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

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This paper investigates whether green investors can influence corporate greenhouse gas emissions through capital markets, and if so, whether they have a larger effect by the stock of polluting companies in order to limit their access to capital, or by acquiring polluters' stock and engaging with management as owners. We focus on public pension funds, classifying them as green or nongreen 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 from 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 nongreen funds changed. Other evidence based on voting, shareholder proposals, and activist pension funds suggests that ownership mattered because of active engagement by green investors, and more through attempts to persuade than voting pressure. We do not find that companies with green investors were more likely to sell off their high-emission facilities (greenwashing). Overall, our findings suggest that (a) corporate managers respond to the environmental preferences of their investors; (b) divestment of polluting companies may lead to greater emissions; and (c) private markets may be able to partially address environmental challenges independent of government regulation.

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1. Introduction

Can environmental problems be addressed through private markets, or is government regulation the only viable solution? This question is being put to the test by shareholder activists who, skeptical of governments' ability to combat climate change, are using capital markets to pressure polluters to reduce their carbon emissions. In addition to the debate over whether private markets can address externalities in the first place, there is disagreement over the most effective strategy for bringing pressure through financial markets: is it *divestment* – selling fossil fuel stocks in order to deprive polluting companies of capital and channel resources to clean energy – or *engagement* – acquiring fossil fuel stocks and using ownership rights to press for pollution cuts?

The purpose of this study is to provide an empirical assessment of how corporations adjust their carbon emissions, if at all, in response to changes in the composition of their shareholders: do they reduce emissions when green investors divest, when they invest, or neither?[1] 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, redirect capital from dirty to clean energy, and take a symbolic stand in support of sustainability. Others argue that divestment is ineffective: in its statement opposing California's divestment bill, CalPERS (2023) argued 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; officials in some red states have threatened to withhold business from banks and investment companies that pursue divestment strategies.

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[1] There is also debate over the magnitude of the damages associated with greenhouse gas emissions and whether these emissions are damaging in the first place. Our focus is on the narrower question of whether capital markets can influence corporate emissions.

The opposite strategy favored by some of these green investors is to *acquire* stocks of polluting companies and engage the companies' management 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 more effective approach than divestment.

The basic theoretical argument for divestment is developed in Heinkel et al. (2001), which shows that divestment can reduce the stock price of targeted firms by limiting risk sharing. The effectiveness of this strategy is limited by the number of non-divesting investors who are willing to purchase the stock. Edmans et al. (2023) identify another limit: by refusing to hold brown stocks, divestment gives polluting companies no incentive to make incremental improvements; they show that it may be more effective for investors to acquire brown companies that have reduced their emissions even if they still pollute. Engagement has its own problems: attempting to put pressure on management by acquiring an ownership stake presents 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. Putting some of these ideas together, Broccardo et al. (2022) develop a model in which investors can influence prices through divestment ("exit") or acquire shares and use them to cut emissions through a binding vote ("voice"); they find that neither strategy achieves socially optimal outcomes for realistic parameter values, but engagement may be more effective if a majority of investors have social preferences.

Conceptually, the question we seek to answer is straightforward: are companies more likely to cut emissions if the fraction of green shareholders increases or decreases? The implementation challenge is that 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 a strategy to identify causal effects of those changes.

To measure green ownership, we focus on an important class of investors: public pension funds. 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 more favorable toward decarbonization than Republicans. We define a public pension fund as "green" in two ways: first, based on the partisan composition of a fund's board of trustees, and second, based on the governor's party affiliation (because governors can influence pension fund investment by their power to appoint trustees and through legislative and regulatory actions).

To address the challenge of causal identification, we rely on two sources of variation in shares held by green investors that are arguably exogenous with respect to company emissions. The first source of variation stems from shifts in political control in a state. Changes in the party composition of the trustees and the governor 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 utilizes the fact that public pension funds typically maintain target ratios for their investment in public equities relative to 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 contrast, we find a positive, but not always statistically significant, association between ownership by nongreen public pension funds and changes in corporate carbon emissions. We show that these patterns are robust to alternative specifications of emissions changes and various fixed effects. These patterns also hold if we control for the party of the governor in a facility's state to remove direct policy effects on emissions and for holdings by other institutional investors. In short, we find that engagement reduced emissions; divestment did not. This suggests that divestment strategies are likely to be counterproductive – resulting in higher emissions compared to the alternative of holding the stock.

We also investigate three 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 if they seek to maximize shareholder utility, as some argue they should (Hart and Zingales 2017). Second, ownership might allow investors to engage management, either through adversarial means, such as voting against incumbent directors and sponsoring shareholder proposals (Krueger et al. 2020), or through collaboration and persuasion, expressing preferences and sharing of knowledge. The evidence we assemble is largely suggestive but points to a primary role for engagement, probably mainly in the form of persuasion. We find that emissions reductions were more strongly associated with ownership by pensions known for actively engaging management than by relatively passive other funds, suggesting the importance of active engagement. We find little evidence that green ownership led to more shareholder proposals or more successful shareholder proposals, or that green pensions cast more hostile votes on shareholder proposals and director elections than nongreen funds.

Finally, we explore how companies achieved their emission reductions. Following a standard decomposition used by environmental economists, we focus on three methods: output reductions (scale and composition), innovation (technique), and asset sales. We find that companies cut output to achieve emission reductions: among plants that generated electricity, reductions in electricity output corresponded almost one-to-one with emission reductions on average. In terms of innovation, we find no evidence that companies with green owners increased the number of patents they filed related to green technology. As for asset sales, we find little evidence that companies with green owners were more likely to divest their high-emission facilities, so-called "greenwashing." For our sample, it appears that companies cut their emissions mainly by reducing the amount of power produced in their dirtiest facilities.

Our study is related to an existing literature that studies whether green investment produces higher or lower stock returns for investors, and if so, why (Delmas et al. 2015, Trinks et al. 2018, Bolton and Kacperczyk 2020, Hsu et al. 2023, Aswani et al. 2023; Atilgan et al. 2023). We focus on the flip side of this issue, whether green 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. Also 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, which we also find, while Chava (2014) finds that polluting firms faced a higher cost of capital. Our study is also related to research that explores the connection between institutional ownership and environmental outcomes, with a key difference that we focus specifically on green versus nongreen ownership: Dyck et al. (2019) find that institutional ownership is positively associated with firms' E&S performance, Azar et al. (2021) finds a negative relation between ownership by BlackRock, State Street, and Vanguard and emissions across 24 countries and Safiullah et al. (2022) study the connection between total institutional ownership and emissions; these studies do not speak directly to the issue of green ownership that animates our study because they do not distinguish green from nongreen institutions.[2]

Our study also contributes to the literature on stock divestment as a strategy to achieve social goals. Activist investors with social goals have pursued divestment strategies going back at least to the 1980s, when many divested from companies doing business in South Africa. California pension funds have 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 markets can cause companies to change their real behavior. Our paper provides some of the first direct evidence on the real effects of divestment.

At the most general level, 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 firms may be exposed to other pressures. The corporate environmental management literature argues 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). Consumers may boycott polluters, as seen in response to major oil spills (Barrage et al. 2020), and they may reduce their own emissions because of disutility from polluting, such as choosing to buy an electric car (Kotchen 2006). Our evidence suggests that pressure from another group of private actors – investors – can reduce carbon emissions even without government regulation.

2. Data and Sources

Emissions. Our core analysis focuses on carbon dioxide emissions, a primary focus of activist investors and regulators.[3] Carbon emissions have a global impact, unlike other forms of air

[2] The causal evidence in these studies is also limited. For example, Azar et al. (2021) rellies on the Russell 1000/2000 reconstitution for identification which produces local treatment effects on firms in the vicinity of size 1000, omitting the big polluters like Exxon that are the target of divestment campaigns.

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

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 undergo 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 when 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. Second, the data exclude emissions from mobile sources, such as airplanes and cars. 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.[4]

We identified a company as a facility's parent if it owned more than 50 percent of the facility. Then, we merged facilities with their parents' 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 emitting 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 list of the 500 largest pension funds in the United States based on assets, according to *Pensions & Investments*. From that list, we captured holdings information on all state government pension funds that filed Form 13F, drawing from Thomson Reuters Institutional Holdings when possible, otherwise scraping the information from the SEC

[4] There is controversy over whether to hold companies accountable for Scope 2 and Scope 3 emissions; these emissions seem conceptually different from Scope 1 emissions that are directly controlled by the company. Based on an 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.

Table 1. Stock Ownership by Top 12 Public Pension Funds 2020

	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

website. Funds are required to file Form 13F if they managed $100 million in qualifying securities in-house, meaning that a fund that outsourced its portfolio management to a third party, such as Blackrock, would not be included in our data. Our final sample includes 29 public pension funds, including all 12 of the 12 largest state public pension funds, and covers approximately 88 percent of public pension fund assets. Annual fund holdings are the average of quarterly holdings. Other information about public pension funds – such as their asset allocation and returns on private equity, fixed income, and real estate – was drawn from Public Plans Data of Boston College's Center for Retirement Research. Table 1 provides a snapshot of the holdings of the 12 largest public pension funds in our 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 data. The largest funds have highly diversified holdings, holding hundreds of companies that emit greenhouse gases.

Party control of pension funds. Information on partisan affiliation of pension fund trustees was hand-collected as follows. First, we identified the main governing board responsible for approving general investment policies and appointing the chief investment officer. We then referred to 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 and state treasurer, and appointed officials such as the state's finance director. Elected officials were classified according to their self-declared party (Governor Bill Walker of Alaska, an independent, was labeled a Republican based on his historical affiliation), 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.* Members appointed by the governor – by far the most common type of appointee – were assigned the party of the governor. Trustees appointed by legislative leaders or legislative committees were assigned the party of the majority party in the legislature.

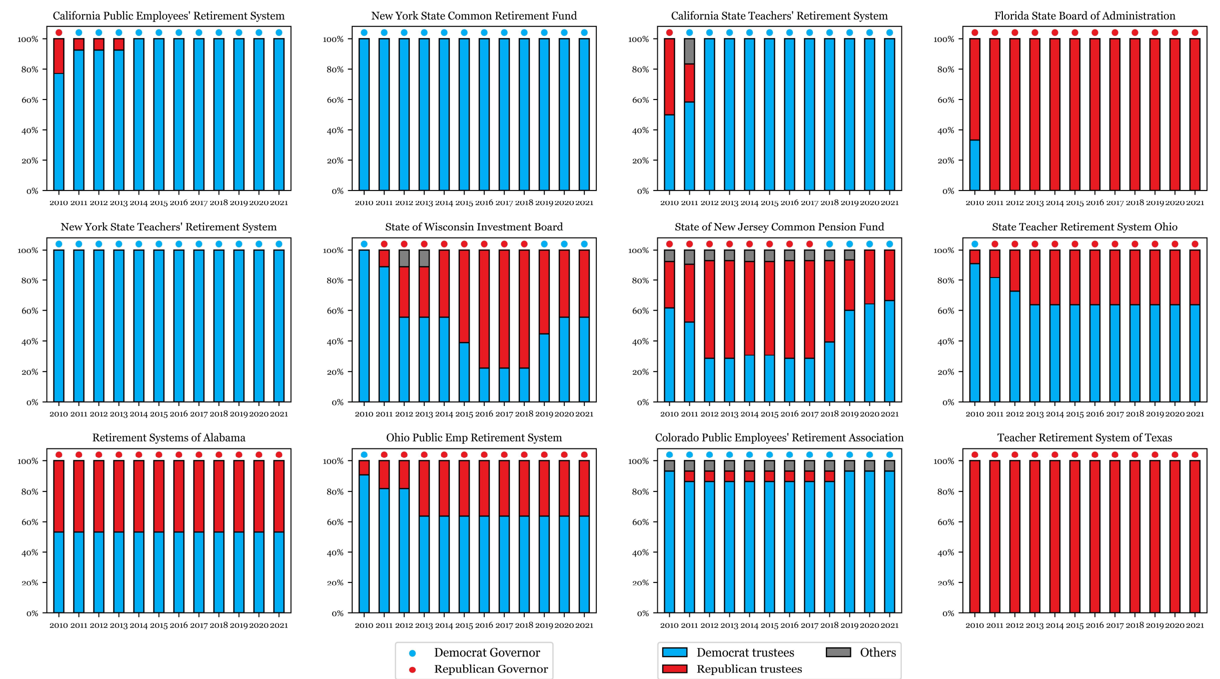
(3) *Members elected by stakeholders.* Examples were trustees elected by teachers, retired workers who were beneficiaries, or by local governments. Since state and local government employees are about twice as likely to identify as Democrats than Republicans (Newport et al. 2011), we categorized members elected by government employees as Democrats, assuming selection by the median voter, unless information on their campaign contributions or self-declarations of party were available. Trustees 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 the "uncertain" category.[5]

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. There is a strong, but not perfect, correlation between the two measures. Some funds displayed substantial time-series variation in party control while others were extremely stable. The State of Wisconsin Investment Board, for example, drifted from 33 percent to 100 percent Democrat. The five largest funds showed little variation in party control, and the huge New York state funds were always 100 percent controlled by Democrats, while Florida and Texas were almost always controlled by Republicans.

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 relied on the crosswalk map provided by the EPA. This map connects the Facility ID in the EPA dataset to the generators' Office of Regulatory Information Systems (ORIS) codes. We successfully matched 1,099 electricity-producing facilities with the EIA dataset. The

[5] 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.

Figure 1. Party Affiliation of Governor and Pension Fund Trustees



majority of these facilities 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. Some facilities in the GHG dataset encompass multiple generators; in such instances, we aggregated electricity output to the facility level by summing output from all of the facility's generators within a given year.

Other pollutants. We obtained information on non-GHG pollutants from the EPA's Toxics Release Inventory (TRI) dataset, covering the years 2010-2020. This dataset provides details on emissions of over 600 toxic chemicals. 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 2010-2021, of which 282,274 are classified as "green patents," meaning technologies or applications for mitigation or adaptation against climate change (CPC Y02). We linked the patent filing companies to company names in the Compustat dataset using a fuzzy matching algorithm. We were able to identify 68,049 green patents associated with 1,564 publicly traded companies. Focusing on the 686 companies in the EPA GHGRP dataset, our working sample includes 185 unique companies that filed at least one green patent during our study period. The mean number of green patents filed by a company per year was 14.9 (median = 1), with a range from zero to 496.

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, of which 1,079 were related to environmental issues, and 17 received a majority of votes in favor. Voting data for public pensions were drawn from the Insightia database by Diligent Market Intelligence. This database categorizes proposals by issue type and distinguishes proposals from director elections. We were able to locate voting records for 25 public pension funds, accounting for 13,194 votes across 1,036 environmental proposals and 4,443,339 votes across 646,447 director elections.

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," 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.[6] 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 partisan affiliation of the fund's trustees and by the party of the state's governor. 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 is able to exert influence over the state's pension funds through laws and regulations.[7] Because both measures are plausible and may

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

[7] For example, Governor Greg Abbot of Texas signed a law in 2021 to ban the state's pension funds from doing business with companies that discriminate against the oil and gas sector.

capture different forces, we typically employ both of them in our analysis. We refer to a fund in a state with a majority of Democrats as trustees or a Democratic governor as a "green" fund.[8]

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

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

where f is a fund, $DEMTRUST$ is the fraction of trustees that were Democrats, and $shares_f$ is the number of shares held by fund f. The analogous measure for the governor is:

$$\%green(GOV) = \frac{\sum_f DEMGO\ \ _f \times share\ \ _f}{shares\ outstanding},$$

where $DEMGOV$ is an indicator equal to one if the state's governor was a Democrat. We also create variables for $\%nongreen$ ownership based on shares controlled by Republicans.

As a plausibility check on our classification of green funds, we collected the annual financial reports of our sample funds, and used a computer script to count the number of times that each report used phrases related to climate change, such as "greenhouse gas" and "carbon emission." The phrases were the top 100 bigrams identified in Sautner et al. (2023). We found a strong an statistically significant relation between %green(TRUST) and the climate change words as a percentage of all words. This basic relation is depicted in Internet Appendix Figure IA1.

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 "nongreen" pension funds. Recall that this captures only emissions from domestic facilities. The two largest greenhouse gas emitters were 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, defined by party of the governor, increased their holdings of these heavy emitters in recent years. This suggests that green funds in aggregate have not been pursuing a divestment strategy. Panel C shows that nongreen funds have not

[8] An oversimplification in our approach is treating all members of a party as if they had the same preferences, because a Democratic governor in Alabama may be less green than a Democratic governor in California. In practice, blue state funds tend to be controlled by Democrats and red state funds by Republicans.

increased their holdings of carbon emitters in recent years, suggesting that the growth in Panel B is not mechanical.

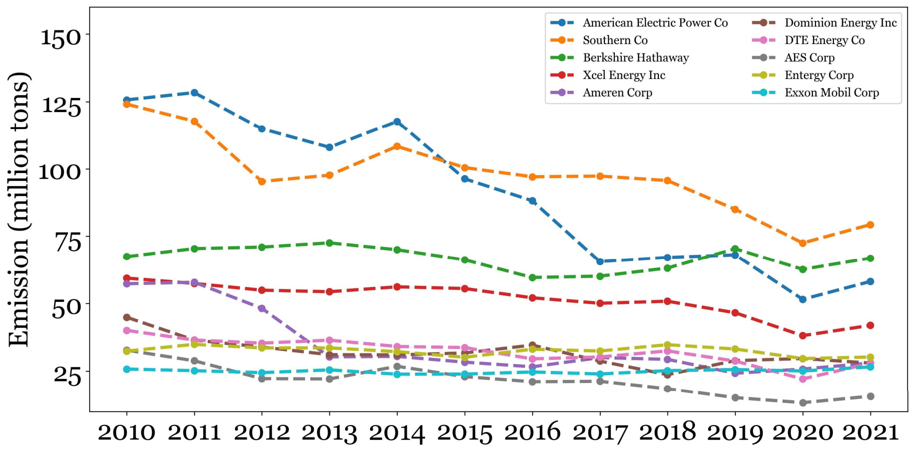
Table 2. Summary Statistics

A. Unit = Facilities × Year	Mean	25%	Median	75%	N
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 one year	7.4	0.0	0.0	0.0	37,841
% sold off in two years	13.8	0.0	0.0	0.0	33,270
% sold off in three years	19.6	0.0	0.0	0.0	28,872
% sold off in four years	24.3	0.0	0.0	0.0	24,701
B. Unit = Company ×Year					
Ownership					
% green fund ownership (TRUST)	0.9	0.4	1.0	1.3	3,726
% non-green fund ownership (TRUST)	0.5	0.1	0.3	0.5	3,726
% green fund ownership (GOV)	0.8	0.4	1.0	1.2	3,726
% non-green fund ownership (GOV)	0.5	0.1	0.4	0.7	3,726
% other institutions	62.4	51.3	71.2	83.4	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
Proposals					
# environmental proposals	0.21	0	0	0	2,346
# environmental proposals approved	0.02	0	0	0	2,346

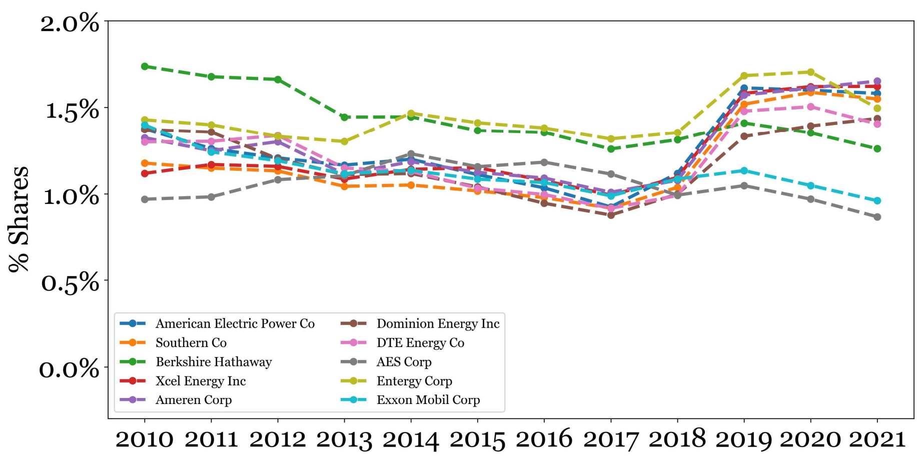
Note. Data cover 2010-2021. For emissions, facility-years with negative emissions are excluded. % change in emissions and electricity are winsorized at 95 percent in the right tail. For proposals, includes all firms with emissions with at least one proposal across all years. For patents, includes all firms with emissions with at least one patent across all years.

Figure 2. Ten Highest Scope 1 Polluting Companies

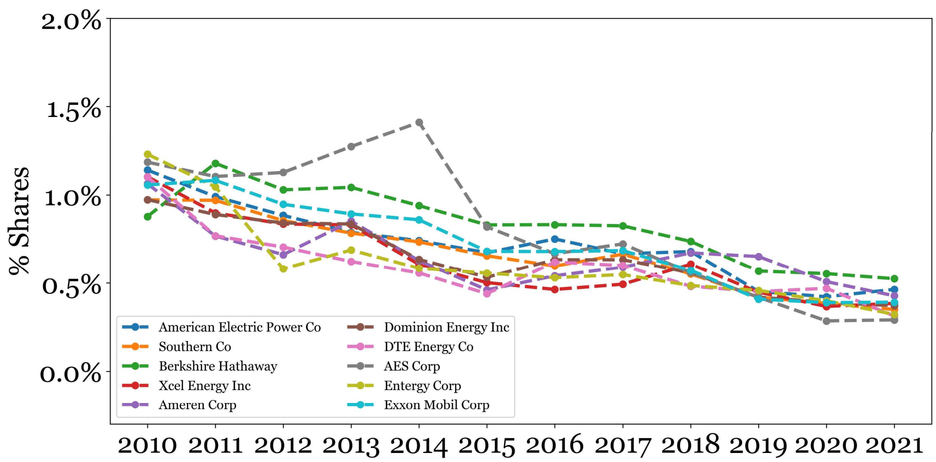
Panel A. Emissions



Panel B. Ownership by Green Funds



Panel C. Ownership by Nongreen Funds



4. Green Ownership Reduces Emissions

A. Baseline Estimates

Our workhorse regression is the following, or some variant thereof:

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

where i indexes a carbon-emitting 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. Our default is to specify the change as a percentage of the current year but we show that the patterns are similar for level changes and for a negative change dummy.[9] We analyze emissions changes at the facility rather than company level in order to estimate real effects – estimates at the company level can be influenced by sales and purchases of polluting assets. We discuss company-level patterns and 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 nongreen public pension funds. The omitted category is shares owned by other institutional investors 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 appear to reward companies based on percentage changes in their emissions. Theoretically, Edmans et al. (2023) argue that it can be optimal for green investors to reward companies based on changes in their emissions rather than levels because, intuitively, investing based on levels provides no lever to induce high polluters to cut back. Any explanatory factors other than green and nongreen ownership that are not constant by year or facility are incorporated into the error term in the equation (1).

We report emission cuts over four different windows because we don't have a strong prior on how quickly firms should react to increased green pressure. The fastest way to cut emissions is

[9] 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.

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

Panel A	One year	Two years	Three years	Four years
% green (TRUST)	-0.99	-2.15**	-3.23***	-3.40**
	(0.64)	(0.93)	(1.12)	(1.25)
% nongreen (TRUST)	2.76***	4.72***	4.90***	4.74**
	(1.02)	(1.52)	(1.91)	(2.31)
N	28,515	24,841	21,296	18,058
Clusters	3,406	3,050	2,705	2,377

Panel B	One year	Two years	Three years	Four years
% green (GOV)	-0.57	-1.90**	-2.87**	-3.09**
	(0.61)	(0.91)	(1.16)	(1.41)
% nongreen (GOV)	0.76	1.68*	1.26	0.96
	(0.65)	(0.91)	(1.19)	(1.32)
N	28,515	24,841	21,296	18,058
Clusters	3,406	3,050	2,705	2,377

Note. Each column in each panel is a regression with year fixed effects. The unit of observation is a facility-year. 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 level in the right tail. Green and nongreen funds are defined by the party of the trustees or the party of the governor. Standard errors clustered at the company-year level are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

simply to cut output, but firms may seek to adjust by altering their production processes instead. If they choose to replace their existing capital stock, they must pay an adjustment cost. In addition to the direct cost of purchasing new plant and equipment, introducing new capital may require shutting down the facility for installation and retraining the workforce to operate the new capital. All of these costs may cause firms to spread out emission cuts over time. Empirical evidence on adjustment costs is limited (Groth and Khan 2010).

Table 3 reports results using different definitions of a green fund, and different adjustment windows. In panel A, where a fund's greenness is defined based on party of the trustees, the first coefficient indicates that a 1 percentage point increase in shares owned by green public pension funds was associated with a 0.99 percent reduction in carbon emissions over the subsequent 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 3.40 percent over four years. Detectable cuts in emissions emerged after two years, and they appear to have been persistent. The coefficients for nongreen funds are positive and also statistically significant, indicating that nongreen ownership was associated with emission increases, which lends some support to the notion that the green ownership coefficient is not mechanical or spurious. In Panel B, a fund is classified as green if the state's governor was a Democrat. 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 panel A. In contrast to A, the coefficients on nongreen ownership in A are usually not statistically significant.

We now consider the issue of causal inference more systematically and report our main findings. There are two sources of variation in the green ownership variable: changes in a fund's preferences, and changes in the amount of stock it owns. A fund's preference is determined largely by election returns that are independent of the emissions of companies in the fund's portfolio. A fund's holdings of a company's stock, on the other hand, may 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 associated with 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).[10] 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 nongreen 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

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

Table 4. First-Stage Regressions Predicting Change in Fund Ownership

	(1)	(2)	(2)
Return on other investments	1.30***	2.98***	2.45***
	(0.34)	(0.37)	(0.35)
Constant	0.20***	…	…
	(0.01)		
N	49,991	49,991	49,726
F-statistic	14.8	64.1	49.6
Fixed effects	None	Year	Year x Company

Note. The table reports first-stage regressions in which the dependent variable is the percentage change in a fund's shares of a company, winsorized at 1 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. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

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. We calculate the standard errors from this procedure using a two-stage bootstrapping procedure adapted from Cameron et al. (2008) and Ashraf and Galor (2013), described in Internet Appendix 2.

Table 4 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 1.30 percent increase in its average holding.[11] The model in the second column, which we use to construct the instrumented shares, 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 2.98 percent increase in its public equity holdings. The third column includes year-company fixed effects. The F-statistic in column (2) is 64.1, well above the conventional threshold for an instrument to be 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 5 shows the second-stage regressions in a format that parallels Table 3. The findings are similar across all panels: increases in green fund ownership reduced carbon emissions out to four years, and the effect was statistically significant in all but one specification. The coefficient on nongreen ownership is less often statistically significant using predicted ownership.

[11] This number is greater than 1 because large percentage increases in small holdings are averaged against small percentage increases in large holdings.

Table 5. Percent Change in GHG Emissions with Predicted Ownership

Panel A	One year	Two years	Three years	Four years
% $\widehat{\text{green}}$ (TRUST)	-1.35***	-1.83***	-2.95***	-3.61***
	(0.52)	(0.76)	(0.94)	(1.13)
% $\widehat{\text{nongreen}}$ (TRUST)	1.84***	1.91	1.30	0.69
	(0.91)	(1.32)	(1.48)	(2.04)
N	26,243	22,516	18,985	15,844
Clusters	3,040	2,691	2,355	2,043

Panel B	One year	Two years	Three years	Four years
% $\widehat{\text{green}}$ (GOV)	-1.20**	-1.34	-2.83***	-3.34**
	(0.55)	(0.85)	(1.10)	(1.32)
% $\widehat{\text{nongreen}}$ (GOV)	0.70	0.12	-0.24	-1.04
	(0.67)	(1.02)	(1.16)	(1.44)
N	26,243	22,516	18,985	15,844
Clusters	3,040	2,691	2,355	2,043

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 nongreen funds, using coefficient estimates from regression (2) in Table 4. Green and nongreen funds are defined according to the party of the trustees or governor, as indicated. Bootstrapped standard errors clustered at the company-year level are in parentheses. All regressions include year fixed effects. The data cover 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

B. Auxiliary Hypotheses

We next modify the basic regression to consider two auxiliary hypotheses. First, we include a dummy variable equal to one if the governor of the state where the facility is located was a Democrat. This is to address a potential concern with our benchmark equation that in addition to influencing whether a state's pension funds are green, the governor may also be able to influence emissions from in-state facilities directly through laws or regulations. During our period, over 60 percent of facilities were located in states with Republican governors. Second, we add a variable equal to the percentage of stock owned by institutional investors other than the pension funds in our sample (so the variable is largely ownership by mutual funds). We include this variable because there is some evidence (not necessarily causal) that a high level of ownership by mutual funds is associated with lower greenhouse gas emissions (Azar et al. 2021; Safiullah et al. 2022). It could be that mutual funds as a group lean green or brown, and therefore could influence emissions themselves. Both hypotheses are interesting in their own right, but our primary concern is whether these variables alter the coefficients on green ownership.

Inclusion of the two new variables does not change the ownership coefficients in a material way, indicating that the green ownership is not simply a proxy for regulatory action by a state's governor or holdings by other institutional investors. The coefficient on the governor dummy itself

Table 6. Percent Change in GHG Emissions with Additional Control Variables

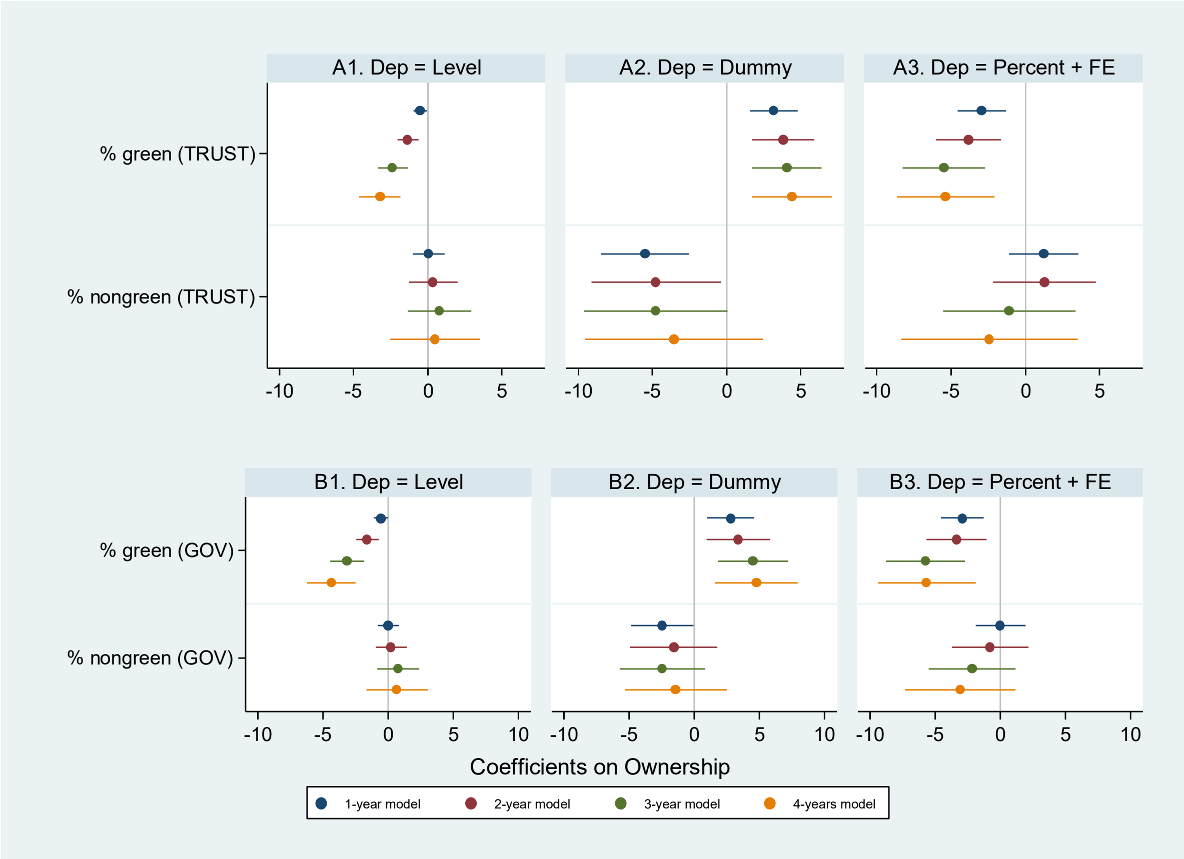
Panel A	One year	Two years	Three years	Four years
% $\widehat{\text{green}}$ (TRUST)	-1.66***	-1.78*	-2.87**	-3.84***
	(0.64)	(0.93)	(1.13)	(1.36)
% $\widehat{\text{nongreen}}$ (TRUST)	2.23**	2.78**	2.05	2.10
	(0.89)	(1.15)	(1.54)	(1.92)
Dummy = 1 if facility-state governor was Democrat	-0.73	-0.82	-1.48*	-2.26**
	(0.47)	(0.66)	(0.83)	(0.96)
% other institutions	0.01	0.01	0.01	-0.004
	(0.01)	(0.02)	(0.03)	(0.04)
N	26,220	21,676	18,287	15,213
Clusters	2,858	2,535	2,220	1,925

Panel B	One year	Two years	Three years	Four years
% $\widehat{\text{green}}$ (GOV)	-1.48**	-1.10	-2.65**	-3.59**
	(0.65)	(1.08)	(1.32)	(1.48)
% $\widehat{\text{nongreen}}$ (GOV)	0.86	0.54	0.21	-0.12
	(0.70)	(1.02)	(1.21)	(1.36)
Dummy = 1 if facility-state governor was Democrat	-0.72	-0.79	-1.45*	-2.21**
	(0.47)	(0.66)	(0.83)	(0.96)
% other institutions	0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.03)	(0.04)
N	25,220	21,676	18,287	15,213
Clusters	2,858	2,535	2,220	1,925

Note. Each column in each panel is a regression 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. Explanatory variables include the predicted percentage of shares owned by green funds and nongreen funds, using coefficient estimates from regression (2) in Table 4. The coefficient on the facility-state governor dummy is multiplied by 100 for ease of interpretation. Bootstrapped standard errors clustered at the company-year level are in parentheses. The data cover 2010 to 2021. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

is always negative and statistically significant, meaning facilities cut emissions faster in states with Democratic than Republican governors. We report the coefficient scaled by 100; its value in the fourth column of Panel A implies that a shift from a Republican to a Democratic governor was associated with 2.26 percent emission cuts. Comparing this to the coefficient of -3.84 on green ownership in the same regression, we can infer that changing from a Republican to a Democratic governor cut emissions by the same amount as a 0.6 percentage point increase in green ownership. This gives a very rough sense of the effect of regulation versus private markets, although we would not push this very far. The coefficient on other institutional ownership is positive but never statistically significant. Unlike previous research, we do not find a connection between institutional

Figure 3. Alternative Specifications of Model (1)



Note. The figure shows the coefficients on predicted green and nongreen ownership for alternative specifications of (1). In A1 and B1, the dependent variable is changes in emission levels, winsorized at 1 percent in each tail; in A2 and B2, the dependent variable is a dummy = 1 if the faculty cut emissions; in A3 and B3 the dependent variable is percentage change in emissions. All regressions include year fixed effects; A3 and B3 also include facility fixed effects. 95% confidence intervals are indicated.

investment in general and emissions.[12] Rather, we find that it is specifically holdings by green investors that matter.

C. Robustness to Alternative Specifications

We next show that the connection between emissions changes and ownership is robust to alternative model specifications: dot plots of regression coefficients from various models are reported in Figure 3. First, one concern with expressing emission changes as percentages is that a given absolute reduction in emissions is larger in percentage terms at a low-emission than a high-emission facility. Indeed, because some ESG ratings focus on percentage changes, Hartzmark and

[12] We also estimated the regressions controlling for ownership by the "big three" of BlackRock, State Street, and Vanguard, with similar null results.

Shue (2023) suggest that companies may game the ratings by concentrating cuts at their low-emission facilities. To explore this issue, we re-estimate the baseline regressions using the change in emissions levels 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). Green and nongreen ownership are the predicted values. Panel A1 shows coefficients on ownership for one-year to four-year models, defining green by the party of trustees; Panel B1 shows the same coefficients defining green by the party of the governor. 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. In terms of magnitudes, the coefficient on green ownership in Panel A1 indicates that a 1 percentage point increase in green fund ownership was associated with 13,400 to 31,170 tons fewer emissions over the next one to four years. This is a meaningful reduction in emissions compared to the average of 506,445 tons in our sample. The coefficient on nongreen ownership is small and always statistically insignificant.

In Panels A2 and B2, 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. In the first model, a 1 percentage point increase in green fund ownership was associated with a statistically significant 3.17 percentage point increase in the probability of carbon emission reduction over the subsequent year. The probability rises to 3.81 percentage points over two years, and 4.40 percentage points over four years, all statistically significant at the 1 percent level. The coefficients on green ownership in Panel B2 tell the same story. The coefficients on nongreen ownership are always negative but not reliably statistically different from zero.

A third alternative specification includes facility fixed effects, essentially a two-way fixed effects model. This removes all time-invariant, facility-specific factors that determined changes in emissions. While this specification has some appeal, since the dependent variable is a change, facility fixed effects strip out a constant level of change, which is not obviously a better approach. Panels A3 and B3 6 report the results using both definitions of a green fund, returning to the percentage change specification of the dependent variable. The coefficient on green ownership, as before, is negative and statistically significant in all regressions in both panels. The coefficients are 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 coefficients on nongreen funds are statistically insignificant in all regressions and the signs vary by years.

Table 7. Separate Effects for Ownership Increase (Δ^{+}) versus Decrease (Δ^{-})

Panel A	One year	Two years	Three years	Four year
% $\widehat{\text{green}}$ (TRUST) × Δ^{+}	-0.42	-1.15	-3.38***	-3.35**
	(0.59)	(0.90)	(1.10)	(1.23)
% $\widehat{\text{green}}$ (TRUST) × Δ^{-}	-1.57***	-1.98***	-2.88***	-3.56***
	(0.53)	(0.74)	(0.89)	(1.07)
% $\widehat{\text{nongreen}}$ (TRUST) × Δ^{+}	1.58	1.40	2.36	2.24
	(1.01)	(1.52)	(1.72)	(2.31)
% $\widehat{\text{nongreen}}$ (TRUST) × Δ^{-}	1.70*	2.06*	0.53	-0.35
	(0.88)	(1.19)	(1.34)	(1.53)
N	26,243	22,516	18,985	15,844
p value: green Δ^{+} = green Δ^{-}	0.004	0.24	0.56	0.70
p value: nongreen Δ^{+} = nongreen Δ^{-}	0.90	0.66	0.34	0.23

Panel B	One year	Two years	Three years	Four year
% $\widehat{\text{green}}$ (GOV) × Δ^{+}	-0.46	-0.33	-3.03**	-2.43*
	(0.58)	(0.97)	(1.22)	(1.42)
% $\widehat{\text{green}}$ (GOV) × Δ^{-}	-1.75***	-1.87**	-2.67**	-3.58***
	(0.59)	(0.91)	(1.17)	(1.38)
% $\widehat{\text{nongreen}}$ (GOV) × Δ^{+}	0.61	0.16	0.28	-0.65
	(0.81)	(1.29)	(1.46)	(1.83)
% $\widehat{\text{nongreen}}$ (GOV) × Δ^{-}	0.87	0.11	-0.67	-1.32
	(0.71)	(1.06)	(1.19)	(1.40)
N	26,243	22,516	18,985	15,844
p value: green Δ^{+} = green Δ^{-}	0.00	0.04	0.69	0.32
p value: nongreen Δ^{+} = nongreen Δ^{-}	0.70	0.96	0.47	0.67

Note. Each column of each panel is a regression in which the dependent variable is the percentage change in emissions fro 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 righ tail. The explanatory variables are the predicted percentage of shares owned by green and nongreen funds, using coefficie estimates from regression (2) in Table 4. Ownership variables are interacted with dummies for whether ownership increased (Δ^{+}) or decreased (Δ^{-}). All regressions include year fixed effects. Standard errors clustered at the company-yea level are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Our models to this point fit a linear relationship between emissions changes and green ownership, implicitly assuming that the effect of increases and decreases in green ownership are symmetric. It is conceivable that companies responded asymmetrically to increases versus decreases. To allow for this possibility, Table 7 reports variants of the baseline regression that allow the slope of the ownership variables to vary depending on whether ownership increased or decreased.[13] The coefficients on green ownership are negative in all regressions, for both

[13] We do not include separate intercepts for increases and decreases. If those intercepts are included, they are always small and statistically insignificant but they make it more difficult to interpret and compare coefficients.

ownership increases and decreases, and statistically significant and similar in magnitude three and four years out. The negative coefficients on green ownership cuts show more specifically than before that divestment led to emission increases. The coefficients on nongreen ownership are positive for both increases and decreases, but usually statistically insignificant, and never statistically different from each other.

5. Why Green Ownership Reduced Emissions: Responsive Managers, Pressure, and Persuasion

Having shown that companies with green investors were more likely to reduce their carbon emissions, we next investigate why green ownership had this effect. We report several pieces of suggestive evidence, much of which points in the same direction. The analysis is framed around three mechanisms.

- *Pressure.* According to this mechanism, a form of "voice," managers must be pressured to reduce emissions. A priori, it is not clear why managers would be opposed to GHG abatement (why there would be an agency problem of this form), but that is often assumed to be the case 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, their preferences, and their willingness to support managers aligned with their preferences. Persuasion 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.[14] There is abundant evidence that some institutional investors communicate extensively with companies in order to persuade them to take a specific

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

course of action, and that these efforts are often successful (Carleton et al. 1998; Dimson et al. 2015).[15]

- *Responsive managers.* According to this mechanism, managers may have cut carbon emissions because they believed that was the preference of their investors. 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.

In practice, of course, more than one of these mechanisms may be operational at the same time.

A. Pressure: Shareholder Proposals and Voting

Investors can engage management by exerting pressure by sponsoring and supporting shareholder proposals or voting against management in corporate elections. An example of a pressure campaign was the Boardroom Accountability Project spearheaded by the New York City pension funds in 2014, which involved filing shareholder proposals at 75 companies in order to force them to expand proxy access. To gauge the importance of the adversarial channel more generally, we explore the connection between shareholder proposals, proxy voting, and green ownership.

In most American corporations, shareholders have 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). Most proposals are precatory, meaning that managers are not required to implement them even if they receive a majority of votes in favor. However, investor groups may withhold support for director candidates who do not implement shareholder proposals, and there is evidence that companies do respond to proposals with majority support, 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).

[15] Carleton et al. (1998) studied private letters that TIAA-CREF sent to 45 companies on governance matters during 1992-1996, finding that they reached an agreement 98 percent of the time, and without resorting to a shareholder vote 70 percent of the time. Dimson et al. (2015) described letters, telephone calls, and direct conversations on environmental and social issues between an unnamed institutional investor and senior management of target companies during 1999- 2009, finding a success rate of 18 percent.

For our purposes, the most relevant type of proposal concerns the environment.[16] For example, an oil company may be asked to report on how it plans to respond to global pressure to achieve net-zero carbon emissions. A company in our sample received at least one environmental proposal in 15 percent of the sample years. Shareholder proposals are usually opposed by managers, and are thus a form of adversarial engagement. Under the pressure hypothesis, an increase in green investors would lead to more shareholder proposals.

Our empirical model is:

$$(4) \qquad Proposal\ dummy_{c,t} = \beta_1 \cdot \%\widehat{green}_{c,t} + \beta_2 \cdot \%\widehat{nongreen}_{c,t} + \beta_3 X_{c,t} + \gamma_t + \lambda_c + e_{c,t},$$

where the unit of observation is a company (c) in a given year (t), for 2010-2021. We include all publicly traded companies with emissions in the EPA data. 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 8 shows the estimates for both measures of green ownership. The dependent variable in column (1) is a dummy equal to one if a company received an environmental proposal. The coefficient on green ownership implies that a 1 percentage point increase in shares held by green pension funds led to a 0.85 to 1.06 percentage point increase in the probability of receiving an environmental proposal, not statistically different from zero. The coefficient on nongreen fund ownership is also statistically insignificant in both panels. The dependent variable in column (2) is a dummy equal to one if a proposal received a majority of votes in favor, conditional on the company receiving a green proposal in the first place. 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 negative but statistically insignificant. The bottom line is that we cannot conclude that green ownership led to more environmental proposals being proposed or approved, 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.

[16] Specifically, we study proposals classified in ISS Voting Analytics as carbon, climate change, coal, energy, environment, environmental, fossil fuel, GHG, global warming, greenhouse, methane, pollution, sustainability.

Table 8. Shareholder Proposals and Green Ownership

Panel A	Dummy = 1 if company received an environmental proposal (1)	Dummy = 1 if an environmental proposal passed (2)
$\% \widehat{\text{green}}$ (TRUST)	1.06	-0.94
	(1.74)	(3.31)
$\% \widehat{\text{nongreen}}$ (TRUST)	-0.06	6.04
	(3.45)	(7.16)
Assets (log)	0.049***	-0.001
	(0.006)	(0.008)
Emissions (trillion tons)	5.22***	-0.06
	(0.51)	(0.40)
N	1,837	279
Panel B		
$\% \widehat{\text{green}}$ (GOV)	0.85	-1.20
	(1.83)	(2.99)
$\% \widehat{\text{nongreen}}$ (GOV)	0.55	4.49
	(2.37)	(4.04)
Assets (log)	0.049***	-0.001
	(0.006)	(0.008)
Emissions (trillion tons)	5.22***	-0.06
	(0.51)	(0.39)
N	1,837	279

Note. Each column of each panel is a regression in which the unit of observation is a company-year. The dependent variable in column (1) is a dummy = 1 if a company received an environmental shareholder proposal, and in column (2) is a dummy = 1 if an environmental proposal was approved by a majority of votes. The data in column (1) cover all companies with emissions in the EPA data, and the data in column 2 cover companies with environmental proposals. All regressions include year fixed effects. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

Another form of adversarial pressure is voting against the recommendations of management in corporate elections. We study this by estimating:

$$(5) \qquad D(yes)_{f,p,c.t} = \beta_1 \cdot D(green)_f + \lambda_p + e_{f,c,p,t},$$

where the unit of observation is a vote cast by fund f on election item p at company c in year t. The dependent variable is a dummy equal to one if a fund voted in favor of the election item.[17] The

[17] For shareholder proposals, we included votes cast "for" and "against", excluding all other options such as abstention. For director elections, we coded votes case "for" as 1 and votes "against", "withheld", abstain", and "did not vote" as 0. Overall, pensions voted in favor of 55 percent of environmental proposals, 66 percent of nonenvironmental proposals, and 93 percent of directors.

Table 9. Yes Votes by Pension Funds on Shareholder Proposals and Director Elections

Panel A	Environmental Proposals (1)	Nonenvironmental Proposals (2)	Director Elections (3)
Dummy = 1 if green (TRUST)	-13.3***	-0.2	-6.5***
	(4.0)	(1.8)	(1.8)
N	4,138	21,997	329,405
Cluster	197	203	206
Panel B			
Dummy =1 if green (GOV)	9.0*	4.4**	0.0
	(4.8)	(1.8)	(1.7)
N	4,370	23,207	344,734
Clusters	210	216	219

Note. Each column in each panel is a regression in which the unit of observation is a public pension fund vote on an election item at a company that emitted greenhouse gases. The dependent variable is a dummy = 1 if a fund voted in favor of the proposal or for the director. Green ownership is a dummy if a majority of trustees or the governor were Democrats. All regressions include election item fixed effects. Coefficients are multiplied by 100 to represent percentages. Standard errors clustered at the fund-year level are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

explanatory variable is a dummy for green funds, so the omitted category is nongreen public pension funds. Funds are defined to be green in Panel A if a majority of the trustees were Democrats and in Panel B if the governor was a Democrat.[18] By including a fixed effect for the election item, we implicitly control for the merits of each proposal.

Table 9 presents the findings. Management typically opposes shareholder proposals, so a vote in favor can be interpreted as a vote against management. For environmental proposals (column (1)), the findings are contradictory: measured by party of the trustees, green funds were 13.3 percent less likely than nongreen funds to support such proposals; measured by party of the governor, green funds were 9.0 percent *more* likely to support them, with both estimates statistically significant at the 10 percent level. For nonenvironmental proposals (column (2)), the coefficient on green funds is negligible in magnitude and statistically insignificant in panel A, while the coefficient is positive and statistically significant in panel B. Finally, for director elections (column (3)), green funds were 6.5 percent less likely to vote in favor in panel A, and no different from nongreen funds in panel B. Across all regressions, the inconsistency between the two measures of green funds stands out. If we conjecture that the trustee measure is more likely than

[18] In Panel A, funds are classified as green if the number of Democratic trustees exceeded the number of Republican trustees, dropping observations with ties. The median voter theorem provides one theoretical justification. The results are similar if we use the percentage of Democratic trustees instead of a dummy variable except that the coefficient in the first column becomes statistically different from zero.

the governor measure to capture the influence on fund voting (that is, if we focus on panel A), the evidence for pressure is still mixed: green funds were less supportive of shareholder proposals but also less supportive of incumbent directors. The cautious conclusion from Table 9 is an absence of support for voting pressure.

B. Active vs. Less Active 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 pension funds that were particularly active, and compare how emissions responded to ownership by these funds compared to less active funds. Our classification is based on SEC Form PX14A6G, which public pension funds must file as a cover letter when they wish 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).[19] 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.[20]

Table 10 shows the results with year fixed effects.[21] Across all specifications, the coefficient on active green ownership is negative and statistically significant. The coefficient on less-active green ownership is always smaller, often considerably so, and statistically insignificant. For regressions two or more years out, the active and less-active coefficients are statistically different from each other in five of six specifications. This evidence suggests that emission reductions were not simply the result of managers responding to changes in their ownership, but partly due to engagement by active green funds. We caution that it does not imply that ownership by less active

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

[20] 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.

[21] The results are similar with facility fixed effects, and with inclusion of party of the governor and other institutional ownership control variables.

Table 10. Active versus Less Active Pension Funds

Panel A	One Year	Two Years	Three Years	Four Years
$\% \widehat{green}(TRUST)$ | active	-1.67**	-3.06***	-5.48***	-5.93***
	(0.76)	(1.06)	(1.46)	(1.88)
$\% \widehat{green}(TRUST)$ | less active	-0.85	-0.06	0.64	-0.33
	(1.18)	(1.55)	(1.88)	(2.23)
$\% \widehat{nongreen}(TRUST)$	1.78**	1.75	0.92	0.40
	(0.78)	(1.13)	(1.31)	(1.69)
p value: active = less active	0.61	0.16	0.03	0.11
N	26,243	22,516	18,985	15,844
Clusters	3,040	2,691	2,355	2,043

Panel B	One Year	Two Years	Three Years	Four Years
$\% \widehat{green}(GOV)$ | active	-1.77**	-3.24***	-5.63***	-6.29***
	(0.75)	(1.09)	(1.44)	(1.87)
$\% \widehat{green}(GOV)$ | less active	-0.10	2.29	3.39	3.60
	(1.22)	(1.80)	(2.20)	(2.81)
$\% \widehat{nongreen}(GOV)$	0.83	0.54	0.12	-0.74
	(0.66)	(1.02)	(1.18)	(1.44)
p value: active = less active	0.30	0.01	0.001	0.01
N	26,243	22,516	18,985	15,844
Clusters	3,040	2,691	2,355	2,043

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. Active funds are CalPERS, CalSTRS, and NYSCRF. Standard errors clustered at the company-year level are in parentheses. All regressions include year fixed effects. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

green funds did not matter – our standard errors allow for the possibility of sizeable effects – but only that the effect of active funds was larger than that of less active funds.

Overall, our evidence on the three mechanisms is not overwhelming. It seems clear that active engagement is part of the story, and we conclude that persuasive engagement was more important than pressure. However, our conclusion for persuasion is more based on an absence of evidence for pressure than affirmative evidence for persuasion. Even so, this interpretation draws some support from fund managers' own characterizations: the joint CalPERS and CalSTRS statement on *The Importance of Corporate Engagement on Climate Change* expresses 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."[22]

[22] 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

6. How Companies Reduced Emissions: Output Reduction, Sell-Offs, and Innovation

A polluter can reduce emissions in three ways: by reducing output from a polluting facility, by changing production processes so that a given level of output emits less pollution, and by selling off polluting facilities. Environmental economists use an accounting framework along these lines to decompose a firm's emissions (Copeland and Taylor 2004). Exxon can reduce its carbon footprint by cutting output (scale) or by shifting its portfolio of products towards cleaner products (composition) or by introducing new technologies such as carbon capture to reduce emissions per unit of output (technique). This section probes for evidence on the use of each channel.

A. Emissions Reduction through Output Reduction

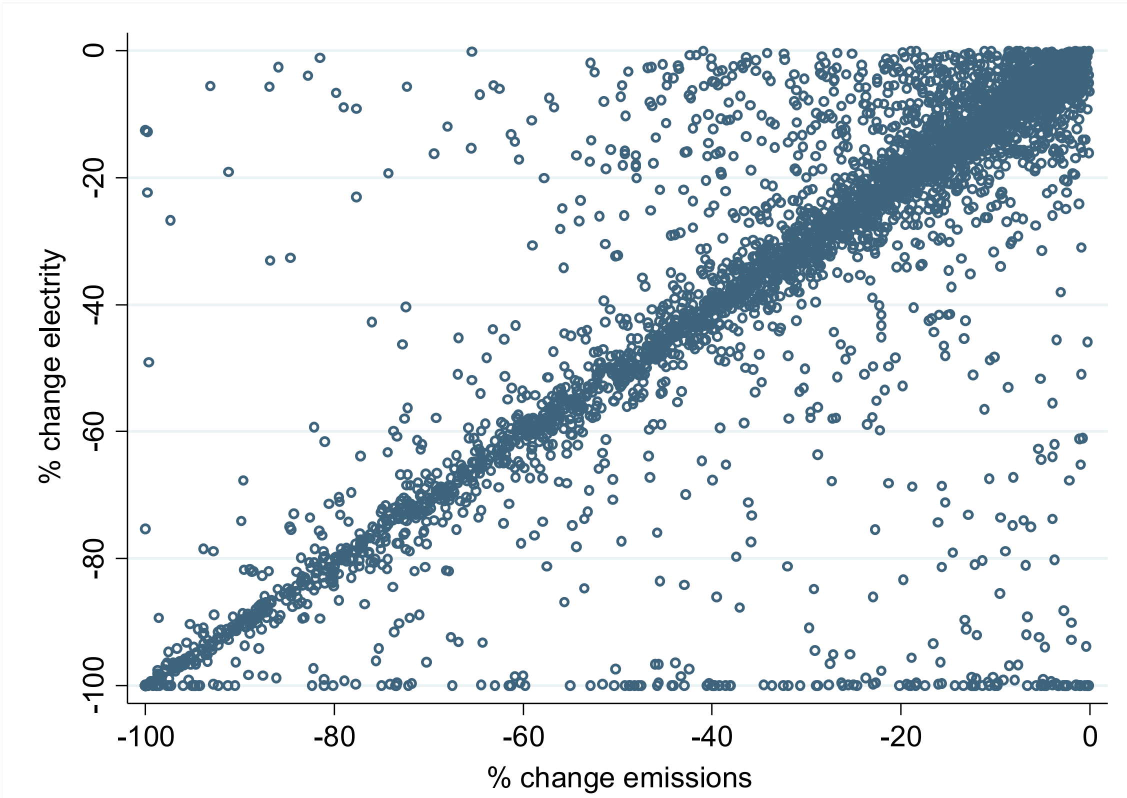
To gauge the importance of emissions cuts through output or scale reduction, we focus on the subset of facilities that produce electricity. These facilities, most of which are power plants and the rest in the waste industry, are required to report their output in terms of electricity generation. We are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

Figure 4 plots changes in emissions against changes in electricity generation from year t to $t + 2$, for the facilities that cut emissions. Emission cuts that were achieved solely through output reductions would appear along the 45-degree diagonal. The figure indicates that output reduction appears to have been a common method for cutting emissions in our sample.

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 average over the first year. Panel A2 replaces the dependent variable with the percentage change in electricity output. The coefficient indicates that electricity cuts were 52.5 percent on average in the first year, meaning that emissions cuts were matched by approximately equal output cuts on average. The coefficients for longer windows tell the same story. 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

persuade companies to do more on climate through `engagement,' which involves lobbying corporate and executive directors, rather than voting to oust them."

Figure 4. Emission Cuts Against Electricity Cuts for Plants that Reduced Emissions



emission reduction was often achieved by cutting output rather than by abatement. Note that this result is not mechanical – firms could have cut emissions without cutting output, such as through abatement (reducing emissions at the point of production) or changing to production technologies with lower emissions.

B. Facility Sell-Offs

Companies can reduce their carbon emissions by selling polluting facilities to another company or spinning them off as stand-alone companies. We reiterate that sell-offs do not drive our core findings in Tables 3 and 5 because that analysis tracks facilities across time regardless of ownership changes – the emission reductions observed in our main results were real cuts. It is nevertheless interesting to ask if green ownership affects a corporation's proclivity to shed polluting assets. Selling off or spinning off a unit in order to reduce a company's reported emissions

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 is 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 a dummy = 1 if the facility reduced emissions over the period. Standard errors clustered at the company-year level are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

is 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.[23] While greenwashing is a pejorative term, there may be efficiency reasons for companies to divest facilities. Some companies may have a comparative advantage in cleaning up polluting facilities, such as Hilcorp, which specializes in acquiring aging oil wells that leak methane (Morenne 2023). Reallocation of plants to emission reduction specialists could be economically efficient.

In our sample, one in four facilities was divested within a four-year time span. To estimate the role of green ownership, Table 12 reports various regressions of the form:

$$(6) \qquad D(facility\ sold)_{i,t,t+s} = \beta_1 \cdot \%\widehat{green}_{i,t} + \beta_2 \cdot \%\widehat{non\text{-}green}_{i,t} + \gamma_t + \lambda_i + e_{i,t}.$$

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

Table 12. Divestiture of Polluting Facilities

Panel A	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (TRUST)	2.09**	3.31**	1.74	0.40
	(1.01)	(1.35)	(1.15)	(1.19)
% $\widehat{\text{nongreen}}$ (TRUST)	-1.07	-1.26	-1.43	-0.51
	(1.01)	(1.43)	(1.58)	(1.67)
N	20,872	18,230	15,638	13,102
Clusters	2,784	2,480	2,180	1,893

Panel B	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (GOV)	-0.39	1.34	0.48	-0.88
	(1.29)	(1.79)	(1.53)	(1.62)
% $\widehat{\text{nongreen}}$ (GOV)	1.99	1.67	0.53	0.84
	(1.33)	(1.49)	(1.38)	(1.40)
N	20,872	18,230	15,638	13,102
Clusters	2,784	2,480	2,180	1,893

Note. Each column in each panel is a regression in which the unit of observation is a facility-year. The dependent variable is a dummy =1 if a 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. All regressions include year and facility fixed effects. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

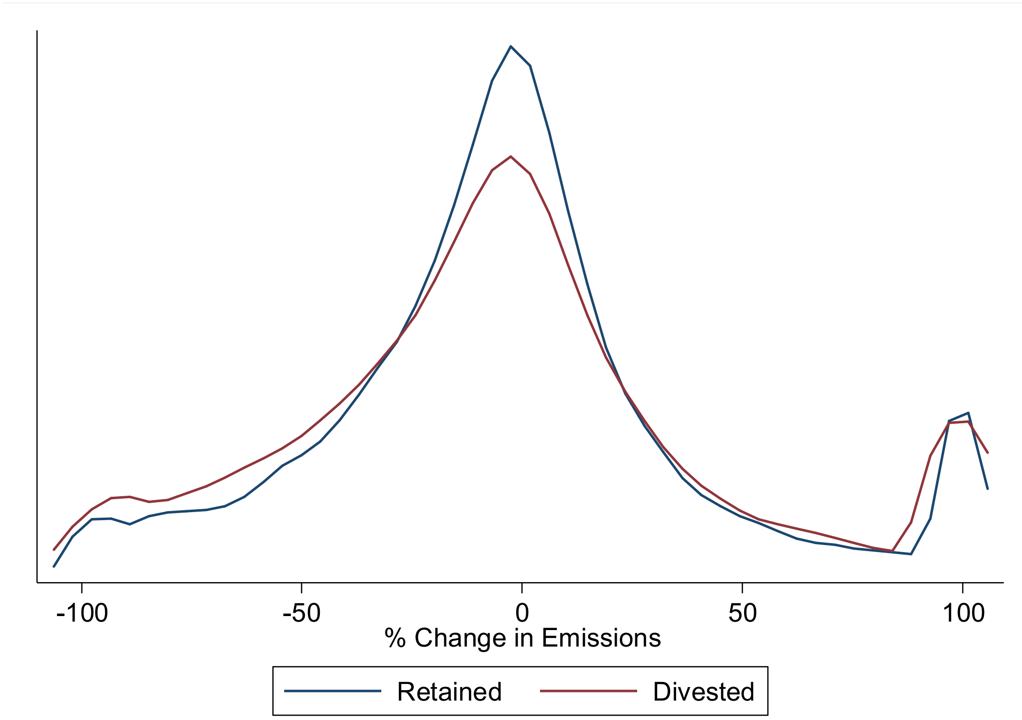
The dependent variable is 1 if facility i was sold or spun off between year t and year $t + s$. Once a facility was sold, we drop it from the analysis. Regressions include year and facility fixed effects.

All told, the regressions provide little evidence that green ownership made companies more likely to shed polluting assets. Companies were more likely to sell off polluting facilities as green ownership increased in six of eight specifications, but the coefficients are statistically significant in only two specifications. The magnitudes are modest: in the first column of panel A, a 1 percentage point increase in green ownership led to a 2.2 percentage point higher chance of selling a facility. The coefficients on nongreen ownership are never statistically significant.

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 retained versus sold facilities. Figure 5 plots emission changes four years out (winsorizing observations with greater than 100 percent change) for retained and divested units, with each observation representing a facility-year. Emission reductions were similar for retained and divested facilities, 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.

Another way to gain insight into potential greenwashing is to examine emission changes at the corporate level. As mentioned earlier, our analysis focuses on emission changes at the facility level; this allows us to measure real effects of ownership – emission changes at the company level are also influenced by asset sales and purchases. In Internet Appendix AI3, we report various

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



regressions of (1) in which the dependent variable is company-level emissions. The coefficients on green ownership remain of similar magnitude as in the facility-level regressions, but the standard errors rise with the fall in the number of observations. Consequently, the green ownership coefficients are not always statistically different from zero. Because the aggregate coefficients roughly mirror the facility-level regressions, it suggests that asset sales and purchases were not a primary contributor to changes in company-level emissions. Interestingly, the coefficients on nongreen ownership are always negative in the company-level regressions, and sometimes but not usually statistically significant. We do not have a theoretical explanation for that pattern.

C. Innovation

Companies can reduce emissions by innovating new, cleaner production techniques (Kowalski 2023). Green investors express the hope that abandoning dirty production processes will free up corporate resources to develop new, cleaner technologies. Jennifer Grancio, of hedge fund Engine No. 1 that led a green campaign to secure seats on the board of ExxonMobil, argued: "[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."[24]

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 to 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. On average, 31 percent of companies increased the number of patents they filed from one year to the next.

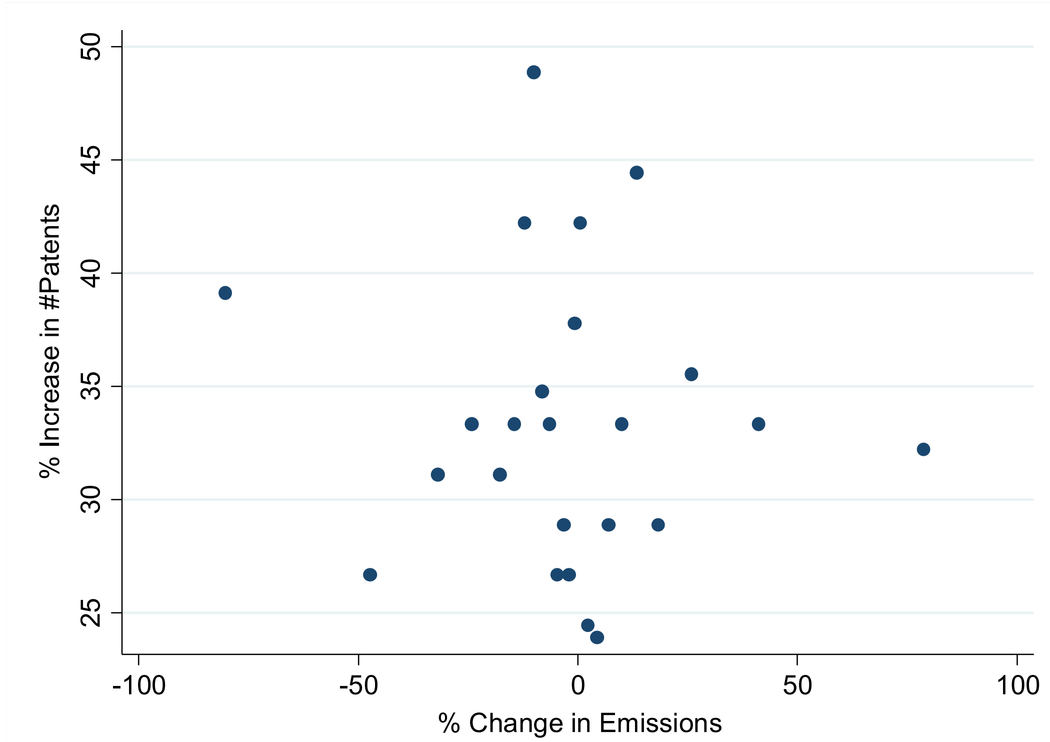
Figure 6 shows the percentage of companies that increased their patents over two years compared to bin changes in emissions. There was not a clear tendency for emission-cutting firms to increase their patents. Table 13 presents regression of green patenting on green and nongreen ownership. The interpretation of the top left (statistically insignificant) coefficient is that a 1 percent increase in green fund ownership was associated with a 0.93 percentage point less likelihood of a company filing more green patents in the next year. Looking across the entire table, while the coefficients on green ownership are usually positive and, in some specifications, statistically different from zero over the three-year range, the overall impression is an absence of a reliable connection between patenting and green ownership. The story is the same for non-green ownership. This may not be a particularly powerful test, but as it stands, it does not offer support for the conclusion that green investors prompted companies to increase their development of new green technologies.

D. Other Pollutants

We next explore whether companies responded to green investors by cutting other types of pollution. These estimates are of interest for two reasons. First, as mentioned above, companies

[24] *CNBC Transcript: Engine No. 1 COE Jennifer Grancio Speaks with CNBC's Sara Eisen Live During CNBS's ESG Impact Today*, October 6, 2022. Consistent with this idea, Cohen et al. (2021) document that the fossil fuel industry produces more green patents than almost every other industry.

Figure 6. Binned Scatterplot of Emission Changes Against Patent Increases over Two Years



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 if so, would not want substitution into other pollutants.

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).

Figure 7 reports the coefficients on ownership from our basic regression (1), except that the dependent variable is the percentage change in emissions of specific chemicals. Panel A shows results for lead emissions. The coefficients indicate that green ownership led to cuts in lead emissions over all four years, but with only the last coefficient is statistically significant. We also detect negative effects of green ownership for nickel, ammonia, and chromium, with coefficients statistically significant about half the time. The coefficients on green ownership are positive for Toluene but not reliably different from zero statistically. At most this offers some suggestive but not

Table 13. Regressions of Increase in Green Patents

Panel A1. Year FE	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (TRUST)	-0.93	0.14	4.91	0.83
	(2.90)	(3.107	(3.28)	(3.33)
% $\widehat{\text{nongreen}}$ (TRUST)	8.25	8.75	-2.08	7.47
	(7.28)	(7.75)	(8.44)	(8.64)
N	1,191	1,071	949	835

Panel A2. Year FE	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (GOV)	-2.55	0.14	4.10	0.70
	(2.93)	(3.13)	(3.42)	(3.51)
% $\widehat{\text{nongreen}}$ (GOV)	7.46*	5.60	1.76	5.00
	(4.07)	(4.21)	(4.47)	(4.54)
N	1,191	1,071	949	835

Panel B1. Year and Company FE	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (TRUST)	-0.48	-0.07	14.08***	2.11
	(4.59)	(4.84)	(5.28)	(5.34)
% $\widehat{\text{nongreen}}$ (TRUST)	-2.15	-3.10	-7.88	9.93
	(9.96)	(10.23)	(10.88)	(10.95)
N	1,173	1,052	926	822

Panel B2. Year and Company FE	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (GOV)	-3.88	-3.94	13.29**	-0.11
	(4.79)	(5.17)	(5.78)	(5.91)
% $\widehat{\text{nongreen}}$ (GOV)	2.65	2.42	2.54	8.73
	(5.44)	(5.49)	(5.85)	(5.97)
N	1,173	1,052	926	822

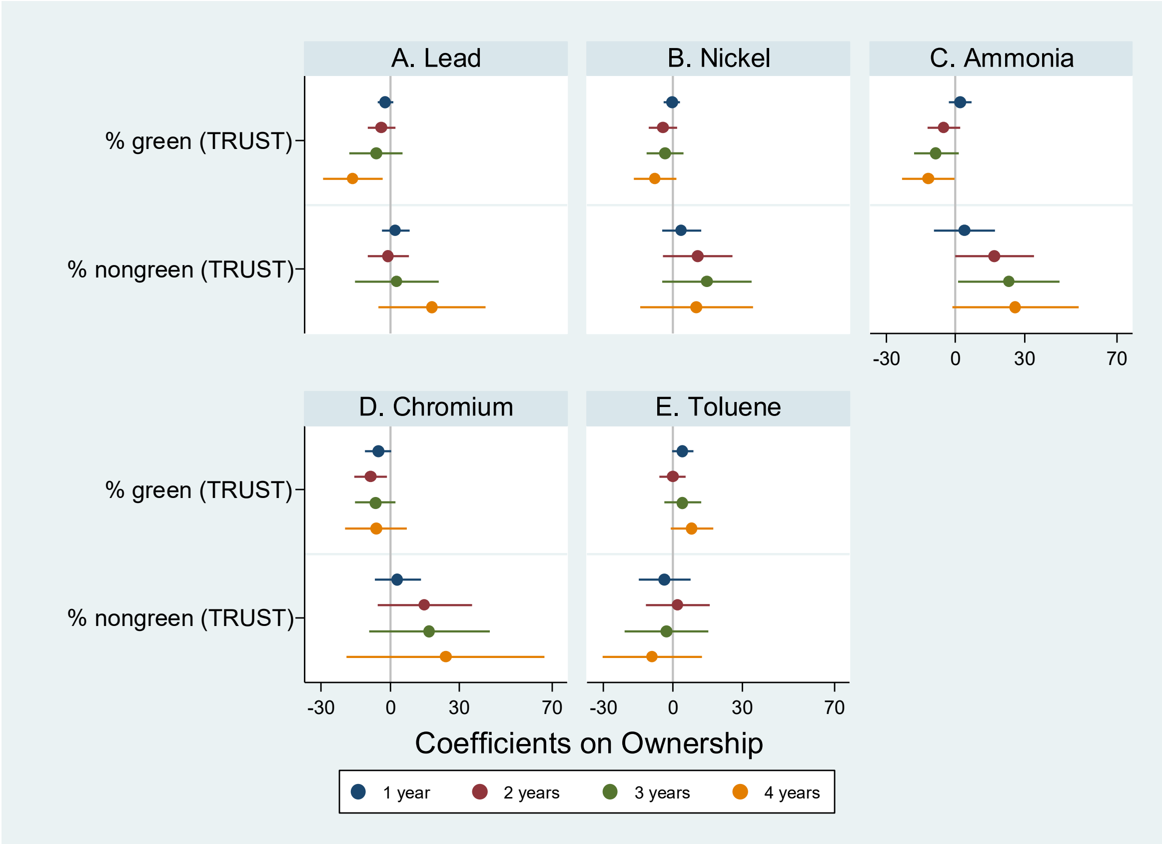
Note. Each column in each panel is a regression in which the unit of observation is a company-year. The dependent variable is a dummy =1 if a company increased the number of green patents filed from the current year t to another year $t + n$ as indicated. Standard errors are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.

compelling evidence that green ownership may cause companies to reduce emissions of some non-GHG chemicals. Alternatively, these findings could be used to reach a null finding, supporting the interpretation that green investors focus primarily on carbon emissions and do not monitor other pollutants.

7. Conclusion

This paper investigates if activism from corporate shareholders can partially substitute for government regulation in encouraging decarbonization. We are particularly interested in the debate over whether environmental investors have the biggest impact when they divest fossil fuel stocks, thereby redirecting capital from dirty to clean energy producers, or when they acquire fossil fuel stocks and work for change through engagement with corporate managers. Our findings point

Figure 7. The Effect of Green Ownership on Other Pollutants



Note. The figure shows the coefficients on predicted green and nongreen ownership for alternative specifications of (1) for emissions of different types of chemicals. All regressions include year fixed effects. 95% confidence intervals are indicated.

to a clear conclusion: engagement is more effective than divestment for investors that want companies to reduce carbon emissions. Green investors make companies greener. We go to some lengths to show that our baseline findings are robust to alternative specifications of the variables, fixed effects, definitions of green ownership, and so forth. Having said that, we believe caution is in order when thinking about whether the findings would extend to other countries or time periods. Divestment of fossil fuel stocks emerged as a broad issue only around the start of our sample period, and market responses during this first decade could have unique characteristics. Another caveat is that we estimate linear effects in the vicinity of existing levels of ownership; larger changes could have significantly different effects; for example, effects could jump if green investors acquire controlling stakes.

A somewhat puzzling aspect of our findings is that relatively small shareholdings seem to influence company behavior. While the number of shares held by public pension funds is large in absolute terms, it is nowhere near enough to give effective control of the company – so why do corporate managers appear to respond to these investors? A recent example may point toward an explanation: in June 2021, the tiny hedge fund Engine No. 1 made headlines when it captured three board seats at ExxonMobil despite owning only 0.02 percent of the oil giant's shares. Engine No. 1 was successful in large part because it secured the support of three giant passive funds, BlackRock, Vanguard, and State Street, which together owned over 20 percent of the company. This suggests that green pension funds might be able to "punch above their weight" because they are able to attract support from other investors. Anecdotally, we observe attempts by large investors to coordinate, such as the formation of the Climate Action 100+ Alliance by large pension funds and asset managers (Doidge et al. (2019) describe an activist alliance in Canada).

Two interesting case studies provide additional suggestive evidence on voting amplification. Fahlenbrach et al. (2023) find that Norges Bank, the world's largest sovereign wealth fund and a long-time activist on corporate governance issues, was able to swing about 3 percent of votes in favor of its positions on shareholder proposals when it pre-disclosed its voting intentions in 2021. Dimson et al. (2015) describe the activities of an anonymous active investor – letters, telephone calls, and direct conversations with senior managers – and highlight the investor's partnership with other investors, including public pensions, SRI funds, and religious groups. Theoretically, the largest pension funds are better suited to take the lead in acquiring information and other engagement efforts because their stakes are larger, mitigating free rider problems, and smaller funds may follow their lead. Along these lines, Levit (2019) shows theoretically that effective engagement by a fund relies on the possibility that other shareholders will support the activist if it launches a public campaign. The economics of forming coalitions and overcoming free-rider problems among green investors is an interesting area for future research. Recently we have seen resistance to such coordination by red-state politicians on the grounds that it facilitates collusion and anti-competitive behavior (Kerber 2023).

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 beyond the scope of our analysis. Nevertheless, as a starting point for readers interested in these issues, we can outline how one might begin 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 1 percentage point increase in shareholding by green pension funds – or a $200 million equity investment on average – leads to a 13,500 ton reduction in carbon emissions on average (Table 5, Panel A), which would translate to a reduction in social cost of $688,500.

The costs of carbon emissions are sometimes characterized as being nonlinear, with particularly bad outcomes occurring beyond a tipping point. From this perspective, the main goal is to reduce emissions enough to prevent the tipping point from being reached. The United States currently accounts for about 11 percent of global greenhouse gas emissions, approximately 50 percent of which comes from industry and power generation. According to our point estimates, if green ownership were to double from 1 to 2 percent on average in all companies, emissions of American firms would decline by about 7 percent, about a 0.5 percent reduction in global emissions. Thus, our estimates suggest that the effect of investor pressure on American corporations is too small if the goal is to avoid critical tipping points.

Finally, our study speaks to an ongoing discussion about the goals of the corporation. Central to this discussion is the question of whether corporations should 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 is sometimes the case.

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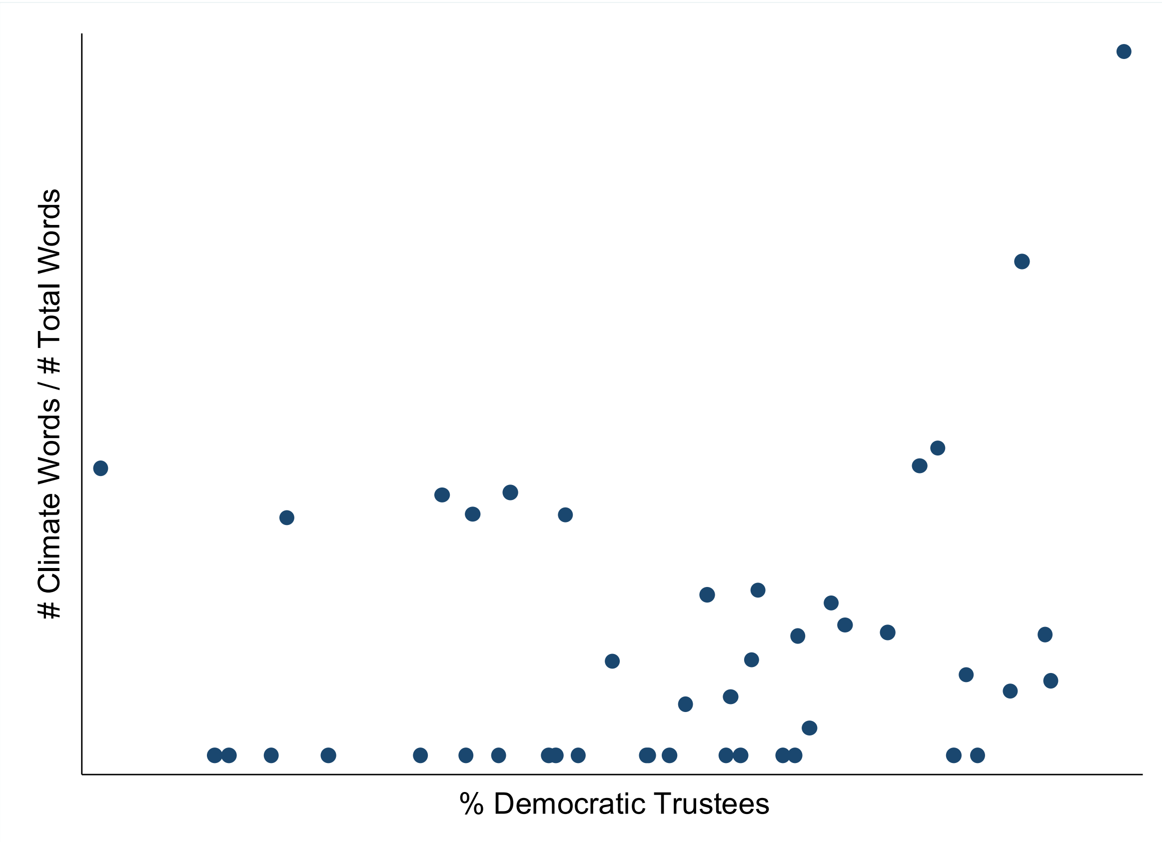
Internet Appendix 1. Climate Language Used by Pension Funds

Figure IA1. Binned Scatterplot of Green Trustees Against Climate Words in Annual Report



Internet Appendix 2. Standard Errors

The regressors in our two step model are generated from equation (3), using coefficients produced from a first-stage regression (2). It is well known that this type of procedure produces consistent estimates of the coefficients in the second stage but inconsistent standard errors because of errors in the generated regressors (Pagan 1984; Murphy and Topel 1985). This can result in standard errors that are biased downwards. To address this concern, we implemented a two-step bootstrapping algorithm adapted from Ashraf and Galor (2013) and Cameron et al. (2008).

First, we drew a random sample with replacement of pension holdings and their returns from other investments to estimate a first-stage regression. Second, we used the first-stage OLS coefficients to calculate the instrumented shareholdings using equation (3). Third, we drew a random cluster of firm-years with replacement and used the facilities of this random cluster to estimate the second-stage regression, recording the resulting OLS coefficients. Fourth, we repeated the previous steps 1,000 times. Finally, we use the standard deviation of the coefficients as the bootstrapped standard errors of our main estimates.

We also implemented block bootstrapping at the company level, which involves drawing random clusters of firms instead of firm-years in the third step. The statistical significance remains substantially unchanged in our main results.

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Internet Appendix 3. Company-Level Regressions

Table IA3. Company-Level Regressions

Panel A. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (TRUST)	-1.45	-3.95**	-3.26	-5.21*
	(0.93)	(1.59)	(2.24)	(3.04)
% $\widehat{\text{non-green}}$ (TRUST)	-2.25	-2.90	-9.67*	-13.07*
	(2.21)	(3.70)	(5.24)	(7.06)
N	2,858	2,400	1,988	1,633

Panel B. Year Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (GOV)	-1.25	-2.56	-2.21	-4.47
	(0.97)	(1.72)	(2.53)	(3.51)
% $\widehat{\text{non-green}}$ (GOV)	-2.29*	-5.24	-8.70	-11.09
	(1.38)	(2.27)	(3.21)	(4.39)
N	2,858	2,400	1,988	1,633

Panel C. Year and Company Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (TRUST)	-2.67*	-6.97**	-5.63*	-7.51*
	(1.51)	(2.35)	(3.11)	(3.86)
% $\widehat{\text{non-green}}$ (TRUST)	-4.60	-2.24	-6.16	-4.47
	(3.05)	(4.64)	(6.19)	(7.40)
N	2,807	2,342	1,933	1,591

Panel D. Year and Company Fixed Effects	One Year	Two Years	Three Years	Four Years
% $\widehat{\text{green}}$ (GOV)	-2.75*	-6.97***	-7.61**	-11.16**
	(1.57)	(2.53)	(3.49)	(4.37)
% $\widehat{\text{non-green}}$ (GOV)	-3.79	-4.04	-3.71	-1.69
	(1.87)	(2.81)	(3.74)	(4.62)
N	2,807	2,342	1,933	1,591

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. Standard errors are in parentheses. Significance: * = 10 percent, **= 5 percent, *** = 1 percent.