0	-0.03	0.03	0.01	0.02	1						
ln(Timeframe Risks)	**0.05**	0.01	0.04	-0.03	**0.08**	**0.19**	1					
ln(Magnitude Risk)	**0.05**	**-0.07**	-0.02	**0.12**	**0.07**	**0.28**	0	1				
ln(CAPEX/Total Assets)	0.05	**-0.09**	**-0.05**	**0.09**	**0.26**	0.02	-0.04	**0.1**	1			
ln(Total Assets)	**0**	0.01	**0.11**	-0.03	**-0.05**	0.01	0.03	**-0.09**	**-0.25**	1		
ln(Price-to-Book)	0.03	**0.11**	0.03	**-0.08**	**-0.07**	**-0.09**	0.02	**-0.14**	**0.07**	**-0.19**	1	
ROA	-0.01	0.04	0.01	-0.01	**-0.07**	-0.03	-0.03	**-0.08**	**0.12**	**-0.21**	**0.45**	1
ln(Volatility)	0	-0.01	-0.03	0.01	**0.08**	0.01	0.03	**0.13**	**0.12**	**-0.27**	**-0.2**	**-0.24**

This table presents Pearson Correlations for variables defined in Appendix 1; bold indicates significance at 5% or better.

Table 3. Science Target Adoption Determinants Model

VARIABLES	Science Firm (Odds ratio)
ln(Past Target Ambition)	1.408***
	(0.129)
Past Target Completed	1.525**
	(0.047)
ln(Low Carbon Revenue)	1.000
	(0.056)
ln(Emissions/Sales)	1.122***
	(0.043)
ln(Likelihood Risk)	0.650
	(0.160)
ln(Timeframe Risk)	1.829***
	(0.278)
ln(Magnitude Risk)	1.760**
	(0.456)
ln(CAPEX/Total Assets)	11.73
	(45.75)
ln(Total Assets)	0.985
	(0.058)
ROA	0.981
	(0.019)
ln(Price-to-Book)	1.266
	(0.203)
ln(Volatility)	0.925
	(0.278)
Constant	0.068*
	(0.101)
Sector FE	Yes
Country FE	Yes
Observations	1,752
Pseudo R-Squared	0.071

Observations are unique firms and all independent variables correspond to values in 2016, apart from *Past Target Ambition* and *Past Target Completed*, which are averaged over the period prior to 2016. Variables are defined in Appendix 1. Sector and country fixed effects are included in the regressions. Coefficients are reported in odds ratios. Standard errors are clustered at the sector level and reported in parenthesis. Significance levels are indicated by $*$, $**$, $***$ for 10%, 5%, and 1%, respectively.

Table 4a. Summary Statistics – Target Setting Analysis

Variable	Obs.	Mean	P50	Std. Dev.	Min	Max
Target Difficulty	7,557	28.04	20	27.68	0	100
Base Year	7,557	2011	2012	5	1990	2019
Target Year	7,557	2022	2020	9	2005	2100
Horizon	7,557	11	8	11	0	95
Coverage	7,557	82	100	31.9	0	100
Base Year Emissions	7,557	63	0.17	51.80	0	4510
Science Target	7,557	0.52	1	0.50	0	1
Total Assets	7,557	89,267	13,457	225,300	332	1,546,000
ROA	7,557	4.21	3.46	5.29	-11.78	23.83
Price-to-Book	7,557	2.56	1.67	2.91	0.24	19.58
CAPEX	7,557	1,153	312	2,510	0	17,080

All variables are defined in Appendix 1. Financial variables winsorized at 1- and 99-percent levels.

Table 4b. Correlation Matrix – Target Setting Analysis

	Science Target	ln(Target Difficulty)	ln(Horizon)	ln(Coverage)	ln(Base Year Emissions)	ln(Total Assets)	ROA	ln(Price-to-Book)
Science Target	1							
ln(Target Difficulty)	**0.21**	1						
ln(Horizon)	**0.22**	**0.48**	1					
ln(Coverage)	**0.12**	**0.15**	**0.23**	1				
ln(Base Year Emissions)	**0.13**	**0.14**	**0.34**	**0.31**	1			
ln(Total Assets)	**0.04**	**0.13**	**0.13**	**0.04**	**0.26**	1		
ROA	**0.06**	**0.02**	0	**0.08**	**-0.04**	**-0.23**	1	
ln(Price-to-Book)	**0.11**	**0.03**	**-0.03**	**0.03**	-0.02	**-0.19**	**0.45**	1
ln(CAPEX/Total Assets)	**-0.04**	**-0.09**	0	**-0.08**	**0.2**	**-0.3**	**0.17**	**0.08**

This table presents Pearson Correlations for variables defined in Appendix 1; bold indicates significance at 5% or better.

Table 5a. Baseline Target Setting Regressions – Relation between Adopting Science Based Targets and Target Difficulty

	(1) ln(Target Difficulty)	(2) ln(Target Difficulty)	(3) ln(Target Difficulty)	(4) ln(Target Difficulty)
Science Target	0.191**	0.223***	0.228***	0.223***
	(0.064)	(0.066)	(0.066)	(0.069)
ln(Horizon)	0.817***	0.808***	0.805***	0.767***
	(0.035)	(0.043)	(0.051)	(0.054)
ln(Coverage)	-0.0254	0.188	1.599	
	(0.027)	(0.350)	(1.722)	
ln(Base Year Emissions)	0.007	-0.013	-0.013	-0.012
	(0.019)	(0.027)	(0.030)	(0.031)
ROA	0.002	0.0002	0.001	0.001
	(0.006)	(0.004)	(0.004)	(0.005)
ln(Total Assets)	-0.137*	-0.0900*	-0.0956*	-0.0748
	(0.061)	(0.046)	(0.050)	(0.060)
ln(Price-to-Book)	-0.0298	0.0183	0.0181	-0.0168
	(0.047)	(0.044)	(0.049)	(0.059)
ln(CAPEX/Total Assets)	-1.424*	-0.548	-0.432	-0.076
	(0.768)	(0.821)	(0.969)	(1.200)
Constant	2.387***	1.137	-5.263	2.003**
	(0.694)	(1.594)	(8.476)	(0.855)
Required Coverage	All	75%	90%	100%
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Scope Fixed Effects	Yes	Yes	Yes	Yes
Observations	7,557	5,838	5,365	4,592
R-squared	0.735	0.779	0.786	0.785

Observations are target-years. Variables are defined in Appendix 1. Column 1 places no restriction on *coverage* for inclusion in the model. Columns 2, 3 and 4 restrict the sample to targets with at least 75%, 90% and 100% *coverage*, respectively. Firm, year and scope fixed effects are included in the regressions. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by ∗, ∗∗, ∗∗∗ for 10%, 5%, and 1%, respectively.

Table 5b. Matched Sample Target Setting Regressions – Relation between Adopting Science Based Targets and Target Difficulty

	(1) ln(Target Difficulty)	(2) ln(Target Difficulty)	(3) ln(Target Difficulty)	(4) ln(Target Difficulty)
Science Target	0.208**	0.236**	0.242**	0.246**
	(0.068)	(0.075)	(0.078)	(0.084)
ln(Horizon)	0.843***	0.847***	0.843***	0.796***
	(0.033)	(0.041)	(0.047)	(0.038)
ln(Coverage)	-0.049	0.355	2.166	
	(0.037)	(0.429)	(1.791)	
ln(Base Year Emissions)	0.021	-0.002	-0.004	-0.008
	(0.023)	(0.033)	(0.035)	(0.038)
ROA	0.001	-0.002	-0.002	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Total Assets)	-0.162*	-0.143*	-0.141*	-0.144
	(0.077)	(0.068)	(0.072)	(0.086)
ln(Price-to-Book)	-0.018	0.041	0.047	-0.005
	(0.049)	(0.054)	(0.053)	(0.071)
ln(CAPEX/Total Assets)	-1.913**	-1.344	-1.361	-1.019
	(0.724)	(1.059)	(1.318)	(1.550)
Constant	2.529**	0.708	-7.582	2.617*
	(0.910)	(2.175)	(8.849)	(1.208)
Required Coverage	All	75%	90%	100%
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Scope Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,179	4,035	3,665	3,071
R-squared	0.720	0.768	0.778	0.776

Table 5b replicates the results of Table 5a with a propensity score matched sample. Variables are defined in Appendix 1. Column 1 places no restriction on *coverage* for inclusion in the model. Columns 2, 3 and 4 restrict the sample to targets with at least 75%, 90% and 100% *coverage*, respectively. Firm, year and scope fixed effects are included in the regressions. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by ∗, ∗∗, ∗∗∗ for 10%, 5%, and 1%, respectively.

Table 6a. Summary Statistics – Emissions Reduction Initiatives

Variable	Obs.	Mean	P50	Std. Dev.	Min	Max
Monetary Savings	14,143	5,523,373	236,923	1,910,000	0	137,000,000
Investment Required	14,143	37,900,000	508,530	18,400,000	0	1,430,00,000
CO2 Savings	14,143	162,777	26,350	714,533	0	5,400,000
Base Year Emissions	14,143	3,861,298	191,015	28,600,000	0	2,030,000,000
Total Assets	14,143	58,232	9,577	167,031	277	1,201,400
Price-to-Book	14,143	2.69	1.80	2.87	0.15	19.59
CAPEX	14,143	923	261	1,967	0	13,450
ROA	14,143	4.78	4.03	5.85	-13.50	25.26
Science Firm	14,143	0.34	0	0.47	0	1
Post Science	14,143	0.13	0	0.34	0	1
Target Ambition	14,143	0.76	0.78	0.62	0	4.62

All variables are defined in Appendix 1. Financial variables winsorized at 1- and 99-percent levels.

Table 6b. Correlation Matrix – Emissions Reduction Initiatives

	Science Firm	Science Target	Target Ambition	ln(Base Year Emissions)	ln(Monetary Savings)	ln(Investment Required)	ln(CO2 Savings)	ln(Total Assets)	ln(Price-to-Book)	ln(CAPEX/Total Assets)
Science Firm	1									
Post Science	**0.49**	1								
Target Ambition	**0.18**	**0.19**	1							
ln(Base Year Emissions)	**0.05**	**-0.14**	-0.01	1						
ln(Monetary Savings)	**0.12**	**0.11**	**0.16**	**0.17**	1					
ln(Investment Required)	**0.14**	**0.13**	**0.15**	**0.15**	**0.68**	1				
ln(CO2 Savings)	**0.08**	**0.05**	**0.05**	**0.2**	**0.43**	**0.41**	1			
ln(Total Assets)	**0.16**	**0.07**	**0.12**	**0.16**	**-0.12**	**-0.06**	**-0.08**	1		
ln(Price-to-Book)	-0.01	**0.04**	**0.08**	**-0.06**	**0.05**	**0.03**	0	**-0.21**	1	
ln(CAPEX/Total Assets)	**-0.04**	-0.03	**-0.08**	**0.19**	**0.21**	**0.17**	**0.25**	**-0.22**	**0.06**	
ROA	0	**0.02**	**0.05**	**-0.06**	**0.06**	**0.06**	0	-0.01	**-0.22**	**0.48**

This table presents Pearson Correlations for variables defined in Appendix 1; bold indicates significance at 5%.

Table 7a. Climate Change Initiatives Regressions – Relation between Adopting Science Based Targets and Emissions Reduction Initiatives

	(1) ln(Investment Required)	(2) ln(Investment Required)	(3) ln(Investment Required)	(4) ln(CO2 Savings)	(5) ln(CO2 Savings)	(6) ln(CO2 Savings)	(7) ln(Monetary Savings)	(8) ln(Monetary Savings)	(9) ln(Monetary Savings)
Science Firm	0.756***	0.572***		0.226***	0.202***		0.584***	0.477***	
	(0.0858)	(0.100)		(0.0325)	(0.0480)		(0.0625)	(0.0792)	
Post Science		0.496***	0.473***		0.158**	0.176**		0.289***	0.196**
		(0.103)	(0.121)		(0.060)	(0.072)		(0.080)	(0.084)
ln(Base Year Emissions)	0.079***	0.079***	0.013	0.033***	0.033***	0.002	0.069***	0.069***	0.007
	(0.007)	(0.007)	(0.010)	(0.005)	(0.005)	(0.003)	(0.010)	(0.010)	(0.006)
ln(Total Assets)	0.065**	0.064*	-0.210	-0.009	-0.009	-0.180***	0.065	0.064	-0.187**
	(0.028)	(0.028)	(0.147)	(0.015)	(0.015)	(0.055)	(0.037)	(0.037)	(0.079)
ln(Price-to-Book)	0.016	0.0142	0.290**	-0.006	-0.007	-0.006	-0.054	-0.056	-0.034
	(0.100)	(0.098)	(0.111)	(0.052)	(0.053)	(0.056)	(0.082)	(0.083)	(0.082)
ln(CAPEX/Total Assets)	6.536***	6.482***	1.706	4.718***	4.712***	1.346	7.561***	7.529***	0.753
	(1.367)	(1.378)	(1.910)	(1.145)	(1.149)	(0.848)	(1.327)	(1.326)	(1.405)
ROA	0.029***	0.029***	0.013**	-0.001	-0.001	-0.002	0.011*	0.011*	0.001
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)
Constant	0.195	0.237	3.816**	0.748***	0.754***	2.573***	-0.459	-0.435	3.552***
	(0.406)	(0.398)	(1.253)	(0.177)	(0.171)	(0.528)	(0.354)	(0.350)	(0.744)
Sector FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Country FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	14,143	14,143	14,143	14,143	14,143	14,143	14,143	14,143	14,143
R-squared	0.173	0.174	0.585	0.186	0.186	0.598	0.199	0.199	0.585

Variables are defined in Appendix 1. Observations are firm-years. For each dependent variable, respectively, columns 1 and 2 include sector, country and firm fixed effects. Column 3 removes sector and country effects and introduces firm fixed effects. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by ∗, ∗∗, ∗∗∗ for 10%, 5%, and 1%, respectively.

Table 7b. Matched Sample Regressions – Relation between Adopting Science Based Targets and Emissions Reduction Initiatives

OLS models	(1) ln(Investment Required)	(2) ln(Investment Required)	(3) ln(Investment Required)	(4) ln(CO2 Savings)	(5) ln(CO2 Savings)	(6) ln(CO2 Savings)	(7) ln(Monetary Savings)	(8) ln(Monetary Savings)	(9) ln(Monetary Savings)
Science Firm	0.490***	0.375***		0.170***	0.136**		0.445***	0.400***	
	(0.0722)	(0.0784)		(0.0415)	(0.0576)		(0.0659)	(0.0677)	
Post Science		0.352**	0.397***		0.230**	0.253**		0.239*	0.207**
		(0.116)	(0.110)		(0.098)	(0.101)		(0.128)	(0.087)
ln(Base Year Emissions)	0.052***	0.052***	0.001	0.028***	0.028***	-0.004	0.056***	0.056***	-0.001
	(0.007)	(0.007)	(0.009)	(0.005)	(0.005)	(0.006)	(0.011)	(0.011)	(0.006)
ln(Total Assets)	0.006	0.005	-0.430*	-0.005	-0.005	-0.133	0.026	0.026	-0.295**
	(0.054)	(0.054)	(0.199)	(0.029)	(0.029)	(0.084)	(0.025)	(0.025)	(0.117)
ln(Price-to-Book)	-0.021	-0.018	0.214	0.023	0.023	0.070	-0.110	-0.109	-0.144
	(0.142)	(0.142)	(0.145)	(0.074)	(0.075)	(0.076)	(0.141)	(0.142)	(0.085)
ln(CAPEX/Total Assets)	7.926***	7.988***	4.243*	6.417**	6.435**	2.696***	9.691***	9.715***	5.095**
	(2.171)	(2.184)	(2.019)	(2.191)	(2.179)	(0.820)	(2.636)	(2.630)	(1.899)
ROA	0.031***	0.031***	0.004	-0.006	-0.007	-0.003	0.002	0.002	-0.006
	(0.006)	(0.006)	(0.012)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Constant	1.297*	1.354*	6.617***	0.629*	0.645**	2.380**	0.498	0.521	5.054***
	(0.697)	(0.701)	(1.848)	(0.290)	(0.285)	(0.822)	(0.526)	(0.530)	(1.151)
Sector FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Country FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7,141	7,141	7,141	7,141	7,141	7,141	7,141	7,141	7,141
R-squared	0.191	0.192	0.544	0.226	0.227	0.612	0.235	0.235	0.546

Table 7b replicates the results of Table 7a with a propensity score matched sample. Variables are defined in Appendix 1. Observations are firm-years. For each dependent variable, respectively, columns 1 and 2 include sector, country and firm fixed effects. Column 3 removes sector and country effects and introduces firm fixed effects. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by ∗, ∗∗, ∗∗∗ for 10%, 5%, and 1%, respectively.

Table 8. Residual Regressions – Relation between Adopting Science Based Targets and Emissions Reduction Initiatives

	(1) ln(Investment Required)	(2) ln(Investment Required)	(3) ln(Investment Required)	(4) ln(CO2 Savings)	(5) ln(CO2 Savings)	(6) ln(CO2 Savings)	(7) ln(Monetary Savings)	(8) ln(Monetary Savings)	(9) ln(Monetary Savings)
Ambitious Firm	0.006	-0.0001		-0.040	-0.044		0.139	0.134*	
	(0.0896	(0.072)		(0.033)	(0.028)		(0.080)	(0.073)	
Ambitious Target		0.024	0.106		0.011	0.018		0.017	0.070
		(0.108)	(0.100)		(0.035)	(0.031)		(0.062)	(0.060)
ln(Base Year Emissions)	0.082***	0.082***	0.013	0.034***	0.034***	0.002	0.071***	0.071***	0.007
	(0.007)	(0.007)	(0.010)	(0.005)	(0.005)	(0.003)	(0.010)	(0.010)	(0.006)
ln(Total Assets)	0.112***	0.112***	-0.209	0.004	0.004	-0.180***	0.099**	0.099**	-0.186**
	(0.030)	(0.030)	(0.153)	(0.017)	(0.017)	(0.055)	(0.039)	(0.039)	(0.082)
ln(Price-to-Book)	0.042	0.0426	0.302**	0.001	0.001	-0.004	-0.034	-0.034	-0.029
	(0.096)	(0.097)	(0.121)	(0.052)	(0.052)	(0.057)	(0.084)	(0.084)	(0.086)
ln(CAPEX/Total Assets)	6.205***	6.205***	1.782	4.634***	4.633***	1.361	7.272***	7.272***	0.780
	(1.394)	(1.393)	(1.902)	(1.099)	(1.099)	(0.846)	(1.131)	(1.131)	(1.391)
ROA	0.030***	0.030***	0.014*	-0.001	-0.001	-0.002	0.012*	0.012*	0.0008
	(0.005)	(0.005)	(0.006)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.006)
Constant	-0.252	-0.249	3.783**	0.596**	0.598***	2.564***	-0.772*	-0.770*	3.540***
	(0.426)	(0.424)	(1.324)	(0.190)	(0.188)	(0.529)	(0.376)	(0.375)	(0.773)
Sector FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Country FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	14,143	14,143	14,143	12,868	12,868	12,868	14,143	14,143	14,143
R-squared	0.161	0.161	0.584	0.180	0.180	0.598	0.189	0.189	0.585

Variables are defined in Appendix 1. Observations are firm-year pairs. For each dependent variable, respectively, columns 1 and 2 include sector, country and firm fixed effects. Column 3 removes sector and country effects and introduces firm fixed effects. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by ∗, ∗∗, ∗∗∗ for 10%, 5%, and 1%, respectively.

Table 9. Climate Change Initiatives Regressions – Relation between Adopting Science Based Targets and Emissions Reduction Initiatives

	(1)	(2)	(3)
	ln(Investment Required)	ln(CO2 Savings)	ln(Monetary Savings)
Target Ambition	0.718***	0.181***	0.671***
	(0.0958)	(0.0484)	(0.112)
Post Science*Target Ambition	0.432***	0.0839**	0.171***
	(0.072)	(0.037)	(0.051)
ln(Base Year Emissions)	0.077***	0.033***	0.067***
	(0.007)	(0.005)	(0.009)
ln(Total Assets)	0.053	-0.009	0.053
	(0.034)	(0.016)	(0.040)
ln(Price-to-Book)	-0.014	-0.011	-0.081
	(0.099)	(0.054)	(0.079)
ln(CAPEX/Total Assets)	6.662***	4.774***	7.740***
	(1.278)	(1.120)	(1.175)
ROA	0.027***	-0.002	0.009*
	(0.005)	(0.002)	(0.005)
Constant	0.480	0.788***	-0.213
	(0.454)	(0.172)	(0.382)
Sector FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	No	No	No
Observations	14,143	12,868	14,143
R-squared	0.184	0.187	0.212

Variables are defined in Appendix 1. Observations are firm-year pairs. Sector, country and year fixed effects are included in the regressions. Standard errors are clustered at the firm level and reported in parenthesis. Significance levels are indicated by $*$, $**$, $***$ for 10%, 5%, and 1%, respectively.

Appendix 1.

Variable Descriptions

Variable Name	Variable Description	Data Source
Science Firm	Firm-level, time-invariant indicator equal to 1 if firm *i* sets a SBT in the sample period, 0 otherwise.	CDP
Science Target	Target-level, time-variant indicator equal to 1 in the year that a *Science Firm*'s target is a SBT, and 0 otherwise.	CDP
Post Science	Firm-level, time-variant indicator equal to 1 in the year a *Science Firm* sets its first SBT and in every subsequent year, 0 otherwise.	CDP
Past Target Ambition	Target difficulty divided by horizon multiplied by coverage (i.e. 100% coverage scales the value by 1, while 90% coverage scale the value by 0.9), averaged over of all targets of a firm prior to 2016.	CDP
Past Target Completed	Indicator variable equal to 1 if firm *i* has ever completed an emissions reduction target prior to 2016, 0 otherwise.	CDP
Ambitious Firm	Time-invariant indicator equal to 1 for firms that never set a SBT in the sample period but have targets which are as, or more, ambitious than SBTs. To calculate this variable, we run annual cross-sectional models per Equation 2 for 2016-2019, omitting the *Science Target* indicator. We take the residuals from this model and calculate, for each firm-year, the difference between its residual and the average residual for all SBTs in the firm's sector in that year. If this difference is zero or greater, the firm is labeled an ambitious firm, conditional on the firm not setting a SBT in the future.	CDP
Ambitious Target	Indicator equal to 1 in the year that firm *i* is identified as an *ambitious firm* and every year thereafter, 0 otherwise.	CDP

Low Carbon Revenue	Percent of revenues that firm *i* generates from the sale of low-carbon products and/or services or that enable a third party to avoid GHG emissions.	CDP
Emissions/Sales	The carbon intensity of the firm, measured in metric tons of CO2 equivalent emitted per million USD of revenue.	CDP and Bloomberg
Likelihood Risk	Likelihood Risks measures a firm's perception of the likelihood climate change related business risks will materialize. Responses are measured between 1 and 8 as follows: 1 = Exceptionally unlikely; 2 = Very unlikely; 3 = Unlikely; 4 = About as likely as not; 5 = More likely than not; 6 = Likely; 7 = Very likely; 8 = Virtually certain. Likelihood Risks is the average likelihood of all risks identified by a firm.	CDP
Timeframe Risk	Timeframe Risks measures a firm's perception of the timeframe in which climate change business risks will materialize. Responses are measured between 1 and 4 as follows: 1 = More than 6 years; 2 = 3 to 6 years; 3 = 1 to 3 years; Up to 1 year. Timeframe Risks is the average timeframe of all risks identified by a firm.	CDP
Magnitude Risk	Magnitude Risks measures a firm's perception of the magnitude of climate change related business risks. Responses are measured between 1 and 5 as follows: 1 = Low; 2 = Low-medium; 3 = Medium; 4 = Medium-high; 5 = High. Magnitude Risks is the average magnitude of all risks identified by a firm.	CDP
Total Assets	The total of all short and long-term assets reported on a firm's balance sheet in the reporting year. Reported in millions. Calculated at fiscal year-end.	Bloomberg field "BS_TOT_ASSET"
Price-to-Book	Price-to-Book ratio is calculated from the last stock price divided by the book value per share. Calculated at fiscal year-end as fiscal year average value.	Bloomberg field "PX_TO_BOOK_RATIO"

ROA	Return on Assets is calculated as trailing 12 month net income divided by average total assets. Calculated at fiscal year-end.	Bloomberg field "RETURN_ON_ASSETS"
Volatility	A measure of the risk of price moves for a security calculated from the standard deviation of day to day logarithmic historical price changes. The 360-day price volatility equals the annualized standard deviation of the relative price change for the 360 most recent trading days closing price, expressed as a percent. Calculated at fiscal year-end.	Bloomberg field "VOLATILITY_360D"
CAPEX	Capital expenditures/property additions of the firm. Includes purchases of (tangible) fixed assets. Excludes purchases of investments. Calculated at fiscal year-end.	Bloomberg field "CF_CAP_EXPEND_PRPTY_ADD"
Target Difficulty	Percent reduction in emissions relative to the level of emissions in the base year of the target.	CDP
Base Year	The year in which a base level of emissions for a target are set.	CDP
Target Year	The year by which a target is to be achieved.	CDP
Horizon	The difference between the target year and the base year.	CDP
Coverage	The percent of a firm's emissions coverage by a target. For example, a target with a coverage of 50% only applies to 50% of a firm's emissions.	CDP
Base Year Emissions	A firm's emissions (in millions) in the base year of their target, which is used as the starting level to measure the percent reduction in emissions.	CDP
Monetary Savings	Total estimated monetary savings of all emissions reduction initiatives implemented in the reporting year.	CDP

Investment Required	Total investment required for all emissions reduction initiatives implemented in the reporting year.	CDP
CO2 Savings	Total estimated CO2 savings of all emissions reduction initiatives implemented in the reporting year.	CDP

Appendix 2a. Matched Sample

	Science Firms	Non-Science Firms	Total
Starting sample	385	1,367	1,752
Less: unmatched from propensity score matching	55	1,037	1,092
Matched	330	330	660

Appendix 2b. Matching Covariates Mean Differences T-test before and after Matching

	Unmatched			Matched		
	Science Firms	Non-Science Firms	t-stat	Science Firms	Non-Science Firms	t-stat
Past Target Ambition	0.95	0.92	0.81	0.94	0.93	0.29
ln(Emissions/Sales)	3.98	3.92	0.57	4.00	3.97	0.33
ln(Total Assets)	9.69	9.24	4.70	9.75	9.61	1.24
Past Target Completed	0.76	0.68	3.01	0.76	0.76	0.08
Low Carbon Revenue	0.78	0.77	0.26	0.80	0.79	0.41
ln(Likelihood Risks)	1.85	1.85	0.46	1.85	1.85	0.02
ln(Magnitude Risks)	1.32	1.29	2.34	1.32	1.31	0.48
ln(Timeframe Risks)	1.25	1.23	1.25	1.25	1.23	0.88