Divestment and Engagement: The Effect of Green Investors on Corporate Carbon Emissions*

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This paper studies whether green investors can influence corporate greenhouse gas emissions through capital markets, either by divesting their stock and limiting polluters' access to capital, or holding polluters' stock and engaging with management. We focus on public pension funds, classifying them as green or non-green based on which political party controlled the fund. To isolate the causal effects of green ownership, we use exogenous variation caused by state-level politics that shifted control of the funds and portfolio rebalancing in response to returns on non-equity investment. Our main finding is that companies reduced their greenhouse gas emissions when stock ownership by green funds increased and did not alter their emissions when ownership by non-green funds changed. We find evidence that ownership and constructive engagement was more effective than confrontational tactics such as voting or shareholder proposals. We do not find that companies with green investors were more likely to sell off their polluting facilities (greenwashing). Overall, our findings suggest that (a) corporate managers respond to the environmental preferences of their investors; (b) divestment in polluting companies may be counterproductive, leading to greater emissions; and (c) private markets may be able to address environmental challenges without explicit government regulation.

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1. Introduction

Can important environmental problems be solved through private markets instead of government regulation? This question is being put to the test by shareholder activists who, skeptical of the ability of governments to combat climate change, are using capital markets to pressure polluters to reduce their carbon emissions. Controversy surrounds these efforts – about whether private markets can address externalities in the first place – and about what is the most effective way to use those markets. A central debate is which of two strategies is most effective: is it *divestment* – selling fossil fuel stocks in order to deprive polluting companies of capital and free up more resources for clean energy – or *engagement* – acquiring fossil fuel stocks and using ownership rights to press for pollution cuts?

The purpose of our study is to provide an empirical assessment of the competing views in this debate. We estimate how corporations adjust their carbon emissions, if at all, in response to a change in the composition of their shareholders: do they reduce emissions when green investors divest, when they invest, or neither?

The debate over divestment versus engagement is taking place in state legislatures, among investment trustees, and in academic discourse. In 2021, Maine became the first state to require its public pension funds to divest from fossil fuel businesses; the huge New York State and New York City pensions have announced their intention to stop investing in fossil fuel companies; and California lawmakers are advancing legislation to compel the state's two massive pension funds, CalPERS and CalSTRS, to do the same. By one estimate, almost $40 trillion in assets has been committed to divestment (Johansmeyer 2022). Proponents justify divestment as a way to reduce portfolio risk from stranded assets, take a symbolic stand in support of sustainability, and redirect capital from dirty to clean energy. Others argue that it is ineffective: in its statement opposing California's divestment bill, CalPERS (2023) said that "divestment has little – if any – impact on a company's operations and therefore does nothing to reduce greenhouse gas emissions. . . . The companies in question can easily replace CalPERS with new investors, ones who are unlikely to speak up as loudly or as consistently as we have about the urgent need to move toward a low-carbon economy." Some critics also claim that divestment is politically motivated, and officials in some red states have threatened to withhold business from banks and investment companies that pursue divestment strategies.

The other – diametrically opposite – strategy that green investors use to press for emission reductions is by *acquiring* stocks in polluting companies and engaging the companies as shareholders. According to CalSTRS (2023), "it is important that long-term investors, such as

CalSTRS, actively engage fossil fuel companies . . . to transition their business models to cleaner forms of energy," and divestment would "severely hinder" such collaboration. To bring about change, the fund argued that it needs to have a "seat at the table." A survey by Krueger et al. (2020) found that many large ESG investors share this perspective, considering engagement a better approach than divestment.

There are theoretical arguments for and against both views. While divestment can affect a company's cost of capital, its effect will be small or nonexistent if other investors are willing to step in; and coordinating a disinvestment campaign among like-minded investors requires overcoming free-rider problems (Heinkel et al. 2001; Berk and van Binsbergen 2021). On the other hand, attempting to put pressure on management by acquiring an ownership stake presents its own free-rider problems (Berle and Means 1967), and managers may feel obligated to follow the so-called Friedman doctrine and focus exclusively on profit (Friedman 1970), even if its shareholders want green policies. In one of the few models that explicitly consider divestment versus engagement (or "exit versus voice"), Broccardo et al. (2022) find that neither strategy achieves socially optimal outcomes for realistic parameter values, but engagement may be effective if a majority of investors have social preferences and shareholders can cut emissions through a binding vote.

Conceptually, our research question is straightforward: we would like to estimate if companies are more likely to cut emissions if the fraction of green shareholders increases or decreases. The challenge lies in the implementation: we need to be able to measure changes in green ownership, and because investors choose whether to acquire or sell a company's stock, we need an identification strategy to separate causal effects of ownership from reverse causality or spurious correlations caused by omitted variables.

To measure green ownership, we focus on an important class of investors, public pension funds, for which we have plausible proxies of environmental preferences. Public pensions control a significant amount of capital, \$5.6 trillion in assets by one measure. We argue that pension funds' preferences concerning carbon emissions can be proxied by the political party that controls the fund, with Democrats being more in favor of decarbonization than Republicans. We define a public pension fund as "green" in two ways: first, based on the governor's party affiliation (because governors can influence pension fund investment through legislative and regulatory actions and by appointing pension board trustees in many states) and second, based on the partisan composition of a fund's board of trustees.

To address the challenge of causal identification, we rely on two sources of variation in shares held by green investors that are arguably exogenous to company emissions. The first source of variation stems from shifts in political control in a state. Changes in the party in control of the governor's office and pension trustees are driven by a state's political dynamics and are not connected to emission changes at companies held by their public pension funds. The second source of exogenous variation comes from the fact that public pension funds typically maintain target ratios for their investment in public equities versus other asset classes such as private equity, real estate, and commodities. If the non-public-equities part of a fund's portfolio experiences an increase in value, the fund must acquire more public equities to restore its target ratio. We show that this rebalancing, which is also unconnected to emissions in portfolio companies, provides a strong instrument for changes in a fund's stock holdings.

Our key finding is that an increase in the fraction of shares held by green public pension funds caused companies to reduce their carbon emissions during the period 2010-2021. In our baseline estimate, a 1 percentage point increase in a company's shares held by green pension funds was associated with an approximately 3 percent reduction in plant emissions over four years. In comparison, we find no association between ownership by non-green public pension funds and changes in corporate carbon emissions. We show this general pattern is robust to alternative specifications of emissions changes, various fixed effects, and raw and instrumented measures of ownership changes. Engagement reduced emissions; divestment did not. These findings suggest that divestment strategies are likely to be counterproductive – resulting in increased emissions compared to the alternative of holding the stock.

We also investigate potential mechanisms by which ownership of a company's stock might lead to emission cuts. First, the mere ownership of a company's stock by green shareholders might cause corporate managers to alter company policies, as would be the case if managers sought to maximize shareholder utility as some argue they should (Hart and Zingales 2017). Second, ownership might allow investors to engage management. Such engagement can be collaborative, involving expressions of preferences, sharing of knowledge, and attempted persuasion, or it can be confrontational, such as against incumbent directors and sponsoring shareholder proposals (Krueger et al. 2020). The evidence we assemble is largely suggestive but points to a primary role for collaborative engagement compared to confrontation. We find that emissions reductions were more strongly associated with ownership by pensions known for actively engaging management than more passive funds, and we do not find that green ownership attracted more shareholder proposals related to environmental issues or that green pension funds had markedly more confrontational voting records.

Finally, we explore how companies achieved their emission reductions. Environmental economists focus on three methods: scale, composition, and technique (Copeland and Taylor 2004). We find evidence that companies used scale reductions to achieve their emission reductions; among plants that generated electricity, reductions in electricity output tracked emission reductions almost one-to-one on average. In terms of composition, we find no evidence that companies with green investors changed their emissions of five other major pollutants (lead, nickel, chromium, ammonia, toluene), suggesting they did not offset their greenhouse gas cuts with other polluting production processes. In terms of technique, we find no evidence that targeted firms increased the number of patents they filed related to green technology. We also find no evidence that companies achieved emission reductions primarily by divesting their high-polluting facilities, so-called "greenwashing."

Our study is related to an existing literature that studies whether green investment produces higher or lower stock returns for investors (Delmas et al. 2015, Trinks et al. 2018, Bolton and Kacperczyk 2020, Hsu et al. 2023, Aswani et al. 2023). We focus on the flip side of this issue, whether green investor shareholdings have real effects on corporate environmental performance. Two studies that consider environmental effects concentrate on the impact of activist campaigns rather than ownership per se: Naaraayanan et al. (2021) study a 2014 campaign by the New York City pension funds targeting 75 companies with proxy access proposals, finding that the targeted companies cut their toxic chemical emissions; and Akey and Appel (2019) study 218 companies targeted by activist hedge funds, also finding that they reduced their emissions. More closely related to our study, Heath et al. (2023) examine the connection between share ownership by socially responsible investment mutual funds and contemporaneous toxic chemical releases, finding a small and statistically insignificant effect, while Chava (2014) finds that polluting firms faced a higher cost of capital.

Our study is also part of the literature on the effect of stock divestment as a strategy to achieve social goals. Divestment has been a prominent strategy for socially activist investors going back at least to the 1980s, when many investors divested from companies doing business in South Africa. California pension funds have previously also divested from Iran, Sudan, thermal coal, tobacco companies, and gun manufacturers (Gedye 2023). The evidence on divestment has focused on its effect on financial markets and asset prices (for example, Teoh et al. (1999) find no effect of South African divestment on the stock prices of companies doing business in South Africa) or on the return to divesting funds themselves (Wilshire Advisors 2022). But little is known about whether financial market effects can cause companies to change their real behavior. Our paper provides some of the first direct evidence on the real effects of divestment.

Finally, our study also speaks to the issue of public versus private solutions to environmental externalities. The United States has not enacted a carbon tax. Standard economic logic suggests that in the absence of such regulation, firms will not take costly actions to mitigate their emissions. Yet there are some reasons to believe the private markets might provide forces toward mitigation. The corporate environmental management literature has argued that large firms have an incentive to build reputations for being "green" in order to reduce the intensity of regulatory inspections (Lyon and Maxwell 2004). On the consumer side, research argues that some consumers will take private actions to reduce their own emissions because they derive disutility from polluting, such as choosing not to drive or opting for a low-emitting vehicle (Kotchen 2006). Consumers have also used boycotts against polluters, such as those seen in response to major oil spills (Barrage et al. 2020). Our evidence suggests that another private actor – investors – may also be able to induce firms to restrict their emissions by acquiring a company's stock and asserting their rights as owners, obviating the need for explicit regulations by governments.

2. Data and Sources

Emissions. Our core analysis focuses on carbon dioxide emissions, a primary focus of activist investors and regulators.[1] Carbon emissions have a global impact, unlike other forms of air pollution, water pollution, and hazardous waste generation that are local in nature. Our primary data are annual facility-level Scope 1 greenhouse gas emissions, from 2010 to 2021. Scope 1 emissions are direct greenhouse gas emissions from sources controlled by a company. Companies are required to provide these data to the Environmental Protection Agency's (EPA) Greenhouse Gas Reporting Program (GHGRP) for every facility in the United States that emits at least 25,000 metric tons of carbon dioxide in a year. The data go through an EPA verification process and are then made publicly available to investors, researchers, and others.

While the EPA data are widely used and considered the most reliable numbers available, they have some limits that should be kept in mind in interpreting the findings. First, they exclude facilities outside the United States, meaning that they undercount the emissions of companies with significant operations outside the United States. This turns out to matter for only a small number of companies, such as Exxon. Second, the data exclude emissions from mobile sources, most

[1] The SEC's proposed climate disclosure rules focus on Scope 1 and Scope 2 gas emissions (SEC 2022).

important, airplanes. This matters for a handful of transportation companies, such as American Airlines. Third, the data do not include Scope 2 and Scope 3 emissions, which are indirect greenhouse gas emissions associated with assets not under the company's control, such as emissions from electricity that the company purchases or emissions within its supply chain.[2]

We classified a company as a facility's parent if it owned more than 50 percent of the facility. Then, we merged facilities with their parent's financial information from Compustat using a fuzzy name-matching algorithm, manually deleting false-positive mismatches. In the end, we were able to match 5,241 facilities from 685 publicly traded companies. The polluting facilities were mainly in sectors such as Petroleum and Natural Gas Systems (26 percent), Power Plants (21 percent), Waste (15 percent), Chemicals (6 percent), Metals (5 percent), and Minerals (4 percent).

Pension fund holdings. We began with the 50 largest public pension funds in the United States, ranked based on assets by *Pensions & Investments*. Of these, we included the 24 that appear in the Thomson Reuters Institutional Holdings database, available through WRDS, that tabulates their portfolio holdings. Funds are excluded from the Thomson Reuters database if they outsourced management of their equity portfolio instead of managing it in-house, or if they did not file a 13F form with the SEC, which is required of all pension funds that manage more than $100 million in qualifying securities. Our final sample includes 9 of the 10 largest American public pension funds, covering 88 percent of public pension fund assets, with New York City Retirement Systems the notable exception because it did not file a 13-F form. Annual fund holdings are the average of quarterly holdings. In cases where a fund's holdings were missing from the Thomson Reuters database, we scraped the SEC's website for the 13F form and calculated holdings directly. Other information about public pension funds – such as their asset allocation and returns in private equity, fixed income, or real estate – were drawn from Public Plans Data of Boston College's Center for Retirement Research.

Party control of pension funds. The data on partisan affiliations of pension fund trustees was collected as follows. First, we identified the main governing board responsible for approving

[2] There is some controversy over whether companies should be held accountable for Scope 2 and Scope 3 emissions, and they seem conceptually different from emissions directly controlled by the company (also, care must be taken to avoid double-counting). Based on exploratory examination of the Scope 2 emissions data from S&P Global Trucost, a commercial vendor, we share the concerns expressed by Aswani et al. (2023) about the reliability of those data. Those numbers are based on reports voluntarily provided by companies, not verified by the EPA, supplemented with estimates made by the vendor.

general investment policies and appointing the chief investment officer. We then referred to the governing documents to determine how the board was constituted. There are three broad categories of appointees: (1) Ex officio members. These included elected officials such as the governor, state treasurer, and CEO of the state school board association, and appointed officials such as the state's finance director. Elected officials were classified according to their self-declared party, and appointed officials were assigned to the party of the official that appointed them, typically the governor. (2) Appointed members, not otherwise part of the government. Most of these trustees were appointed by the governor. Sometimes the governor's choice had to be approved by the legislature. In some cases, the governor chose from a list of nominees provided by another body, such as retirees or public school teachers. We assigned these trustees to the party of the governor. Trustees appointed by legislative leaders or legislative committees were assigned the party of the majority party in the legislature. (3) Members elected by stakeholders. Examples would be trustees elected by retired workers who are beneficiaries, by current workers, or by local governments. In most cases, the voters were public employees. Since state and local government employees are about twice as likely to identify as Democrats than Republicans (Newport et al. 2011), we categorized these trustees as Democrats. Trustees that were selected by groups whose orientation was more uncertain – judges, police officers, and school boards – were classified according to their self-declared party when we could locate this information, and otherwise to a residual ``uncertain'' category.[3] The party of each state's governor each year was identified from public records. All of them were either Democrats or Republicans, except for Bill Walker of Alaska, an independent who we classified as a Republican based on his historical affiliation.

Electricity output. For a subset of electricity-producing facilities within the GHGRP dataset, we obtained data regarding electricity output from the Energy Information Administration (EIA) via Form EIA-923. To link the greenhouse gas dataset from the EPA with the electricity generation dataset from the EIA, we rely on the crosswalk map provided by the EPA. This map connects the

[3] In making these classifications, we took into account departures and vacancies in seats that were not concurrent with a change in the officeholder who appoints the trustee. For example, in some states, the trustees appointed by the governor serve terms that are asynchronous with gubernatorial elections, so that a new governor can change the trustees only with a lag. If a governor of one party reappointed a trustee that had been appointed by a governor of another party, we classified the trustee according to the party of the governor that first appointed the trustee. We also made an attempt to track vacancies in boards. If there was turnover in a seat within a calendar year, we classified half of the year to the party of one member and half of the year to the party of the other member.

Facility ID in the EPA dataset to the generators' Office of Regulatory Information Systems (ORIS) codes. It is worth noting that some individual facilities in the GHG dataset might encompass multiple generators. In such instances, we aggregate the electricity output to the facility level by summing the outputs from all the facility's generators within a given year. We successfully matched 1,099 electricity-producing facilities with the EIA dataset. The majority of these were power plants (876 facilities), with a smaller number within the waste industry (87 facilities). Electricity output is measured in megawatt-hours at the generator level.

Other pollutants. We obtained information on other pollutants from the EPA's Toxics Release Inventory (TRI) dataset, covering the period from 2010 to 2020. This dataset provides details on the types and quantities of over 600 different toxic chemicals released. The most common among them, and our primary focus, are Lead, Nickel, Ammonia, Chromium, and Toluene. To merge the TRI dataset with Compustat, we used the linking table provided by Duchin, Gao, and Xu (2023). We were able to match 5,740 facilities with 778 publicly traded companies.

Green Patents. We obtained patent data from PatentsView, which provides each patent's filing date, inventor, assignee, and Cooperative Patent Classification (CPC). We identified 3,903,010 patents for the period 2010 to 2021, of which 282,274 were classified as “green patents.” A patent is classified as a "green patent" if its CPC is "Y02": technologies or applications for mitigation or adaptation against climate change. We linked the patent filing company to company names in the Compustat dataset using a fuzzy matching algorithm. This step allowed us to identify 68,049 green patents associated with 1,564 publicly traded companies. We confined our analyses to firms included in the EPA GHGRP dataset, thereby limiting our sample to 185 unique companies.

Shareholder proposals and voting. We obtained information on shareholder proposals from ISS Voting Analytics. The data provide a description of each proposal, sponsor information, and the voting outcome. There were 11,225 shareholder proposals filed during 2010-2021, among which 1,079 proposals related to environmental issues, of which 17 passed. Among the environmental proposals, 25 percent were sponsored by socially responsible mutual funds, and 20 percent were sponsored by public pension funds. Voting data for public pensions was taken from the Insightia database by Diligent Market Intelligence. This database categorizes proposals by issue type, allowing us to focus on environmental proposals specifically. We located voting records for 22 public pension funds, accounting for 9,764 votes across 793 environmental proposals.

3. Definition of Green Funds and Descriptive Information

Our operating assumption is that Democrats are more supportive of carbon emission reductions than Republicans. This squares with conventional wisdom and casual observation. For example, the 2022 Inflation Reduction Act, touted by the EPA as "the most significant climate legislation in U. S. history,"[4] was approved in the U. S. House of Representatives with all 220 Democrats voting in favor and 207 Republicans voting against, and in the U. S. Senate with 51 Democrats and aligned independents voting in favor and 50 Republicans voting against. Similarly, Cragg et al. (2013) found that conservative members of Congress were less likely than liberal members to vote for the American Clean Energy and Security Act of 2009, which would have introduced carbon pricing. A recent Pew survey of the American public found that 49 percent of Democrats wanted to phase out oil, coal, and natural gas entirely, compared to only 11 percent of Republicans (Tyson et al. 2023); and Kahn and Matsusaka (1997) found that partisan affiliation was the strongest predictor of votes on environmental ballot initiatives.

We capture differences in fund preferences by the party of the state's governor or the partisan affiliation of the fund's trustees. The board of trustees sets the rules for a fund's investment and governance policies and is its ultimate decision-maker. The governor matters because in many states the governor appoints some or all of the trustees, and in every state has the ability to influence state laws and regulations.[5] Because both measures are plausible and may capture different forces, we typically employ both measures in our analysis. They usually point in the same direction, with the governor's party usually the stronger predictor. We refer to a fund in a state with a Democratic governor or a majority of Democrats as trustees as a "green" fund.[6]

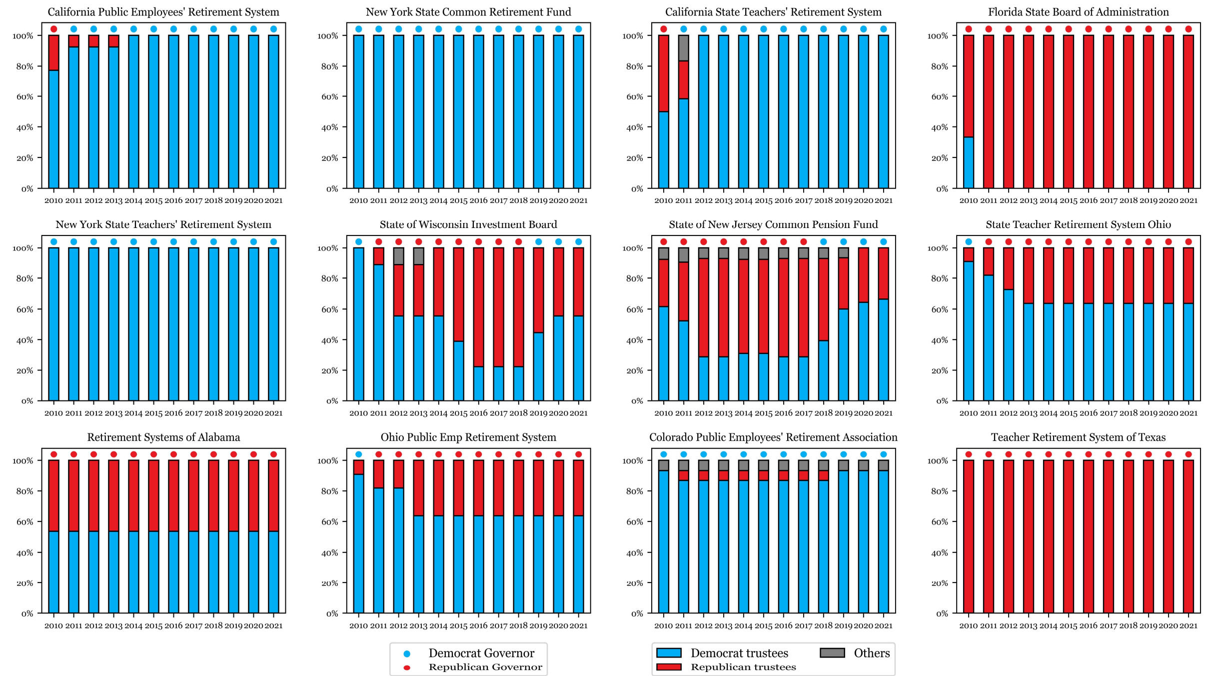
Figure 1 shows the party of the governor and partisan composition of the trustees of the 12 public pension funds with the largest equity holdings. The figure reveals substantial time-series variations in party control for some funds, and extreme stability for others. The State of Wisconsin

[4] From the EPA web site: https://www.epa.gov/green-power-markets/inflation-reduction-act.

[5] For example, Greg Abbot of Texas signed a law in 2021 to ban the state's pension funds from doing business with companies that have policies that discriminate against the oil and gas sector; and Maine passed a law requiring its public pension funds to divest from fossil fuel companies.

[6] An oversimplification in our approach is treating all members of a given party as if they had the same preferences: a Democratic governor in Alabama may be less green than a Democratic governor in California. In practice, this concern seldom arises since blue state funds tend to be controlled by Democrats and red state funds are usually controlled by Republicans.

Figure 1. Party Affiliation of Governor and Pension Fund Trustees



Investment Board, for example, drifts from 33 percent to 100 percent Democrat. The five largest showed little variation in party control, and the huge New York state funds were always 100 percent controlled by Democrats.

We calculate green ownership of a company's stock as the percentage of shares controlled by green funds. Using the governor measure, the percent green ownership is:

$$\%green(GOV) = \frac{\sum_f DEMGO_{\ f} \times share_{\ f}}{shares\ outstanding},$$

where f is a fund, $DEMGOV$ is an indicator equal to one if the state's governor was a Democrat, and $shares_f$ is the number of shares held by fund f. The analogous measure for trustees is:

$$\%green(TRUST) = \frac{\sum_f DEMTRUST_f \times share_{\ f}}{share\ \ outstanding},$$

where $DEMTRUST$ is the fraction of trustees that were Democrats.

Table 1 provides a snapshot of the public pension funds in our data. We report public equity investment by market value, number of companies held, and number of portfolio companies with EPA data as of December 2020. The nation's largest public pension fund, CalPERS, held stock worth

$101.3 billion, spread across 3,505 companies, 332 of which appeared in the EPA's pollution data. The largest funds have highly diversified holdings, holding hundreds of polluting companies.

Table 2 provides summary statistics on facilities and companies that were carbon emitters according to the EPA data. Figure 2 shows the greenhouse gas emissions of the 10 companies with the most combined facilities emissions across the sample period and the holdings of each parent company by "green" or "non-green" pension funds. Recall that this captures only emissions from domestic facilities. The two largest greenhouse gas emitters are power companies, American Electric Power and Southern Company. Panel A shows a downward drift in emissions for most facilities over time. Panel B shows that green funds increased their holdings of these heavy polluters in recent years. This suggests that green funds overall have been pursuing an engagement rather than a disinvestment strategy. Panel C shows that non-green funds have not increased their holdings of polluters in recent years, meaning that the growth in Panel B is not mechanical.

4. Green Ownership Reduces Emissions

A. Baseline Estimates

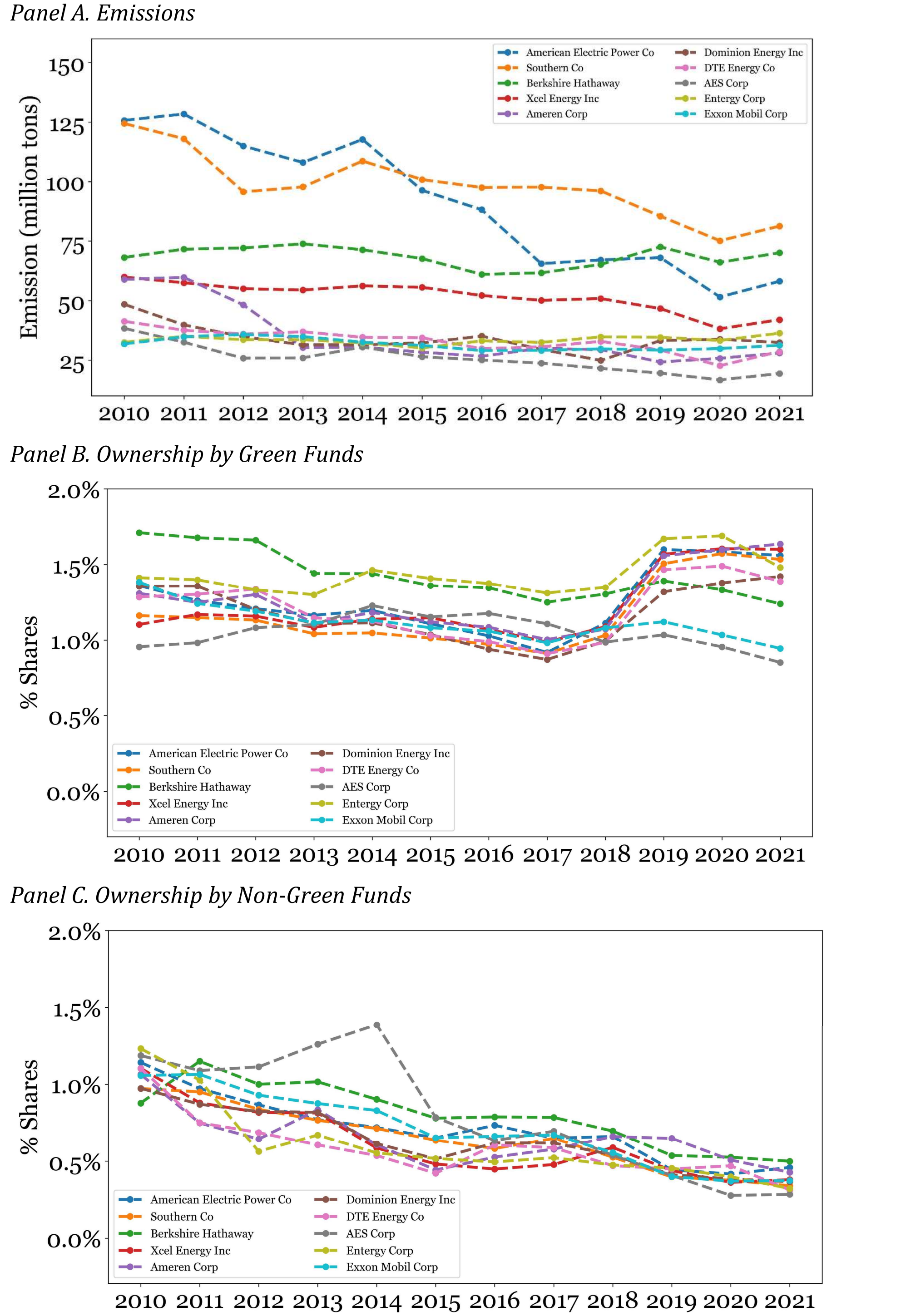
This section estimates the relationship between green public pension plan ownership and carbon emissions. We first show that a robust relation exists and then argue that it is likely to be causal. Our workhorse regression is the following, or some variant thereof:

$$(1) \qquad \Delta emissions_{i,t,t+s} = \beta_1 \cdot \%green_{i,t} + \beta_2 \cdot \%non\text{-}green_{i,t} + \gamma_t + \lambda_i + e_{i,t}.$$

where i indexes a polluting facility, t indexes the year, and s is the number of years ahead. The dependent variable is a facility's change in emissions from the "current" year to $s \in \{1,2,3,4\}$ years later. In our main regressions, we specify the change as a percentage of the current year but we also show that the patterns are similar for level changes and for a negative change dummy.[7] In our main estimates, we include facilities even if they were sold off by the company during the period because we want to determine if green ownership led to pollution reduction, regardless of the facility's subsequent ownership. We consider sell-offs separately after presenting the main results. The independent variables are the percent of the parent company's stock owned by green and non-green public pension funds. The omitted category is shares owned by other institutional investors

[7] We winsorized the percentage change at 5 percent in the right tail. This is necessary because cases with very small baseline emission levels produce huge percentage changes. The findings are similar if we instead delete changes greater than 1,000 percent in magnitude. We winsorized level changes at 1 percent in each tail.

Figure 2. Ten Highest Scope 1 Polluting Companies



and retail investors. We always include year fixed effects, which remove possible macro-level correlations between partisan political outcomes and emissions (which could arise, for example, if partisan outcomes are associated with aggregate economic conditions.) The case for facility fixed effects is less obvious, so we report estimates with and without them.

The implicit economic model underlying equation (1) is that green funds have preferences over *changes* in emissions rather than over the levels. This is a natural starting point for investigation since media outlets often focus on reductions in emissions and, as Hartzmark and Shue (2023) show, sustainable investors reward companies based on reductions rather than levels of emissions. Our estimates are robust to controlling for initial emissions.

Any explanatory factors other than green and non-green ownership that are not constant by year or facility are incorporated into the error term in the equation (1). This might include other institutional investors such as BlackRock that attempt to exert pressure on leading polluters. If BlackRock coordinated its activities with green public pensions, then it would introduce a potential bias in our regressions.

Table 3 reports results using different definitions of a green fund, and different specifications of $\Delta emissions$. In Panel A, the change in emissions is a percentage. In panel A1 regressions, where a fund is green if the state's governor was a Democrat, the first coefficient indicates that a 1 percentage point increase in shares owned by green public pensions funds was associated with a 0.59 percent reduction in carbon emissions over the next year, a coefficient that is not statistically different from zero. The regressions in the second, third, and fourth columns show a statistically significant reduction in emissions that grew over time, reaching 3.10 percent over four years. Detectable cuts in emissions emerge after two years, and they appear to have been persistent. The coefficients for non-green funds are usually smaller in magnitude and statistically insignificant.

In Panel A2, green ownership is calculated based on the partisan affiliation of the trustees. The coefficients on green ownership are negative for all intervals and statistically significant for all but the one-year interval, telling essentially the same story as the top set of regressions. In contrast to the top regressions, the coefficients on non-green ownership are positive and statistically significant, suggesting that plants with non-green owners tended to increase their emissions.

We next show that underlying connection between emissions changes and ownership is robust to alternative specifications of the dependent variable. One concern with expressing emission changes as percentages is that a given absolute reduction in emissions is larger in percentage terms at a low-polluting compared to a high-polluting facility. Indeed, because some ESG ratings focus on percentage changes, Hartzmark and Shue (2023) suggests that companies may game the ratings by concentrating cuts at their low-polluting facilities. To explore this issue, Panel B of Table 3 re-estimates the regressions using the absolute change in pollution emissions as the dependent variable. The limitation of this specification is that it tends to overweight facilities with the largest initial emission levels (in a sense, the opposite problem from the percentage change variable). The story that emerges from this specification is quite similar to that in Panel A. The coefficient on green fund ownership is negative over all time periods and for both definitions of green funds, and always statistically different from zero. To understand the units: the coefficient on green ownership indicates that a 0.1 percentage point increase in green fund ownership was associated with 99,000 to 553,000 tons fewer emissions over the next one to four years. This is a substantial number compared to the average of 484,241 tons in our sample. The coefficient on non-green ownership remains small and statistically insignificant in panel B1 and positive and usually significant at the 10 percent level in B2.

In Panel C of Table 3, the dependent variable is simply a dummy equal to 1 if emissions declined. Although crude, this strips out scale effects entirely. Over any given year, 53 percent of facilities reduced emissions, and over four years, 57 percent reduced emissions. The first regression shows that a 1 percentage point increase in green fund ownership is associated with a statistically insignificant 1.60 percentage point increase in the probability of carbon emission reduction over the subsequent year. The probability increase rises to 3.65 percentage points over two years, and 5.20 percentage points over four years, statistically significant at the 1 percent level. The coefficients on green ownership in C2 tell essentially the same story. The coefficients on non-green ownership again indicate that an associated lower probability of emission reductions.

B. Treatment Effects Using Facility Fixed Effects and Plausibly Exogenous Sources of Variation

We next consider to what extent the emission cuts associated with green ownership can be viewed as a causal relation. Our first approach is to include facility fixed effects, essentially a two-way fixed effects strategy. This removes all time-invariant, facility-specific factors that determine emissions. As noted when discussing Figure 1, there isn't much variation in partisan control of the largest blue state pension funds so with facility fixed effects, these funds contribute to the estimates only through variation in their holdings.

Table 4 reports the results using both definitions of a green fund. The coefficient on green ownership, as before, is negative in all regressions in both panels and statistically significant for two, three, and four years out. The coefficients are noticeably larger in magnitude with facility fixed effects than without, suggesting that (in the cross section) there is not a lot of sorting of green investors into facilities that would bias the baseline regressions. The negative coefficients here provide stronger evidence that green investors caused the emissions reductions. The coefficients on non-green funds remain relatively small and are statistically insignificant in all regressions.

Our second approach employs an instrumented two-stage process for share ownership. There are two sources of variation in the green ownership variable: changes in a fund's preferences, and changes in the amount of stock owned by a fund. A fund's preference is determined typically by political events that are independent of a company's emissions, and thus largely exogenous. A fund's holdings of a company's stock, on the hand, may well be related to the company's emissions: green shareholders may "cherry-pick"' companies that have already decided to reduce their greenhouse gas emissions or avoid those not planning to cut emissions. To identify causal effects of the number of shares held, we exploit the institutional fact that pension funds have target ratios for the allocation of their portfolio between public equity and other investments. (for example, in 2021 CalPERS targeted its public equity investment at 50 percent).[8] If a fund's other investments experience an unusually high return, the fund must acquire more public equity in order to restore its portfolio to the target ratio, and conversely, if other investments experience an unusually low return. With this as motivation, we estimate a first-stage regression to predict fund f's percentage change in holdings of company j as a function of the return of its "other investments" (private equity, fixed income, real estate, hedge fund, and commodities) in the previous year:

$$(2) \qquad \%\Delta shares_{f,j,t,t+1} = \alpha_0 + \alpha_1 \cdot RET\_OTHER_{f,t} + e_{f,j,t}.$$

If pension funds rebalance annually, then $\alpha_1 > 0$. The estimated parameters $\hat{\alpha}_0$ and $\hat{\alpha}_1$ from (2) and the fund's holdings in $t-1$ are used to calculate predicted shares held by fund f in company j at time t based on that fund's holdings at time $t-1$:

$$(3) \qquad \widehat{shares}_{f,j,t} = \left(1 + \hat{\alpha}_0 + \hat{\alpha}_1 \cdot RET\_OTHER_{f,t}\right) \cdot shares_{f,j,t-1}.$$

Finally, we use the predicted shares from (3) to calculate predicted green and non-green ownership for each company and fund, aggregate across funds, and then run versions of regression (1). This two-step procedure is similar to an instrumental variable regression where returns on other investments serve as the instrument. The analogue to the exclusion restriction is that a pension fund's return on its other investments is not related to the future change in facility emissions of the companies in which it invests, which seems plausible.

[8] See CalPERS's annual report, https://www.calpers.ca.gov/docs/forms-publications/acfr-2022.pdf.

Table 5 shows the first-stage regression with different fixed effects. The model in the first column, with no fixed effects, shows that a 1 percentage point increase in a pension fund's return on other investments was associated with a 1.39 percent increase in its public equity. The model in the second column, which we use in the second stage, includes year fixed effects, and indicates that a 1 percentage point increase in a pension fund's return on other investments was associated with a 3.44 percent increase in its public equity holdings. The third column includes year-company fixed effects. The F-statistic in column (2) is 60.3, indicating that the instrument is a good predictor. We report all three regressions to illustrate the robustness of the connection between other investment returns and changes in public equity holdings.

Table 6 shows the second-stage regressions.[9] Panel A includes year fixed effects and Panel B includes year and facility fixed effects. The findings are similar in both panels: increases in green fund ownership reduced carbon emissions out to four years, and the effect is statistically significant, in most cases at the 1 percent level. The coefficient on non-green ownership is smaller and statistically insignificant in all regressions. The instrumented effects are broadly consistent with the baseline estimates. Because predicted ownership values offer a more compelling causal interpretation, we usually report estimates using the predicted values from here on.

C. Change in Green Ownership vs. Change of Parent Company

The green ownership of a facility could change if its parent company's green ownership changed, but also if the facility was sold to another parent with different green ownership. Our estimates to this point do not distinguish the two sources of change, which runs the risk that our estimates compound green ownership changes with changes associated with have a new corporate parent. Here we explore two strategies to isolate the effect of green ownership changes.

Panel A of Table 7 re-estimates the basic regression but includes facility-parent fixed effects. This removes parent-company effects from the estimates of green ownership effects. We use the predicted value of green ownership. The key coefficients are similar to those in Panel B of Table 6, suggesting that our estimated effects are not coming primarily from changes in corporate parent. Panels B and C of Table 7 adopt the simple approach of deleting all facilities that experienced a change in corporate parent during the sample period. We report regressions with year and with year and facility fixed effects, and continue to use the predicted ownership variables. Again, the

[9] To account for the two-stage estimation procedure, the standard errors in the second stage can be adjusted by using a bootstrap procedure. The results are essentially similar with coefficients significant at the 1 percent level.

coefficients are fairly similar in magnitude to estimates that include the full sample. We conclude from this that our estimated ownership effects are not the result of changes of corporate parent.

4. Why Ownership Works: Activism, Passive Support, and Confrontation

Having provided substantial evidence that companies with green owners reduced their greenhouse gas emissions, in this section we investigate why this happened. We report several pieces of suggestive evidence, much of which points in the same direction. The analysis is framed around three mechanisms.

- *Responsive managers.* Corporate executives are employees of the company's owners, and as Friedman (1970) noted, have a "responsibility to conduct the business in accordance with their desires." Usually, investors are motivated to make money but in some cases they may have additional objectives, such as emissions reductions. According to this mechanism, managers cut carbon emissions because they believed it was the preference of their investors.

- *Pressure.* According to this mechanism, a form of "voice", managers are unfaithful agents, and must be forced to reduce emissions. It is not clear why managers would be opposed to GHG abatement in general if they understood that their shareholders wanted them to go down this path, but this is nevertheless a maintained assumption in public discourse. Pressure can be applied through shareholder proposals or by voting against managers that do not cut emissions (Aggarwal et al. 2023; Michaely et al. 2023).

- *Persuasion.* According to this mechanism, managers can be persuaded by green investors. Investors may share information about the consequences of cleaner facilities, or share information about their preferences and their willingness to back managers who are aligned with their preferences. This is a nonadversarial form of voice. CalPERS characterizes its engagement strategy as "constructive" and describes it as: (1) gathering facts about the issues and expressing its concerns to the company; (2) sharing CalPERS' principles and investment beliefs with the company; (3) seeking the company's perspective on the issue; and (4) seeking a resolution to address its concerns.[10]

[10] Available at https://www.calpers.ca.gov/page/investments/corporate-governance/corporate-engagements.

A. Engaged vs. Non-Engaged Green Investors

According to the "responsive managers" mechanism, a company's response to green ownership should not vary depending on whether the investor is actively engaged or passive. To assess this empirically, we identify a set of pensions funds that are particularly active, and compare company responses to ownership by these funds compared to less active funds. We start by identifying public pension funds that filed SEC Form PX14A6G. This form is included as a cover letter when a shareholder wishes to communicate with other shareholders on matters related to voting, such as expressing a preference for director candidates or opposing a proposal. Of the 27 funds in our sample, three of them filed PX14A6G forms at our sample companies during our sample period: CalPERS (216 filings), New York State Common Retirement Fund (NYSCRF) (25 filings), and CalSTRS (14 filings).[11] We classify these three as the "active" green funds, and define the others as "less active." We then estimate the connection between emission changes and green ownership separately for active and non-active funds.[12]

Table 8 shows the results, using the party of the governor to define a green fund and predicted ownership (the coefficients of interest are similar using the trustee definition of green funds, and using the raw instead of predicted measure of ownership), with year fixed effects in the top panel and year and facility fixed effects in the bottom panel. Across all specifications, the coefficient on active green ownership is negative and statistically significant. The coefficient on less active green ownership is always smaller and never statistically significant. These estimates generally imply that ownership by active green funds resulted in larger emissions cuts than ownership by less-active green funds. This suggests that emission reductions were not simply the result of managers responding to changes in their ownership, but also due to the engagement by activist green funds.

B. Adversarial Engagement: Shareholder Proposals

Investors can engage management through adversarial means, such as fielding an opposition slate of director candidates or advancing shareholder proposals opposed by

[11] The highly active New York City pension funds are not included in our data because they do not submit 13F filings of their holdings.

[12] These three funds also happen to be among the largest, meaning that activism as we define it is correlated with size. This is not a problem for our test since the main question is whether managers take into account overall shareholder preferences or gives more weight to some investors than others.

management, or they can engage in persuasion, informing management about investor preferences and sharing their knowledge about corporate strategies. A notable example of a pressure campaign was the one spearheaded by the New York City pension funds in 2014. Although there is some evidence that this campaign had an effect (Naraayanan et al. 2021), it appears to be a somewhat unique case. To gauge the importance of the adversarial channel more generally, we explore the connection between shareholders proposals and green ownership.

In most American corporations, a shareholder has a right to make proposals that are voted on by shareholders collectively, subject to meeting certain minimum conditions, such as having held stock worth at least $2,000 or 1 percent of firm value continuously for the preceding year (Matsusaka et al. 2021). Usually, if a proposal receives a majority of votes, it is said to have been approved, but most proposals are precatory, meaning that managers are not required to implement them even if they pass. However, investor groups may withhold support for director candidates that do not implement shareholder proposals, and there is evidence that companies do respond to successful proposals, and may even partially accommodate unsuccessful proposals if they attract a sizeable block of votes (Thomas and Cotter 2007; Ertimur et al. 2010; Matsusaka and Ozbas 2017).

Here we focus on environmental proposals. A common type calls for the company to study and issue a report on an environmental concern and asks for an analysis of how the company plans to manage risk associated with the matter. For example, an oil company may be asked to report on how it expects to respond to global pressures to achieve net-zero carbon emissions. A company in our sample received at least one environmental proposal in 13 percent of the sample years. Shareholder proposals are usually opposed by managers, and are thus a form of adversarial pressure. Under the pressure hypothesis, an increase in green investors would lead to more shareholder proposals.

Our empirical model is:

$$(4) \qquad Proposal\ dummy_{c,t} = \beta_1 \cdot \%green_{c,t} + \beta_2 \cdot \%non\text{-}green_{c,t} + \beta_3 X_{c,t} + \gamma_t + \lambda_c + e_{c,t},$$

where the unit of observation is a company (c) in a given year (t). We measure green funds by the party of the governor. In addition to ownership, we control for firm size, since large firms are known to attract more proposals, and for the level of greenhouse gas emissions.

Table 9 shows the estimates with different fixed effects. The dependent variable in the first column is a dummy equal to one if a company received a green proposal. The coefficient on green ownership implies that a 1 percent increase in shares held by green pension funds was associated with a 1.15 percentage point increase in the probability of receiving an environmental proposal in panel A, and a 2.08 percentage point increase in panel B, neither coefficient statistically different from zero. The coefficient on non-green fund ownership is also statistically insignificant in both panels. Columns (2) and (3) distinguish between proposals from other pension funds and proposals from non-pension shareholders. In all specifications, the coefficient on green ownership remains quantitatively small and statistically insignificant. We turn up no evidence that green ownership leads to more shareholder proposals, which runs against the hypothesis that green ownership works through adversarial pressure. Our failure to find a connection between green ownership and proposals is distinct from but parallels evidence in Appel et al. (2016) that the presence of passive mutual funds did not attract more hedge fund activism.

Another metric of adversarial pressure is votes in support of shareholder proposals. Even if green ownership did not attract more proposals, it could have increased support for those proposals that came to a vote. One way to assess this possibility is to estimate whether environmental proposals were more likely to pass when green ownership was high. Column (4) of Table 9 reports regressions in which the dependent variable is a dummy equal to one if a proposal received a majority of votes in favor. This is not a strong test because of the limited number of environmental proposals, and the limited variation in outcomes: only 2 percent of proposals received more than 50 percent support. The coefficients on green ownership are positive but too noisy to distinguish from zero in both panels, so we are unable to conclude that the presence of green investors enhanced the prospects for green proposals to pass. The magnitudes (leaving aside statistical significance), tell conflicting stories: in panel A, a 1 percentage point increase in green ownership is associated with a 0.18 percentage point increase in the chance of passage, a muted effect, while in panel B, a 1 percentage point increase in green ownership is associated with a 3.43 percentage point increase in passage, an amplification effect if taken at face value.

A related way to approach this issue is by examining the votes cast by public pension funds themselves on environmental proposals:

$$(6) \qquad \Pr(vote\ yes)_{f,p,c.t} = \beta_1 \cdot D(green)_f + \beta_2 X_{c,t} + \gamma_t + \lambda_p + e_{f,c,p,t},$$

where the unit of observation is a vote cast by fund f on proposal type p at company c at time t. The key explanatory variable is a dummy equal to 1 for green funds. We continue to include firm size and emissions as control variables. The time effect allows for popularity of environmental proposals to change over time, and the proposal type fixed effect allows for inherent differences in popularity between different types of proposals. For our sample as a whole, environmental proposals received 23 percent approval on average.

The evidence, reported in Table 10, is somewhat mixed. When a fund is defined to be green based on the party of the governor, we see that a green fund was 13 more likely to support environmental proposals than non-green funds (the omitted category). This effect is statistically significant and quantitatively nontrivial for both fixed effects specifications. On the other hand, when a fund's greenness is defined by the majority of its trustees, the coefficient on green ownership is tiny and statistically insignificant for both fixed effects specifications. Speculatively, one interpretation is that governors put pressure on their funds to adopt confrontational stances, but trustees were not similarly inclined. In any event, this provide some evidence for adversarial pressure, but it leaves the impression that this may not be the most common channel.

From the evidence in this section taken together, we tentatively conclude that persuasive engagement is more important than adversarial pressure. To be sure, we arrive at this point by something of a process of elimination rather than a direct test. And the dichotomy between the two forms of activism may be a bit artificial – an effective persuasion strategy may go hand-in-hand with implied threats that are occasionally carried out in order to establish credibility. The idea that funds seek to persuade managers through collaborative process has the virtue of aligning with how fund managers often describe their interactions. The joint CalPERS and CalSTRS statement on *The Importance of Corporate Engagement on Climate Change* states a preference for "constructive engagement" over divestment, and that "we firmly believe that active and direct engagement as a first line approach is the best way to resolve issues . . . [and] that engagement, or having a voice at the table, is an effective tool to mitigate risk such as climate change."[13]

5. A Decomposition Approach for Understanding the Determinants of Emission Reductions

Environmental economists decompose a firm's emissions using an accounting approach that emphasizes the role of scale, composition and technique (Copeland and Taylor 2004). Exxon can reduce its carbon footprint by cutting output (scale), shifting its portfolio of products towards cleaner products (composition), or introducing new technologies such as carbon capture to reduce

[13] The undated statement is available at: https://www.calpers.ca.gov/docs/corporate-engagement-climate-change.pdf. See also Wilkes (2023) which notes that most members of the Climate Action 100+ "seek to persuade companies to do more on climate through `engagement', which involves lobbying corporate and executive directors, rather than voting to oust them,"

its emissions per unit of output. Companies can also reduce their emissions simply by selling off polluting facilities (Duchin et al. 2023). This section probes for evidence on the use of each channel.

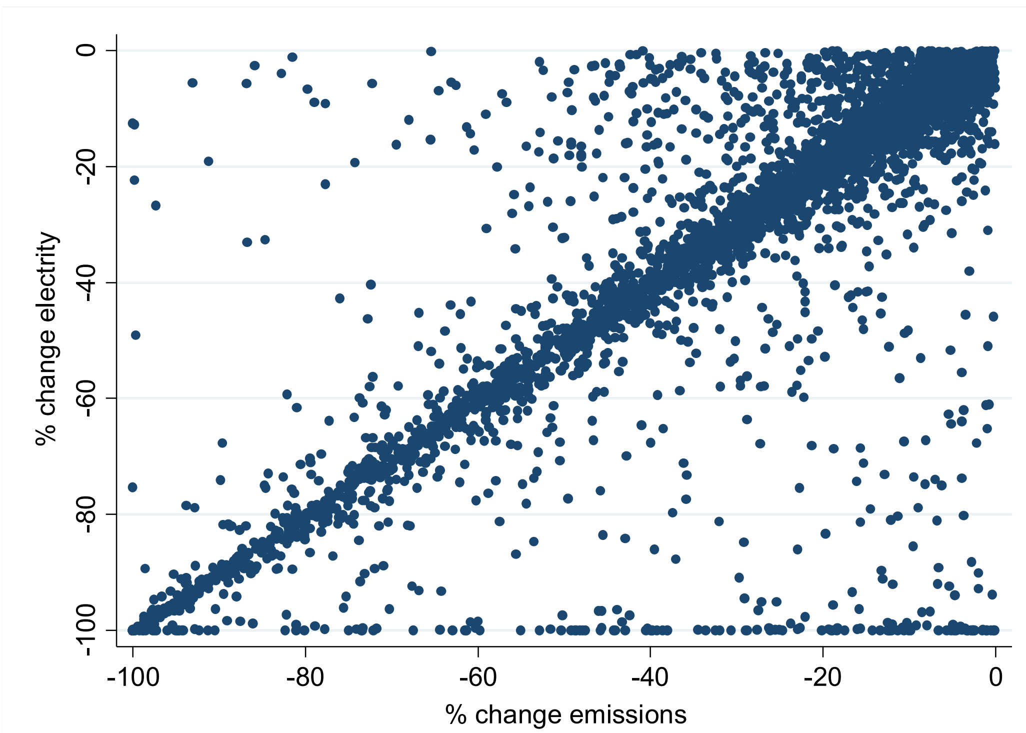
A. Emissions Reduction through Scale Reduction

To gauge the importance of emissions cuts through scale reduction, we focus on the subset of facilities that produce electricity. These facilities, most of which are power plants and the rest in the waste industry, are required to report their output in terms of electricity generation. We test if the facilities that reduced emissions also reduced electricity output, a scale reduction, or if their output stayed the same, implying emission cuts through abatement.

Figure 3 plots emission changes against electricity generation changes over the years t to $t+2$, for those facilities that cut emissions. Emission cuts that were achieved by scale reductions appear along the 45-degree diagonal. Scale reduction appears to have been a common way to achieve emission reductions. There were some cases in which electricity fell more or less than emissions, with perhaps more of the former than the latter.

Table 11 explores the relationship parametrically. Panel A1 establishes a benchmark by regressing the percentage change in emissions on a dummy for facilities that reduced emissions. The first coefficient indicates that facilities that reduced emissions cut them by 55.4 percent on

Figure 3. Emission Cuts Against Electricity Cuts for Plants that Reduced Emissions



average over the first year. Panel A2 regresses the percentage change in electricity output on the dummy for emission cuts. The coefficient indicates that electricity cuts were 52.5 percent on average in the first year. Thus, pollution cuts were matched by approximately equal electricity cuts on average. The coefficients for longer windows tell the same story. This is not a mechanical relationship. The coefficients for regressions that control for facility fixed effects (panels B1 and B2) are similar. Across all specifications, emissions cuts were accompanied on average by proportionate cuts in output, suggesting that pollution reduction was often achieved by cutting output rather than by abatement.

B. Composition and Other Pollutants

We next explore if companies responded to green investors by cutting other types of pollution. These estimates are of interest for two reasons. First, as mentioned above, companies might respond to green investors by shifting the composition of their output, reducing production that emits carbon and increasing production that emits other pollutants (Greenstone 2003). Such a "Peltzman Substitution Effect" is more likely to occur in cases where environmentalists prioritize a specific pollutant's reduction and pay less attention to other pollution margins.

Second, while green investors have emphasized greenhouse gas emissions, they may favor reducing other pollutants as well, and certainly would not favor substitution into other pollutants. Did companies respond only to concerns about carbon emissions, or did they make adjustments across the pollution spectrum?

The EPA collects data on hundreds of chemicals that are emitted by production facilities. We focus our analysis on the five most common types: lead, nickel, ammonia, chromium, and toluene. After greenhouse gas emissions, lead emissions may be the highest profile pollutant, known to cause loss of I.Q. and brain functions to those exposed (Clay et al. 2023).

Table 12 reports versions of our basic regressions with changes in emissions of these chemicals as the dependent variable. Panel A shows results for lead emissions. The coefficients indicate that green ownership was associated with significantly lower levels of lead and ammonia emissions over three and four years. We do not find a robust relation between green ownership and emissions of nickel, chromium, or toluene. The coefficients on non-green ownership are usually positive, but statistically significant in only one case. Overall, the estimates provide little support for the hypothesis that companies substituted into other pollutants; rather, it seems that green ownership reduced emissions of chemicals other than greenhouse gases.

C. Technique and Innovation

Polluters can reduce emissions by innovating new, cleaner production techniques. Green investors express the hope that emission cuts will free up corporate resources to invest in new, cleaner technologies. Explained Jennifer Grancio, of hedge fund Engine No. 1 that led a green campaign to secure seats on the board of ExxonMobil: "[W]e need these huge engineering and development companies to also apply resources where they can . . . to look at new technologies and how do these companies maintain value after that transition when we're in more of a renewable environment or carbon capture environment."[14]

To explore the possibility of accelerated technique innovations by firms with green investors, we look at patenting activity by major emitting firms (Grubb et al. 2021; Popp 2005). For each company, we identify the number of green patents each year, which represent technologies intended to mitigate or adapt against climate change. Innovation depends on research that takes time, so we would not expect to see an increase in patents immediately. The number of patents is highly right-skewed and formulating changes in levels or percentages creates outlier problems, so the dependent variable we study is a dummy variable equal to one if a company increased the number of green patents over time.

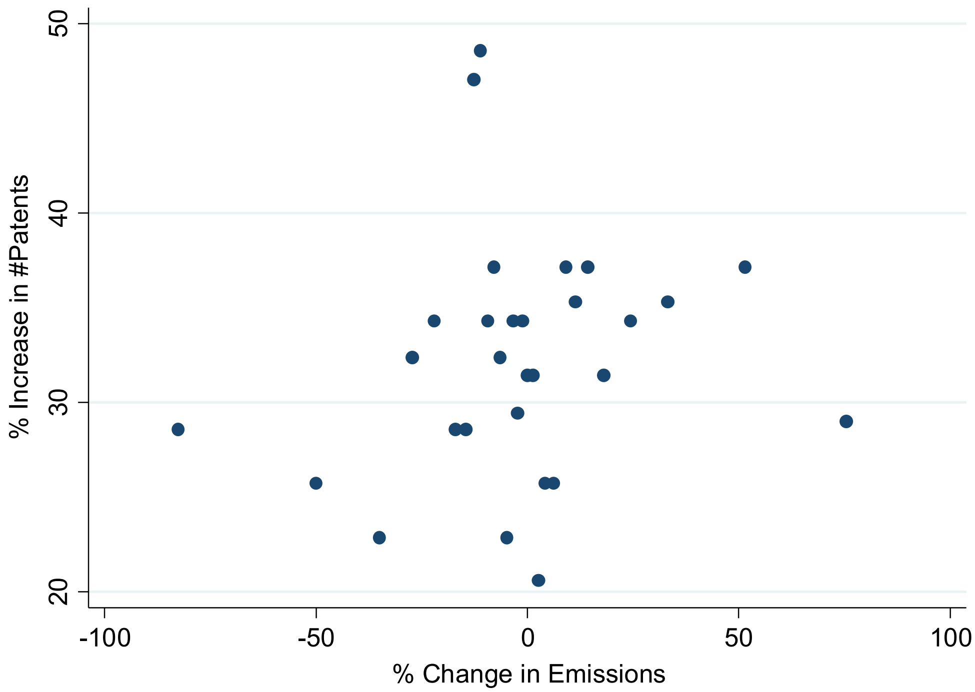
For our sample, the mean number of patents filed by a company per year was 15.2, with a range of zero to 496. On average, 31 percent of companies increased the number of patents they filed from one year to the next. We keep the firms that filed at least one green patent during our sample period, restricting the sample to 185 unique firms out of 686 total firms in the EPA dataset.

Figure 4 shows the percentage of companies that increased their patents over two years compared to bin changes in emissions. There is no obvious tendency for emission-cutting firms to increase their patents.

Table 13 presents regression estimates for two measures of green funds, and for two fixed effect specifications. The interpretation of the top left (statistically insignificant) coefficient is that a 1 percent increase in green fund ownership was associated with a 2.18 percentage point decrease in the likelihood of the company filing more green patents in the next year. Looking across the entire table, the coefficients on green ownership are usually positive and in some specifications statistically different from zero over the three-year range, but the general impression is an absence of a reliable connection between patenting and green ownership. The story is the same for non-

[14] *CNBC Transcript: Engine No. 1 COE Jennifer Grancio Speaks with CNBC's Sara Eisen Live During CNBS's ESG Impact Today*, October 6, 2022.

Figure 4. Binned Scatterplot of Emission Changes Against Patent Increases over Two Years



green ownership. We are thus unable to establish that green investors prompted companies to increase their development of new technologies.

D. Facility Sell-Offs

Companies can reduce their carbon emissions by selling polluting facilities to another company or spinning it off as a stand-alone company. Ringleb and Wiggins (1990) document that polluting industries have divested risky assets to reduce their liability risk exposure. While selling off or spinning off a unit would reduce the selling firm's emissions, it would not reduce overall pollution, and is therefore sometimes labeled "greenwashing." In a sample of 888 divestitures of polluting plants during 2000-2020, Duchin et al. (2022) show that divested plants did not reduce their emissions but divesting companies earned higher ESG ratings.[15] In contrast to this skeptical view, there may also be efficiency reasons for companies to sell off facilities. For example, some companies may have a comparative advantage in cleaning up polluting facilities, such as Hilcorp

[15] Similarly, Andonov and Rauh (2023) find that public corporations have reduced their ownership of electricity producers while private equity companies have increasd their ownership – but this has not occurred via transfers of facilities but through closure and new entry.

which specialized in acquiring aging oil wells that leak methane (Morenne 2023). Reallocation of plants to emission reduction specialists could be economically efficient.

We begin by investigating whether green ownership effects the likelihood that a company sold a plant. In our sample, one in four facilities was divested on average within a four-year time span. Table 14 reports a series of regressions to explain whether a facility was divested:

$$(5) \qquad \Pr\,(divested)_{i,t,t+s} = \beta_1 \cdot \%\widehat{green}_{i,t} + \beta_2 \cdot \%\widehat{non\text{-}green}_{i,t} + emissions_{i,t} + \gamma_t + e_{i,t}.$$

The dependent variable is 1 if a facility was sold off some between year t and year $t+s$. The independent variables include the predicted ownership variables, as well as time-t emissions; the latter is to test if companies were more likely to sell their dirtier plants. Once a facility was sold, we drop it from the analysis, meaning that repeat sales are excluded.

The top two panels, which include year fixed effects, show that facilities with green investors were significantly less likely to be divested than other facilities. The four-year-out coefficients imply that a 1 percent increase in green ownership was associated with a 7.87 (panel A) or 7.24 (panel B) percentage point lower probability of a plant being divested. Interestingly, this suggests that companies with green investors were more likely to hold their polluting plants. One possible explanation is that green investors prefer companies to clean up their dirty facilities rather than pass along the problem to another company. The regressions also indicate that increases in non-green ownership were associated with a lower probability of divestiture. Which is to say that increased ownership by pension funds in general meant less divestiture of polluting facilities. The coefficient on emissions is negative and never statistically different from zero, offering no evidence that companies were inclined to shed their high-polluting facilities.

The bottom two panels, which add facility fixed effects, produce a different pattern: the coefficients on the two ownership variables are generally positive and usually but not always statistically insignificant. The different patterns in the top compared to the bottom panels implies that the negative relation between ownership and sales is largely due to cross-sectional rather than time-series variation in ownership. Again, the coefficient on emissions is never statistically different from zero.

The evidence is somewhat mixed across the four panels, but two conclusions can be drawn. There is little evidence that increased green ownership led companies to divest polluting facilities. And there is no evidence that companies tended to sell off their plants with the highest carbon emissions, somewhat in contrast with Duchin et al. (2022), which finds a higher sell-propensity, This does not support the hypothesis that pressure from green investors led companies to divest polluting assets, or that companies tended to sell off their dirtiest assets.

To gain perspective on the possibility that facilities were sold to companies with a comparative advantage in emissions reduction, we compare the emission changes of the retained versus sold facilities. Figure 5 plots emission changes four years out (winsoring observations with greater than 100 percent change) for units that were retained and units that were divested, with each observation representing a facility-year. The figure shows that emission reductions were similar for retained and divested facility, with retained facilities modestly more likely to cut emissions than divested units. This matches the finding in Duchin et al. (2022) for a different but partially overlapping sample.

A company's carbon emissions picture would be muddy if, at the same time it cut emissions at existing plants, it acquired new polluting plants. Taking all channels into account, a company's emissions profile could evolve due to emissions changes at existing facilities, sales of polluting facilities, and acquisitions of polluting facilities. Green investors may be interested in the overall emissions of the companies they hold. To explore this issue, we aggregate emissions from all of a corporation's facilities in each year, thereby encompassing asset sales and purchases, and estimate a version of (1) at the company level.

Figure 5. Density of Emission Changes for Retained and Divested Facilities

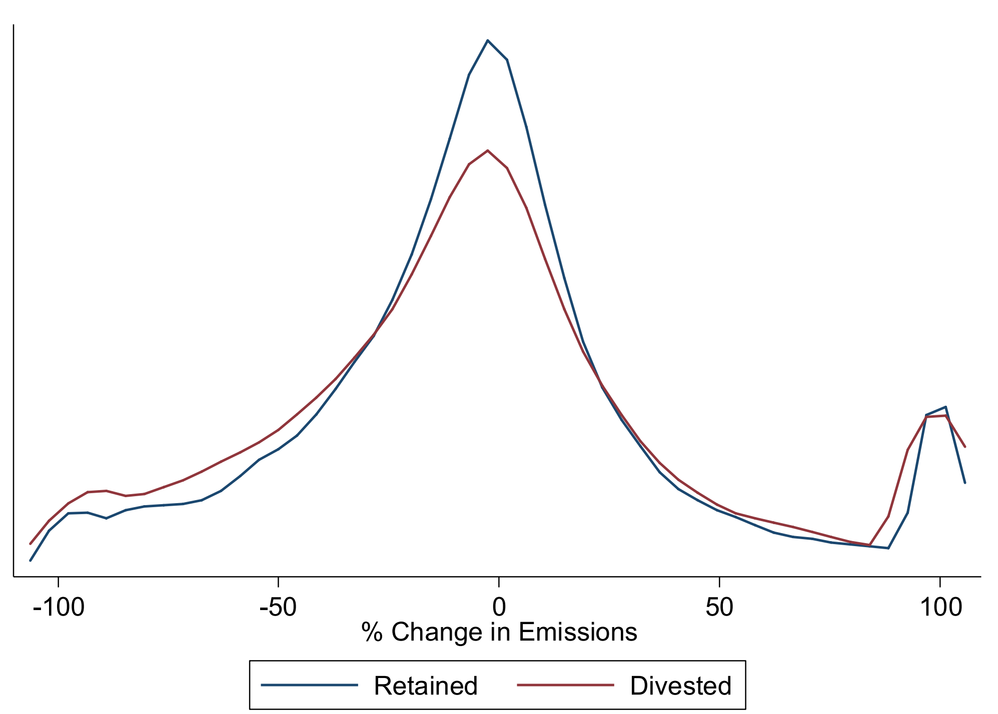


Table 15 reports several specifications, using different fixed effects, different measures of green ownership, and the predicted measures of ownership. All coefficients on green ownership are negative, and they are statistically insignificant when company fixed effects are included. The regressions also usually show a negative relation between non-green ownership and emission reductions as well, but these coefficients are statistically significant in only a few cases. The smaller number of observations is something of a challenge, but for the most part, the evidence suggests that green ownership resulted in corporate-level reductions in emissions, in addition to the plant-level reductions, that is, corporations did not "undo" their plant-level reductions by acquiring more high-polluting plants.

6. Conclusion

The 2022 Inflation Reduction Act includes several subsidies for investments in various green technologies but does not make polluters pay for their emissions. In the absence of a national carbon tax, polluters face weak incentives to reduce their carbon dioxide emissions. This paper investigates whether financial pressure can partially substitute for government regulation in encouraging decarbonization. The most heated current debate is whether environmentally inclined investors can be most effective by divesting fossil fuel stocks in order to redirect capital from dirty to clean energy producers, or by acquiring fossil fuel stocks and working for change through engagement with corporate managers. Our study points to clear conclusions: yes, capital markets can influence corporate emissions, and engagement is better than divestment for investors that want companies to reduce carbon emissions. Green investors make companies greener.

Although we are motivated by the question of whether green investors in general can bring about changes in corporate pollution policies, our analysis focuses on one particular class of green investors – public pension funds. We chose to focus on public pensions because they are identifiable and thus can be studied, and variation in preferences across funds can be captured by political affiliation. However, public pension funds are different from other green investors in important respects, so the lessons from studying them may not necessarily carry over to other green investors. For example, Heath et al. (2023) find that ownership by green mutual funds did not cause a reduction in non-GHG chemical emissions. Mutual funds might be less effective than public pensions because they face a strong market test to deliver returns to the investors – they are in the business of earning profit – and their willingness to press for emission cuts may be tempered by concerns over the cost. Public pension funds, on the other hand, often can expect asset shortfalls to be backfilled by taxpayers, reducing pressure to maximize returns; and they are often controlled by political actors with incentives to take political actions. An interesting example are the activist campaigns undertaken by New York City Comptroller Scott Stringer, the sole trustee of the New York City pension funds, in the runup to his (unsuccessful) run for governor in 2022.

Previous research has investigated the effect of divestment in other policy areas, such as the 1980s campaign against Apartheid in South Africa (Teoh et al. 1999). That research focused on the impact of divestment on financial markets, especially asset prices. Less research attention has been paid to the real effects of divestment in part because of the difficult of establishing causal relations between divestment and (say) the dismantling of Apartheid. We are not aware of research that has produced rigorous causal estimates of divestment on greenhouse gas emissions, or other social policies.

A somewhat puzzling aspect of our findings is that relatively small shareholdings seem to influence company behavior. The number of shares held by public pension funds is large in absolute terms, but nowhere near large enough to have effective control of the company. Why do companies seem to respond to these investors? One possibility is that even a relatively large minority shareholder can mitigate the free-riding problem. Another possibility is that public pension funds are followed by other investors or are effective in forming coalitions. A natural follow up to our study would be to explore the economics of coordination among green investors. Anecdotally, we observe attempts to coordinate, such as formation of the Climate Action 100+ Alliance by large pension funds and asset managers. At the same time, we have seen resistance to such coordination by red state politicians on grounds that it facilitates collusion and anti-competitive behavior (Kerber 2023). The effectiveness of these alliances and the mechanisms by which they attempt to manage collective action problems would be an interesting area for future research.

Our study is not intended to advance a normative claim about the desirability of using capital markets to bring about emission reductions, or about the normative value of those reductions in the first place. Those are complicated issues that go well beyond the scope of our analysis. Nevertheless, as a starting point for readers interested in normative issues, we can outline how one might begin to go about a benefit-cost analysis. Suppose we adopt the Biden administration's estimate of $51 per ton as the social cost of carbon (Chemnick 2021). Our regressions suggest that a 10 basis point increase in shareholding by green pension funds – or a $20 million equity investment on average – leads to a 0.056 million-ton reduction in carbon emissions on average, which would translate to a reduction in social cost of $2.9 million.

Finally, our study speaks to an ongoing discussion about the goals of the corporation. Central to this discussion is the question of whether corporations solely maximize profit or instead seek to maximize shareholder utility, as Hart and Zingales (2017) and others argue they should. We find that companies appear to weigh the preferences of green shareholders. When companies have more green investors, they adopt greener policies. This does not necessarily imply that companies are willing to forgo profits when they reduce emissions, but it would not be a stretch to think that this is sometimes the case.

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Table 1. Stock Ownership by Public Pension Funds

	Stock owned ($B)	# Companies held	# Companies with EPA data
California Public Employees' Retirement System (CalPERS)	101.3	3,505	332
New York State Common Retirement Fund (NYSCRF)	78.2	3,154	304
California State Teachers' Retirement System (CalSTRS)	56.8	3,017	293
Florida State Board of Administration	40.5	2,317	283
New York State Teachers' Retirement System	39.8	1,620	246
State of Wisconsin Investment Board	36.1	1,701	233
State of New Jersey Common Pension	23.9	1,602	242
State Teachers Retirement System of Ohio	22.9	2,156	246
Retirement Systems of Alabama	20.7	917	197
Ohio Public Employees Retirement System	17.5	1,909	266
Public Employees Retirement Association of Colorado	17.5	1,853	267
Teacher Retirement System of Texas	12.3	865	188
Treasurer of the State of North Carolina	12.1	1,009	192
Virginia Retirement System	8.5	1,084	149
Kentucky Teachers' Retirement System	8.4	1,762	258
Alaska Retirement Management Board	7.8	1,632	244
Oregon Public Employees Retirement Fund	6.8	1,579	242
Employees Retirement System of Texas	6.6	728	109
Utah Retirement Systems	5.4	981	187
Pennsylvania Public School Employees' Retirement	5.3	1,606	271
Municipal Employees' Retirement System of Michigan	4.0	250	84
Arizona State Retirement System	0.8	261	50

Note. The table describes the equity investments of public pension funds in our sample at the end of 2020.

Table 2. Summary Statistics

	Mean	25%	Median	75%	N
A. Unit = Facilities × Year					
Emissions					
GHG emissions (Million tons)	0.51	0.03	0.07	0.21	42,504
Lead emissions (Thousand pounds)	2.76	0.00	0.00	0.00	8,487
Nickel emissions (Thousand pounds)	1.75	0.00	0.00	0.02	6,985
Ammonia emissions (Thousand pounds)	60.30	1.16	10.33	45.32	6,572
Chromium emissions (Thousand pounds)	4.10	0.00	0.00	0.02	6,024
Toluene emissions (Thousand pounds)	10.42	0.45	1.59	8.72	5,789
% change in GHG emissions, year t to $t + 1$	-0.94	-13.50	-1.08	10.16	37,803
% change in GHG emissions, year t to $t + 2$	-1.77	-19.59	-2.56	12.12	33,242
% change in GHG emissions, year t to $t + 3$	-2.28	-23.82	-3.46	12.12	28,847
% change in GHG emissions, year t to $t + 4$	-1.77	-26.85	-4.16	15.27	24,676
Electricity					
Electricity generated (Terawatt-hour)	1.94	0.05	0.40	2.56	10,688
% change in electricity, year t to $t + 1$	5.01	-18.44	-1.23	14.73	9,678
% change in electricity, year t to $t + 2$	8.28	-24.17	-2.39	17.00	8,740
% change in electricity, year t to $t + 3$	11.50	-29.33	-3.48	18.27	7,795
% change in electricity, year t to $t + 4$	15.52	-32.23	-4.30	20.05	6,814
Divestitures					
% sold off in any year	7.4	0.0	0.0	0.0	37,841
% sold off in any two-year period	13.8	0.0	0.0	0.0	33,270
% sold off in any three-year period	19.6	0.0	0.0	0.0	28,872
% sold off in any four-year period	24.3	0.0	0.0	0.0	24,701
B. Unit = Company ×Year					
Ownership					
% green fund ownership (governor)	0.8	0.4	0.9	1.16	3,726
% non-green fund ownership (governor)	0.5	0.1	0.4	0.7	3,726
% green fund ownership (trustees)	1.0	0.4	1.1	1.4	3,726
% green fund ownership (trustees)	0.3	0.1	0.3	0.5	3,726
GHG emissions					
Emissions (M tons)	4.39	0.08	0.36	1.97	4,902
# facilities in EPA data	8.67	1	3	8	4,902
Green patents filed	15.2	0	1	5	1,690
Proposals					
# environmental proposals	0.13	0	0	0	2,324
# proposals sponsored by pension funds	0.10	0	0	0	2,324
# environmental proposals approved	0.02	0	0	0	2,324
Financials					
Assets ($B log)	8.97	7.78	9.02	10.35	4,858

EBIT/Assets	0.08	0.04	0.06	0.10	4,843
Debt/Assets	0.54	0.34	0.48	0.62	4,825
R&D/Assets	0.03	0.00	0.01	0.03	2,139
Market/Book	6.55	1.34	1.99	3.13	4,265

Note. The data cover 2010-2021. For emissions, only facility-years with positive emissions are included. For ownership, a fund is defined as green according to the party of the governor or the partisan balance of the trustees, as indicated in parentheses. Percent changes in emissions and electricity are winsorized at 95 percent in the right tail. For patents, includes all firms with at least one patent across all years. For proposals, includes all firms with at least one proposal across all years.

Table 3. Percent Change in GHG Emissions and Pension Fund Ownership

Panel A. Dependent = % Change in Emissions

Panel A1	One year	Two years	Three years	Four years
% green (governor)	-0.59	-1.92**	-2.88**	-3.10**
	(0.61)	(0.91)	(1.16)	(1.41)
% non-green (governor)	0.78	1.74*	1.30	1.01
	(0.66)	(0.92)	(1.20)	(1.32)
N	28,515	24,841	21,296	18,058
Clusters	3,406	3,050	2,705	2,377

Panel A2	One year	Two years	Three years	Four years
% green (trustees)	-0.82	-1.86**	-2.86***	-3.08**
	(0.64)	(0.93)	(1.12)	(1.23)
% non-green (trustees)	1.83**	3.21***	3.27**	3.23*
	(0.85)	(1.25)	(1.58)	(1.90)
N	28,515	24,841	21,296	18,058
Clusters	3,406	3,049	2,705	2,377

Panel B. Dependent = Absolute Change in Emissions

Panel B1	One year	Two years	Three years	Four years
% green (governor)	-0.99***	-2.36***	-3.78***	-5.53***
	(0.31)	(0.44)	(0.59)	(0.89)
% non-green (governor)	0.02	-0.07	-0.004	0.34
	(0.23)	(0.38)	(0.52)	(0.69)
N	28,526	24,852	21,305	18,066
Clusters	3,406	3,050	2,705	2,377

Panel B2	One year	Two years	Three years	Four years
% green (trustees)	-1.03***	-2.39***	-3.63***	-4.86***
	(0.29)	(0.39)	(0.51)	(0.69)
% non-green (trustees)	0.52	1.02**	1.52**	2.16**
	(0.36)	(0.49)	(0.69)	(0.94)
N	28,526	24,852	21,305	18,066
Clusters	3,406	3,050	2,705	2,377

Panel C. Dummy = 1 if Emissions Declined

Panel C1	One year	Two years	Three years	Four years
% green (governor)	1.60	3.65***	4.71***	5.20***
	(1.02)	(1.33)	(1.46)	(1.82)

% non-green (governor)	-2.31*	-2.90*	-2.69	-2.82
	(1.26)	(1.60)	(1.68)	(1.87)
N	28,526	24,852	21,305	18,066
Clusters	3,406	3,050	2,705	2,377

Panel C2	One year	Two years	Three years	Four years
% green (trustees)	1.78*	3.99***	4.63***	4.70***
	(1.00)	(1.30)	(1.41)	(1.68)
% non-green (trustees)	-4.27**	-6.49***	-6.08***	-6.19*
	(1.82)	(2.31)	(2.62)	(3.42)
N	28,526	24,852	21,305	18,066
Clusters	3,406	3,050	2,705	2,377

Note. Each column is a regression with year fixed effects. The unit of observation is a facility-year. The dependent variable is change in emissions from the current year t to another year $t + n$ as indicated in the panel title and at the top of each column; % change is winsorized at the 5 percent level in the right tail. Green and non-green funds are defined either by the party of the governor or the party of the trustees. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021.The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 4. Percentage Change in GHG Emissions with Facility Fixed Effects

Panel A	One Year	Two Years	Three Years	Four Years
% green (governor)	-1.21	-4.69***	-6.02***	-5.26**
	(0.99)	(1.62)	(1.97)	(2.35)
% non-green (governor)	0.34	0.69	-0.55	-0.41
	(1.04)	(1.55)	(2.18)	(2.55)
N	28,104	24,345	20,783	17,548
Clusters	3,371	3,006	2,664	2,340

Panel B	One Year	Two Years	Three Years	Four Years
% green (trustees)	-1.63	-4.60***	-6.08***	-4.56*
	(1.11)	(1.74)	(2.10)	(2.37)
% non-green (trustees)	1.55	2.61	1.82	1.12
	(1.25)	(1.91)	(2.61)	(3.60)
N	28,104	24,345	20,783	17,548
Clusters	3,371	3,006	2,664	2,340

Note. Each column is a regression with year and facility fixed effects. The unit of observation is a facility-year. The dependent variable is the percentage change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent level in the right tail. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 5. First-Stage Regressions Predicting Change in Fund Ownership

	(1)	(2)	(2)
Return on other investments	1.39***	3.44***	2.77***
	(0.44)	(0.44)	(0.41)
Constant	0.23***	...	...
	(0.02)		
N	43,779	43,779	43,518
F-statistic	11.7	60.3	45.0
Fixed effects	None	Year	Year x Company

Note. The table reports first-stage regressions, where the dependent variable is the percentage change in a fund's shares of a company, winsorized at 5 percent in each tail. The unit of observation is a fund-company-year. Each column is a regression with fixed effects as indicated. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 6. Regressions with Predicted Ownership

Panel A. Year Fixed Effects

Panel A1	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-1.26**	-1.43*	-2.92***	-3.45***
	(0.55)	(0.86)	(1.10)	(1.27)
% $\widehat{\text{non-green}}$ (governor)	0.89	0.31	0.08	-0.64
	(0.66)	(1.01)	(1.14)	(1.33)
N	26,117	22,420	18,895	15,782
Clusters	3,014	2,671	2,337	2,030

Panel A2	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-1.36***	-1.83****	-2.86***	-3.53***
	(0.52)	(0.71)	(0.87)	(1.03)
% $\widehat{\text{non-green}}$ (trustees)	2.09***	2.08*	1.48	0.97
	(0.79)	(1.09)	(1.28)	(1.66)
N	26,117	22,420	18,895	15,782
Clusters	3,014	2,671	2,337	2,030

Panel B. Year and Facility Fixed Effects

Panel B1	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-2.97***	-3.62***	-5.86***	-5.71***
	(0.82)	(1.17)	(1.47)	(1.83)
% $\widehat{\text{non-green}}$ (governor)	0.44	-0.38	-1.65	-2.46
	(0.95)	(1.48)	(1.64)	(2.06)
N	25,679	21,910	18,365	15,175
Clusters	2,975	2,630	2,299	1.989

Panel B2	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-2.91***	-3.97***	-5.32***	-5.15***
	(0.82)	(1.07)	(1.32)	(1.56)
% $\widehat{\text{non-green}}$ (trustees)	1.75	1.80	-0.76	-2.11
	(1.19)	(1.77)	(2.27)	(2.98)
N	25,679	21,910	18,365	15,175
Clusters	2,975	2,630	2,299	1,989

Note. This table reports regressions in which the dependent variable is the percentage change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent level in the right tail. The explanatory variables are the predicted percentage of shares owned by green funds and non-green funds, using coefficient estimates from regression (2) in Table 5. Green and non-green funds are defined according to the party of the governor or trustees, as indicated. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 7. Ownership Effects After Adjusting for Changes in Parent Company

Panel A. Year and Facility-Parent Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$	-2.02**	-3.05**	-5.15***	-5.15***
	(0.93)	(1.29)	(1.41)	(1.65)
% $\widehat{\text{non-green}}$	0.40	-0.19	-0.95	-1.57
	(0.98)	(1.56)	(1.68)	(2.12)
N	25,054	21,288	17,880	14,877
Clusters	2,936	2,591	2,262	1,960

Panel B. Single-Parent Facilities Only with Year Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$	-0.94	-1.52	-2.54*	-3.34**
	(0.68)	(1.12)	(1.41)	(1.60)
% $\widehat{\text{non-green}}$	0.79	0.25	0.41	-0.12
	(0.69)	(1.11)	(1.27)	(1.37)
N	17,284	14,773	12,486	10,406
Clusters	2,434	2,108	1,800	1,521

Panel C. Single-Parent Facilities Only with Year and Facility Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$	-2.80**	-4.25**	-6.08***	-7.20***
	(1.26)	(1.73)	(1.82)	(1.95)
% $\widehat{\text{non-green}}$	0.51	-0.51	-1.09	-1.12
	(1.08)	(1.69)	(1.86)	(1.75)
N	17,028	14,542	12,272	10,139
Clusters	2,399	2,067	1,769	1,487

Note. This table reports regressions in which the dependent variable is the percentage change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent level in the right tail. The explanatory variables are the predicted percentage of shares owned by green funds and non-green funds, and green and non-green funds are defined according to the party of the governor. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 8. Active versus Less Active Pension Funds

Panel A. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (active)	-1.83**	-3.27***	-5.67***	-6.39***
	(0.75)	(1.09)	(1.41)	(1.82)
% $\widehat{\text{green}}$ (less active)	-0.13	2.17	3.29	3.49
	(1.24)	(1.80)	(2.24)	(2.86)
% $\widehat{\text{non-green}}$	1.01	0.67	0.37	-0.41
	(0.66)	(1.00)	(1.16)	(1.39)
p-value: active = less active	.30	.02	.001	.009
N	26,117	22,420	18,895	15,782
Clusters	3,014	2,671	2,337	2,030

Panel B. Year and Facility Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (active)	-3.46***	-5.25***	-6.86***	-5.98**
	(1.18)	(1.78)	(2.26)	(2.70)
% $\widehat{\text{green}}$ (less active)	-2.09	-0.77	-3.72	-5.11
	(1.74)	(2.39)	(3.19)	(3.86)
% $\widehat{\text{non-green}}$	0.47	-0.25	-1.60	-2.46
	(0.95)	(1.48)	(1.65)	(2.07)
p-value: active = less active	.56	.19	.49	.87
N	25,679	21,910	18,365	15,175
Clusters	2,975	2,630	2,299	1,989

Note. Each column is a regression in which the unit of observation is a facility-year. The dependent variable is the percentage change in emissions from the current year t to another year $t + n$ as indicated at the top of each column; winsorized at the 5 percent level in the right tail. Green and non-green funds are defined by the party of the governor; active funds are CalPERS, CalSTRS, and NYSCRF. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover the period from 2010 to 2021.The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 9. Shareholder Proposals and Green Ownership

	Dummy = 1 if green proposal (1)	Dummy = 1 if green proposal from public pension (2)	Dummy =1 if green proposal not from public pension (3)	Dummy = 1 if green proposal passed (4)
Panel A. Year Fixed Effects				
$\widehat{\%\ \text{green}}$	1.15	-0.65	1.26	0.18
	(1.72)	(0.92)	(1.60)	(3.01)
$\widehat{\%\ \text{non-green}}$	-0.20	-0.30	-0.40	2.47
	(2.20)	(1.18)	(2.04)	(4.11)
Assets (log)	0.045***	0.016***	0.040***	0.000
	(0.006)	(0.003)	(0.005)	(0.008)
Emissions (trillion tons)	3.63***	0.65**	0.04***	-0.08
	(0.48)	(0.26)	(0.01)	(0.42)
N	1,837	1,837	1,837	234
Panel B. Year and Company Fixed Effects				
$\widehat{\%\ \text{green}}$	2.08	0.31	1.78	3.43
	(2.03)	(1.14)	(1.85)	(6.40)
$\widehat{\%\ \text{non-green}}$	0.93	-0.09	0.66	-0.99
	(2.56)	(1.44)	(2.34)	(8.21)
Assets (log)	0.059*	0.047***	0.022	-0.048
	(0.033)	(0.018)	(0.030)	(0.073)
Emissions (trillion tons)	-0.27	-0.13	0.09	1.16
	(1.89)	(1.06)	(1.72)	(2.68)
N	1,826	1,826	1,826	193

Note. Each column is a regression in which the unit of observation is a company. The dependent variable is a dummy = 1 if a company received an environmental shareholder proposal, as indicated at the top of each column. Green funds are defined according to the party of the governor. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 10. Yes Votes by Pension Funds on Environmental Proposals

	(1)	(2)	(3)	(4)
Dummy = 1 if green fund (governor)	0.13***	...	0.12***	...
	(0.02)		(0.01)	
Dummy = 1 if green fund (trustees)	...	0.01	...	-0.003
		(0.02)		(0.020)
Assets (log)	-0.027***	-0.029***	0.007	0.005
	(0.008)	(0.008)	(0.012)	(0.012)
Emissions	0.30	0.29	0.33	0.35
	(0.43)	(0.44)	(0.68)	(0.69)
Fixed effects	Year	Year	Year, Proposal type	Year, Proposal type
N	3,347	3,347	3,342	3,342

Note. Each column is a regression in which the unit of observation is a pension fund vote on an environmental shareholder proposal at company that emitted greenhouse gases. The dependent variable is a dummy = 1 if a fund voted in favor of the proposal. Green funds are defined according to the party of the governor or the majority of the trustees, as indicated. Estimates for the emissions are multiplied by 1,000. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 11. Change in Electricity Generation at Facilities that Cut Emissions

	One Year	Two Years	Three Years	Four Years
A1. Dependent = % change in emissions				
Dummy if emission cut	-55.4***	-71.4***	-83.4***	-95.8***
	(1.0)	(1.4)	(1.6)	(2.0)
A2. Dependent = % change in electricity				
Dummy if emission cut	-52.5***	-69.8***	-81.8***	-96.0***
	(1.6)	(2.2)	(2.7)	(3.4)
Fixed effects	Year	Year	Year	Year
N	9,676	8,740	7,795	6,814

	One Year	Two Years	Three Years	Four Years
B1. Dependent = % change in emissions				
Dummy if emission cut	-55.5***	-68.1***	-75.5***	-81.7***
	(1.1)	(1.4)	(1.6)	(2.0)
B2. Dependent = % change in electricity				
Dummy if emission cut	-52.8***	-66.9***	-74.3***	-83.3***
	(1.8)	(2.4)	(2.9)	(3.7)
Fixed effects	Year, Facility	Year, Facility	Year, Facility	Year, Facility
N	9,662	8,715	7,779	6,749

Note. Each panel and column reports a regression in which the unit of observation is a facility. In panels A1 and B1, the dependent variable is the percent change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent in the right tail. In panels A2 and B2, the dependent variable is the percent change in electricity generated, winsorized in the same way. The explanatory variable is dummy = 1 if the facility reduced emissions over the period. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 12. Other Pollutants and Green Ownership

	One Year	Two Years	Three Years	Four Years
A. Lead				
% $\widehat{\text{green}}$	-2.25	-4.17	-10.94*	-21.77***
	(1.77)	(3.10)	(6.24)	(6.89)
% $\widehat{\text{non-green}}$	0.82	-0.60	4.79	9.69
	(1.58)	(2.21)	(4.52)	(6.62)
N	2,769	2,261	1,786	1,446
Clusters	570	492	423	365
B. Nickel				
% $\widehat{\text{green}}$	0.14	-5.58*	-3.56	-6.36
	(1.91)	(3.35)	(4.22)	(4.66)
% $\widehat{\text{non-green}}$	2.01	6.24	6.69	1.54
	(2.52)	(4.25)	(4.89)	(5.42)
N	2,417	2,040	1,721	1,434
Clusters	472	414	361	312
C. Ammonia				
% $\widehat{\text{green}}$	0.84	-6.80	-11.26*	-14.92*
	(2.66)	(4.25)	(6.45)	(7.60)
% $\widehat{\text{non-green}}$	5.16	11.49*	14.34	14.33
	(4.24)	(6.16)	(8.75)	(10.84)
N	4,167	3,638	3,148	2,688
Clusters	1,057	946	841	737
D. Chromium				
% $\widehat{\text{green}}$	-2.23	-2.06	1.27	2.76
	(2.86)	(3.35)	(4.74)	(6.20)
% $\widehat{\text{non-green}}$	-2.88	-1.21	-0.76	3.31
	(2.28)	(3.70)	(5.54)	(9.00)
N	1,861	1,558	1,311	1,097
Clusters	407	353	308	266
E. Toluene				
% $\widehat{\text{green}}$	1.89	-1.18	-1.07	5.23
	(2.77)	(3.23)	(3.89)	(4.58)
% $\widehat{\text{non-green}}$	2.04	3.27	7.35	1.65
	(4.00)	(4.28)	(4.80)	(5.77)
N	3,060	2,668	2,292	1,961
Cluster	582	508	440	376

Note. Each column in each panel is a regression with year fixed effects. The unit of observation is a facility. The dependent variable is the percent change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent in the right tail; the type of pollutant is shown in the panel title. Green funds and non-green funds are defined according to the party of the state's governor. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 13. Increase in Green Patents

Dependent variable = Dummy if company increased patents

Panel A. Year Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-2.18	0.38	4.69	2.51
	(2.84)	(3.02)	(3.28)	(3.35)
% $\widehat{\text{non-green}}$ (governor)	7.14*	5.61	1.46	3.38
	(3.97)	(4.09)	(4.31)	(4.35)
N	1,186	1,066	944	831

Panel B. Year Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-0.74	0.10	6.02*	2.91
	(2.89)	(3.05)	(3.23)	(3.27)
% $\widehat{\text{non-green}}$ (trustees)	8.29	9.66	-4.73	2.79
	(7.57)	(8.04)	(8.66)	(8.82)
N	1,186	1,066	944	831

Panel C. Year and Company Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-3.27	-3.59	12.65**	1.81
	(4.61)	(4.94)	(5.49)	(5.60)
% $\widehat{\text{non-green}}$ (governor)	1.25	2.19	1.78	7.02
	(5.26)	(5.31)	(5.63)	(5.69)
N	1,168	1,047	921	818

Panel D. Year and Company Fixed Effects

	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	0.35	0.87	15.59***	6.26
	(4.51)	(4.74)	(5.09)	(5.13)
% $\widehat{\text{non-green}}$ (trustees)	-5.74	-5.67	-15.45	-0.76
	(10.45)	(10.78)	(11.32)	(11.30)
N	1,168	1,047	921	818

Note. Each column in each panel is a regression in which the unit of observation is a company. The dependent variable is a dummy =1 if a company increased the number of green patents filed from the current year t to another year $t + n$ as indicated. Green and non-green funds are defined as indicated in the panel titles. Standard errors are in parentheses beneath coefficient estimates. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 14. Divestiture of Polluting Facilities

Panel A. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-2.83**	-5.38***	-7.13***	-7.87***
	(1.38)	(1.78)	(1.99)	(2.21)
% $\widehat{\text{non-green}}$ (governor)	-0.79	-3.12**	-5.41***	-6.36***
	(1.16)	(1.32)	(1.57)	(1.82)
Emissions (trillion tons)	-1.15	-1.58	-2.16	-2.23
	(1.44)	(2.04)	(2.43)	(2.83)
N	23,415	28,751	16,175	13,741
Clusters	2,827	2,524	2,225	1,943

Panel B. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-1.52*	-3.95***	-6.28***	-7.24***
	(0.92)	(1.34)	(1.57)	(1.69)
% $\widehat{\text{non-green}}$ (trustees)	-3.00***	-5.38***	-6.52***	-7.04***
	(1.11)	(1.48)	(1.75)	(1.92)
Emissions (trillion tons)	-1.35	-1.81	-2.31	-2.35
	(1.44)	(2.02)	(2.41)	(2.81)
N	21,415	18,751	16,175	13,741
Clusters	2,827	2,524	2,225	1,943

Panel C. Year and Facility Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	0.06	1.73	1.09	-0.08
	(1.23)	(1.74)	(1.51)	(1.54)
% $\widehat{\text{non-green}}$ (governor)	1.98	1.79	0.98	0.95
	(1.35)	(1.49)	(1.37)	(1.35)
Emissions (trillion tons)	1.96	-0.59	-1.95	-6.32
	(2.69)	(4.62)	(5.89)	(5.81)
N	20,783	18,148	15,560	13,057
Clusters	2,762	2,460	2,162	1,881

Panel D. Year and Facility Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	2.39**	3.59***	2.24*	1.03
	(1.00)	(1.30)	(1.15)	(1.13)
% $\widehat{\text{non-green}}$ (trustees)	-1.32	-1.38	-1.08	-0.58
	(1.05)	(1.45)	(1.52)	(1.59)
Emissions (trillion tons)	1.84	-0.84	-2.04	-6.38
	(2.69)	(4.61)	(5.87)	(5.79)
N	20,783	18,148	15,560	13,057
Clusters	2,762	2,460	2,162	1,881

Note. Each column in each panel is a regression in which the unit of observation is a facility. The dependent variable is a dummy =1 if the facility was divested between the current year t and year $t + n$ as indicated at the top of each column. Standard errors clustered at the company-year level are in parentheses beneath coefficient estimates. Coefficients on emissions are multiplied by 1000. The data cover 2010-2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Table 15. Company-Level Percent Change in GHG Emissions and Pension Fund Ownership

Dependent variable = % change in emissions

Panel A. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-1.36	-2.45	-2.67	-4.43
	(0.95)	(1.69)	(2.62)	(3.65)
% $\widehat{\text{non-green}}$ (governor)	-1.86	-5.64***	-8.26**	-11.41***
	(1.36)	(2.27)	(3.39)	(4.65)
N	2,834	2,386	1,983	1,635

Panel B. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-1.46	-3.55**	-4.09*	-5.53*
	(0.91)	(1.58)	(2.35)	(3.20)
% $\widehat{\text{non-green}}$ (trustees)	-1.82	-4.35	-7.72	-12.75
	(2.28)	(3.85)	(5.76)	(7.79)
N	2,834	2,386	1,983	1,635

Panel C. Year and Company Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (governor)	-2.47	-6.37**	-7.80**	-9.69**
	(1.53)	(2.49)	(3.69)	(4.65)
% $\widehat{\text{non-green}}$ (governor)	-3.19*	-4.78*	-3.32	-3.97
	(1.85)	(2.84)	(4.08)	(5.10)
N	2,787	2,328	1,930	1,595

Panel D. Year and Company Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (trustees)	-2.28	-6.27***	-6.68**	-7.25*
	(1.46)	(2.32)	(3.29)	(4.11)
% $\widehat{\text{non-green}}$ (trustees)	-4.22	-3.92	-3.01	-6.38
	(3.25)	(5.03)	(7.24)	(8.76)
N	2,787	2,328	1,930	1,595

Note. Each column is a regression in which the unit of observation is a company-year. The dependent variable is the percentage change in emissions from the current year t to another year $t + n$ as indicated at the top of each column, winsorized at the 5 percent level in the right tail. Fixed effects are indicated in the panel titles. The data cover the period from 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.