Real, Disclosure and Spillover Effects of U.S. State-Level Climate Change Regulations

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Abstract: Given the barriers to national and global climate change regulations, what are the real, disclosure and spillover effects of subnational regulations? Using the staggered adoption of U.S. state-level greenhouse gas (GHG) regulations as a natural experiment, I find significant reductions in corporate GHG emissions in adopting states. Affected firms report more representative GHG emissions information and reduce GHG-related 10-K risk disclosures. This effect is stronger in states which have statutory targets, moderately aggressive targets, and with own GHG registries. Furthermore, I document large spillover reductions in GHG emissions for treated firms' affiliated operations in non-adopting states. These findings suggest possible alternate pathways to reduce GHG emissions and improve GHG disclosure if national or global policy coordination is not possible.

Key Terms: ESG; disclosure; risk disclosure; real effects; GHG emissions; climate change; state regulation; spillover effects

*I am grateful to my dissertation committee: Peter Wysocki (Chair), Rui Albuquerque, Francois Brochet, and Eddie Riedl for their invaluable advice and mentorship. I thank Ana Albuquerque, Mark Bradshaw, Jesse Chan, Brandon Gipper (discussant), Amy Hutton, Alibek Korganbekov, Malika Korganbekova, Pete Lisowsky, Alvis Lo, Shirley Lu, Krish Menon, George Serafeim, and Joseph Weber for their helpful feedback and suggestions. I thank seminar participants from *Boston University* 2023; *MIT* Rising Scholars Conference 2023; Boston Empirical Accounting Conference 2023; *Stanford University* Organizations and Environmental Sustainability Conference 2024; *Boston University* IMAP Seminar 2023; *City University New York* 2024; *Harvard Business School* 2024; *HEC Paris* 2024; *Lancaster University* 2024; *Northeastern University* 2024; *Norwegian School of Economics* 2024; *Toulouse School of Management* 2024; *University of Melbourne* 2024; *University of Oxford* 2024; FARS Midyear Meeting 2025. All errors are my own.

1 Introduction

Global climate change represents a major societal threat, requiring both national and supranational cooperation.[1] However, significant barriers hinder national and international coordination to address global climate change including conflicts of interests, competition between economies, and disagreement in target metrics (Barrett 1999; Nordhaus 2015). Given these barriers, subnational climate change initiatives present a potential alternate approach to reduce the effects of climate change (Rabe 2011). However, little empirical evidence exists on the causal impact of subnational regulations on corporate GHG emissions and firms' disclosures about their climate actions and risks.

This paper provides a quasi-experimental estimation of the impact of subnational *action-based* environmental regulations on corporate greenhouse gas (GHG) emissions, GHG-related disclosures, and associated spillover effects. Specifically, I exploit the staggered adoption of GHG reduction targets across 26 U.S. states between 2006 and 2022, to examine their impact on corporate GHG emissions and disclosures.[2] I combine corporate GHG emissions and disclosure data at both firm and facility level and use a staggered difference-in-differences (DiD) empirical strategy to assess the impact of state-level GHG regulations. I document that state-level climate change regulations lead to significant reductions in direct corporate GHG emissions intensity and 10-K GHG-related risk disclosures, while also impacting firms' willingness to provide more representative GHG emissions disclosure (proportion of total GHG damage cost that is accounted for in a firm's public disclosures). This effect is more pronounced in states with statutory and moderately aggressive targets, as well as those with own state-level GHG registries. Furthermore, I find large spillover reductions in GHG emissions for treated firms' affiliated operations in non-adopting states. My tests suggest that these beneficial environmental spillover effects are through a corporate parent channel rather than a geographic proximity channel. Overall, findings can inform policy deliberations on climate change regulations and the effectiveness of subnational regulatory actions.

This study is motivated by the slow pace and numerous setbacks to achieve national and international coordination to address climate change. For example, the U.S. has

[1] See for instance Pew Research Center Survey 2022 and IMF Survey 2023.

[2] State-level GHG reduction targets establish quantifiable emissions goals to be achieved within a predetermined period within a given U.S. state.

had inconsistent federal climate policy (e.g., rollbacks)[3] which can negatively affect firms' environmental strategies (Biais and Landier 2022; Ramadorai and Zeni 2023).[4] Because of these setbacks and inconsistencies, U.S. state-level environmental regulations may provide another channel to reduce U.S. GHG emissions (Goulder and Stavins 2011) and improve disclosure. To mitigate GHG emissions from various sources, U.S. states have been enacting legislation or passing executive orders establishing GHG reduction targets as a form of emissions regulations. These GHG reduction targets define a desired percentage of emissions reduction and the period for this to occur for a state. Thus, these are *action-based*, rather than reporting, regulations. GHG reduction targets imply subsequent additional regulations for a large set of industries including utilities, oil and gas, manufacturing, consumer durables, transportation, and others. These additional regulations are enforceable in the form of significant fines and penalties. The adoption of state-level targets is geographically and intertemporally dispersed, covering half of the U.S. states from 2006 to 2022. Thus, the staggered adoption of state-level GHG reduction targets provide a source of quasi-experimental variation in exposure to environmental regulation, which I use to establish causal identification.

Several factors can impact the outcomes of U.S. state-level GHG emissions targets on firms' direct emissions intensity, GHG emissions disclosures, and spillover effects. On the one hand, U.S. state-level GHG reduction targets often represent diffuse "call to action" policies encouraging voluntary corporate compliance during the first several years until additional regulations come into force. Further, the GHG reduction targets often specify long-term goals, which may dilute any observable change in short-term corporate compliance. In addition, state governments generally have fewer resources to implement and monitor environmental policies relative to federal mandates. As a result, both corporate emissions and related disclosures might not change. Alternatively, firms might increase disclosures without changing underlying environmental performance (greenwashing). On the other hand, firms may quickly respond to state-level environmental regulations due to (i) increasing probability of enforcement (penalties and fines) in the near future, (ii) state governments' stronger institutional knowledge of the local industrial composition and sources of emissions, (iii) systematic monitoring through state-

[3]Almost 100 environmental regulations were reversed during the Trump administration. See for instance: Almost 100 environmental regulations were reversed during Trump administration

[4]Related, in the UK government green policy rollbacks might make it harder to achieve net-zero targets.

level reports, (iv) and firms' long-term commitments. In this case, firms might decrease GHG emissions and will be motivated to improve GHG-related disclosures in order to signal to stakeholders about their enhanced environmental activities (Verrecchia 1983).

I use two main samples for my empirical analyses. First, I use a firm-level sample for which the identification of firms subject to a given state-level GHG regulation is based on the state headquarters of each firm. Second, I use more granular facility-level data from the *Greenhouse Gas Reporting Program* (GHGRP), where assignment to emissions regulation treatment is based on each facility's actual U.S. state location. Facility-level data helps to overcome potential measurement error issues associated with the firm-level ESG data.

My empirical approach is a two-way fixed effects difference-in-differences (TWFE DiD) methodology, which enhances identification and helps to rule out potential confounding factors. Firm (or facility) fixed effects control for time-invariant characteristics and year fixed effects control for time trends that affect all firms (facilities). I use entropy-balancing to address firm-level covariate imbalance. In addition, I use alternative fixed effects structures to account for potential confounding effects. Recent econometric advances show that heterogeneity in treatment effects can affect the validity of staggered DiD estimates (see, for example, Callaway and Sant'Anna 2021; Sun and Abraham 2021; Baker et al. 2022). I address these concerns by implementing a stacked DiD research design, and applying alternative estimators to confirm the robustness of the findings in my baseline estimators.

My main findings are that state-level climate change regulations, on average, lead to significant improvement in GHG performance and enhancement in GHG-related disclosure.[5] With regard to direct emissions effects, I find that introduction of state-level GHG emissions targets result in an average incremental 7% reduction in firms' GHG Scope 1 intensity post regulation.[6] There are no statistically-significant changes in indirect emissions intensities (Scope 2 and Scope 3). Regarding the associated disclosure effects, I use two different GHG-related disclosure metrics. The first metric is from the *Trucost Environmental* database, and it captures the proportion of total GHG damage cost that is accounted for in a firm's public

[5]In baseline estimations California is excluded from the analysis, because its' regulatory stringency differs from other states.

[6]Scope 1 represents GHG emissions from sources owned or controlled by the company; Scope 2 are those from consumption of purchased electricity, heat or steam; and Scope 3 are those from other upstream activities not covered in Scope 2. Scope 1 (2 and 3) emissions are considered direct (indirect) emissions.

disclosures (*representative* disclosure). I construct the second disclosure metric from firms' 10-K Risk Factors section using a natural language processing (NLP) technique: it quantifies the volume of GHG-related *risks* disclosed by a firm. I find that firms exposed to state-level GHG regulations provide 16% more representative GHG disclosure and disclose, on average, about 3% fewer GHG-related risks relative to firms in unregulated states.

I then use facility-level GHGRP data to provide more granular insights on direct GHG emissions reductions, and to explore potential spillover effects. Facility-level data provides three advantages. First, the firm-level sample is constrained to large- and mid-cap firms with available GHG emissions data. Thus, the facility-level data provides a more comprehensive picture of state-level emissions by covering all facilities emitting more than 25,000 metric tons of GHGs. Second, the exposure of a firm to a state-level GHG reduction target regulation can be better measured using the GHGRP data as it isolates each *facility* directly impacted by a state-level regulation. Third, the GHGRP data provides information on each parent company associated with facilities in treated and untreated states, thus, enabling the study of potential spillover effects within the same parent.

Using this more granular facility-level data, I provide two insights. First, I show that facilities located in states adopting GHG reduction targets decrease average emissions (intensity) by 7% (5%) relative to untreated facilities, consistent with my firm-level analyses.[7] Second, I find across-facility environmental spillover benefits associated with the adoption of state-level GHG reduction targets through a corporate parent channel. Prior literature finds transborder spillover effects associated with environmental regulation (Bartram et al. 2022). In my setting, I do not find evidence of post-regulation emissions reductions for firms in neighboring non-adopting states (i.e., through a geographic-proximity channel). However, I do find evidence of a parent-company environmental spillover channel: the GHG emissions of facilities located in non-adopting states (denoted as "indirectly-treated" facilities) significantly decline if the parent company has other facilities that are subject to GHG emissions regulation in another state. This result is consistent with the "California Effect", which predicts that

[7]Main facility-level analysis is executed using a *non-staggered* version of TWFE DiD. It compares facilities in states that adopted GHG reduction targets in 2019 to never-treated states. The reason is that GHGRP data is available from 2011, and most of states adopted regulations in 2019 within the period of GHGRP data availability. Section 4.2 further discusses the details, Section 6.2 provides results for the main sample. Section 7 provides full sample analysis.

businesses operating in multiple jurisdictions tend to comply with the strictest regulation that they face in any jurisdiction globally, even if the regulation does not require global compliance (Vogel 1997; Frankenreiter 2022).

Empirically, the staggered implementation of regulations can significantly help the identification of causal estimates (Leuz and Wysocki 2016). However, there are two identification issues that warrant discussion. First, while there is spatial and temporal variation of the adoption of state-level regulations, the adoption is not purely random. In particular, state-level characteristics could have affected the timing of regulation in different states. Therefore, it can be possible that differences in GHG emissions across states induced regulations in certain states, leading to reverse causality issue. Using a hazard model analysis, I do not find evidence of GHG emissions driving the adoption of GHG regulations. However, I document that Democratic-leaning states have a higher propensity to implement climate change regulations.[8] To take into account the political ideology, I compare outcomes of treated and control group facilities located in Republican and Swing states. Furthermore, I follow the methodology of Bertrand and Mullainathan (2003), and control for a political ideology factor by comparing facilities in unregulated states through treatment assignment based on parent company location. The second issue is a potential omitted variable bias. If an omitted variable coincides with the adoption of regulation and affects changes in GHG-related outcomes, the observed effects will not be causal. However, I use an identification strategy where GHG reduction regulations are adopted by different states in different years. Thus, it is unlikely that an omitted variable would coincide with all regulation adoption events.

My analysis also explores the underlying channels through which climate change regulations exert their impact, considering both firm-level and state-level regulatory characteristics. From the perspective of state attributes, the most effective states in meeting their targets are those that implement statutory goals, set moderately ambitious targets, and maintain their own GHG registries to track emissions. Additionally, states that participate in climate alliances and communicate their targets clearly to the public tend to achieve stronger outcomes. On the firm side, I find that the regulation-induced improvement in Scope 1

[8] I use factor analysis to measure the political ideology of the state in a given year based on several variables such as political ideology of state governor, partisan composition of state legislature, state-level political ideology based on presidential elections. I also confirm the results by using these variables as individual predictors.

emissions intensity is (i) concentrated in larger firms, (ii) spread across different industries including utilities, manufacturing, oil & gas, and others, (iii) driven by firms with higher institutional ownership, and (iv) is more pronounced in states with more stringent statutory GHG reduction targets. I also validate my baseline results by showing robustness to alternative fixed effects, alternative clustering specifications, and alternative samples.

My findings provide three contributions. First, I build on the literature studying the factors influencing firms' environmental outcomes. Nation-level institutions (Ioannou and Serafeim 2012) and various stakeholders including managers (Davidson et al. 2019; Shive and Forster 2020; Cohen et al. 2023b) and investors (Krueger et al. 2020; Flammer et al. 2021; Chen and Xie 2022; Cohen et al. 2023a; Ilhan et al. 2023) can shape corporate ESG practices. Governments represent another major stakeholder, with prior literature showing that disclosure and reporting regulation leads to positive corporate real and disclosure effects (Christensen et al. 2017; Downar et al. 2021; Fiechter et al. 2022; Grewal et al. 2023; Tomar 2023). While most of this literature focuses on national reporting regulations, I provide causal tests of the real and disclosure effects of subnational *action-based* GHG regulations. I also examine the features of state regulations to identify those most effective ones in driving corporate decarbonization, with the goal of offering informed policy recommendations.

Second, this paper relates to the literature examining the link between environmental, social and governance (ESG) performance and disclosure (Patten 2002; Clarkson et al. 2008; Dhaliwal et al. 2011). This link is especially important in light of growing cases of greenwashing, which impede stakeholders' informed decisions (Cong et al. 2020; Kim and Yoon 2023; Grewal et al. 2023). This paper documents contemporaneous real and disclosure effects in a response to state-level regulations. I document that decreased corporate GHG emissions are associated with a reduction in environmental risk disclosures, consistent with firms making a long-term commitment to lower emissions, and also higher levels of accountability for their GHG emissions. Furthermore, my new evidence on firms' environmental risk disclosures likely captures more credible disclosures than typical voluntary environmental disclosures due to the heightened litigation exposures for 10-K risk disclosures.

Finally, I contribute to the literature examining spillover effects associated with environmental regulation. Prior research documents the existence of negative transboundary

spillover effects (Sigman 2005; Fowlie et al. 2016; Bartram et al. 2022). However, spillover benefits also can arise due to learning effects, benchmarking, and/or the spread of innovations (Cho et al. 2021; Tomar 2023). I complement this literature by showing positive environmental spillover effects for affected firms' affiliated operations in non-adopting jurisdictions.

The remainder of the paper is organized as follows. Section 2 describes the state-level GHG reduction targets setting. Section 3 reviews the related literature and presents my hypotheses. Section 4 describes the data sources and presents descriptive statistics. Section 5 discusses the empirical strategy, and Section 6 presents the empirical results. Section 7 provides additional analyses and robustness checks. Section 8 concludes.

2 Background and State-Level GHG Reduction Targets

The corporate sector produces a significant amount of GHG emissions, contributing to climate change. Voluntary operational changes to decrease emissions can be costly to firms because their incentives reflect the trade-off between economic benefits (profits, competitive advantage, productivity) and costs. Various stakeholders, including governments, can also influence companies' decisions to implement active environmental strategies to decrease emissions and pollution, and to improve disclosure.

The U.S. has shown varying regulatory approaches concerning climate change in general, and to reducing GHG emissions in particular.[9] For instance, the Kyoto Protocol has never been ratified in the U.S. In 2015 the U.S. entered the Paris Agreement (which aims to maintain global warming below 2°C), while in June 2017 the U.S. government announced withdrawal from it. Under the Trump Administration more than 100 environmental rules governing clean air, water, wildlife, and toxic chemicals were rolled back.[10] Subsequently, in 2021 the U.S. entered the Paris Agreement again, set GHG reduction targets to be achieved by 2030, and introduced the Inflation Reduction Act in 2022. Recently the U.S. restarted the withdrawal process from Paris Agreement.

There is a divergence between federal and state governments' willingness to act on climate change in the U.S. (Lutsey and Sperling 2008). In contrast to the seeming inconsistencies in federal environmental rules, states have adopted (and generally retained) local

[9] See U.S. Congressional Research Service 2021 Report.
[10] See for instance: Climate Deregulation Tracker.

environmental rules including: GHG reduction target regulations; market-based instruments such as — cap and trade policies for carbon emissions; and alliances to mitigate climate change (e.g., the Regional Greenhouse Gas Initiative among northeastern states). Accordingly, I focus on state-level GHG reduction targets as they: (i) represent a framework to reduce emissions, (ii) are widely applicable across industries (versus industry-targeted regulations), and (iii) are temporally and spatially dispersed.

State-level GHG reduction targets represent goals to reduce emissions by a state, by a specific amount, and by a pre-determined date. These targets vary across states by the amount of reductions, the period of time to achieve reductions (existence of intermediate goals), and base year for assessing reductions. The regulations have a reporting component since the main prerequisite for emissions reductions is measurement and accounting for emissions. First, states usually collect the emissions data from publicly-available sources (such as GHGRP, CDP, Inventory of U.S. GHG emissions provided by EPA), or create their own inventories. Second, states provide state-level progress reports annually or bi-annually, which monitor the dynamic of emissions within a state by industry categories, and provide information on policies and achievements. These progress reports: (i) are available to public, (ii) help to understand dynamics of emissions across industries, identify challenges and areas requiring extra focus, and thus (iii) help to correct the regulatory actions towards specific industries or adjust the targets over time.

GHG reduction targets can be established either through a statutory action or a governor's executive order. The key difference lies in the legal status and enforceability. Statutory GHG reduction targets are established through the enactment of laws and regulations and hold relevant entities accountable for failing to meet the determined goals, such as through fines or penalties. Executive targets are non-legally binding goals or commitments, that are established at the executive or administrative level.

It is important to note that state-level GHG reduction targets are generally long-run targets. Thus, these targets do not mean that each firm within a state has to decrease emissions by the amount set in the target. Instead, implementation of GHG reduction targets implies adoption of various additional regulations, acts and/or standards to mitigate emissions across all categories of emissions sources for specific industries. Firms within these industries

are impacted by the regulations equally. States typically start with establishing additional regulations for key industries such as power plants, oil gas, manufacturing, and transportation. These additional regulations entail enforcement in the form of significant penalties and fines in case of non-compliance. For example, the Cap-and-Invest program was adopted in 2023 by the state of Washington in 2023 after targets were previously set in 2020, that entailed up to $50,000/day penalty for violation. However, it might take several years to finalize these regulations after the GHG reduction targets were originally adopted.[11] Until then states actively raise awareness about climate change among businesses and the public to promote voluntary action. In fact, some states encourage and incentivize voluntary action prior to thefinalization of regulations.[12]

Overall, I identify 26 states adopting economy-wide GHG reduction targets from 2006 to 2022 (Figures A1 - A2 and Table A2): 16 via statutory targets and 10 via executive targets. One of the first states to adopt GHG regulations was California in 2006, which set a target to reduce GHG emissions at least 10% below 1990 levels by 2020 and 80% below 2001 levels by 2050 as part of its Global Warming Solutions Act. More recent adopters of statutory GHG reduction targets include Vermont, Virginia and Washington. Over time, states also can update GHG reduction targets.

3 Prior Literature and Hypothesis Development

Prior literature examines the causes and effects of companies' environmental performance and disclosures (see Grewal and Serafeim 2020; Christensen et al. 2021; Gillan et al. 2021; and Tsang et al. 2022 for reviews). The accounting literature largely focuses on reporting regulations, generally documenting significant real effects: that is, reductions in GHG emissions. For example, Downar et al. (2021) uses a UK regulatory setting mandating publicly listed firms to provide standardized annual disclosures of their GHG emissions. The paper documents that firms responding to the legislation exhibit 8% lower GHG emissions relative to a control group of European firms. Similar results occur in Jouvenot and Krueger (2019). In the US, the GHGRP was the first nationwide mandatory regulation requiring facility-level

[11] Usually states solicit public comments from interested stakeholders prior to finalizing the regulations.

[12] For instance, Maryland provides for early reduction credits that can be applicable in any future laws requiring GHG reductions.

reporting. Tomar (2023), focusing on the non-utility sector, shows that U.S. facilities decrease emissions by 7% relative to Canadian facilities after introduction of the GHGRP. Yang et al. (2021) focuses on electric power plants' GHG emissions, finding a decrease, as well as evidence of strategic reallocation of emissions between GHGRP and non-GHGRP plants.

While the above research investigates the effects of *national reporting* regulations, I examine the effects of *subnational GHG reduction (action-based)* regulations. In particular, I focus on U.S. state-level GHG reduction regulations which might be an effective way to decrease emissions (Goulder and Stavins 2011) and improve corporate GHG disclosure. An advantage of state-level regulations is that they reflect enhanced local expertise about the sources of emissions (Lutsey and Sperling 2008). Since state-level GHG reduction regulations represent an overarching framework to decrease emissions and are binding, it can significantly increase the probability of future enforcement and stakeholder pressure on companies/facilities located in that state. Thus, companies may quickly respond to state-level GHG reduction targets to gain future competitive advantage, and possibly achieve reputational benefits. Overall, I hypothesize the following:

> ***H1:*** *Firms headquartered (facilities located) in states adopting GHG reduction targets decrease their total emissions and emissions intensity.*

However, the nature of these regulations also adds tension to the above expectation. First, it may take several years (depending on the state) for additional regulations and climate plans to finalize after the initial adoption of GHG reduction targets. During this time, there are no direct fines or potential violation risks to firms associated with non-compliance, thus reducing a firm's motivation to decrease emissions and improve disclosure. In addition, states usually set targets to be achieved by 2050. This long-term nature of targets can further delay actions by a firm.

Following H1, according to the signaling theory, firms with improved performance might provide more voluntary disclosure (Verrecchia 1983). Firms have further incentives to enhance disclosure if their environmental performance improves. In particular, firms may experience better access to financing, an increase in firm value, and a decrease in implied cost of capital (Matsumura et al. 2014; Cheng et al. 2014; Ioannou and Serafeim 2017; Bolton and Kacperczyk

2021). Thus, to the extent that firms decrease emissions (as expected by H1), they also are expected to provide improved GHG-related information. Prior literature has shown that unrepresentative GHG disclosure (i.e., the extent to which GHG disclosures are less indicative of overall GHG damage) decreases after the regulatory intervention (Grewal et al. 2023). I focus on the opposite metric – representative disclosures (fraction of total estimated GHG damage that is disclosed by the firm), and my second hypothesis is as follows:

> ***H2(a):*** *Firms headquartered in states adopting GHG reduction targets provide more representative GHG disclosures.*

However, the state-level GHG reduction regulations do not directly require companies to provide either general GHG-related disclosure in general or representative GHG disclosures. Thus, it might be the case, that despite improved environmental performance companies would not improve their voluntary GHG emissions disclosures. One reason behind this behavior is that companies might be reluctant to share information with the competitors (Verrecchia 1983; Verrecchia 2001). Another reason could be the difficulty to track, measure, and aggregate all the necessary information for GHG emissions disclosure (Bolton and Kacperczyk 2021).

Next, I consider a second dimension of GHG-related disclosures – 10-K GHG risk factor disclosures. These GHG risk disclosures are financially material, reflect the confirmation of real actions, and are arguably more credible than typical voluntary environmental disclosures. Effective 2005, the SEC required public companies to discuss their most significant (i.e., "material") risk factors in Item 1A of the Forms 10-K and 10-Q, defined as those "to which reasonable investors would attach importance in making investment or voting decisions".[13] This materiality threshold mitigates potentially false and misleading information on environmental practices. Prior literature has shown that 10-K risk factor disclosure has significant information content for market participants. For instance, Campbell et al. (2014) document that as negative/pessimistic qualitative risk disclosures increase, market-based measures of firm risk also increase. Bozanic et al. (2023) show that credit ratings tend to be lower when firms provide more disclosures pertaining to credit risk and debt. Similarly, recent studies show that environmental risk disclosures are a significant source of information for investors and other

[13]Securities and Exchange Commission, Final Rule: Modernization of Regulation S-K Items 101, 103, and 105, Release No. 33-10825 (Aug. 26, 2020) [85 FR 63726, 63744 (Oct. 8, 2020)].

stakeholders (Matsumura et al. 2022; Ilhan et al. 2023). In particular, Berkman et al. (2024) show that climate risk disclosures are negarively associated with market valuations.

In line with the H1 prediction of improved environmental performance and prior risk disclosure literature, I expect that firms exposed to a regulation reduce GHG-related risk disclosures relative to the counterfactual due to improved GHG risk management leading to better GHG performance:

> ***H2(b):*** *Firms headquartered in states adopting GHG reduction targets decrease their 10-K GHG-related risk disclosures.*

Environmental regulations can also lead to unintended consequences: i.e., spillover effects. I consider two sources of potential spillovers: corporate parent and geographic proximity channels. The corporate channel implies that any spillover effect may occur *within* a parent firm having facilities in both states adopting and states not adopting climate change regulations. The geographic proximity channel implies potential GHG effects extending to neighboring states without a condition of facilities sharing a parent.

According to the "pollution haven" hypothesis, environmental regulations lead to a reallocation of economic activity from regulated locations to less regulated locations. (Levinson and Taylor 2008). Recent research confirms this concern: Bartram et al. (2022) studies the impact of California cap-and-trade program using GHGRP data, finding that financially constrained firms shift emissions from California to other states. Thus, the adoption of GHG reduction target regulations may lead to a relative decrease in emissions in adopting states and a consummate increase in emissions in non-adopting states either through the corporate or geographic proximity channels.

On the other hand, several mechanisms suggest the spillover effect of state-level climate change regulations can be beneficial. First, recent research shows that the diffusion of policies is predicted by proximity (DellaVigna and Kim 2022). If the adoption of similar regulations is predictable, facilities in neighboring states may anticipate similar climate change regulations to occur in the future, and thus take voluntary actions to decrease emissions in advance. Second, other potential mechanisms include learning and benchmarking. For example, improvements in affected facilities' environmental performance through innovations that increase the competitiveness of these facilities might affect the behavior of linked facilities

in non-adopting states (Porter and Linde 1995). Similar effects might take place due to benchmarking (Tomar 2023; Cho et al. 2021). Such beneficial spillover effects might be even easier to achieve through a corporate channel: once a parent company improves environmental performance, it can extend these improvements to all facilities (including in non-adopting states) due to scale economies and learning effects. This can lead to decreased emissions for facilities in non-adopting states. This expectation is in line with the so-called "California Effect", which represents the upward ratcheting of regulatory standards in competing political jurisdictions through market mechanisms (Vogel 1997; Fredriksson and Millimet 2002; Perkins and Neumayer 2012). In particular, "businesses active in multiple jurisdictions sometimes adopt the strictest regulatory standards that they face in any jurisdiction globally, even if the jurisdiction's law does not require global compliance" (Frankenreiter 2022).[14]

However, facilities in non-adopting states may not change their behavior following regulations as they are not directly treated (i.e., not directly subject to the regulation). Furthermore, the long regulatory process in adopting states suggests facilities in non-adopting states will not experience pressure to react (at least in the short-term).

Combined, I set the following expectations stated separately for the corporate and geographic proximity channels:

H3(a): *Facilities sharing the parent with another facility in states adopting GHG reduction targets will not change their emissions.*

H3(b): *There is no leakage of GHG emissions to neighboring non-adopting states.*

4 Data Sources, Sample Selection and Descriptive Statistics

I use two primary samples to study the real and disclosure effects of state-level GHG reduction targets: firm-level and facility-level observations. The firm-level analysis focuses on the effect of GHG reduction targets based on the state location of firms' headquarters. Thus, I assign treatment based on headquarter state as centralized managerial decisions are made at headquarters. When a state, in which the firm is headquartered, adopts climate

[14] Frankenreiter (2022) posits the existence of the "California Effect"; however, the empirical evidence is scarce.

change regulation, I assume it is more likely that firm management will react by introducing operational changes and/or increasing investment in renewable energy sources. On the other hand, my facility-level analysis focuses on the location of individual facilities.[15] The rationale behind using facility location is twofold. First, adopting states aim to decrease emissions within the state and firms' GHG-emitting operations might be located in states other than the corporate headquarters. Second, if a firm is exposed to climate change regulation through a state where the facility is located, it may only focus on decreasing emissions in that state, limiting any firm-level effect. Based on the level of analysis, the sources of data differ. Table A1 provides definitions of the main variables used in the analysis and the sources of data.

My analysis relies on several main data sources. I use the *Center for Climate and Energy Solutions* (C2ES) website to collect data on the timing of state-level GHG reduction target regulations. I hand collect the corresponding state-level statutory legislation and executive orders to confirm the years of state-level environmental regulation adoption and also extract GHG reduction target descriptions.

4.1 Firm-Level Data Sources and Sample

I obtain firm-level GHG emissions and disclosure data from the *Trucost Environmental* database (*Trucost*), and firm-level GHG-related risk disclosures from SEC 10-K filings. Firm-level control variables are collected from *Compustat, CRSP, TR Refinitiv,* and *Violation Tracker* databases. The sample spans 2005 to 2021. I remove firms headquartered in states adopting GHG reduction targets in 2022, due to unavailability of data. I remove firms headquartered in California because it was the first state to adopt GHG reduction targets in 2006 (and thus lacks sufficient pre-regulation observations), and it fundamentally differs in terms of its environmental regulatory framework.[16] I exclude firms in the financial sector which are less likely to emit GHGs and are subject to other regulations. I focus on the four years preceding and following the adoption of GHG reduction targets. The final firm-level sample includes 11,225 firm-year observations for 1,885 unique firms (see Table 1 Panel A).

A primary data source for my firm-level analysis is *Trucost*, which assesses the impact of

[15] Section 7 provides analysis where the facility's parent company location is used as a base for treatment assignment as a robustness test.

[16] The results are robust to including California when the data points are available.

a company's direct, supply chain and downstream operations and includes GHG emissions as well as disclosure information. *Trucost* collects information from annual reports, sustainability reports, websites and other publicly available sources including third-party datasets (e.g., EPA, CDP). Trucost advertises that it uses vigorous data control procedures, standardizes data, and conducts annual engagements with each company to ensure data accuracy and timeliness. The *Trucost* sample generally focuses on large- and mid-cap companies, and its coverage significantly increased in 2016.

4.1.1 *Real Effects*

To estimate the real effects of state-level GHG reduction targets, I use *Trucost* emissions *intensity* data, provided in metric tons of CO_2e per $ 1 million revenues. Despite the fact that state GHG reduction targets are aimed at decreasing GHG *levels* produced within a state, there are several reasons to consider the GHG *intensity* rather than GHG *levels* data at a firm level. First, while states aim to decrease GHG emissions produced within a state, they also care about the economic activity, and do not want to sacrifice economic growth and competitive power to other states. Second, firms operate and produce GHG emissions in several states. Thus, in order to capture an overall decrease of GHG-intensive operations it is important to consider GHG *intensity* rather than *levels*. Third, there are measurement challenges associated with ESG data. *Trucost* firm-level data is gathered from various public sources. If the emissions data is missing, *Trucost* (like other data vendors) estimates it using a proprietary model. Thus, *Trucost*-derived emissions data raises concerns about the validity of the proprietary estimation (Busch et al. 2022; Aswani et al. 2024). This is a significant concern if the unscaled emissions are used for analysis because proprietary estimation relies heavily on firm fundamentals and industry characteristics. In addition, recent research shows that results differ for disclosed and estimated emissions (Aswani et al. 2024; Atilgan et al. 2024). Thus, I use GHG emissions *intensity* levels in my firm-level analysis, which is less susceptible to these concerns. To sum up, while Trucost data might introduce measurement error, more granular facility-level data helps to overcome this issue and confirm the firm-level analysis.

Overall, the main emissions intensity outcome variables at a firm-level are *GHG Scope 1, GHG Scope 2, and GHG Scope 3 Intensity*, defined respectively as the natural logarithm

of Scope 1, 2 and 3 emissions intensity levels. Scope 1 represents GHG emissions from sources owned or controlled by the company; Scope 2 are those from consumption of purchased electricity, heat or steam; and Scope 3 are those from other upstream activities not covered in Scope 2. The main rationale for estimating the impact on Scope 3 emissions is that companies may comply with regulations and decrease Scope 1 emissions, only to potentially offset this reduction by elevating their supply chain (Scope 3) emissions through increased outsourcing levels. However, the concern will still remain because Scope 3 emissions are not precisely estimated (Kaplan and Ramanna 2021).

4.1.2 *Disclosure Effects*

To estimate the disclosure effects of state-level GHG reduction targets, I use two disclosure variables estimated by *Trucost*: weighted Environmental Disclosure (*ENV Disclosure*) and weighted Carbon Disclosure (*GHG Disclosure*), which represent the natural logarithm of the proportion of all direct environmental impact and GHG emissions damage costs disclosed by the company.[17] These measures capture the representativeness of carbon information disclosures: i.e., how much of a firm's total carbon damage is accounted for in its public disclosures. Higher values reflect more representative and useful carbon disclosures.

As an alternative disclosure measure to capture risks related to GHG emissions, I use the data from SEC 10-K filings. I apply a natural language processing (NLP) technique to create a GHG-related risk disclosure measure as follows: (i) For each firm, I extract the Item 1A Risk Factor section from the 10-K report; (ii) I create a list of environmental keywords related to state-level GHG reduction targets;[18] and (iii) From the 10-K Risk Factor section, I identify the number of sentences containing these keywords, which represent GHG-related risks. The difference between total number of sentences and GHG-related sentences represents the non-GHG risks. Thus, *GHG Risk Disclosure* and *Non-GHG Risk Disclosure* reflect the

[17] GHG damage costs reflect the environmental impact of a business activity in monetary terms. Trucost uses its proprietary Environmentally-Extended Input-Output (EEIO) model (developed by the US Environmental Protection Agency) for GHG damage cost estimation. Weighted Carbon disclosure = Company reported GHG damage/Total Trucost Estimated GHG damage. Company reported GHG damage is a product of company reported GHG emissions and carbon damage cost factor (estimated by Trucost). Total Trucost estimate GHG damage represents a weighted sum of products of company segment revenues and carbon-per-dollar factors (both estimated by Trucost). This measure is also used and described in Marquis et al. (2016) and Grewal et al. (2023). For additional details, please see Marquis et al. (2016) and the appendix of Grewal et al. (2023).

[18] The list of keywords includes the following words and their variations: 'carbon", "climate", "climate change", "CO_2", "CO_2e", "emissions" , "ghg", "greenhouse gas", "methane", "pollution", "scope 1", "scope 2", "scope 3".

natural logarithm of GHG-related and non-GHG risk sentences, each scaled by the firm size (and alternatively by the total number of risk factor sentences). Higher levels of *GHG Risk Disclosure* indicate that the firm faces higher GHG-related risks and is less likely to manage them.

I control for firm-level characteristics predicted to be associated with environmental outcomes, obtained from the *CRSP/Compustat Merged* database. I use the *CRSP Monthly Stock File* database to calculate annual volatility of market-adjusted stock returns. I collect institutional ownership from 13F filings on *WRDS Thomson Reuters Stock Ownership* database. Additionally, I also include the number of environment-related penalties from the *Violation Tracker* database.

4.2 Facility-Level Sample

I use more granular facility-level emissions data from the GHGRP, which provides information on actual locations of facilities. The GHGRP is the first U.S. reporting regulation covering multiple industries and was enacted by the U.S. Environmental Protection Agency (EPA) in 2009. GHGRP requires large U.S. GHG emitters (defined as those with GHG emissions of 25,000+ annual metric tons CO_2 in the US) to report the direct emissions (Scope 1) data.[19] GHGRP is intended to enhance the understanding of the sources of GHG emissions to allow further development of regulations to reduce emissions. While GHGRP does not represent total U.S. GHG emissions, data collected from direct emitters represent around half of U.S. GHG emissions. When suppliers information is added, it covers 85-90% of the total U.S. GHG emissions from large industrial sources (more than 8,000 facilities).[20] Facilities report their emissions based on methodologies prescribed by the GHGRP and the emissions include carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O).[21] GHGRP emissions data is provided in units of metric tons of carbon dioxide equivalent.[22] To verify that information submitted by facilities is accurate, complete, and consistent, the GHGRP implements a multi-

[19] Unless a facility is required to report regardless of total annual emissions. Emissions from Agriculture sector are not part of GHGRP.

[20] Environmental Protection Agency.

[21] The reporters have some flexibility to choose among several available methodologies. They also can change methodology from year to year.

[22] GHGRP uses Global warming potentials (GWPs) from Intergovernmental Panel on Climate Change's (IPCC's) Fourth Assessment Report (AR-4).

step verification process.[23] The reporting data is available at a facility level on an annual basis.[24]

Unlike firm-level data, facility-level data is more precise as it provides the GHG emissions produced within specific state, and it is not estimated. Thus, I can analyse GHG *levels* at a facility-level. To account for state economic activity, I also collect real GDP values from the *Bureau of Economic Analysis* as a control variable or scaling factor in my facility-level analysis.

Within the time frame of GHGRP data (2011-2021), most GHG reduction targets were adopted in 2019 (around 60% of observations). Thus, I focus on facilities located in states which adopted GHG reduction targets in 2019 and facilities located in states which never adopted such targets as a control group. This sample has 27,759 facility-year observations for 5,093 unique facilities.[25] To overcome the issue that the decrease of emissions might be related to the fact that facilities exit GHGRP, I also focus on a balanced sample of facilities. The sample selection process is described in Panel B of Table 1.

I calculate my facility-level GHG emissions variable (GHG) by taking the natural logarithm of the sum of all emission types in carbon dioxide equivalent: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) – provided by the GHGRP.[26] To take into account potential changes in the economic activity within the state, I use the natural logarithm of GHG emissions scaled by state-level real GDP (GHG_GDP).

4.2.1 *Spillover Effects*

I use GHGRP data to investigate potential spillover effects through corporate and geographic proximity channels. To investigate the corporate channel, I link facilities by their parent companies' names.[27] To study the geographical proximity channel, I identify the list of directly neighboring states to the states that adopted GHG reduction targets in 2019.

[23] See GHGRP Methodology and Verification.

[24] Depending on the sector, some facilities have to report starting 2010 and some starting 2011. Thus, the number of observations in 2010 is very small.

[25] Analysis using a full sample is discussed in Section 7.

[26] I repeat the analysis using only CO_2 emissions as an outcome variable and confirm the results (untabulated).

[27] GHGRP parent names are not consistent across years, and facilities. To achieve consistency, I manually checked and corrected the data.

4.3 Descriptive Statistics

4.3.1 *State-Level Descriptive Information*

On average, according to Table A3, states adopting GHG reduction targets are Democratic, have higher levels of GDP, lower levels of emissions and number of facilities per million of population. The facilities' industry composition looks quite similar across treated and control group of states.[28] According to this descriptive analysis, the adoption of state-level environmental regulations is not random, and thus not exogenous. In fact, prior research finds that political and ideological orientation of citizens and proximity to states which have adopted GHG reduction targets is associated with a higher probability of adopting climate change regulation (Cale and Reams 2013; DellaVigna and Kim 2022). If the level of GHG emissions in states predict the adoption of regulations, the reverse causality might be an issue.

I start by analyzing the role of state-level characteristics influencing the timing of adoption of GHG reduction targets by estimating a hazard model. To estimate the likelihood of a state adopting the environmental GHG reduction targets based on covariates, I use a Weibull regression model, representing a parametric model that provides an estimate of the baseline hazard function. In my setting the hazard is defined as the likelihood of eventually adopting the GHG reduction target regulation, whereas survival represents the likelihood of not adopting. This analysis is run based on state-level data for years from 2010 to 2020.[29] The period from the beginning of the sample until the adoption of GHG reduction target is considered as time before the regulation, which is a dependent variable in the model. Once a state adopts GHG reduction targets, it is dropped from the sample.

The results are reported in Table A4. The main state-level covariates in Column (1) include the state governor's political ideology, state-level GHG intensity, industry distribution (based on the GHGRP data) of facilities, an indicator variable showing whether bordering states adopted the regulation, and state-level environmental expenditures. Since there are various methods to measure political ideology of a state, I use factor analysis to create a "*Political Ideology*" factor reflecting several variables such as political ideology of state governor,

[28] Untabulated.

[29] The time period is restricted by data availability. In untabulated analysis I confirm the results using the longer time interval by dropping some variables which are available for shorter horizon.

partisan composition of state legislature, and the state's political ideology based on presidential elections. Similarly, I create a "*Climate Opinion*" factor based on public opinion on climate warming (Howe et al. 2015). The "*Pollution Level*" factor is created based on the state-level GHG emissions, median air quality index and average percentage of unhealthy days within a state. The results are presented in Column (2) of Table A4.

Overall, across both columns, I do not observe that GHG emissions predict the adoption of regulations. However, the political ideology variables are positive and statistically significant. This implies that after controlling for other covariates, Democratic states have a higher hazard rate. In other words, they have a higher likelihood to adopt GHG reduction targets.

4.3.2 *Firm-Level Descriptive Information*

Panel A of Table 2 represents summary statistics for the primary firm-level sample. According to the table, there is higher variation in *Scope 1 Intensity* compared to *Scope 2* and *Scope 3 Intensity* levels. The weighted GHG and environmental disclosures have comparable magnitudes. The share of GHG risk disclosures in the 10-K Risk Factor section is much lower compared to non-GHG risk disclosures. Panel B reports the NAICS 2-digit industry distribution of the sample firm-year observations along with firms headquartered in states adopting GHG reduction targets. Firms operating in manufacturing dominate the sample. On average, 35% of observations within each industry group are firms headquartered in adopting states (treatment group). Figure 1 panel (A) presents the distribution of average Scope 1 Intensity levels by NAICS 2-digit industries, showing that utilities, transportation, mining, oil and gas, and manufacturing industries are the largest contributors to emissions. The correlation matrix for main variables is presented in Panel C of Table 2.

4.3.3 *Facility-Level Descriptive Information*

Panel D of Table 2 presents descriptive information for facility-level unbalanced and balanced samples. The balanced sample, on average, has facilities with higher levels of emissions. Treated and control facilities' emissions information can be inferred based on Table A3 which shows that facilities in treated states have lower (higher) level of emissions intensity (GHGRP GHG_GDP) compared to control states. Panel E reports the industry distribution for the facility-level sample, which is similar to the firm-level sample. Figure 1 panel (B) presents

the distribution of average *GHG_GDP* levels by NAICS 2-digit industries.

4.3.4 *Validation of Trucost firm-level data using the GHGRP facility-level GHG data*

Due to concerns associated with the validity of Trucost data, described in Section 4.1.1, I cross-validate the Trucost data using the GHGRP facility-level data. First, I aggregate the GHGRP facility-level data at a parent level. Second, I use the intersection of GHGRP parent-level data with the Trucost data. This intersection contains 2,121 firm-year observations for 307 unique firms with GHG emissions information from both Trucost and GHGRP. I then find that the correlation between the GHG emissions provided by Trucost and GHGRP is 72.25%, which is significant at the 0.01 level.

Furthermore, Trucost outlines how it quality checks the GHG data it gathers from various public sources. Once Trucost collects/estimates the GHG data for a firm, it shares this data with a firm. Firms have one month to review, respond and dispute this data. Overall, since firms will dispute the overestimated GHG emisisons numbers, but will not have incentives to dispute underestimated GHG emissions numbers, it can be expected that Trucost data reflects (or underestimates) the actual GHG performance.

5 Empirical Strategy

5.1 Firm-Level Analysis

In this paper, I study the role of state-level GHG reduction target regulations on direct real and disclosure outcomes, as well as spillover effects.

5.1.1 *Parallel Trends*

To validate the identifying assumptions of the DiD model, I estimate an event-study version of the TWFE DiD model for all outcome variables (including *Scope 1,2,3 Intensity*, *GHG Disclosure*, and *GHG Risk Disclosure*) with indicators for relative distance in years to/from the adoption of GHG reduction targets and check for potential pre-trends. I use an entropy-balanced sample to achieve a better covariate balance (Hainmueller 2012).[30] Table A5 presents summary statistics for the treatment and control samples prior to and after entropy

[30]Untabulated results are robust to using the sample without entropy-balancing and entropy balancing using both pre and post periods.

balancing based on the main covariates in the pre-treatment period. Overall, firms in the treatment group are smaller, have more negative *ROA*, exhibit lower level of *Leverage* and have higher level of cash flow volatility (*Std_CFO*) compared to the control group. Figure 2 depicts the parallel trends tests for all the main outcome variables: *GHG Scope 1 Intensity, GHG Disclosure* and *GHG Risk Disclosure* as well as *Non-GHG Risk Disclosure*. There is no evidence that the parallel trends assumption is violated. In particular, the outcome variables of interest were not trending differently for the treated and control groups in the pre-regulation period. Furthermore, the graphs show the significant change of the outcomes in the post-regulation period.

5.1.2 *Research Design*

I begin with exploring real and disclosure effects, performing the analysis at the firm-year level. To obtain causal estimates, I exploit the variation in the timing of GHG reduction target regulations and GHG emissions intensity as well as GHG-related disclosures across states and time. I use a two-way fixed effects (TWFE DiD) difference-in-differences research design, which helps to compare the before-and-after difference in outcomes between firms headquartered in states adopting GHG reduction target regulations (treatment group) versus those headquartered in non-adopting states (control group).

To test for direct real and disclosure effects (i.e., H1, H2(a) and H2(b)) I estimate:

$$y_{it} = \alpha + \beta_1 StateReg_{it} + \theta X_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{1}$$

where i and t represent firms and years, respectively. y_{it} is the outcome variable of interest, alternatively measured as: the natural logarithm of GHG emissions scaled by firm's revenue (*Scope 1,2,3 Intensity*); the natural logarithm of GHG-related weighted disclosures (*GHG Disclosure*); or the natural logarithm of GHG-related 10-K environmental risk disclosures scaled by firm's size (*GHG Risk Disclosure*). *StateReg* is the independent variable of interest, and is coded as an indicator variable equal to 1 for years after the GHG target regulations are adopted in states where a firm is headquartered, and 0 otherwise.[31] X_{it} is a vector of firm-level controls consistent with prior literature: *Size, ROA, Loss, MB, Leverage, Std_CFO,*

[31] Analysis based on alternative assignment to treatment methodology (states of significant subsidiaries) is provided in Section 7.

Std_Ret, Inst Own (all defined in Table A1). I include firm fixed effects (δ_i) to account for time-invariant firm characteristics, and year fixed effects (γ_t) to control for market trends. I estimate Equation (1) using ordinary least squares (OLS) and cluster standard errors at the firm level.[32] The main coefficient of interest is β_1, which captures the average treatment effect on the treated (ATT) of the adoption of state-level GHG reduction targets on firms' emissions and disclosures. Per H1 and H2(b) (H2(a)) $\hat{\beta}_1$, is expected to be negative (positive).

5.1.3 *Heterogeneity of treatment effects*

My empirical approach relies on the identifying assumption of parallel trends between treated and control firms. Furthermore, in a staggered DiD model, heterogeneity of treatment effects between treated groups and over time can affect the validity of ATT estimators even under the random assignment of treatment (Barrios 2021; Callaway and Sant'Anna 2021; Sun and Abraham 2021; Goodman-Bacon 2021; Baker et al. 2022). In my setting, the adoption years of GHG reduction targets vary across a long period of time, which increases the risk of heterogeneous treatment effects significantly affecting the validity of ATT estimator. To alleviate this concern, I follow Baker et al. (2022) recommendations and use alternative estimation strategies to ensure that treated firms are not compared to the firms that have been treated in the past. Below I describe these additional tests.

First, I estimate a stacked DiD model by creating event-specific datasets (Cengiz et al. 2019). The event-specific dataset includes the outcome and control variables for firms headquartered in treated states and for firms headquartered in non-adopting states (never-treated) within the estimation window from t=-4 to t=4 around the treatment year. Next, I identify a cohort of companies in the states that have never adopted GHG reduction targets, which represents a clean control. Then, for each of the GHG reduction target adoption years, I create an event-specific dataset (cohort) by appending the clean control and treated group observations around that target-year period. Next, I assign a dataset-specific identifying variable and stack all event-specific databases together in relative time and estimate the following model:

$$y_{itc} = \beta_1 StateReg_{itc} + \theta X_{itc} + \delta_{ic} + \gamma_{tc} + \epsilon_{itc} \tag{2}$$

[32] Robustness to alternative fixed-effects structure and clustering methods is provided in Section 7.

where c represents the corresponding event-specific dataset (or cohort) and the rest of the variables are consistent with Equation (1). δ_{ic} capture a firm-cohort fixed effects and γ_{tc} capture a year-cohort fixed effects. Standard errors are clustered at the firm-cohort level. I also validate the parallel trends assumption using the stacked sample (unplotted).

In addition to the stacked regression model, I estimate alternative estimators introduced by Callaway and Sant'Anna (2021) and Sun and Abraham (2021). Both alternative models help to increase the credibility of the TWFE DiD estimator in Equation (1). Furthermore, I utilize the Goodman-Bacon (Goodman-Bacon 2021) decomposition of the TWFE DiD estimator. I create a balanced sample because it is a necessary requirement for the decomposition analysis.[33]

5.2 Facility-Level Analysis

Next, I undertake a facility-level analysis to obtain causal estimates of the direct and spillover effects of GHG reduction target regulations.

5.2.1 *Parallel Trends*

I compare facilities in states adopting GHG reduction targets in 2019 (treatment group) and facilities located in never-adopting states (control group). I focus on the three years before and three years after the adoption of GHG reduction targets. The year 2019 is included in the post-period sample because there might be significant expectations of climate change regulations happening in later-adopting states, and most of the regulations in 2019 took place in the first half of the year. According to Figure 3, there is no indication of the existence of pre-trends.

5.2.2 *Research Design*

I employ a regular TWFE DiD research design to the facility-level data (Equation (3)). The conceptual difference is that the assignment to the treatment group is based on facility location. The regression model is:

$$y_{ft} = \beta_1 StateReg_{ft} + \beta_2 RGDP_{st} + \delta_f + \gamma_t + \epsilon_{ft} \tag{3}$$

[33]Balanced sample is created by keeping firms that are present for all years between 2005 and 2021.

where f and t represent facilities and years respectively. y_{ft} is the outcome variable of interest: the natural logarithm of facility-level GHG emissions (GHG) or the natural logarithm of GHG emissions scaled by state-level real GDP (GHG_GDP). I include facility fixed effects δ_f and year fixed effects γ_t. Standard errors are clustered at the facility level.[34] When levels of GHG emissions (GHG) are used as an outcome variable, I also control for state-level real GDP ($RGDP$) to take into account changing economic conditions which might influence emissions. When the GHG intensity level is used as an outcome variable, $RGDP$ is not included as a control

As described in Section 4, facilities might discontinue reporting if they produce less than 25,000 metric tons of GHG emissions. Thus, a decrease in emissions might be associated with exits from GHGRP. To overcome this concern, I estimate Equation (3) using a balanced panel of facilities that are present in the GHGRP for all sample years. I also follow Tomar (2023) and estimate the following model with additional covariates:

$$\begin{aligned} y_{ft} = \beta_1 StateReg_{ft} + \beta_2 StateReg_{ft} * Exit_f + \beta_3 StateReg_{ft} * Entry_f \\ + \beta_4 RGDP_{st} + \delta_f + \gamma_t + \epsilon_{ft} \end{aligned} \tag{4}$$

where $Exit_f$ represents an indicator variable which is equal to 1 for facilities that eventually exit the GHGRP, and 0 for facilities that do not exit the GHGRP. $Entry_f$ represents an indicator variable which is equal to 1 for facilities that enter the GHGRP later, and 0 for facilities that are present since the beginning of the GHGRP program sample (2011).

5.2.3 *Spillover Effects*

To study the corporate channel of spillover effects, I use facilities' parent company names provided by the GHGRP.[35] One parent company might have several facilities located in treated and control states. For each parent company, I identify facilities that are located in the states which adopted GHG reduction targets the earliest. This way I focus on the first instance of GHG reduction target adoption and avoid potential lagged effects. These facilities are considered directly treated. On the other hand, facilities that are located in states

[34] Robustness to alternative specifications, including industry-year fixed effects to control for time trends that are common within industries, and clustering at the state level, is provided in Section7.

[35] GHGRP parent names are not consistent across years, and facilities. To achieve consistency, I manually checked and corrected the data.

that have never been treated, but share the parent with facilities in treated states, constitute the indirectly treated group. In addition, I assign facilities to the indirect group if they are located in the states that adopted GHG reduction targets at least five years later relative to the first-treated facility of the parent. This alleviates the potential confounding effects of additional treatment or an expectation of treatment. The third group is the never-treated group which contains parents with all facilities located in states which never adopted GHG reduction targets. I then use a TWFE DiD regression model to estimate the effect of state-level GHG reduction target adoption on directly-affected and indirectly-affected facilities relative to the never-treated group. Estimation for the directly treated facilities is based on Equation (3). For indirect group facilities, I use the same treatment period as the facilities in the direct group. The sample of facilities is unbalanced to allow for the potential reallocation effect that might happen if a firm opens a new facility in the control state. The regression model is:

$$y_{jt} = \beta_1 StateReg_{ft} + \beta_2 RGDP_{st} + \delta_j + \gamma_t + \epsilon_{jt} \tag{5}$$

where j represents facilities whose parent was treated through another facility located in another state.

To further explore spillover effects for each of the treated states, I identify all states that share direct geographic borders. I then run a similar regression for the indirectly treated group based on the location of the state: if it is bordering or not to the state where the other facility of the parent is treated.

To test whether spillover effects arise from proximity to the treated states, I identify the list of bordering states to all states that have adopted GHG reduction targets. For each of these bordering states, I identify the earliest year when the neighboring treated state adopted the GHG reduction target regulation. I then remove the states that were directly treated and compare the indirectly-treated group (which were before the part of the control group) to the never-treated group (facilities in states that were not affected by bordering states being treated).

6 Empirical Results

6.1 Firm-Level Analysis

6.1.1 *Real Effects*

Table 3 presents estimates of *StateReg* ($\hat{\beta}_1$) in Equation (1) based on GHG emissions intensity to test H1. Overall, consistent with H1, the results show that state-level GHG reduction targets have a negative and significant effect on GHG *Scope 1 Intensity*. As shown in Columns (1) and (4), the adoption of GHG reduction targets in firms' headquarter states is associated with about an average 7% decrease in GHG *Scope 1 Intensity* levels post adoption relative to firms in non-adopting states. There is no significant change in indirect (*Scope 2* and *Scope 3*) GHG intensity levels. This suggests that, as a response to state-level environmental regulations, firms tend to focus on direct emissions only.

Companies can decrease of GHG emissions intensity including through the modernization of infrastructure and the use of data analytics tools. Anecdotally, for example, Hess Corporation, headquartered in New York state, achieved a decrease in emissions intensity after regulation by purchasing new compressor stations and using data analytics and machine learning to optimize carbon efficiency.[36] Other examples include Analog Devices, Archer Daniels Midland (ADM), and Woodward Inc. that purchased and upgraded equipment to achieve decarbonization after the regulations.[37]

6.1.2 *Disclosure Effects*

Table 4 presents similar estimations of *StateReg* ($\hat{\beta}_1$) in Equation (1) for Environmental and GHG-weighted disclosure outcome variables. In Columns (1) and (2), the coefficient of interest is positive, but not statistically significant. Conditional on covariates, the coefficient on *StateReg* becomes statistically significant and suggests that after regulation, firms tend to provide 16% more representative GHG disclosures. This finding is consistent with H2(a).

Next, I repeat the estimation of the model in Equation (1) for 10-K environmental risk disclosures as a main outcome variable. The 10-K GHG-related risk disclosures decrease post GHG target adoption relative to the control group as expected in H2(b). Overall, according

[36] Hess Corporation Sustainability Report 2021.

[37] Analog Devices 2010-2011; ADM 2021; Woodward Inc. 2020 Sustainability Reports.

to Column (3) in Table 5, the magnitude of the effect is around 3%, implying that firms headquartered in treated states tend to have lower levels of post-adoption GHG-related 10-K risk disclosures relative to the control group. This effect appears to be the result of better GHG risk management by treated firms, as evident from the reduction in emissions intensity. In addition, considering the positive dynamics of risk-factor disclosures in 10-Ks over time, I observe that firms in the control group expect similar environmental regulations to be implemented in the states where they are headquartered and thus increase the disclosure related to these potential regulatory changes and potential costs. There is no apparent effect of regulation on non-GHG related risk disclosures (Columns (2) and (4)).

Overall, my finding that firms' 10-K environmental risk disclosures decrease after the enactment of state emissions regulations also suggests that firms' associated emissions reductions are long-term commitments.

6.1.3 *Heterogeneity of treatment effects*

To account for treatment effect heterogeneity, I perform the estimation of stacked DiD described in Equation (2) for three main outcome variables. Panel A of Table 6 Column (1) documents the results for GHG *Scope 1 Intensity*, Column (2) for *GHG Disclosure*, and Column (3) for *GHG Risk Disclosure* respectively. Overall, the results are consistent with the estimates from Tables 3-5, with even larger in magnitude effects for *Scope 1 Intensity* and *GHG Risk Disclosure*. I repeat the estimation of the event-study version of TWFE DiD for a stacked sample for all three outcome variables of interest and confirm that there is no significant pre-trend (untabulated). In addition, I implement Callaway and Sant'Anna (2021) and Sun and Abraham (2021) estimators and get similar results (Panel B and Panel C of Table 6) for *Scope 1 Intensity* and *GHG Risk Disclosure* variables. *GHG Disclosure* loses significance using alternative estimators. One potential reason for this might be a delayed disclosure effect.

Significant variation of treatment timing (from 2006 to 2022) in the state-level regulations setting might suggest the possibility of biases. However, as Baker et al. (2022) state, higher percentage of never-treated observations makes these biases less problematic. In my firm-level sample, 61% of total firm-level observations constitute a never-treated group, which alleviates the issue of significant biases.

6.2 Facility-Level Analysis

Table 7 Panel A presents estimates of *StateReg* ($\hat{\beta}_1$) in Equation (3) on facility-level GHG emissions. The assignment to treatment is based on facilities' location. Columns (1) and (2) in Table 7 Panel A report estimates for unbalanced sample. In Columns (3) and (4) I repeat the analysis for a balanced sample of facilities that report to GHGRP in all years from 2011 to 2021.

Overall, facility-level analysis confirms the results obtained using firm-level analysis (Table 3 and Table 6) and shows that facilities located in states adopting GHG reduction targets in 2019 decrease their GDP-scaled emissions by approximately 5%.[38]

To explore the effect of entries/exits to/from GHGRP, I estimate Equation (4). I create a new variable *Exit* which is equal to 1 for facilities that exit the GHGRP anywhere between 2015 to 2020, and *Entry* for facilities entered the program from 2015. Table 7 Panel B shows that reduction of emissions for facilities that exit the GHGRP is quite large in magnitude, whereas for entering facilities the emissions increase, which is consistent with Tomar (2023). However, the main coefficient of interest *StateReg* remains significant, and its magnitude is comparable to prior analyses.

6.2.1 *Spillover Effects*

Next, I explore potential spillover effects. Panel A of Table 8 focuses on spillover effects across facilities that share a parent, using a balanced sample.[39] Columns (1) and (2) provide the estimation of direct effects for unscaled and scaled GHG emissions respectively. The results for direct effects are in line with the prior analysis. Columns (3) and (4) report the estimation results for spillover effects based on Equation (5). Columns (3) and (4) compare some part of the control group that is indirectly treated through another facility of the common parent with the rest of the control group, which has never been exposed to treatment through a parent. The results indicate that indirectly treated facilities experience around 10% emissions decrease post regulation adoption.

Next, I test whether there is a leakage of emissions to neighboring states. Table 8 Panel

[38]The results are similar when I use just CO_2 emissions as an outcome variable (untabulated). The results are robust to scaling GHG emissions by state population (untabulated). With a full sample using a staggered TWFE DiD I find comparable results (Table 11) Panel A.

[39]I repeat the analysis using an unbalanced sample and confirm the results.

B reports the results of this estimation. Columns (1) and (2) provide estimation results for unscaled and scaled GHG emissions. I find no evidence of effects extending to neighboring states.

7 Additional Analyses and Robustness Checks

7.1 Channel Tests

The effect of state-level climate change regulations can vary depending on various firm-specific characteristics. I consider the following mechanisms: firm size, level of institutional ownership and industry.

I start by exploring whether state-level climate change regulations have a differential effect on firms' real and disclosure outcomes based on firm size. I divide main sample into three terciles based on average firm's size across all years, with tercile 1 representing small firms, tercile 2 representing medium-sized firms, and tercile 3 representing large firms. Panel A of Table 9 shows that large firms account for significant decrease of *Scope 1 Intensity* levels as a response to state-level climate change regulations. *GHG Risk Disclosure* effect is larger in magnitude for smaller firms but is also significant for large firms. Overall, across all size groups main effects have consistent signs.

Panel B of Table 9 shows the results based on levels of institutional ownership. Firms with highest levels of institutional ownership account for significant decrease of *Scope 1 Intensity* level. This finding is consistent with argument that large institutional investors are able to force firms to improve environmental performance as response to climate change regulations. *GHG Risk Disclosure* effect is negative and statistically significant for firms with low and medium levels of institutional ownership.

Panel C of Table 9 shows that main effects are common to firms operating in various industries. Columns (1-3) show that the effect is not driven by firms operating in Utilities. Columns (4-6) focus on firms operating in Manufacturing and Oil&Gas industries, and Columns (7-9) focus on firms operating in industries other than Utilities, Manufacturing, or Oil&Gas.

While state-level GHG reduction targets have a common long-term goal to decarbonize, there is a variation across states based on characteristics of these targets. Panel D of Table 9 estimates the effect of state-level GHG reduction regulations based on characteristics of these

regulations. In particular, it shows that states with statutory targets, moderately aggressive (achievable) targets, and with reporting requirements (own GHG inventory registries) have stronger decarbonization and impovement in disclosure. In addition, states which are part of climate alliances and those with clear communication strategies show similar results (untabulated).

7.2 Robustness Checks

7.2.1 *Alternative specifications*

To test the sensitivity of results to the empirical design choice, I examine the robustness of main results to alternative specifications. I use industry-year fixed effects to account for common trends within the (NAICS 4-digit) industry. I use standard errors clustered at the state level since the treatment allocation is based on states. I also include clustering at the industry-year level. Table 10 Panel A (Panel B) provides the estimation results using alternative specifications for firm-level (facility-level) analysis. Estimated coefficients for *Scope 1 Intensity* and *GHG Disclosure* in Panel A are generally similar to those reported in prior analysis (Tables 3-6). Facility-level GHG emissions analysis results are robust to alternative specifications as shown in Panel B.

7.2.2 *Alternative samples*

I repeat the estimation of Equation (3) for full facility-level sample. The results are reported in Panel A of Table 11. The TWFE coefficients are negative and statistically significant, which is consistent with prior analysis using 2019 as a treatment year.

Several states have intermediate targets due in 2020, which can drive main results. I create an alternative sample by removing states with intermediate targets: New Jersey, Oregon, Hawaii, Connecticut, Massachusetts, Maryland and Rhode Island from the sample. Panel B confirms the robustness of results for subsample of states with no intermediate targets.

I use both firm- and facility-level data, which do not perfectly overlap. Panel C of Table 11 analyzes the intersection of the primary firm-level sample with GHGRP facility-level data, yielding a smaller subsample. The reason for that is that GHGRP data have around five hundred public companies which do not perfectly overlap with the *Trucost* emissions data.

However, I provide an estimation of Equation (3) for approximately three hundred firms that match with the GHGRP facility-level data. The results for this smaller sample are weaker, however they are negative and depending on the specification are statistically significant.

Next, I turn to firm-level alternative sampling. Some states have several state-level regulations in place. Several states are part of Regional Greenhouse Gas Initiative (RGGI) — the first mandatory cap-and-trade program, established in 2005. Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont, and Virginia are part of this program. To check that results are not driven by these states, I remove firms headquartered in states that are part of RGGI. In Panel D of Table 11 reports the estimation results which are robust.

I partition the sample based on Paris Agreement adoption because firms might be more willing and prepared to address climate change after large international treaty came into force in 2015. The results in Panel E of Table 11 indicate that *Scope 1 Intensity* (*GHG Risk Disclosure*) has a negative (positive) and significant coefficient in both subsamples. The improvement in *GHG Disclosure* takes place in the period before Paris Agreement was adopted. Overall, these results indicate, that state-level climate change regulations had significant impact on firms' real and disclosure practices before large international climate change treaty was adopted.

The partition based on Paris Agreement adoption also helps to address the concern related to the differences in sample size. As mentioned above, *Trucost* data coverage substantially increases after 2016 (Bolton and Kacperczyk 2021). By showing that the effect holds in both subsample (before and after Paris Agreement), I confirm that the results do not depend on the data coverage provided by *Trucost*.

7.2.3 *Parent-level analysis*

Table 12 provides the analysis based on the GHGRP parent information. First, I test whether firms decrease the number of facilities. For each parent firm I calculate the number of unique facilities per year. I then use the earliest year when the parent is exposed to a regulation through any of these facilities to test whether the number of facilities per parent changes. Panel A provides the estimation results: I do not observe significant change in number of facilities per parent. Panel B provides the estimation based on location of these facilities - in treated or

control states. In addition, in Panel C I repeat the baseline analysis using the parent location for treatment assignment. Panel C presents the results, which are consistent with firm-level analysis.

8 Conclusion

There have been worldwide challenges to achieve national and international coordination to reduce GHG emissions and fight climate change. However, subnational actions (such as U.S. state-level regulations) and their ensuing effects on corporate environmental policies and disclosures are both interesting and previously unexplored.

In this paper, I use spatial and temporal variation in the adoption of U.S. state-level GHG reduction targets to analyze the direct and spillover effects on firms' environmental performance and disclosure practices. By adopting a staggered TWFE DiD research design around GHG emissions regulations, I find that treated firms (facilities) decrease their GHG emissions intensity relative to the untreated entities. Affected firms provide more representative GHG emissions information in their public disclosures, while reducing their number of the GHG-related risk disclosures in 10-Ks relative to the control group. In addition, using facility-level data, I show that there are positive environmental spillover effects for non-treated facilities that share a parent with facilities in other states affected by GHG emissions regulations.

My findings have important policy implications for the design of decentralized environmental policies. While national or international climate change regulations may not be feasible, my empirical results for the U.S. setting suggest that subnational initiatives can play a significant role in reducing GHG emissions and improving related disclosures.

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Appendix I

Table A1: Variable Definitions

Variable	Definition	Source
StateReg	Indicator variable equal to 1 for firms headquartered (or with significant subsidiaries, or with facilities located) in states that adopt GHG reduction targets in years after the adoption, and zero otherwise.	C2ES, State-level legislation
	Environmental Disclosure Variables	
GHG Risk Disclosure	Natural logarithm of 1 plus total GHG/Climate-related sentences in 10-K Risk Factors section scaled by firm size (or total number of risk factor sentences).	SEC EDGAR 10-K
Non-GHG Risk Disclosure	Natural logarithm of 1 plus total non-GHG sentences in 10-K Risk Factors section scaled by firm size (or total number of risk factor sentences). Non-GHG sentences are calculated as a difference between total number of 10-K Risk Factor section sentences and GHG-related sentences.	SEC EDGAR 10-K
GHG Disclosure	Natural logarithm of 1 plus the proportion of GHG emissions damage which is disclosed by the firm (Firm reported GHG Damage/Total Trucost estimated GHG damage). See Section 4 for details.	Trucost Environmental
ENV Disclosure	Natural logarithm of 1 plus the proportion of all direct environmental damage costs which is disclosed by the firm. See Section 4 for details.	Trucost Environmental
	Environmental Performance Variables	
Scope 1 Intensity	Natural logarithm of 1 plus Scope 1 GHG emissions divided by firm's revenue.	Trucost Environmental
Scope 2 Intensity	Natural logarithm of 1 plus Scope 2 GHG emissions divided by firm's revenue.	Trucost Environmental
Scope 3 Intensity	Natural logarithm of 1 plus Scope 3 GHG emissions divided by firm's revenue.	Trucost Environmental
GHG	Natural logarithm of 1 plus carbon dioxide equivalent emissions (CO2, N2O, CH4) at a facility level.	GHGRP
GHG_GDP	Natural logarithm of 1 plus emissions carbon dioxide equivalent emissions (CO2, N2O, CH4) at a facility level scaled by state-level real GDP.	GHGRP, Bureau of Economic Analysis
	Control Variables	
Size	Natural logarithm of a firm's market capitalization.	Compustat
ROA	Net income, divided by total assets.	Compustat
Loss	Indicator variable equal to 1 if net income is negative, and 0 otherwise.	Compustat
MB	Market value of equity, divided by book value of equity.	Compustat
Leverage	Sum of long-term liabilities and short-term liabilities, divided by book value of equity.	Compustat
Std_Ret	12-month standard deviation of firm's market-adjusted monthly stock returns. Market return is proxied using the value-weighted index including dividend distributions.	CRSP
Std_CFO	5-year standard deviation of firm's annual operating cash flows scaled by total assets.	Compustat

Continued on next page

Table A1: Variable Definitions (Continued)

Variable	Definition	Source
Inst Own	Total number of shares held by institutional investors, divided by the total number of outstanding shares. Missing values are replaced with zero values.	Thomson Reuters 13-F
Log N E Pnlt	Natural logarithm of number of environmental penalties.	Violation Tracker
RGDP	Natural logarithm of state-level real GDP.	Bureau of Economic Analysis
	Additional Variables	
Exit	Indicator variable that takes a value of 1 for facilities that exit GHGRP, and zero otherwise.	GHGRP
Entry	Indicator variable that takes a value of 1 for facilities that enter GHGRP for the first time after 2011, and zero otherwise.	GHGRP
N Facilities	Natural logarithm of total number of facilities per state-year.	GHGRP
GHG State	Natural logarithm of total EPA-reported state-level emissions.	EPA
GHG State_GDP	Natural logarithm of total EPA-reported state-level emissions scaled by state-level real GDP.	EPA, Bureau of Economic Analysis
Democrat	Indicator variable equal to 3 if state governor is Democrat, 1 if Republican, and 2 if belongs to a political party other than mentioned above.	National Governors Association
Political Ideology	Factor created based on political ideology of state governor, partisan composition of state legislature, and state's political ideology based on presidential elections.	Census, National Governors Association
Pollution Level	Factor created from State-level GHG emissions, Median Air Quality index, average percentage of unhealthy days, and percentage of facilities operating in different industries.	EPA, GHGRP
Climate Opinion	Factor created from estimated percentage of people who are worried about the effects of climate change and support funding research into renewable energy sources.	Yale Climate Opinion
Bordering State	Indicator variable that takes value of 1 if a state has a bordering state which adopted the GHG reduction target since the year of adoption. If several bordering states adopted the targets, the earliest year is chosen.	C2ES, State-level legislation
% Manufacturing	Percent of facilities operating in manufacturing industry.	GHGRP
% Utilities	Percent of facilities operating in utilities industry.	GHGRP
% Oil & Gas	Percent of facilities operating in Oil & Gas industry.	GHGRP
% Transportation	Percent of facilities operating in transportation industry.	GHGRP
% Waste	Percent of facilities operating in waste industry.	GHGRP
% Other	Percent of facilities operating in other than above mentioned industries.	GHGRP
% State Env Expenditure	Percent of state-level environmental expenditures (natural resources) to total expenditures.	Census
Log State Env Expenditure	Natural logarithm of state-level environmental expenditures (natural resources).	Census
Unscaled GHG Risk Disclosure	Natural logarithm of number of GHG-related sentences in 10-K Risk Factor section.	SEC EDGAR 10-K
Unscaled Non-GHG Risk Disclosure	Natural logarithm of number of sentences in 10-K Risk Factor section that are not GHG-related.	SEC EDGAR 10-K

FIGURE A1: States With and Without GHG Reduction Targets

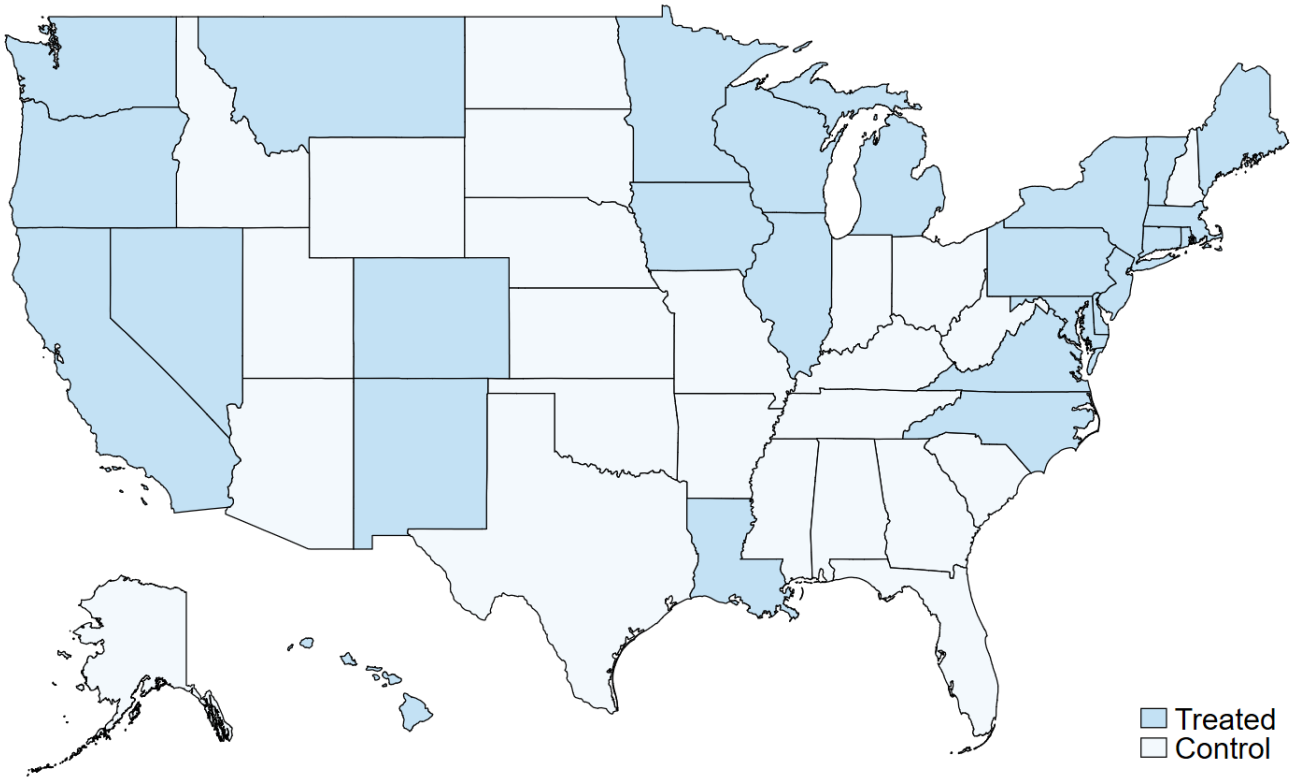


FIGURE A2: Timing of GHG Reduction Target Adoption

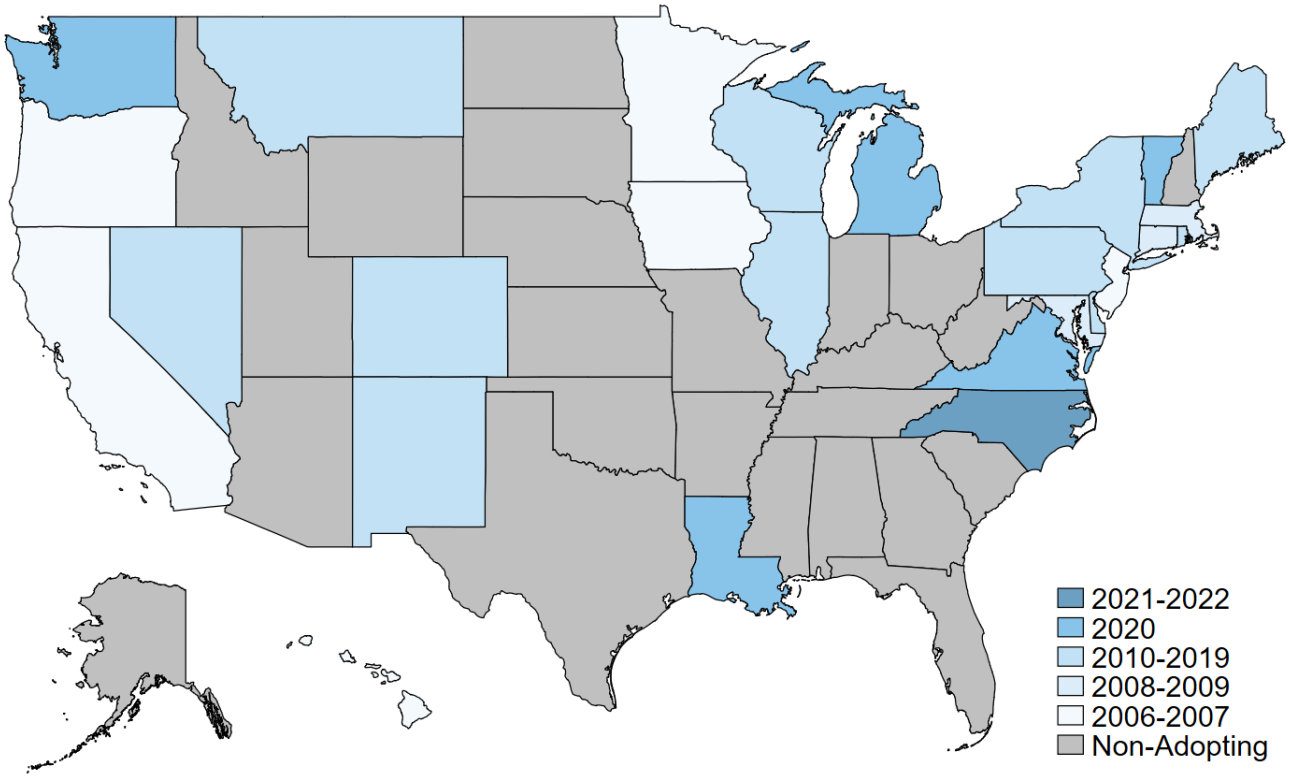


Table A2: Timing and Description of GHG Targets

N	Reporting/ Monitoring	State Code	State	Statutory Target	Executive Target	Description of Targets
1	Yes	CA	California	2006		*Global Warming Solutions Act (AB 32).* Reduce GHG emissions at least 10% below 1990 levels by 2020 and 80% below 2001 levels by 2050.
2	Yes	MN	Minnesota	2007		*Next Generation Energy Act (HF436).* Reduce GHG emissions 15% below 2005 levels by 2015, 30% below 2005 levels by 2025 and 80% below 2005 levels by 2050.
3	Yes	NJ	New Jersey	2007		*Global Warming Response Act (C.26:2C-37).* Reduce GHG emissions to 1990 levels by 2020 and 80% below 2006 levels by 2050.
4	Yes	OR	Oregon	2007		*Act HB 3543.* Reduce GHG emissions 10% below 1990 levels by 2020 and 75% below 1990 levels by 2050.
5	Yes	HI	Hawaii	2007		*Act 234.* Reduce GHG emissions to 1990 levels by 2020.
6	Yes	CT	Connecticut	2008		*Global Warming Solutions Act (N 08-98).* Reduce GHG emissions at least 10% below 1990 levels by 2020 and 80% below 2001 levels by 2050.
7	Yes	MA	Massachusetts	2008		*Global Warming Solutions Act (Chapter 298).* Reduce GHG emissions 10-25% by 2020; 80% by 2050 (1990 baseline).
8	Yes	MD	Maryland	2009		*Greenhouse Gas Reduction Act (Chapter 171).* Reduce GHG emissions 25% below 2006 levels by 2020 and establish a long-term goal of reducing by up to 90% below 2006 levels by 2050.
9	No	RI	Rhode Island	2014		*Resilient Rhode Island Act.* Reduce GHG emissions by 10% by 2020; 45% by 2035; 80% by 2050 (1990 baseline).
10	Yes	CO	Colorado	2019		*Climate Action Plan to Reduce Pollution (House Bill 19-1261).* Reduce GHG emissions 26% by 2025, 50% by 2030, and 90% by 2050, all compared to 2005 levels.
11	Yes	ME	Maine	2019		*38 MRSA §576-A.* Reduce GHG emissions to 45% below 1990 levels by 2030, to 80% below 1990 levels by 2050.
12	Yes	NV	Nevada	2019		*Next Generation Energy Act.* Reduce GHG emissions 28% by 2025 and 45% by 2030, compared to 2005 levels, and reach zero or near-zero emissions by 2050.
13	Yes	NY	New York	2019		*Climate Leadership and Community Protection Act (A.8429).* Reduce GHG emissions by 40% by 2030; 85% by 2050 (1990 baseline); net-zero GHG emissions by 2050.
14	Yes	VT	Vermont	2020		*Global Warming Solutions Act (H.688 Act 153).* Reduce GHG emissions to 26% below 2005 levels by 2025. Emissions would need to be 40% below 1990 levels by 2030 and 80% below by 2050
15	Yes	VA	Virginia	2020		*Senate Bill 94.* Net-zero GHGs across economic sectors by 2045
16	Yes	WA	Washington	2020		*HB 2311.* Reduce GHG emissions 45% by 2030; 70% by 2040; 95% by 2050 (1990 baseline); net-zero economy by 2050.
17	Yes	IA	Iowa		2007	*455B.* Reduce GHG emissions 50% and 90% by 2050 from 2005 levels.
18	No	DE	Delaware		2014	*Executive Order 41.* Reduce GHG emissions by 30% by 2030.
19	Yes	PA	Pennsylvania		2019	*Executive Order 2019-01.* Reduce GHG emissions 26% by 2025, and 80% by 2050 from 2005 levels.
20	No	IL	Illinois		2019	*Executive Order 2019-06.* Reduce GHG emissions by 26-28% by 2025 compared to 2005 levels.
21	No	MT	Montana		2019	*Executive Order 8-2019.* Net zero goal by 2035.
22	No	NM	New Mexico		2019	*Executive Order 2019-003.* Reduce GHG emissions 45% by 2030.
23	No	WI	Wisconsin		2019	*Executive Order 38.* Net zero by2050.
24	No	LA	Louisiana		2020	*Executive Order JBE 2020-18.* Reduce GHG emissions by 26-28% by 2025, 40-50% by 2030, and 100% by 2050.
25	No	MI	Michigan		2020	*Executive Order 2020-182.*Reduce GHG emissions 28% below 2005 levels by 2025.
26	No	NC	North Carolina		2022	*Executive Order 246.* Reduce GHG emissions 50% by 2030 and net zero by 2050

Table A3: State Characteristics

	States with GHG Reduction Targets								States without GHG Reduction Targets						
			(1)	(2)	(3)	(4)	(5)	(6)			(7)	(8)	(9)	(10)	(11)
	State Code	State	D/R/S	D/R Target	N Facilities per M People	GHGRP GHG/GDP	EPA GHG/GDP	Average GDP	State Code	State	D/R/S	N Facilities per M People	GHGRP GHG/GDP	EPA GHG/GDP	Average GDP
1	**CA**	**California**	D	R	9	0.03	0.17	2,441,000	AL	Alabama	R	30	0.4	0.73	195,852
2	**CO**	**Colorado**	D	D	22	0.13	0.4	320,272	AK	Alaska	R	87	0.28	0.65	54,064
3	**CT**	**Connecticut**	D	R	12	0.04	0.16	242,432	AZ	Arizona	S	10	0.17	0.37	298,226
4	DE	Delaware	D	D	17	0.09	0.25	62,987	AR	Arkansas	R	36	0.34	0.82	113,776
5	**HI**	**Hawaii**	D	R	16	0.11	0.25	74,997	FL	Florida	S	7	0.14	0.31	881,468
6	IL	Illinois	D	D	18	0.13	0.35	747,387	GA	Georgia	S	12	0.13	0.32	503,908
7	IA	Iowa	R	D	46	0.27	0.75	167,860	ID	Idaho	R	22	0.06	0.48	66,854
8	LA	Louisiana	R	D	81	0.46	0.95	231,171	IN	Indiana	R	27	0.38	0.7	320,885
9	**ME**	**Maine**	D	D	20	0.09	0.31	56,576	KS	Kansas	R	39	0.21	0.75	151,426
10	**MD**	**Maryland**	D	D	9	0.06	0.2	351,842	KY	Kentucky	R	26	0.43	0.88	185,176
11	**MA**	**Massachusetts**	D	D	11	0.03	0.15	477,172	MS	Mississippi	R	32	0.33	0.77	100,845
12	MI	Michigan	S	D	21	0.17	0.43	447,113	MO	Missouri	R	17	0.24	0.59	280,339
13	**MN**	**Minnesota**	S	R	23	0.12	0.42	321,296	NE	Nebraska	R	38	0.25	0.78	111,978
14	MT	Montana	R	D	27	0.4	1.24	45,093	NH	New Hampshire	D	13	0.05	0.22	73,282
15	**NV**	**Nevada**	S	D	13	0.12	0.31	141,455	ND	North Dakota	R	73	0.68	1.57	53,483
16	**NJ**	**New Jersey**	D	D	11	0.04	0.2	535,019	OH	Ohio	S	20	0.18	0.43	582,577
17	NM	New Mexico	D	D	38	0.32	0.87	90,103	OK	Oklahoma	R	41	0.27	0.76	188,791
18	**NY**	**New York**	D	D	10	0.03	0.14	1,399,367	SC	South Carolina	R	17	0.18	0.42	196,611
19	NC	North Carolina	S	D	10	0.12	0.31	483,543	SD	South Dakota	R	33	0.1	0.9	45,761
20	**OR**	**Oregon**	D	D	12	0.06	0.25	197,942	TN	Tennessee	R	15	0.14	0.37	310,126
21	PA	Pennsylvania	S	D	22	0.16	0.41	680,666	TX	Texas	R	26	0.2	0.52	1,613,193
22	**RI**	**Rhode Island**	D	L	10	0.06	0.21	52,506	UT	Utah	R	22	0.23	0.51	151,871
23	**VT**	**Vermont**	D	D	12	0.01	0.28	29,366	DC	Washington, D.C.	D	7	0	0.03	118,695
24	**VA**	**Virginia**	D	D	14	0.08	0.27	465,533	WV	West Virginia	R	50	0.96	1.76	71,042
25	**WA**	**Washington**	D	D	11	0.04	0.18	469,819	WY	Wyoming	R	156	1.39	2.4	38,396
26	WI	Wisconsin	S	D	23	0.17	0.45	289,740							
		Average:	D	D	**19.86**	**0.13**	**0.36**	**416,241**		Average:	R	**34.2**	**0.31**	**0.72**	**268,345**
		W/t CA	D	D	**20.3**	**0.13**	**0.37**	**335,250**							

Notes. This table presents descriptive information for adopting GHG reduction targets states (Columns 1-6) and non-adopting states (Columns 7-11). States with statutory targets are in bold. Columns (1-2) and (7) reflect political ideology of a state. D denotes Democratic, R denotes Republican and S denotes Swing states. Columns (1) and (7) political ideology information is based on recent presidential elections, Column (2) is based on political ideology of a state governor, signing the GHG reduction targets. The average number of facilities is calculated based on facility-level GHGRP data as a mean for the 2011-2021 period by state. Average emissions are calculated based on facility-level GHGRP data (2011-2021) and state-level EPA data (2011-2020) and are represented in thousands of metric tons scaled by real state-level GDP. EPA emissions data includes residential emissions and emissions from facilities/sources that do not report to GHGRP. Average state GDP is in millions of chained 2012 dollars.

Table A4: Hazard Model: Timing of GHG Reduction Targets Adoption

	(1) Likelihood of Regulation	(2) Likelihood of Regulation
Democrat	0.594**	
	(0.27)	
GHG State_GDP	0.353	
	(0.54)	
Political Ideology		2.189***
		(0.50)
Pollution Level		-0.409
		(0.53)
Climate Opinion		-1.198*
		(0.68)
Bordering State	1.537	15.969
	(1.10)	(4141.74)
% Manufacturing	-2.846	
	(3.91)	
% Utilities	-0.137	
	(4.43)	
% Oil & Gas	-1.04	
	(4.29)	
% Transportation	-4.287	
	(5.60)	
% State Env Expenditure	-44.904	6.733
	(36.86)	(43.31)
Log State Env Expenditure	0.394	-0.041
	(0.33)	(0.47)
Constant	-12.079***	-36.167
	(4.17)	(4141.75)
N	529	430

Notes. This table reports the coefficients from the estimation of Weibull hazard model, identifying state characteristics associated with the likelihood to adopt the GHG reduction targets. The unit of analysis is state-year. Sample size differs based on data availability. In Column (1) sample period is from 2008 to 2020, in Column (2) sample period is from 2010 to 2020. The dependent variable is *Likelihood of Regulation*, which represents the speed to regulation. A state is dropped from the sample after it adopts GHG reduction targets. In Column (1) the estimation is based on individual analysis, whereas in Column (2) variables are grouped based on factor analysis technique. All continuous variables are winsorized at 1 (99)%. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions.

Table A5: Entropy Balancing for Firm-Level Sample (Pre-Treatment Period)

Before:

	Treated			Control		
	Mean	SD	Skewness	Mean	SD	Skewness
Size	6.242	4.359	0.202	6.452	4.373	-0.008
ROA	-0.078	0.095	-3.104	-0.022	0.061	-4.560
Leverage	0.211	0.053	1.318	0.274	0.052	0.949
MTB	3.213	35.150	2.656	2.836	38.790	3.792
Std_CFO	0.079	0.011	3.187	0.061	0.007	4.658
Std_Ret	0.128	0.007	1.943	0.127	0.008	2.532
Inst Own	0.554	0.120	-0.121	0.539	0.136	0.001

After:

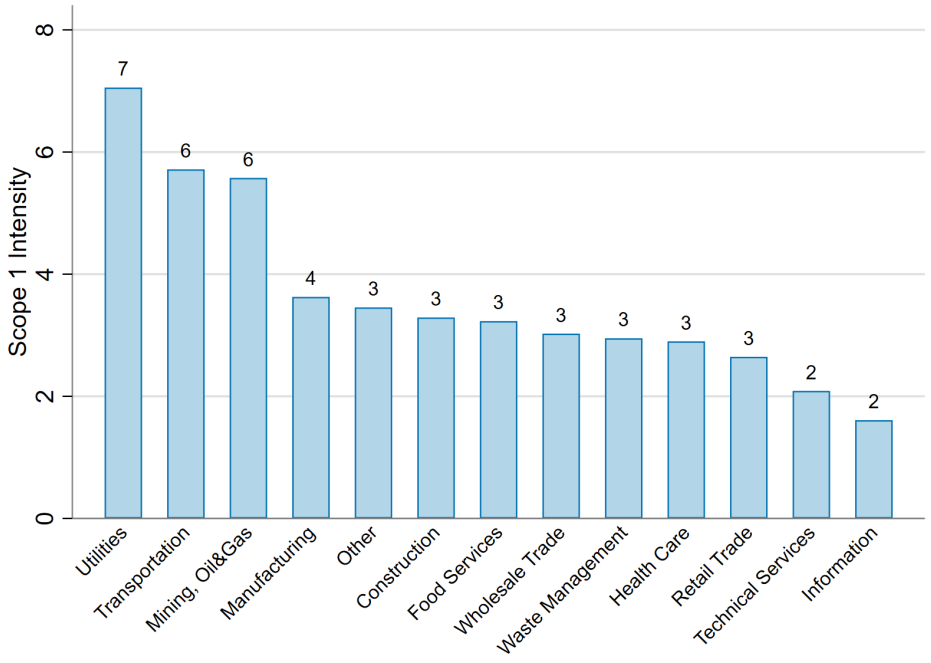
	Treated			Control		
	Mean	SD	Skewness	Mean	SD	Skewness
Size	6.242	4.359	0.202	6.242	4.359	0.202
ROA	-0.078	0.095	-3.104	-0.078	0.095	-3.104
Leverage	0.211	0.053	1.318	0.211	0.053	1.318
MTB	3.213	35.150	2.656	3.213	35.150	2.656
Std_CFO	0.079	0.011	3.187	0.079	0.011	3.187
Std_Ret	0.128	0.007	1.943	0.128	0.007	1.943
Inst Own	0.554	0.120	-0.121	0.554	0.120	-0.121

Notes. These tables report descriptive statistics (sample means, standard deviations and skewness) for the treatment and control samples before and after employing entropy balancing based on the pre-treatment period. All continuous variables are winsorized at 1 (99)%. Table A1 provides variable definitions, Table 1 provides details on sample selection.

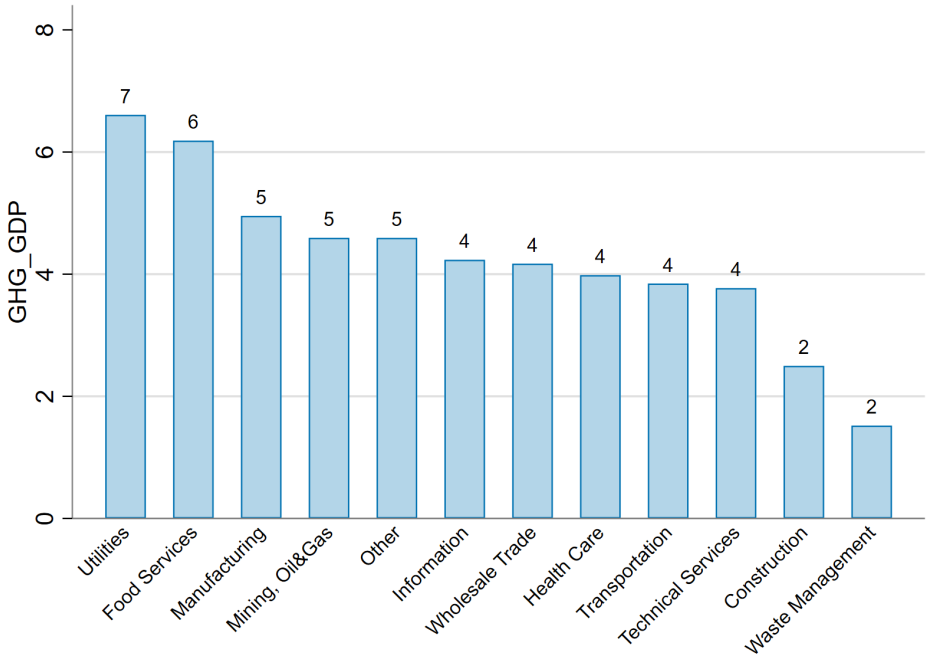
Figures

FIGURE 1: Average Scope 1 Intensity By NAICS 2-Digit Codes

(A) Firm-Level Sample



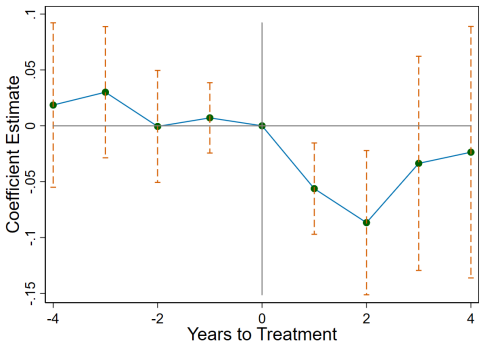
(B) Facility-Level Sample



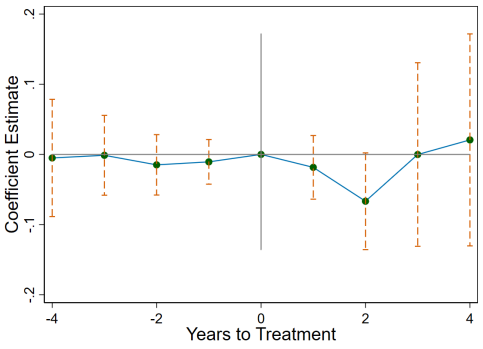
Notes. These graphs plot average GHG emission intensity levels by NAICS 2-digit industry classification system. Figure (A) plots the distribution for the firm-level sample. Figure (B) plots the distribution for the facility-level sample. Table A1 provides variable definitions, Table 1 provides details on sample selection.

FIGURE 2: Parallel Trends for Firm-Level Analysis

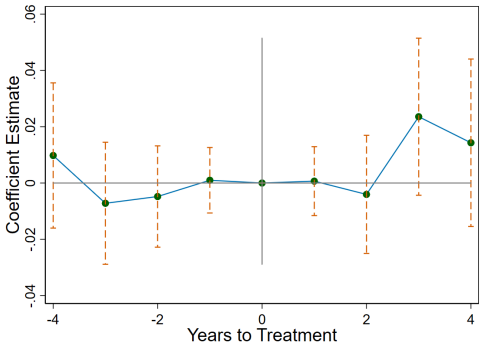
(A) Scope 1 Intensity



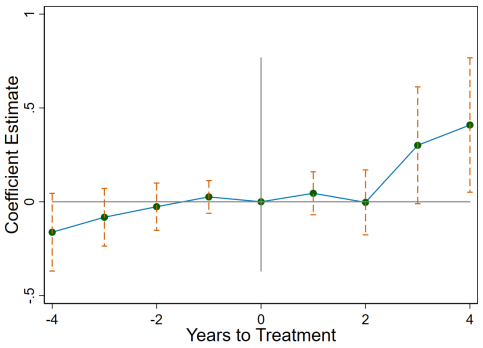
(B) Scope 2 Intensity



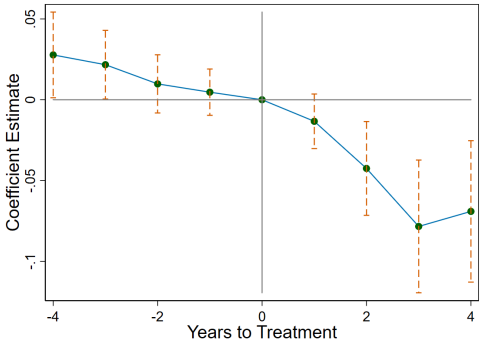
(C) Scope 3 Intensity



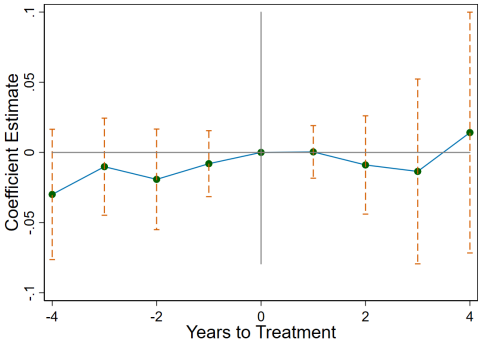
(D) GHG Disclosure



(E) GHG Risk Disclosure

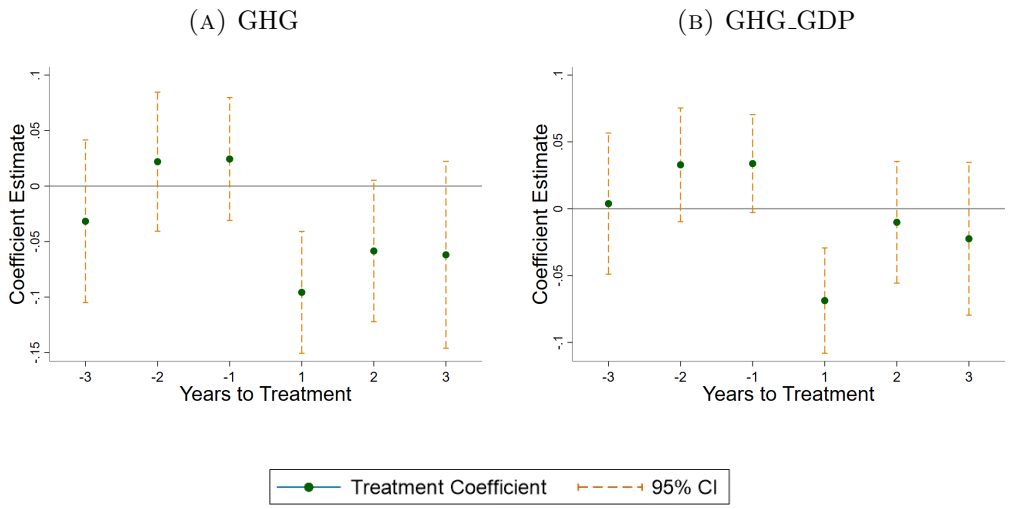


(F) Non-GHG Risk Disclosure



Notes. These graphs plot the difference-in-difference coefficients and their 95% confidence intervals for *GHG Scope 1 (2 and 3) Intensity, GHG Disclosure, GHG Risk Disclosure* and *Non-GHG Risk Disclosure* outcome variables. As described in section 5.1 these coefficients are estimates using the event-study version of TWFE DiD model for all outcome variables with indicators for relative distance in years to/from the adoption of GHG reduction targets. The sample comprises firms headquartered in states adopting GHG reduction targets and firms headquartered in non-adopting states. Adoption year is set as the benchmark period (coefficient equals to zero) and periods from -4 to 4 denote years before and after the adoption of GHG reduction target. Table A1 provides variable definitions, Table 1 provides details on sample selection.

FIGURE 3: Parallel Trends for Facility-Level Analysis



Notes. These graphs plot the difference-in-difference coefficients and their 95% confidence intervals for *GHG* and *GHG_GDP* outcome variables. As described in section 5.1 these coefficients are estimates using the event-study version of TWFE DiD model for all outcome variables with indicators for relative distance in years to/from the adoption of GHG reduction targets. The sample comprises facilities located in states adopting GHG reduction targets in 2019 and facilities located in non-adopting states. The year before adoption is set as the benchmark period (coefficient equals to zero) and periods from -3 to 3 denote years before and after the adoption of GHG reduction target. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Tables

Table 1

Sample Selection

Panel A: *Sample Selection for Firm-Level Analysis*

Description	Firm-Years
Intersection of Compustat and CRSP firms located in the USA for the period from 2000-2022 fiscal years with valid CIKs.	112,430
Less: non-merged with the SEC EDGAR 10-K filings firm-years (Note: the full sample of all 10-K filings from the SEC EDGAR filed during the period from 2001 to 2023 is 189K)	(21,430)
Merged 10-K filings from the SEC EDGAR with intersection of Compustat and CRSP with valid CIK and GVKEY identifiers	91,000
Less: firm-years in states where GHG reduction targets were set in 2021 or 2022 (for these observations there is insufficient post period data)	(2,159)
Less: firm-years with absent Trucost GHG emissions data	(60,773)
Less: firm-years in Fama-French Finance industry	(6,300)
Less: firm-years with missing control variables (Compustat, CRSP)	(1,102)
Less: observations more than 4 years before or after the state-level GHG reduction target events, California observations	(9,441)
Final Sample: Firm-years (2005-2021 fiscal years) with valid identifiers, GHG intensity levels, available 10-K filings, and control variables	**11,225**

Panel B: *Sample Selection for Facility-Level Analysis*

Description	Facility-Years
GHGRP facility-year observations	66,120
Less: observations that had GHG reduction targets in years other than 2019	(20,420)
Less: facility-years before 2015 and singleton observations, California observations	(17,941)
Final Sample: Facility-years (2015-2021 fiscal years)	**27,759**
Final Balanced Sample: Facilities that are present for all years	**21,224**

Notes. This table presents the sample selection process for firm-level (Panel A), and GHGRP facility-level (Panel B) samples. Facility-level sample concentrates on facilities located in the states adopting GHG reduction targets in 2019 and facilities in never-adopting states.

Table 2

Summary Statistics

Panel A: *Descriptive Statistics for Firm-Level Sample*

	N	Mean	SD	P25	P50	P75
Scope 1 Intensity	11,225	3.536	1.798	2.354	3.091	4.500
Scope 2 Intensity	11,225	3.162	0.986	2.509	3.118	3.791
Scope 3 Intensity	11,225	4.903	0.825	4.238	4.881	5.558
GHG Disclosure	11,225	1.451	2.128	0.000	0.000	4.612
ENV Disclosure	11,225	1.361	1.951	0.000	0.000	3.803
GHG Risk Disclosure	11,225	0.443	0.484	0.092	0.271	0.669
Non-GHG Risk Disclosure	11,225	3.385	0.731	2.988	3.424	3.840
Size	11,225	7.900	1.715	6.779	7.951	9.063
ROA	11,225	0.013	0.176	0.001	0.041	0.081
Loss	11,225	0.245	0.430	0.000	0.000	0.000
Leverage	11,225	0.301	0.219	0.140	0.283	0.418
MTB	11,225	3.510	7.888	1.401	2.351	4.136
Std_CFO	11,225	0.045	0.064	0.016	0.029	0.050
Std_Ret	11,225	0.105	0.079	0.058	0.084	0.125
Inst Own	11,225	0.749	0.300	0.630	0.814	0.927
Log N E Pnlt	11,225	0.148	0.373	0.000	0.000	0.000

Panel B: *Industry Distribution Firm-Level Sample*

NAICS 2	Industry	Firm-Years Total	Firm-Years Treatment	% Treatment
31-33	Manufacturing	4,762	2,147	45%
51	Information	1,121	581	52%
21	Mining, Oil and Gas Extraction	961	133	14%
44-45	Retail Trade	725	233	32%
22	Utilities	565	193	34%
48-49	Transportation and Warehousing	526	101	19%
42	Wholesale Trade	495	211	43%
54	Professional, Scientific, and Technical Services	436	201	46%
72	Accommodation and Food Services	361	154	43%
56	Waste Management and Remediation Services	324	162	50%
23	Construction	285	50	18%
62	Health Care and Social Assistance	269	77	29%
Other	Other	395	112	28%
Total		**11,225**	**4,355**	
Average				**35%**

Panel C: *Correlation Matrix for Firm-Level Sample*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Scope 1 Intensity	1														
(2) Scope 2 Intensity	0.30*	1													
(3) Scope 3 Intensity	0.50*	0.35*	1												
(4) GHG Disclosure	0.24*	0.09*	0.23*	1											
(5) ENV Disclosure	0.36*	0.15*	0.25*	0.93*	1										
(6) GHG Risk Disclosure	0.49*	0.15*	0.27*	0.16*	0.24*	1									
(7) Non-GHG Risk Disclosure	-0.13*	-0.07*	-0.22*	-0.26*	-0.25*	0.31*	1								
(8) Size	0.09*	-0.01	0.08*	0.50*	0.48*	-0.10*	-0.52*	1							
(9) ROA	0.02	0.01	0.11*	0.12*	0.10*	-0.12*	-0.37*	0.39*	1						
(10) Loss	-0.03*	0.01	-0.11*	-0.14*	-0.12*	0.15*	0.40*	-0.40*	-0.59*	1					
(11) Leverage	0.07*	0.06*	-0.01	0.08*	0.09*	0.16*	0.15*	0.05*	-0.07*	0.11*	1				
(12) MTB	-0.09*	-0.05*	-0.05*	0.01	0.00	-0.07*	-0.02*	0.13*	0.03*	-0.03*	-0.07*	1			
(13) Std_CFO	-0.08*	0.01	-0.11*	-0.16*	-0.16*	0.01	0.27*	-0.31*	-0.47*	0.27*	-0.06*	0.04*	1		
(14) Std_Ret	-0.02*	0.06*	-0.10*	-0.20*	-0.17*	0.18*	0.41*	-0.48*	-0.43*	0.46*	0.10*	-0.01	0.39*	1	
(15) Inst Own	-0.05*	-0.04*	-0.02*	0.01	0.00	-0.04*	0.00	0.17*	0.15*	-0.09*	0.02*	0.03*	-0.12*	-0.13*	1
(16) Log N E Pnlt	0.31*	0.21*	0.22*	0.27*	0.29*	0.14*	-0.23*	0.33*	0.07*	-0.10*	0.03*	-0.01	-0.10*	-0.13*	-0.03*

Panel D: *Descriptive Statistics for Facility-Level Sample*

	N	Mean	SD	P25	P50	P75
Unbalanced Sample						
GHG	27,759	10.583	2.787	10	10.788	11.994
GHG_GDP	27,759	4.878	2.424	3.427	4.922	6.435
RGDP	27,759	12.858	1.095	12.144	12.731	13.689
Balanced Sample						
GHG	21,224	10.891	2.703	10.219	11.004	12.36
GHG_GDP	21,224	5.173	2.442	3.754	5.255	6.716
RGDP	21,224	12.826	1.075	12.133	12.707	13.562

Panel E: *Industry Distribution Facility-Level Sample*

NAICS 2	Industry	Firm-Years Total	Firm-Years Treatment	% Treatment
31-33	Manufacturing	10,744	2,556	24%
22	Utilities	6,410	2,126	33%
48-49	Transportation and Warehousing	3,471	769	22%
21	Mining, Oil and Gas Extraction	3,240	509	16%
56	Waste Management and Remediation Services	2,919	1,183	41%
Other	Other	975	423	43%
Total		**27,759**	**7,566**	
Average				**30%**

Notes. This table provides summary statistics for main variables used in firm-level and facility-level analysis. In Panels A-C the observations are at the firm-year level. The sample period is from 2005 to 2021. Panel A presents summary statistics for all variables in the final firm-level sample (used in the analysis in Tables 4-7) after entropy balancing. Panel B presents sample distribution by NAICS 2-digit industry classification for all observations and for treatment group. Panel C provides the correlations matrix for main variables. * indicates significance level of 5%. In Panels D-E observations are at the facility-year level. Panel D displays summary statistics for GHGRP facility-level sample. Panel E provides industry distribution of total and treated observations. All continuous variables are winsorized at 1 (99)%. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 3

State-Level GHG Reduction Targets and GHG Intensity

	GHG Emissions					
	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 Intensity	*Scope 2 Intensity*	*Scope 3 Intensity*	*Scope 1 Intensity*	*Scope 2 Intensity*	*Scope 3 Intensity*
StateReg	**-0.070****	**-0.025**	**0.003**	**-0.070*****	**-0.033**	**0.007**
	(0.028)	**(0.030)**	**(0.008)**	**(0.027)**	**(0.030)**	**(0.009)**
Size				0.016	-0.000	0.009
				(0.016)	(0.014)	(0.006)
ROA				-0.108*	-0.039	-0.031
				(0.057)	(0.064)	(0.032)
Loss				0.035**	0.019	-0.006
				(0.017)	(0.017)	(0.008)
Leverage				-0.048	-0.114*	-0.007
				(0.070)	(0.062)	(0.033)
MTB				-0.002**	-0.001	0.000
				(0.001)	(0.001)	(0.000)
Std_CFO				0.149	0.229	-0.160*
				(0.233)	(0.191)	(0.097)
Std_Ret				0.064	-0.194	-0.035
				(0.120)	(0.125)	(0.052)
Inst Own				0.004	-0.038	0.015
				(0.038)	(0.031)	(0.016)
Constant	3.581***	3.174***	4.917***	3.231***	3.187***	4.795***
	(0.004)	(0.004)	(0.001)	(0.132)	(0.114)	(0.052)
Adj R2	0.94	0.82	0.97	0.94	0.83	0.97
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
N	11,225	11,225	11,225	11,225	11,225	11,225

Notes. This table reports results from staggered TWFE DiD model (Equation 1) which estimates the effect of state-level GHG reduction targets on emissions intensity. The observations are at the firm-year level. Sample period is from 2005 to 2021. Specifications vary by inclusion of control variables. The dependent variables are direct (*Scope 1 Intensity* in Columns (1) and (4)) and indirect (*Scope 2* and *Scope 3 Intensity*) GHG emissions scaled by firm's revenue. *StateReg* is an indicator variable that takes a value of 1 for firms headquartered in states adopting GHG reduction targets in years after adoption, and zero otherwise. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 4

State-Level GHG Reduction Targets and GHG Disclosure

	GHG Disclosure			
	(1) *ENV Disclosure*	(2) *GHG Disclosure*	(3) *ENV Disclosure*	(4) *GHG Disclosure*
StateReg	**0.095**	**0.085**	**0.143****	**0.158****
	(0.068)	**(0.075)**	**(0.065)**	**(0.072)**
Size			-0.012	-0.032
			(0.030)	(0.035)
ROA			-0.070	-0.181*
			(0.074)	(0.104)
Loss			0.059	0.020
			(0.039)	(0.043)
Leverage			-0.011	-0.119
			(0.140)	(0.158)
MTB			-0.003*	-0.002
			(0.002)	(0.002)
Std_CFO			0.085	0.165
			(0.272)	(0.366)
Std_Ret			-0.599***	-0.547**
			(0.213)	(0.254)
Inst Own			0.061	0.036
			(0.076)	(0.086)
Log N E Pnlt			0.034	0.009
			(0.052)	(0.060)
Constant	1.374***	1.462***	1.398***	1.724***
	(0.009)	(0.010)	(0.244)	(0.286)
Adj R2	0.74	0.74	0.76	0.76
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm
N	11,225	11,225	11,225	11,225

Notes. This table reports the results from staggered TWFE DiD model (Equation 1) which estimates the effect of state-level GHG reduction targets on GHG-related disclosure. The observations are at the firm-year level. Sample period is from 2005 to 2021. Specifications vary by inclusion of control variables. The dependent variables are *ENV Disclosure* in Columns (1) and (3) and *GHG Disclosure* in Columns (2) and (4). *StateReg* is an indicator variable that takes a value of 1 for firms headquartered in states adopting GHG reduction targets in years after adoption, and zero otherwise. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 5

State-Level GHG Reduction Targets and 10-K GHG Risk Disclosure

	10-K GHG Risk Disclosure			
	(1) *GHG Risk Disclosure*	(2) *Non-GHG Risk Disclosure*	(3) *GHG Risk Disclosure*	(4) *Non-GHG Risk Disclosure*
StateReg	**-0.040*** **	**0.008**	**-0.028** **	**0.004**
	(0.011)	**(0.014)**	**(0.011)**	**(0.014)**
ROA			-0.054***	-0.135***
			(0.020)	(0.034)
Loss			0.029***	0.060***
			(0.008)	(0.011)
Leverage			0.089***	0.217***
			(0.030)	(0.041)
MTB			-0.000	-0.001*
			(0.000)	(0.001)
Std_CFO			-0.090	0.116
			(0.083)	(0.117)
Std_Ret			0.033	0.089*
			(0.046)	(0.052)
Inst Own			-0.025	-0.077***
			(0.017)	(0.022)
Log N E Pnlt			0.029***	0.020
			(0.010)	(0.014)
Constant	0.456***	3.378***	0.392***	3.374***
	(0.001)	(0.002)	(0.017)	(0.021)
Adj R2	0.86	0.89	0.87	0.91
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm
N	11,225	11,225	11,225	11,225

Notes. This table reports the results from staggered TWFE DiD model (Equation 1) which estimates the effect of state-level GHG reduction targets on GHG-related Risk Disclosure. The observations are at firm-year level. Sample period is from 2005 to 2021. Specifications vary by inclusion of control variables. The dependent variables are *GHG Risk Disclosure* in Columns (1) and (3) and *Non-GHG Risk Disclosure* in Columns (2) and (4). *StateReg* is an indicator variable that takes a value of 1 for firms headquartered in states adopting GHG reduction targets in years after the adoption, and zero otherwise. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 6

Panel A: *Stacked Regression Analysis*

	GHG Emissions and Disclosure		
	(1)	(2)	(3)
	Scope1 Intensity	*GHG Disclosure*	*GHG Risk Disclosure*
StateReg	**-0.080*** **	**0.132***	**-0.052*** **
	(0.026)	**(0.071)**	**(0.010)**
Size	0.018	-0.040	
	(0.012)	(0.026)	
ROA	-0.046	-0.179**	-0.035**
	(0.044)	(0.083)	(0.014)
Loss	0.044***	0.028	0.018***
	(0.012)	(0.031)	(0.005)
Leverage	-0.021	-0.123	0.126***
	(0.052)	(0.109)	(0.022)
MTB	-0.001**	-0.001	-0.000
	(0.001)	(0.001)	(0.000)
Std_CFO	0.049	0.187	-0.085
	(0.166)	(0.272)	(0.063)
Std_Ret	0.079	-0.292	0.010
	(0.091)	(0.197)	(0.035)
Inst Own	0.008	0.069	-0.032***
	(0.027)	(0.061)	(0.012)
Log N E Pnlt	0.043***	-0.009	0.022***
	(0.015)	(0.038)	(0.006)
Constant	3.355***	1.687***	0.401***
	(0.097)	(0.217)	(0.012)
Adj R2	0.95	0.78	0.88
Firm-Cohort FE	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes
Clustered SE	Firm-Cohort	Firm-Cohort	Firm-Cohort
N	23,904	23,904	23,904

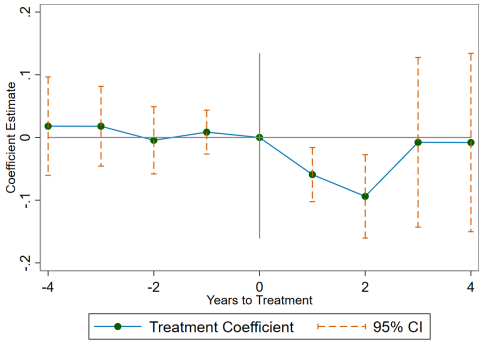
Notes. This table reports the results from stacked TWFE DiD model (Equation 2), estimating the effect of state-level GHG reduction targets on emissions intensity and disclosure variables. The observations are at the firm-year level. Sample period is from 2005 to 2021. Specifications vary by inclusion of control variables. The dependent variables are *Scope 1 Intensity* in Column (1), *GHG Disclosure* in Column (2) and *GHG Risk Disclosure* in Column (3). *StateReg* is an indicator variable that takes a value of 1 for firms headquartered in states adopting GHG reduction targets in years after the adoption, and zero otherwise. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm-stack level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Panel B: *Callaway and Sant'Anna Estimator*

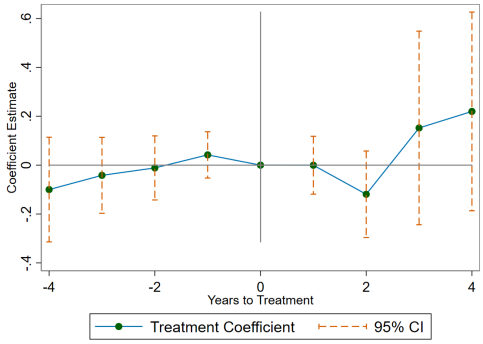
	$\hat{\beta}$StateReg	Std. Err.	z	P z
Scope 1 Intensity	**-0.050*** **	0.024	-2.080	0.037
GHG Disclosure	-0.026	0.068	-0.380	0.706
GHG Risk Disclosure	**-0.031*** **	0.010	-3.020	0.002

Panel C: *Sun and Abraham (2021) Estimator*

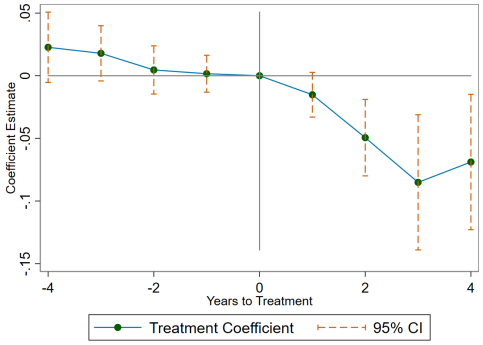
(A) Scope 1 Intensity



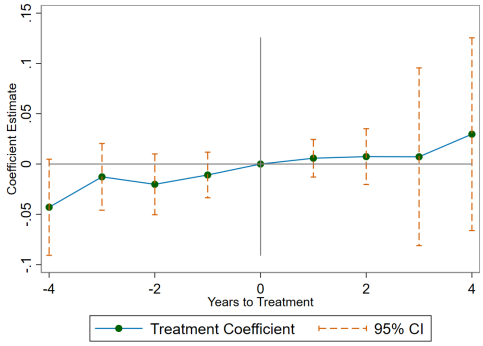
(B) GHG Disclosure

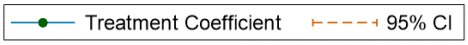


(C) GHG Risk Disclosure



(D) Non-GHG Risk Disclosure





Notes. These graphs plot the difference-in-difference coefficients and their 95% confidence intervals for *GHG Scope 1 Intensity, GHG Disclosure, GHG Risk Disclosure* and *Non-GHG Risk Disclosure* outcome variables using Sun and Abraham (2021) estimator. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 7

State-Level GHG Reduction Targets and GHGRP Facility-Level Emissions

Panel A: *State-Level GHG Reduction Targets and GHGRP Emissions*

	Facility-Level GHG Emissions (Intensity)			
	(1)	(2)	(3)	(4)
	Unbalanced Sample		Balanced Sample	
	GHG	*GHG_GDP*	*GHG*	*GHG_GDP*
StateReg	**-0.069****	**-0.052****	**-0.095*****	**-0.064*****
	(0.030)	**(0.022)**	**(0.032)**	**(0.023)**
RGDP	0.492*		0.432	
	(0.297)		(0.302)	
Constant	4.261	4.884***	5.359	5.178***
	(3.822)	(0.003)	(3.873)	(0.003)
Adj R2	0.92	0.95	0.94	0.96
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Facility	Facility	Facility	Facility
N	27,759	27,759	21,224	21,224

Panel B: *Effect of Entries and Exits to/from GHGRP*

	Facility-Level GHG Emissions (Intensity)	
	(1)	(2)
	GHG	*GHG_GDP*
StateReg	**-0.059***	**-0.043****
	(0.030)	**(0.022)**
*StateReg*Exit*	-0.548***	-0.497***
	(0.188)	(0.113)
*StateReg*Entry*	0.203	0.189**
	(0.125)	(0.096)
RGDP	0.492*	
	(0.297)	
Constant	4.258	4.883***
	(3.820)	(0.003)
Adj R2	0.92	0.95
Facility FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Facility	Facility
N	27,759	27,759

Notes. This table reports the results from TWFE DiD model (Equation 3), estimating the effect of state-level GHG reduction targets adopted in 2019 on facility-level emissions. The observations are at the facility-year level. Sample period is from 2015 to 2021. In Panel A Columns (1) and (2) provide results for unbalanced sample, and Columns (3) and (4) for facilities that are present during all years. *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. Panel B further uses interactions of *StateReg* with indicator variable showing whether the facility eventually exits the GHGRP (*Exit*), and with an indicator variable showing the facilities entering the GHGRP after its' launch (*Entry*). All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the facility level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively. Table A1 provides variable definitions, Table 1 provides details on sample selection.

Table 8

Spillover Effects

Panel A: *Corporate Channel*

	Corporate Channel			
	(1)	(2)	(3)	(4)
	Direct		Indirect (Spillover)	
	GHG	*GHG_GDP*	*GHG*	*GHG_GDP*
StateReg	**-0.088****	**-0.068****		
	(0.043)	**(0.030)**		
StateReg			**-0.099***	**-0.076****
			(0.052)	**(0.038)**
RGDP	0.602		0.619	
	(0.495)		(0.498)	
Constant	2.848	4.881***	2.770	5.018***
	(6.363)	(0.004)	(6.363)	(0.004)
Adj R2	0.92	0.95	0.91	0.94
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Facility	Facility	Facility	Facility
N	13,424	13,424	11,729	11,729

Panel B: *Geographic Proximity Channel*

	Geographic Proximity Channel. Indirect Effect	
	(1)	(2)
	GHG	*GHG_GDP*
StateReg	**-0.021**	**0.010**
	(0.035)	**(0.007)**
RGDP	0.382	
	(0.347)	
Constant	5.812***	0.429***
	(4.424)	(0.001)
Adj R2	0.91	0.97
Facility FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Facility	Facility
N	20,194	20,194

Notes. This table reports the results from the DiD model, estimating the direct and spillover effects of state-level GHG reduction targets on facility-level total GHG emissions. Panel A and Panel B examine the corporate channel of spillover effects, Panel C examines the geographic proximity channel. In Columns (1 and 2) of Panel A *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. In Columns (3 and 4) of Panel A *StateReg* is applied with respect to facilities that are not located in states adopting GHG reduction targets but share the parent firm which has other facility in treated states in years after the adoption for the latter facility (indirectly treated), and zero otherwise. Panel B focuses only on indirectly treated facilities which are located in bordering to the treated facility states (Columns (1-2)) and not-bordering (Columns (3-4)). Panel C reports the results for geographic proximity channel. Refer to Table A1 for variable definitions and to Table 1 for details on sample selection. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively.

Table 9

Channel Tests

Panel A: *Firm Size*

	GHG Intensity and Disclosure								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Tercile 1			Tercile 2			Tercile 3	
	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure
StateReg	**-0.025**	**-0.040**	**-0.056*** **	**-0.060**	**0.184**	**-0.025**	**-0.114** **	**0.153**	**-0.041** **
	(0.047)	**(0.107)**	**(0.019)**	**(0.051)**	**(0.137)**	**(0.020)**	**(0.046)**	**(0.134)**	**(0.019)**
Adj R2	0.94	0.51	0.89	0.93	0.67	0.85	0.95	0.71	0.86
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
N	3,710	3,710	3,710	3,750	3,750	3,750	3,764	3,764	3,764

Panel B: *Institutional Ownership*

	GHG Intensity and Disclosure								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Tercile 1			Tercile 2			Tercile 3	
	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure
StateReg	**-0.033**	**-0.008**	**-0.046** **	**-0.070**	**0.058**	**-0.050** **	**-0.098** **	**0.191**	**-0.020**
	(0.053)	**(0.130)**	**(0.022)**	**(0.044)**	**(0.122)**	**(0.020)**	**(0.047)**	**(0.131)**	**(0.017)**
Adj R2	0.96	0.76	0.87	0.93	0.77	0.87	0.94	0.66	0.86
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
N	3,699	3,699	3,699	3,766	3,766	3,766	3,759	3,759	3,759

Panel C: *Industry Groups*

	GHG Intensity and Disclosure								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Without Utilities			Manufacturing and Oil&Gas			Other	
	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure
StateReg	**-0.076*** **	**0.090**	**-0.040*** **	**-0.075***	**-0.082**	**-0.044*** **	**-0.070** **	**0.283*** **	**-0.041*** **
	(0.027)	**(0.075)**	**(0.011)**	**(0.041)**	**(0.102)**	**(0.015)**	**(0.035)**	**(0.109)**	**(0.015)**
Adj R2	0.93	0.73	0.86	0.91	0.73	0.88	0.94	0.72	0.82
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
N	10,660	10,660	10,660	5,723	5,723	5,723	4,936	4,936	4,936

Panel D: *State GHG Reduction Targets: Characteristics of Regulations*

	Statutory Targets			Moderate Aggressiveness			Reporting		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure
StateReg	**-0.065***	**0.131**	**-0.041*** **	**-0.119***	**0.367** **	**-0.040** **	**-0.116** **	**0.100**	**-0.061*** **
	(0.036)	**(0.092)**	**(0.013)**	**(0.071)**	**(0.159)**	**(0.021)**	**(0.049)**	**(0.117)**	**(0.016)**
Adj R2	0.94	0.76	0.87	0.95	0.78	0.88	0.95	0.78	0.88
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,140	9,140	9,140	7,704	7,704	7,704	8,442	8,442	8,442

Notes. his table reports the results of TWFE DiD estimation using partition by size (Panel A), institutional ownership (Panel B), and industry groups (Panel C). Panel D reports the results based on characteristics of state-level regulations. In Panels A and B the sample is divided into terciles based on average partition variable value for each firm across all years in the sample. Tercile 1 reflects lower values, Tercile 3 reflects higher values of these partition variables. *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. Refer to Table A1 for variable definitions and to Table 1 for details on sample selection. All continuous variables are winsorized at 1 (99)%. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively.

Table 10

Alternative Specifications

Panel A: *Alternative Fixed Effects Structure and Clustering Methods for Firm-Level Analysis*

	Alternative Specifications								
	(1) Scope 1 Intensity	(2) GHG Disclosure	(3) GHG Risk Disclosure	(4) Scope 1 Intensity	(5) GHG Disclosure	(6) GHG Risk Disclosure	(7) Scope 1 Intensity	(8) GHG Disclosure	(9) GHG Risk Disclosure
StateReg	**-0.070****	**0.158***	**-0.027**	**-0.069****	**0.146***	**-0.011**	**-0.069*****	**0.146****	**-0.011**
	(0.027)	**(0.085)**	**(0.018)**	**(0.034)**	**(0.084)**	**(0.013)**	**(0.021)**	**(0.065)**	**(0.009)**
Constant	3.231***	1.724***	0.747***	3.297***	0.909***	0.726***	3.297***	0.909***	0.726***
	(0.174)	(0.237)	(0.057)	(0.156)	(0.312)	(0.060)	(0.118)	(0.246)	(0.049)
Adj R2	0.94	0.76	0.87	0.95	0.78	0.88	0.95	0.78	0.88
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No	No	No	No
Ind-Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State	State	State	Firm	Firm	Firm	Ind-Year	Ind-Year	Ind-Year
N	11,225	11,225	11,225	10,257	10,257	10,257	10,257	10,257	10,257

Panel B: *Alternative Fixed Effects Structure and Clustering Methods for Facility-Level Analysis*

	Alternative Specificatiions					
	(1)	(2)	(3)	(4)	(5)	(6)
	GHG	GHG_GDP	GHG	GHG_GDP	GHG	GHG_GDP
StateReg	**-0.069****	**-0.052****	**-0.097*****	**-0.070*****	**-0.097*****	**-0.070*****
	(0.033)	**(0.021)**	**(0.032)**	**(0.023)**	**(0.019)**	**(0.019)**
RGDP	0.492		0.291		0.291	
	(0.298)		(0.304)		(0.249)	
Constant	4.261	4.884***	6.853*	4.888***	6.853**	4.888***
	(3.828)	(0.002)	(3.914)	(0.003)	(3.201)	(0.002)
Adj R2	0.92	0.95	0.92	0.95	0.92	0.95
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No	No
Ind-Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
Clustered SE	State	State	Facility	Facility	Ind-Year	Ind-Year
N	27,759	27,759	27,619	27,619	27,619	27,619

Notes. This table reports the results of TWFE DiD estimation using alternative fixed effects structure and clustering methods for firm-level analysis (Panel A) and for facility-level analysis (Panel B). The analysis is repeated using clustering at a state-level since the assignment to treatment is at state level. Industry-Year fixed effects are used to account for trends that are common within industries. Industry-year clustered standard errors are used to control for trends that are correlated within industries. *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. Refer to Table A1 for variable definitions and to Table 1 for details on sample selection. All continuous variables are winsorized at 1 (99)%. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively.

Table 11

Alternative Samples

Panel A: *Staggered TWFE DiD for GHGRP Facility-Level Analysis Full Sample*

Sample Selection for Facility-Level Analysis

Description	Facility-Years
GHGRP facility-year observations	66,120
Less: observations more than 4 years before or after the state-level GHG reduction target events, and singleton observations	(19,940)
Final Sample: Facility-years (2011-2021 fiscal years)	**46,180**
Final Balanced Sample: Facilities that are present for all years	**34,050**

Summary Statistics for Facility-Level Analysis

	N	Mean	SD	P25	P50	P75
Unbalanced Sample						
GHG	46,180	10.593	2.736	9.992	10.758	11.945
GHG_GDP	46,180	4.955	2.386	3.548	5.02	6.445
RGDP	46,180	12.766	1.057	12.109	12.675	13.532
Balanced Sample						
GHG	34,050	10.937	2.665	10.24	11.019	12.379
GHG_GDP	34,050	5.273	2.403	3.934	5.345	6.76
RGDP	34,050	12.75	1.028	12.109	12.673	13.507

Staggered DiD Results for full GHGRP Sample

	GHG (Intensity)			
	(1)	(2)	(3)	(4)
	Unbalanced Sample		Balanced Sample	
	GHG	*GHG_GDP*	*GHG*	*GHG_GDP*
StateReg	**-0.065****	**-0.032***	**-0.052***	**-0.014**
	(0.026)	**(0.018)**	**(0.027)**	**(0.019)**
RGDP	0.097		0.010	
	(0.198)		(0.194)	
Constant	9.357***	4.958***	10.807***	5.270***
	(2.529)	(0.001)	(2.476)	(0.002)
Adj R2	0.91	0.94	0.93	0.95
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Facility	Facility	Facility	Facility
State SE	46,180	46,180	34,050	34,050

Panel B: *Removing states with goals in 2020*

	GHG (Intensity)			
	(1)	(2)	(3)	(4)
	Unbalanced Sample		Balanced Sample	
	GHG	*GHG_GDP*	*GHG*	*GHG_GDP*
StateReg	**-0.069*** **	**-0.035***	**-0.054***	**-0.016**
	(0.026)	**(0.018)**	**(0.028)**	**(0.019)**
RGDP	0.108		0.016	
	(0.198)		(0.195)	
Constant	9.213***	4.954***	10.734***	5.267***
	(2.354)	(0.001)	(2.482)	(0.001)
Adj R2	0.91	0.94	0.93	0.95
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Facility	Facility	Facility	Facility
N	45,675	45,675	33,673	33,673

Panel C: *Intersection of Firm-Level Data with GHGRP Facility-Level Data*

	GHG (Intensity)			
	(1)	(2)	(3)	(4)
	All Targets		Statutory Targets only	
	GHG	*GHG_GDP*	*GHG*	*GHG_GDP*
StateReg	**-0.057** **	**-0.007**	**-0.065**	**-0.023***
	(0.026)	**(0.009)**	**(0.049)**	**(0.014)**
RGDP	0.341		0.312	
	(0.219)		(0.242)	
Constant	-0.175	0.552***	0.289	0.581***
	(2.803)	(0.001)	(3.092)	0.000
Adj R2	0.95	0.97	0.95	0.96
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Facility	Facility	Facility	Facility
N	14,645	14,645	11,647	11,647

Panel D: *Removing RGGI States for Firm-Level Analysis*

	GHG Intensity and Disclosure		
	(1)	(2)	(3)
	Scope 1 Intensity	*GHG Disclosure*	*GHG Risk Disclosure*
StateReg	**-0.070****	**0.190****	**-0.021**
	(0.033)	**(0.090)**	**(0.014)**
Constant	3.337***	1.664***	0.815***
	(0.154)	(0.327)	(0.059)
Adj R2	0.94	0.75	0.87
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm
N	9,597	9,597	9,597

Panel E: *Before and After Paris Agreement*

	GHG Intensity and Disclosure					
	(1)	(2)	(3)	(4)	(5)	(6)
	Before Paris Agreement			After Paris Agreement		
	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure	Scope 1 Intensity	GHG Disclosure	GHG Risk Disclosure
StateReg	**-0.094***	**0.305****	**-0.109*****	**-0.068****	**-0.046**	**-0.030****
	(0.050)	**(0.149)**	**(0.021)**	**(0.033)**	**(0.088)**	**(0.014)**
Adj R2	0.96	0.78	0.86	0.95	0.76	0.90
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	11,706	11,706	11,706	12,198	12,198	12,198

Notes. This table presents results of TWFE DiD estimation using alternative samples. Panel A repeats facility-level analysis using a full sample (not only facilities in states adopting GHG reduction targets in 2019). Corresponding sample selection process and summary statistics are provided prior to the estimation results. Panel B provides facility-level analysis for the main sample (GHG reduction targets adopted in 2019 only) by removing states that have 2020 as the closest target year. Panel C provides the estimation for the intersection of main firm-level sample and facility-level sample. Panel D provides alternative sample analysis for firm-level observations: it removes states participating in RGGI. Panel E partitions the sample based on Paris Agreement adoption. *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. Refer to Table A1 for variable definitions and to Table 1 for details on sample selection. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively.

Table 12

Parent-Level Analysis

Panel A: *Number of Facilities per Parent*

	Number of Facilities per Parent	
	(1)	(2)
	All	Only Corporate
	N Facilities	*N Facilities*
StateReg	**-0.000**	**0.003**
	(0.008)	**(0.009)**
RGDP	-0.018	-0.018
	(0.018)	(0.018)
Constant	0.508**	0.548**
	(0.228)	(0.228)
Adj R2	0.96	0.96
Parent FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Parent	Parent
N	9,829	8,322

Panel B: *Number of Facilities in Treated and Control States per Parent*

	Number of Facilities per Parent	
	(1)	(2)
	Treated States	Control States
	N Facilities	*N Facilities*
StateReg	**-0.006**	**0.000**
	(0.004)	**(0.006)**
Log RGDP	0.006	-0.007
	(0.008)	(0.015)
Constant	0.226**	0.720***
	(0.104)	(0.187)
Adj R2	0.99	0.97
Parent FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Parent	Parent
N	9,829	9,829

Panel C: *Facility-Level Analysis Treatment Based on Parent*

	GHG (Intensity)	
	(1)	(2)
	GHG	*GHG_GDP*
StateReg	**-0.120*** **	**-0.080*** **
	(0.036)	**(0.025)**
RGDP	-0.171	
	(0.390)	
Constant	12.737**	4.772***
	(5.196)	(0.003)
Adj R2	0.92	0.95
Parent FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Facility	Facility
N	23,385	23,385

Notes. This table presents results of TWFE DiD estimation for parent-level analysis. Panel A (Panel B) presents estimation for number of facilities per parent (*N Facilities*) (based on the treated/control states). *StateReg* is an indicator variable that takes a value of 1 for facilities located in states adopting GHG reduction targets in years after the adoption, and zero otherwise. Panel C provides estimation of TWFE DiD for parent-level analysis. The treatment is assigned based on state of parent location. Refer to Table A1 for variable definitions and to Table 1 for details on sample selection. All continuous variables are winsorized at 1 (99)%. Standard errors are clustered at the parent level and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels, respectively.