Corporate governance and pollution externalities of public and private firms

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Abstract

The number of U.S. publicly traded firms has halved in 20 years. How will this shift in ownership structure affect the economy's externalities? Using comprehensive data on greenhouse gas emissions from 2007-2016, we find that independent private firms are less likely to pollute and incur EPA penalties than are public firms, and we find no differences between private sponsor-backed firms and public firms, controlling for industry, time, location and a host of firm characteristics. Within public firms, we find a negative association between emissions and mutual fund ownership and board size, suggesting that increased oversight may decrease externalities.

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1 Introduction

As human activity tilts the global environmental balance, governments have come under pressure to coordinate, regulate and monitor in order to reduce its effects. The recent withdrawal of the United States, the second largest global emitter of greenhouse gases, from the Paris Climate Accord, however, has shown that much of the burden of curtailing pollution may rest on the millions of daily decisions of concerned individuals and firms.

Can we expect costly prosocial actions from firms and their investors? Friedman (1970) argues that firms should focus on maximizing returns to shareholders, who can privately donate their wealth to causes of their choosing. Thus, Friedman prescribes that firms should refrain from costly prosocial behavior regardless of their ownership structure. As Baron (2007), Benabou and Tirole (2010) and Hart and Zingales (2017) point out, however, Friedman's argument breaks down if investors incur frictions when reversing harmful choices of firms, or if firms have a comparative advantage in creating prosocial outcomes. The existence of these frictions and advantages is highly plausible. For example, the cost of neutralizing a given pollutant might exceed the benefits derived from emitting it.

In the small theoretical literature that has emerged to study prosocial behavior by firms, the optimal extent of this behavior depends on assumptions about organizational structure and the resulting incentives of investors and managers, as well as whether there are any compensating long-term benefits to the firm from the prosocial behavior. In theory and in practice, there are many reasons to think that the equilibrium level of prosocial behavior of publicly and privately held firms may be different. On one hand, investors evaluate public companies quarterly, potentially encouraging managers of public firms to sacrifice long term value for more observable short-term results. Hart and Zingales (2017) propose a model in which investors' preferences include environmental concerns when they vote on corporate policies. Their model predicts that public firms, with their diffuse ownership and resulting low level of personal responsibility felt by each voting investor, will tend to incur an "amoral drift" away from prosocial decisions, while closely-held private firms will more often make prosocial decisions. In potential support of this hypothesis, Bernstein and Sheen (2016) find that health records of restaurants improve when they are taken over by private equity owners and Cohn, Nestoriak, and Wardlaw (2018) find that workplace safety improves. However, these may simply be profit maximizing decisions within the investor's time horizon.

On the other hand, private owners may have clearer incentives to focus exclusively on shareholder returns. Individual business owners may have no other sources of wealth. Private equity sponsors and the managers they hire are highly motivated to maximize financial returns due to the strong alignment of their incentive structure with the firm's exit value. Perhaps as a result, there is controversy about whether private equity buyouts have negative externalities like reducing employment (Davis et al., 2014). Furthermore, some private firms may benefit from the relatively limited distribution of their financial statements. Public firm financial statements must disclose events such as material Environmental Protection Agency (EPA) fines, which could damage their reputation. Thus, it is not immediately obvious that we should expect more prosocial behavior from private firms. This question assumes increased importance as the structure of the US economy changes. Doidge, Karolyi, and Stulz (2017) find that there are fewer public firms today than there were 40 years ago while the total number of firms has held steady, implying a larger and growing proportion of private firms in the U.S. economy.[1]

[1] An active recent literature investigates other differences between public and private firms such as their differential access to capital (Brav, 2009; Michaely and Roberts, 2012; Gao et al., 2013) and how this affects their ability to innovate (Bernstein, 2015; Acharya and Zhu, 2017) or invest in new opportunities (Mortal and Reisel, 2013; Asker et al., 2015; Gilge and Taillard, 2016; Phillips and Serstios, 2017). Our paper expands this literature into the area of governance and incentives.

We focus on greenhouse gas emission decisions as a measure of prosocial choices because the potential harm is widely shared and may only be minimally borne by the polluter. Importantly, Fowlie (2010) shows that, for utilities, reducing greenhouse gas emissions is costly and therefore not an obvious profit-boosting decision. A recent Wall Street Journal analysis suggests that the same is true for airlines.[2] In this study, we will assume that firms maximize profits in cases where this does not clash with ethical concerns. However, our lack of data on other industries leaves open the possibility that findings of differences in emissions between public and private firms can be ascribed to one or the other structure being more conducive to making cost-saving, profit maximizing decisions.

Emissions have been studied in a handful of past and contemporaneous studies. For example, Ilhan, Sautner, and Vilkov (2019) show that S&P 500 firms that emit more have higher left tail risk, as measured from options and higher analyst uncertainty about firm fundamentals. Krueger, Sautner, and Starks (2018), in a survey of institutional investors, reveal that many believe that climate risks from emissions of greenhouse gases have already begun to materialize. Many also believe that engagement, rather than divestment, is an appropriate way to address climate risks.[3]

Our data source is the detailed documentation that the EPA provides on permits and emission levels of its regulated facilities and on its enforcement actions against some of these facilities. We hand-link this facility-level data with firm-level accounting data from Capital IQ. For each linked firm, we use the SEC's EDGAR website along with news articles and company websites to look up the history of its public or private status during each year of

[2] "Just How Green Are U.S. Airlines?" Wall Street Journal, February 13, 2019 https://www.wsj.com/articles/just-how-green-are-u-s-airlines-11550068428?mod=hp_lead_pos8.

[3] Our paper is also related to the growing literature on corporate social responsibility (CSR). This literature has focused on large public firms and generally on the question of whether CSR activities generate increased earnings or returns (Heinkel, Kraus and Zechner, 2001; Hong and Kacperczyk, 2009; Ferrell, 2016; Lins et al, 2017). Starks, Venkatz, and Zhu (2017) find that long-term investors have a preference for high-CSR firms.

2007-2016, the period when Capital IQ financial data is available. We record in each year whether a private firm is sponsor-backed or whether it is independently run.

With this data, we proceed to test whether private or public EPA-regulated firms have a greater propensity to emit greenhouse gases and whether any firm characteristics mitigate this effect. We examine both raw emissions and emissions scaled by revenue, and control variables include total assets, leverage, and the proportion of property, plant and equipment in total assets, as well as state, year, and 4-digit SIC code fixed effects. In data from the two EPA databases that report greenhouse gas emissions, we find that private independent firms emit less than comparable public firms, while there is no strong difference between sponsor-backed private firms and public firms. The effect is economically significant, with independent private firms emitting roughly one third of a standard deviation less CO_2 equivalent greenhouse gases than do public firms. The result survives when we match each private firm to a similar public firm, and an adjustment that divides emissions by the SIC-code average in that year.

As total revenues can be a rough measure of output, we obtain electricity generation data for a subset of utilities at the generator level. When emissions are scaled by generation, we find similar results. We also find that weighted average generator age does not fully explain the results, which suggests that the age of the production assets, even if it were entirely exogenously due to younger firms being more likely to be private, does not drive the result.

Next, we test whether public or private firms are more likely to run afoul of EPA regulations. We do not claim that Friedman advocated breaking the law in order to enhance shareholder value, but he would endorse coming as close as possible to the legal limits, a policy which, if implemented imperfectly, risks more fines and regulatory actions. We find that independent private firms are less likely to incur actions and penalties than are public firms. This result is weaker in the smaller sample of matched firms and with the process of adjusting for industry averages.

It is possible that firms' listing decisions are correlated with their decisions about how much to pollute. Following related literature, we address this possibility by estimating the probability of being a private independent and private sponsored firm as in Acharya and Xu (2017) and control for the inverse mills ratios in our regressions. Our results are unchanged and appear in the Online Appendix.

We next investigate potential causes of our findings using a subsample of public firms for which we have rich data on investor holdings and governance characteristics, with the caveat that the results we find will only be indicative in terms of the differences between public and private firms. First, we test whether measures of disclosure and personal responsibility, proxied by concentrated decision-making power, are related to differences in pollution choices across public firms. We find a positive effect of required disclosure among private firms, and no effect of firm age (as a proxy for reputation). We do find that firms emit less when they have higher mutual fund ownership and larger boards. This suggests that the presence of concerned oversight, either at the investor level or at the firm level, could be a driver of reduced emissions.

Next we construct proxies for short-term investor pressure to perform. We find that the earnings response coefficient (as measured by the SUE decile) is positively related to emissions, suggesting that short-term pressure is indeed important. However, the presence of a golden parachute at the firm is also positively associated to emissions, which adds nuance to this result and suggests that that CEO job security in particular is not driving it. The presence of a staggered board or a poison pill are not associated with emissions among public firms. On the whole, these results provide partial evidence that governance by concerned investors could be at play in a firm's decision to pollute.

2 Data

2.1 Public and private firm data

Firm financial data are from Capital IQ, which is also used by Gao, Harford, and Li (2013), Phillips and Sertsios (2016), and Acharya and Xu (2017) in their studies of public and private firms. We download time-series financial data 13,393 U.S. firms and subsidiaries from 2007-2016. Of these entities, 10,957 have more than one year of data with total assets, total debt and total revenue defined. Capital IQ often obtains its data from publicly available financial statements, so our private firm data over-samples larger private firms and those that issue publicly traded debt that involves SEC disclosure requirements. It is possible that our results may not apply to the more opaque private firms that are not in our data. We investigate whether 10-K disclosure requirements among private firms in our sample are related to emissions levels, which should partially address this concern. Lastly, results may not apply to non-U.S. settings where different managerial incentives may be present. Facilities of U.S. businesses abroad are subject to home country pollution requirements and are also not in our data. Ben-David, Kleimeier, and Viehs (2018) find that firms have incentives to "export" their polluting activities to countries with less stringent pollution regulations.

We obtain the full name history of EPA facilities, and the dates associated with each name via a Freedom of Information Act request. For each Capital IQ firm, we search the dataset of EPA facilities for matches by name. The full hand-matching process is described in Appendix A. We find that 2,345 firms in the Capital IQ database have matching facilities in the EPA database during a time period that overlaps with that of data availability in

Capital IQ.

Capital IQ provides a variable indicating whether the firm is public or private, but it is not a time-series variable and it labels subsidiaries of public firms, government owned entities, religious institutions, etc. as private. Thus, for each Capital IQ entity that has one or more facilities in the EPA data, we search the SEC's EDGAR website for the private, public or subsidiary status for the firm in each year since 2007. For firms that file a 10-K, Item number 5 provides information on whether the stock is publicly traded and on which exchange it is listed. We consider a stock publicly traded if it trades via Pink Sheets or over-the-counter, but in order to avoid gray areas we remove firms that trade and yet do not file a 10-K in a given year (stocks that trade via Pink Sheets are not required to). If the firm is private, we determine whether the firm is owned by a private equity sponsor or is independent from company websites or news events. We also remove the handful of municipally-owned entities from the sample.

We delete any firm with assets or revenues below \$1M, but using a cutoff of \$10M or \$100M does not change the results. In the firm-level analysis, we also remove conglomerates which do not easily fit into one industry - for example, Berkshire Hathaway sells Fruit of the Loom underwear, but also has energy subsidiaries, and thus there is no reasonable SIC code at the firm level. We can retain them in facility-level analyses because we have facility level SIC codes. Figure 2 presents the number of firms in each year classified by public or private status. In the full sample, approximately 7.4% of our firms are private: 5.4% are private independent firms and 2% are private sponsor-backed firms. In the subsample that has carbon emissions data described in the next section, 10.7% of firms are private, with 8.4% being private independent firms and 2.3% being sponsor-backed. While more than 7% of firms are private prior to 2014, Capital IQ data is missing for some of the private firms in later years, resulting in their being only 7%, 5.8% and 5% of private firms in 2014, 2015 and 2016. In untabulated regressions, we find that dropping these years does not affect the nature of the results. A related point is that the number of public firms in our data set is not decreasing over the years like it is in the broader Compustat data. This is because there is a slightly better coverage and therefore a better match rate between EPA data and Capital IQ data in the later years of the sample period (for example, 1-800 Flowers exists in Capital IQ from the inception of the data set, but is only in the EPA data starting in 2015), but also because the firms in our matched sample of Capital IQ and EPA firms are not the smaller firms that are dropping out of Compustat as documented by Doidge, Karolyi, and Stulz (2017). This may result in our having fewer private firms in our sample than we would like.

The public firms in our sample have relatively uniform governance structures due to regulation, though we do include firms issuing publicly tradable units, which are common in the energy sector. In contrast, private firms have more leeway to adapt their structures and governance to the needs of their owners. As a result, beyond being more closely held, the private firms in our sample have a spectrum of organizational structures. One example of a private firm in our sample is a private equity portfolio company like Avaya, Inc. or Tesla, Inc. prior to its IPO in 2010. Another firm type is Golden Grain Energy, for which private units are tradable on an online matching system available on the company's website, and in practice is held by farmers. Still others, for example Ace Hardware, are owned by their customers. While we are able to separate out sponsor-backed firms, distinguishing between the other types of private firm is beyond the limits of our data set. While their structures vary, the private firms in our sample have in common that their owners are more involved in the management of the firm than are transient atomistic investors of public firms.

Public and private energy firms in particular have corporate structures that are rare outside of the energy sector. Among public energy firms, master limited partnerships, which issue units instead of shares, are common alternatives or complements to a common stock structure. These structures are only legal in the energy industry and in real estate. Units have limited voting rights. In cases where an MLP is partially owned by a parent public company, effectively giving investors a choice of whether to invest in tax advantaged units or in common stock, we allocate the facilities to this traditionally structured parent. Among private energy firms, the most common structure is the cooperative, which is owned by its customers. Cooperatives return profits to shareholders in proportion to their energy usage and not in proportion to their ownership percentage. In this sense they purport to be nonprofit, but none of the cooperatives we identified reported zero EBIT in Capital IQ. Also, energy prices are more often than not regulated, and can generally not be raised and lowered without a petition to the local government. Conclusions drawn from our study are influenced by characteristics of this sector, which is the heaviest producer of greenhouse gases and thus crucial in the study of climate change, but may have more limited application to corporate externalities that are unrelated to air pollution.

We use several firm-level financial variables from Capital IQ which we describe in Table 1. Summary statistics of the current firm-level sample appear in Table 2, and summary statistics on the facility-level sample appear in Table C1 of the Online Appendix. In these tables, we also present the results of t-tests comparing private independent firms to public firms in column (3), and private sponsor-backed firms in column (5). Total assets average \$9,685M for public firms and \$12,890M for private independent firms, and this difference is significant at the 5% level. Total assets for sponsor-backed firms averages \$3,910M and this difference is significantly different from the public firm average at the 1% level. Figure 1 shows that though the means are different, the distributions of firm sizes for public and private firms in our sample are visually similar. In untabulated results, the study's findings are similar if we remove all public firms that are larger than the largest private firm. The average of total revenues is higher for public firms, at $6,543M compared to $3,321M and $2,187M for private independent and private sponsor-backed firms. The private independent firms in our sample tend to be more asset-intensive than the public firms or the private sponsor-backed firms with ratios of PP&E to assets averaging 0.39 vs. 0.30 for public and private sponsor-backed firms.

2.2 Emission and enforcement data

Pollution data are from the EPA's Enforcement and Compliance History Online (ECHO).[4] Data sets include environmental permit, inspection, violation, enforcement action, and penalty information on EPA-regulated facilities. The following sections describe the emissions, violation and other data that we use in this study.

2.2.1 Greenhouse gas emissions

We focus on air emissions because the detrimental effects, and therefore permit limits, of the release of of chemicals into water and earth depend strongly on the location of release. For example, the release of a toxic chemical into into a large body of water can be less harmful than release of the same amount of the chemical into a stream that is home to a protected species, and permit limits vary accordingly. The EPA measures and collects air emissions data under four programs: The Greenhouse Gas Reporting Program (GHGRP), the Clean Air Markets Division (CAMD), the National Emissions Inventory (NEI) and the

[4] https://echo.epa.gov/tools/data-downloads

the Toxics Release Inventory (TRI). The GHGRP collects greenhouse gas[5] emissions data from larger facilities since 2010. These emissions are converted into metric tons of carbon dioxide equivalent to standardize their potency in causing global warming.[6] The program covers 8,000 large emitters. Table 1 contains variable definitions and Table 2 summarizes this data in millions of metric tons of CO_2e. The data are available from 2010-2016, and we call this variable *CO2eG*.

The second source of emissions data we use is the Clean Air Markets programs data. These data are for the largest emitters and measure emissions of fine particles, ozone, sulfur dioxide (SO_2), nitrogen oxides (NOx), mercury, and other significant air pollutants. Most of the reported emissions from these programs are from hourly sampling performed by Continuous Emission Monitoring Systems (CEMS) and are generally considered the highest quality air emissions data according to the EPA website. The data include over 1,300 facilities that are covered under the Acid Rain Program and Clean Air Interstate Rule. The data are available from 2007-2015: as of this writing, the EPA had not included the 2016 data on the central download website. However, we were able to find the 2016 data on the EPA's Air Markets Division website[7] under a different set of facility identifiers. With the help of a master file of EPA identifiers, we are able to include the 2016 data, but as Figure 2, Panel (b) shows, there is slightly less data in this year. Removing the 2016 data does not change the direction or general magnitude of the results. We call the variables from the CAMD data *CO2C*, *SO2C*, and *NOC*.

We do not use the NEI data or the TRI data. NEI data are are all reported in pounds with

[5]These are sulfurhexafluoride, perfluorocarbons, nitrous oxide, nitrogentrifluoride, methane, hydrofluorocarbons, HFEs and carbon dioxide itself.

[6]Each emitted gas has a "global warming potential" defined in relation to carbon dioxide. For example, a pound of nitrous oxide (N_2O) has a global warming potential of 298 times that of a pound of carbon dioxide.

[7]ampd.epa.gov

no adjustment for the toxicity of each substance, making aggregates difficult to interpret. Also, given our requirement for lagged data, only two waves of the NEI intersect with our data set: the 2011 and 2014 waves. The TRI also has no standardization for toxicity, and as Currie, Davis, Greenstone, and Walker (2015) and others point out, the data itself is of poor quality.[8]

Emission reports from the CAMD and the GHGRP are almost identical ($\rho = 0.98$) in the subset of of 523 firm years where both are available. Differences arise in part because the GHGRP data provides one number of carbon dioxide equivalent emissions while the CAMD data breaks down emissions into carbon dioxide, nitrogen oxides and sulphur dioxides. In tests where power is desirable, we will use a combined variable that is equal to the CAMD data when this is available since this is the highest quality data, and the GHGRP data otherwise. Table 1 describes the construction of this variable.

Figure 3 presents the emissions data by year for our sample of firms. Subfigures (a) and (b) present data from the GHGRP program and subfigures (c) and (d) present data from the CAMD. Emissions are in millions of metric tons of carbon-dioxide equivalent. For an intuitive sense, one metric ton of CO_2 is emitted by driving one average passenger car for 2,445 miles, or by charging 127,512 smartphones according to the EPA's "Greenhouse Gas Equivalencies Calculator"[9]. Subfigures (a) and (c) present raw emissions data and (b) and (d) present data scaled by the firm's revenues from Capital IQ. While there is a slight decreasing trend in raw emissions, this trend is absent when emissions are scaled by revenues. Subfigures (c) and (d) also show that emissions of sulphur dioxide and nitrogen oxides are small in terms of CO_2-equivalent compared to emissions of carbon dioxide. While these

[8]The EPA website warns that "While facilities must report chemical releases over a certain threshold, calculation methods are not prescriptive and there is a wide variation in accuracy of emissions reported under TRI."

[9]https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator

substances are toxic in other ways, they are not the principal causes of global warming at the levels at which the facilities in our data emit them.

Figure 4 presents the data by SIC code for the 10 SIC codes with the highest averages in each data set. Not all SIC codes have firms with emissions data. The GHGRP program draws data from 131 SIC codes and the CAMD draws data from 17 SIC codes. As in Figure 3, subfigures (a) and (b) present data from the GHGRP program and subfigures (c) and (d) present data from the CAMD. Subfigures (a) and (c) present raw emissions data and (b) and (d) present data scaled by revenues. Even within the top 10 industries, there is great variation in average annual greenhouse gas emissions, and one challenge of the analysis will be to control for this. Lyubich, Shapiro, and Walker (2018) use proprietary data on plant-level fuel inputs to show that even within 6-digit NAICS industries (they use the production of carbon black as an illustrative example), there is great variation in the amount of energy used and resulting amount of carbon dioxide emitted per unit of output. These differences are driven by the cleanliness of the production technology and the energy inputs that the firms choose to use. Managers even within narrowly defined industries have considerable leeway in their emission choices.

In addition to industry, we are also required to control for state, as environmental regulations vary considerably by state. For example, deregulation of electricity markets was not uniform across states. Also, under the 2015 Clean Power Plan, the EPA assigned to each state a unique target and interim goals for emission reduction based on estimated feasibility, and allowed states to achieve reductions how they saw fit, and even to coordinate with other states to achieve the joint reductions. Target reductions ranged from zero reduction for Hawaii, Alaska and Washington D.C. to over 40% for Illinois, Wisconsin, Minnesota and others.

2.2.2 Enforcement data

Enforcement data is one measure of the severity that the EPA assigns to pollution more broadly, by varying substances in varying locations, as we do not have the expertise to determine this ourselves. EPA enforcement data come from the Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). This data set contains information on informal and formal administrative cases and on judicial cases.[10] Administrative cases are those that take place before state or federal governing bodies, while judicial cases are those actions that take place in court, such as a breach of contract suit or other civil actions. State cases are available for some states but not for others,requiring the use of state fixed effects in all of our tests.

For example, Consumers Energy, a subsidiary of CMS Energy, settled with the EPA in 2014 for modifying five of its coal-fired plants in such a way that caused releases of excess NOx and SO_2. While not admitting wrongdoing, Consumers Energy agreed to install technology to reduce the emissions and was required to spend at least $7.7 million on environmental mitigation projects and to pay a $2.75 million civil penalty.[11]

The enforcement data include general case information, information on which section of law was violated and over which periods, pollutants involved, the names of the defendants and the milestone dates of the case, and any penalty amounts. Penalty amounts are categorized as federal penalties, state and local penalties, Supplemental Environmental Project (SEP) costs, compliance action costs, and federal and state and local cost recovery amounts. SEP

[10] These cases fall under the Clean Air Act (CAA), the Clean Water Act (CWA), the Resource Conservation and Recovery Act (RCRA), the Emergency Planning and Community Right-to-Know Act (EPCRA) Section 313, the Toxic Substances Control Act (TSCA), the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA or Superfund), the Safe Drinking Water Act (SDWA), and the Marine Protection, Research, and Sanctuaries Act (MPRSA).

[11] https://www.epa.gov/enforcement/consumers-energy-clean-air-act-settlement

and complying action costs are estimates and are not paid directly to the EPA but incurred by the firm in order to clean up the pollution. Cost recovery amounts are incurred by the EPA in order to clean up the site and then billed to the responsible parties. We use total monetary outlay by the violator as an indicator of case severity, and we use the first date that the case was filed with the EPA to assign a year to the case. Table 2 presents summary statistics on the enforcement data at the firm level, and the Online Appendix Table C1 presents the data at the facility level. These tables illustrate that enforcement actions are rare. Also, it is clear that there are far more firms in the enforcement data than in the greenhouse gas emissions data set, because only a subset of firms are required to report emissions. Figure 5 presents formal and judicial actions by year. In this figure, it is apparent that that the number of judicial actions has dropped off in recent years, while the number of formal actions have remained steady. Figure 6 presents the enforcement data for the top 10 SIC codes for various measures. While SIC code 4931 (Electric and other services combined) has the highest average total penalty, SIC code 3390, Miscellaneous primary metal products, has the highest average penalty scaled by revenue.

3 Public and private firms and greenhouse gas emissions

3.1 Choosing a dependent variable

There are two broad approaches to creating a dependent variable for this analysis. Although we are the first study in finance to our knowledge to use comprehensive data on greenhouse gas emissions, other studies have used related data and have faced this choice. Matsumura, Prakash, and Vera-Munoz (2014), Ben-David, Kleimeier, and Viehs (2018) and Ilhan, Sautner, and Vilkov (2019) use voluntary annual disclosure data from CDP, which covers roughly half of S&P 500 firms. All three studies use the log of emissions as their dependent variable and control for size using the log of assets.

To add structure, one might instead scale emissions by a measure of output. The resulting "emission intensities" are commonly used for industrial production purposes when there is a precise measure of productive output that emissions are tied to. Emissions intensities are highly variable across industries however, and we know of no study that uses emission intensities over different industries. Lyubich, Shapiro, and Walker (2018) infer CO_2 emissions from fuel consumption data for the year 2007 and examine variability of inverse emission intensities *within* 6-digit NAICS industries, but do not compare them across industries. In our study, we can only feasibly scale emissions by total firm revenues, with the further caveat that fiscal year revenues may not completely overlap with calendar year emissions.

Since no dependent variable is perfect, we choose to calculate both. When we scale firms' annual emissions by its *TotalRevenue* as a proxy for its annual output, we indicate this by using the extension *_R* in the variable's name. The ratios are highly skewed (skewness = 35 for *CO2eC_R* in the firm-level data, for example), so we take their log, and the resulting variables are no longer skewed (skewness = -0.45 for *logCO2eC_R* in the firm-level data). When the dependent variable is the log of emissions, we also control for the log of contemporaneous total revenue. Scaling or controlling for contemporaneous revenue assumes that firms do not choose to decrease their production in order to emit less.[12]

[12] This seems to be true at least for airlines. See "Just how green are US airlines?" Wall Street Journal, Feb 13 2019: https://www.wsj.com/articles/just-how-green-are-u-s-airlines-11550068428?mod=hp_lead_pos8

3.2 Summary statistics

Table 2 presents the summary statistics and the associated t-tests for differences between private firms and public firms. Raw measures of emissions are lower for private independent firms compared to public firms. For example, in the first line of the table, average annual emissions for the GHGRP program firms are 4.310 MMT (millions of metric tons) for public firms and 2.299 MMT for private independent firms. For large emitters in the CAMD program in the following row, average public firm emissions are 17.82 MMT for public firms and 5.048 MMT for private independent firms. These differences are significant in t tests as indicated by the stars in the table. Values are more similar between private sponsor-backed firms and public firms. When we scale by revenues, we find the opposite relation: public firms emit less per dollar of revenue than private independent firms, and this difference is significant in a t-test for GHGRP firms. Scaling by electricity generation yields inconclusive t-tests. Thus, it is not clear, without controlling for industry and other variables that are plausibly exogenous to the decision about how much to pollute, if there is a relation between corporate structure and emissions. Private independent firms make up 7.5% of the sample with any emissions data, but 12% of the sample with CAMD emissions data, indicating that private firms are more concentrated in heavy emissions industries. Also, private firms tend to use more leverage and are more asset intensive than public firms. All of these characteristics may influence emissions.

3.3 Multivariate results

This subsection presents specifications that control for industry and other firm characteristics. Table 3 presents the regression results, with the unscaled dependent variable in Panel A and the scaled dependent variable in Panel B. Columns (1)-(4) of each panel examine CO_2-

equivalent emissions in metric tons at the firm level and columns (5)-(8) use the facility-level sample. Columns (1) and (5) present the CO_2 emissions from the broader GHGRP program, and columns (2)-(4) and (6)-(8) present the CO_2 and CO_2-equivalent emissions of NOx and SO_2 from the CAMD programs. We control for size, *loglagTotalAssets*, the debt to asset ratio, *lagDA*, and capital intensity *lagNetPPEA*, the construction of which we describe in Table 1. For facility level analyses, we divide total revenue and total assets by the number of emitting facilities. Some dependent variables in the paper have limited or binary outcomes; however, in order to be able to include fixed effects, we still elect to use OLS throughout the paper. We include fixed effects for 131 (17) 4-digit SIC codes and 38 (45) states for the GHGRP (CAMD) data sets, as well as for each of the years. We double-cluster the standard errors by year and by industry.

Coefficients in Table 3 suggest that private independent firms tend to emit less than their public counterparts. In the GHGRP data in Column (1), a private independent firm has log CO_2-equivalent emissions that are 0.399 lower, which is 38% of the dependent variable's standard deviation of 1.042 from Table 2, column (7). In terms of units of carbon emissions, private independent status is associated with a $1 - \exp(-0.399) = 33\%$ decrease in the dependent variable from its geometric mean of 0.408 MMT of CO_2 equivalent (the arithmetic mean is 4.31 in Table 2, column (1)) For an intuitive sense, this 0.13 MMT of CO_2 is equivalent to the annual emissions of 27,601 passenger vehicles or 0.033 coal-fired power plants according to the EPA calculator. In column (2), for the large emitters in the CAMD program, emissions for private independent firms are 1.276 lower, which is 55% of the standard deviation of this variable (2.370 in Table 2, column (7)). In units of carbon emissions, this is a $1 - \exp(-1.276) = 72\%$ decrease from the geometric mean of 3.56 (the arithmetic mean is 17.79 Table 2), or 0.658 coal-fired power plants. This suggests that private independent firms emit less, especially in industries that have the highest emissions - those covered by the CAMD program. It is possible that firms in less carbon-intensive industries are less careful about their emissions of greenhouse gases. Results are stronger for the CAMD data on NOx and SO_2. Private independent firms have lower values of the dependent variable by 2.132, 82% of a standard deviation of NOx, and 4.585, 111% of a standard deviation of SO_2.

Facility-level results in columns (5)-(8) are similar. In column (5), the coefficient on private independent firms is 0.0808, which is 16% of a standard deviation of the dependent variable (0.495 from Appendix C1). In terms of units of emissions, this is 7.8% drop from the geometric mean of 0.0978 MMT per facility, or 0.0076 MMT (the arithmetic mean of emissions per facility is 0.607 in Online Appendix Table C1). This is equivalent to the annual emissions of 1,614 cars or 0.002 coal-fired power plants. In the CAMD data in column (6), private independent firms have emissions that are 1.477 lower which is 63% of a standard deviation of the dependent variable (2.340 from Online Appendix Table C1) and this represents a 77% drop from the geometric mean emissions per facility of 0.459 (the arithmetic mean is 2.26 from Online Appendix Table C1). This is equivalent to 75,038 cars or 0.091 coal-fired power plants.

Results are also similar in Panel B using scaled dependent variables. For example, in column (1) for GHGRP firms, emissions scaled by revenues are 0.588 lower, which is 26% of a standard deviation of the dependent variable, and for CAMD firms in column (2), emissions are 1.294 lower, which is 56% of a standard deviation of the dependent variable. In these regressions, private sponsor-backed firms are rarely significantly different from public firms. This could be due to the smaller number of observations in sponsor-backed firms, but a look at the summary statistics confirms that mean values of variables tend to be closer to those of public firms. On the flip side, we find no evidence that private equity sponsors improve the pro-social behavior of their portfolio companies.

Some control variables are significantly associated with emissions as well. For the unscaled dependent variable in Panel A, $logTotalRevenue$ is significantly positively related to emissions, as expected. The relation between emissions and revenues is weak for the GHGRP data (0.182 in column (1) of Table 3 Panel A), possibly due to the large heterogeneity of relations between emissions and revenues in these industries. In this setting, a 1% increase in total revenue from the geometric mean of 22,384 for public firms is associated with an $(1.01^{0.182} - 1) * 100 = 0.18\%$ increase in the dependent variable from its geometric mean of 0.408, or 734 MT of carbon dioxide emissions, which is equivalent to the annual emissions of 156 cars. This rather weak relation suggests that scaling by total revenue and forcing a one-to-one relation for such a broad panel of industries may not capture much of the variation in the dependent variable. The relation between revenue and emissions is stronger for the large emitters in the CAMD data, with coefficients of 0.831 and 0.775 in columns (2) and (3). Using the coefficient in column (2), a 1% increase in total revenue is associated with an $(1.01^{0.831} - 1) * 100 = 0.83\%$ increase in the dependent variable from its geometric mean of 3.56, or 0.030 MMT of carbon dioxide emissions, which is 6,273 cars or 0.008 coal-fired plants. This relation disappears for the facility level results in columns (5)-(8), possibly because our estimate of facility level revenue, total revenue divided by the number of emitting facilities, is too imprecise.

The debt-to-asset ratio is also significantly related to emissions in columns (2), (3) and (4) of Table 3, Panel A, which presents the firm-level data from the CAMD. In column (2), an increase of 0.01 in this ratio is associated with an increase in emissions of 2.097*0.01, which is 0.9% of the standard deviation of the dependent variable. In units of emissions, this increase in the debt-to-asset ratio is associated with a $\exp(0.10 * 2.097) - 1) = 2.1\%$

increase in emissions from the geometric mean of 3.56, which is 0.0754 MMT, 16,016 cars or 0.02 coal-fired plants.

The ratio of property, plant and equipment to assets is related to emissions in these regressions in the GHGRP data with the scaled dependent variable. Size as measured by assets is generally negatively related to emissions for the scaled dependent variable, suggesting that, in that specification, there are economies of scale in emission reduction.

Since the emissions reports from the GHGRP and the CAMD programs are almost identical for the same firm-year, for much of the remainder of the paper, we will use the combined greenhouse gas emissions dependent variables $logCO2e$ and $logCO2e\_R$, which use CAMD data when it is available, and GHGRP data otherwise. Including the GHGRP data makes the results weaker but more reflective of the broader cross-section of firms. These combined variables appear in columns (1) and (5) of Table 4, Panels A and B. The estimated coefficients are closest to those in Column (1) of Table 3, Panels A and B, since the majority of the data is from the GHGRP.

Regressions in Table 3 include industry fixed effects, but it is possible that a level effect is not sufficient to capture all of the effects of variation across industries. A similar argument is made by Lerner and Seru (2017) regarding commonly used data on citations per patent, a variable that also varies greatly across industries. Their solution is to adjust citations per patent in each industry by the mean in that industry-year, and we do the same here. We require at least 3 observations in that industry-year in order to calculate the adjusted dependent variable, so this shrinks our sample somewhat. Columns (2) and (5) of Table 4 provides regression results when the dependent variable is adjusted by dividing by the mean within the industry and year, and results continue to be statistically and economically significant at the firm and facility levels.

These results could also be driven by differences between the sample of private firms and that of public firms that may not be adequately captured by our fixed effects and control variables. For example, perhaps some public firm data outside the relevant range of the private firm observations could be driving the calculated coefficients. To address this possibility, we follow a matching approach. Each year, one public firm is matched to each private firm in the sample. The firms must be in the same 4-digit SIC code and we chose the closest in total assets as the match. The matching is performed with replacement.[13] Results appear in Columns (3) and (6) of Table 4. Results are statistically and economically significant in each case. It appears that the decrease in variance achieved by these normalizations compensates for the large loss of observations.

In untabulated regressions, we control for several other variables, none of which affect the results. We divide the debt-to-assets ratio into bank and non-bank debt, and find a small positive association between bank debt and emissions and no association between non-bank debt and emissions. Similarly, a breakdown of secured vs. unsecured debt finds that the former is generally positively related to emissions. We also create an indicator variable for utilities that are in locations and years where electricity prices are deregulated, and find that these utilities emit more, confirming findings in Fowlie (2010), but results are unaffected. We also use 2-digit rather than 4-digit SIC code fixed effects, and results are somwhat weaker and appear in the Online Appendix Table C3. We insert firm fixed effects to identify the 21 firms with emissions data that switch between private and public, and we find generally statistically significant negative coefficients (Online Appendix, Table C5). We do not jump to conclusions, however, as the decision to switch from public to private entails many changes

[13] Maksimovic, Phillips, and Yang (2017) argue that matched public and private firms appear different because they are at different stages in their life cycle and firms should be matched at the beginning of their lives and not contemporaneously, but we do not have the data to perform this type of match.

at the firm level. Lastly, in untabulated regressions, we control for characteristics of the location of the facility: distance (as the crow flies) from the closest EPA office, population density within a 3-mile radius, and the percentage of minority inhabitants within a 3-mile radius around the facility (see Online Appendix, Table C6). None of these changes to thee specification significantly affect the results.

3.4 Subset of electric utilities

We next investigate electric utilities, a subset of our sample where one can control for electricity generation which is more closely related to emissions than revenue. The Energy Information Administration (EIA) provides electricity generation data in survey Form EIA-923[14] on all utilities in the US at the generator level. An additional benefit is that this data provides generator age, which may be a choice that utilities can make in order to regulate their emissions, but may also be relatively fixed in the short term due to the high cost of upgrading equipment. We match the data to the emissions data at the facility level using identifiers provided by the EIA. We aggregate electricity generation in megawatt hours (MWH) and also generator age in years up to the facility level, weighting each generator's age by its annual electricity output. We also aggregate these values up to the firm level, weighting age by generation. The dependent variable in Table 5, columns (1)-(4) is the log of the entity's CO_2 output, and in columns (5)-(8) emissions are scaled by annual electricity generation. We call the scaled variable *logCO2e_GEN*. As in prior tables, these regressions include the usual control variables, state, year and 4-digit SIC fixed effects.

As in the earlier analysis, we find a negative relation between emissions and the indicator for private independent firms. In column (1), a private independent firm has log of emissions

[14]The data is available at https://www.eia.gov/electricity/data/eia923/ (Page 1, Generation and Fuel Data).

that are 0.187 lower than comparable publicly traded utilities, which is 8% of the standard deviation of the dependent variable (2.33). In units of emissions, switching from a public firm to a private independent firm is associated with emissions that are lower by 21% at the geometric mean of the dependent variable, which is 0.498. This amounts to 0.104 MMT of CO_2, which is the annual emissions of 22,204 cars or 0.027 coal-fired power plants. The coefficient halves when controlling for the weighted average age of the facility's generators.

Not surprisingly, *logPlantAge* is significantly related to emissions. Increasing plant age by 10 years raises the log of plant age by 0.325 and using the coefficient of 0.269 in column (2) of Table 5, this is associated with an increase in log emissions of 0.087, or 3.7% of a standard deviation of the dependent variable. In terms of units of emissions, 10 years represents 47% of the geometric mean of weighted generator age for public firms. Raising generator age by this amount is associated with an increase in emissions of $(1.47^{0.269} - 1) * 100 = 10.91\%$. From the geometric mean of 0.498, this is 0.054 MMT of CO_2, which is equivalent to annual emissions from 11,535 cars or 0.014 coal-fired plants. In untabulated results, we find that private independent utilities have a weighted average generator age of 24.0 years compared to 26.8 years for public firms, but we cannot say whether this is a choice that is made in part to reduce emissions.

Electricity generation is also statistically and economically related to emissions. The coefficients in columns (1)-(4) of Table 5 are close to 1, so a 1% increase in revenues is associated with a 1% increase in the dependent variable. This seems to justify scaling emissions by electricity generation as we do in columns (5)-(8). In these columns, we find that the indicator for a private independent firm is associated with a decrease in scaled emissions of 0.188 in column (5), which is 47% of a standard deviation of the dependent variable. Note that we expect this result to be stronger in units of standard deviation than for the unscaled dependent variable, as we have taken out much of the variation in the dependent variable by scaling by output. As in columns (2) and (4), the size of the effect decreases by half when controlling for weighted generator age, and is not statistically significant at the firm level in column (6) but is statistically significant in column (8).

4 EPA actions and fines

We next examine EPA actions and penalties. Dependent variables include the number of formal and judicial actions per firm-year or facility-year, and also the log of one plus the total dollar penalty assigned. We choose to use OLS in order to be able to include fixed effects and guarantee convergence, even though the first three dependent variables are count variables and the fourth is strictly positive. Table 6 shows that actions and penalties are generally lower for independent private firms. For example, in column (1) of Panel A, for private independent firms the coefficient on the number of formal actions is -0.227, and the standard deviation of the dependent variable is 2.229 so this is a 10%-of-a-standard deviation effect. In Table 6 Panel B, we examine an adjusted dependent variable by scaling by the annual industry average value as recommended by Lerner and Seru (2017). Here, we find at the firm level that private independent firms have fewer judicial actions, and at the facility level that they have fewer formal administrative actions, judicial actions, and also lower penalties scaled by average facility revenue. We examine a matched sample in Table 6 Panel C. In this table, results are only statistically significant for the most serious judicial actions, possibly due to the lower number of observations.

5 Potential drivers of differential emissions

This section explores potential drivers of the differences that we find between public and private firms. Our strategy is to use the rich data that is available for public firms to explore the variation in emissions among public firms, and use these insights and our knowledge of the governance differences between public and private independent firms to craft an educated guess about the drivers of the difference in emissions among public and private firms.

In these analyses, we use the combined emissions variable that uses both GHGRP and CAMD data, and we examine only firm-level data because all explanatory variables of interest are at the firm-level. We leave emissions unscaled while controlling for the log of revenues as in prior tables. Tests using the scaled dependent variable produce very similar conclusions.

5.1 Transparency

We first test whether disclosure requirements and other drivers of transparency affect firms' decisions as reputation effects may be heightened if the public is aware of a corporate leader's decisions. There is some evidence in the literature that this may be the case. Karpoff, Lott Jr., and Wehrly (2005) find that there are reputational penalties for polluting, and Duflo, Greenstone, Pande, and Ryan (2013) find that transparency in the environmental auditing process decreases pollution among Indian firms. We use three measures of exposure to the public eye. The first measure is the log of the firm's age, which we compute using the founding and IPO dates from Jay Ritter's website.[15] We construct this as the year minus the founding date if it is available, or the year minus the IPO date otherwise. We hypothesize that older firms are more familiar to the public and have a more valuable reputation. Age could also be a measure of how technologically innovative a firm is, however, with younger

[15]https://site.warrington.ufl.edu/ritter/ipo-data/

firms potentially being more innovative and polluting less, so it is unclear which way the relation should go. Table 7, column (1) shows that firm age is not significantly related to emissions.

Next, we use our hand collected data on whether each firm files a 10-K on EDGAR in a given year. While there are no specific SEC disclosure requirements related to carbon emissions, any information must be disclosed in a 10-K if it is material. Materiality of climate change-related information is discussed in the SEC's Commission's interpretive release entitled *Guidance Regarding Disclosure Related to Climate Change.*[16] In this regression, we use only private firms because all public firms in our sample file 10-Ks. Table 7, column (2) shows that a 10-K filing requirement among private firms is associated with higher (not lower) emissions, so this type of transparency requirement is not likely to drive down emissions. Private firms that file a 10-K have emissions that are $(\exp(0.812) - 1) * 100 = 125\%$ change in emissions at its geometric mean among these 287 observations of 0.35. This amounts to 0.4375 MMT, or the annual emissions of 92,887 cars or 0.11 coal-fired power plant. Our sample of private firms that file 10-Ks appears to be concentrated in the highest producing energy companies.

To further explore the possibility that public attention affects emissions choices, we create variables measuring the presence in the 10-K (for 10-K filers only) of language related to climate change. Under the assumption that firms will disclose only what they believe is necessary, we relate the existence of material climate change information about the firm to the emissions choices of the firm. We believe that firms are unlikely to insert spurious language about climate change in their disclosures because the SEC's *Guidance Regarding Disclosure Related to Climate Change* states that registrants should "avoid generic risk factor

[16]SEC. 2010: https://www.sec.gov/rules/interp/2010/33-9106.pdf. Washington, DC: The Securities and Exchange Commission (SEC).

disclosure that could apply to any company" (p. 22).

Using the SEC suite in WRDS, we count matches to the string "climate change" or the string "greenhouse gas" in 10-Ks in each year during our sample period. According to the SEC interpretive release, discussion of climate change could be appropriate in the Description of business, Legal proceedings, Risk factors, and/or Management's discussion and analysis (MDA) sections of the 10-K. From reading through the instances where these words appear, in most cases the words are used in the discussion of existing or potential future regulation of greenhouse gases that might affect the company. We create an indicator variable for the presence for each of these words in the 10-K, and also variables that are the log of 1+ the number of times each string appears in the 10-K. Among firms that file 10-Ks, the correlation among the two indicator variables is 0.69 and the correlation in the log count variables is 0.49.

As Table 7, column (3) shows, the log of the count of instances of "greenhouse gas" is positively related to the dependent variable of greenhouse gas emissions per dollar of revenue, controlling for the usual control variables and fixed effects. The indicator variable for the presence of the word in the 10-K produces a similar result and is not shown. The indicator for the presence, or the count of the instances of string "climate change" are not related to the dependent variable and also remain untabulated. For a sense of the economic size of the coefficient on *logCountGreenhouseGas*, one extra instance of thee word in the 10-K, which is a 23% increase over the geometric mean of 4.33, is associated with an $(1.23^{0.0998} - 1) * 100 = 2.09\%$ increase in emissions, which at the geometric mean in this data of 0.444, is 9,280 MT - the emissions of 1,970 passenger cars annually.

Our interpretation of this result is that firms with risk factors related to their carbon emissions are rightly flagging these in their 10-Ks, and hence the direction of causality is from the emissions to the flagging. We conclude that we find no evidence that reputation effects of age, or transparency regarding carbon emissions that is either forced (the firm must file a 10-K) or slightly more discretionary (discussing emissions as a risk factor) are associated with lower emissions, controlling for industry, year, and other control variables.

5.2 Personal responsibility

In order to test the hypothesis of Hart and Zingales (2017) that personal responsibility for corporate decisions caused by concentrated power, as opposed to amoral drift caused by diffuse ownership, will drive more prosocial behavior, we examine variables that are related to how much personal responsibility corporate decision makers - the CEO or a large influential investor - are likely to feel. Since private firms tend to have more concentrated power, a finding here could shed light on why private firms tend to pollute less than do comparable public firms. We note that our prior finding that sponsor-backed firms pollute similarly to public firms does not support the hypothesis that concentrated power itself leads firms to pollute less, but perhaps there is a role for personal responsibility.

We first consider an indicator variable for whether the CEO is also the chairperson of the board in a particular firm-year. We obtain this from the IRRC directors database. We expect this measure to be negatively related to emissions if concentrated power induces the CEO to feel more personally responsible, but we find no relation and this regression remains untabulated.

Edmans (2009) shows that blockholders manage to influence the firm to pursue long term goals through threatening to vote with their feet, so we consider variables measuring concentration of power at the large investor level. *Maxinstown* is the ownership percentage of the largest institutional investor. Table 2, Panel B shows that this variable has a mean of 9%

in public firms with emissions data. Although this variable is not statistically significantly related to emissions in column (4), controlling for other variables like mutual fund ownership in column (10), it is significantly negatively related to emissions.

We also construct the proportion of mutual fund ownership using the CRSP mutual fund database, as mutual funds are increasingly demanding governance changes at the firms they invest in. We divide this variable into *ActiveMFown* and *PassiveMFown*, where passive mutual fund ownership is all ownership by mutual funds with any index fund indicator, combined with exchange traded funds (not exchange-traded notes). We call the remainder of funds active funds. Table 2, Panel B shows that active ownership averages 15% while passive ownership averages 10.2% of shares in our sample of firms with emissions data. Table 7, column (5) shows that active ownership is associated with lower emissions, while passive ownership is not significantly related to emissions. A one percentage point increase in active ownership is associated with an $(\exp(-0.790 * 0.01) - 1) * 100 = 0.79\%$ decrease in emissions at the geometric mean in this sample of 0.472, or 3,720 MT which is the equivalent of 790 passenger cars. When including all independent variables in column (10), however, we find that passive ownership is significantly negatively related to emissions, while active ownership is not. In that regression, an one percentage point increase in passive ownership is associated with a 7.28% drop in emissions from its geometric mean. This sample is much smaller, however, due to the requirement that all of these additional variables are defined. In untabulated results, mutual fund ownership as a whole is significantly negatively related to emissions in both specifications, with a coefficient of approximately 1.11, which is closer to the coefficient for active ownership. Using this coefficient for total mutual fund ownership in this specification, we would find that a 10 percentage point increase in mutual fund ownership is associated with a $(\exp(-1.11 * 0.1) - 1) * 100 = 10.5\%$ drop in emissions, which at the geometric mean would represent 49,560 MT or the equivalent of the annual emissions of 10,522 passenger cars. This is approximately 38% of the difference we find between public and private independent firms in able 3. We conclude that either mutual funds search for companies that emit less, or that mutual fund managers pressure their portfolio companies to some extent. This result is consistent with findings by Dyck, Lins, Roth, and Wagner (2019), who find that institutional investors positively influence ESG in the firms they hold.

Lastly, we consider that the potential effect of boards, who are selected by investors. Members of a smaller board may feel greater personal responsibility to act in environmentally sound ways. We find the opposite. The variable *Boardsize*, which averages 10.5 in Table 2, Panel B, negatively related to emissions. An additional board member is associated with emissions that are 7.19% lower at their geometric mean of 0.668 in that sample. This is 48,096 MT, or the equivalent of 10,211 passenger cars. This is roughly a third of the difference associated with the private independent firm indicator in Table 3. We hypothesize that this variable may in fact be a measure of whether the board has a specific committee or member responsible for environmental matters and who can thus devote attention to them.

Thus, we find some support for the personal responsibility of large investors having an effect on emissions decisions, but no support for the personal responsibility of CEOs or board chairs in these decisions. How might this shed light on the differing rates of pollution among public and private firms? Like the managers of private firms, large investors of public firms may feel that their reputation is at stake, since their holdings are most often publicly disclosed, and they cannot sell their holdings quickly without incurring significant liquidity penalties. For this same reason, they might be the most desirous to maximize long-term value and reduce the long-term risks associated with pollution. In contrast, smaller investors and CEOs of public companies, and private equity managers may have a shorter horizon. We investigate specific measures of short-term pressure in the next section.

5.3 Short-termism

We now turn to the possibility that investor short-termism causes public firms to pollute more than comparable private firms, as suggested in Hart and Zingales (2017). The first variable that we examine is the earnings response coefficient. This is the coefficient from a regression of firm-level excess returns over the CRSP value-weighted market portfolio on the earnings announcement date on unexpected portion of companies' earnings announcements, measured by standardized unexpected earnings, or SUE. This variable has a long history in the literature (see for example Collins and Kothari (1989)). We use the decile that this coefficient falls in because Mendenhall (2004) shows that this is more linearly related to returns than the coefficient itself. Table 7, column (7) shows that this variable is positively related to emissions as one might expect, but this relation disappears in column (10) when the other variables are included.

We also include *GParachute*, which is an indicator for whether the firm has a golden parachute, *CBoard*, indicating that the firm has a staggered board. In Table 2, Panel B, 83% of firms with emissions data have golden parachutes while 32% have staggered boards. In untabulated results, an indicator variable for whether the firm has a poison pill is unrelated to emissions. These features make it more difficult for top decision makers at the firm to be replaced quickly in the event of poor short-term financial performance. We find that the presence of a golden parachute is positively related to emissions. A firm with a golden parachute is associated with emissions that are 45% lower relative to the geometric mean which is 0.676 in that sample. This is equivalent to 310,284 MT, or 65,878 passenger cars. The other two variables are unrelated to emissions. This provides at best partial support for the hypothesis that pressure to perform in the short term is associated with more pollution.

6 Conclusion

In a hand-matched sample of EPA facilities and Capital IQ firms, we find evidence that private firms have lower greenhouse gas emissions than do comparable public firms, and that private firms incur fewer and lower EPA fines in some specifications. Hypothesizing that private firms have more concentrated ownership and less investor pressure for short-term financial performance, we investigate whether variables proxying for these effects among public firms drive differences in emissions among these firms. We find some evidence in favor of concentrated ownership and personal responsibility and mixed evidence in favor of short-term investor pressure driving these results. Among the many possible explanations that we cannot test using this data, personal experiences and beliefs of managers may play a large role in their decisions with regard to emissions, and may be a promising avenue for future research.

A question that arises is whether these results can inform policy decisions in the U.S. and in other countries. Let us first consider the energy sector, as it is the biggest producer of greenhouse gases in our data. In the U.S, the energy sector includes publicly traded firms that are often master limited partnerships, and private utilities are often cooperatives. In Europe, firms tend to be larger and there is greater involvement of governments, and in China, there is even stronger involvement in the state in the energy sector. In these situations, the state could potentially exert pressure in the same way that mutual funds appear to in our data. A common theme in the U.S., Europe and Chinese energy sectors in the last three decades has been the separation of generation and transmission of energy into separate corporate entities. In the U.S., private generation cooperatives that are owned by customers partially re-create the the vertical integration that existed in the past. Perhaps, vertical integration creates more personal responsibility because producers, transmitters and end-users cannot pin the blame on one another as they can when they are separate entities. Clearly, we see the benefits of separation for competitive reasons, and there may be better ways to assign personal responsibility, however, so we stop short of recommending re-integration without further study.

Beyond the energy sector, we can say that the variables that seem to drive differences in emissions among public firms (mutual fund ownership and probable oversight, better board oversight), and that we hypothesize drive the differences among public and private firms, can carry over to an international setting. For example, European large investors are at an advanced stage of Environmental, Social and Governance (ESG) adoption.[17] Furthermore, some countries, like Germany, require firms to have board members who are representatives of stakeholders other than shareholders. These measures may result in firms better internalizing any externalities that they create.

[17] https://www.schroders.com/en/media-relations/newsroom/all_news_releases/european-investors-lead-us-counterparts-for-esg-adoption/

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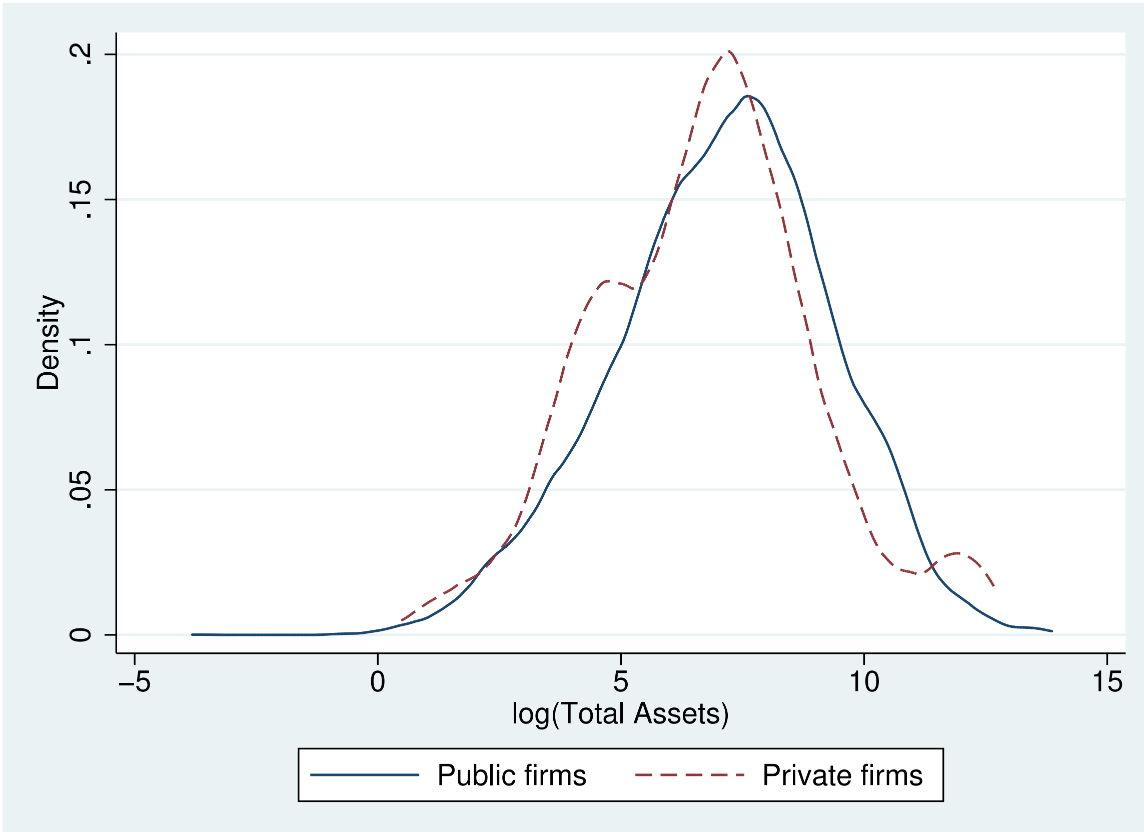
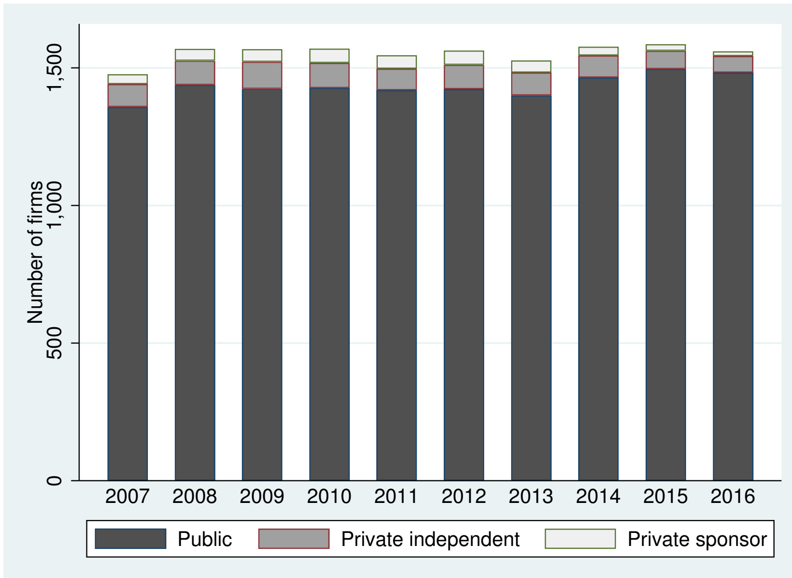
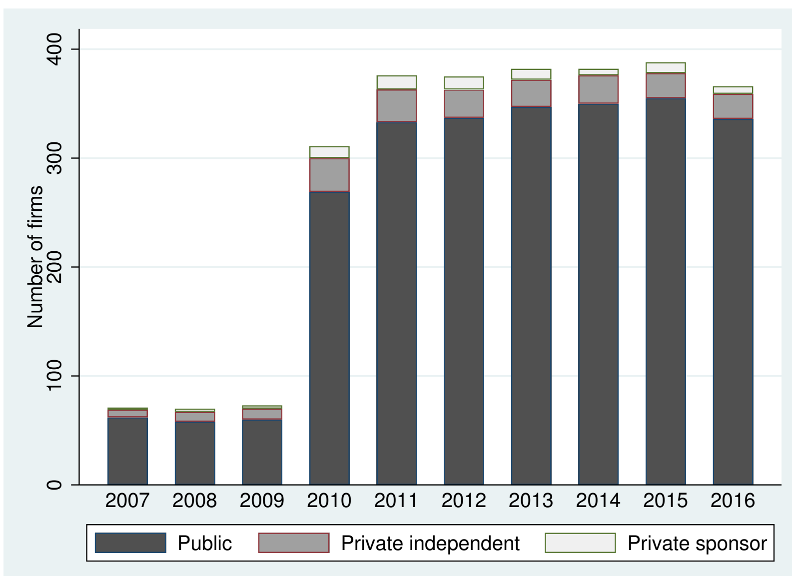


Figure 1: Kernel densities of size for public and private firms.

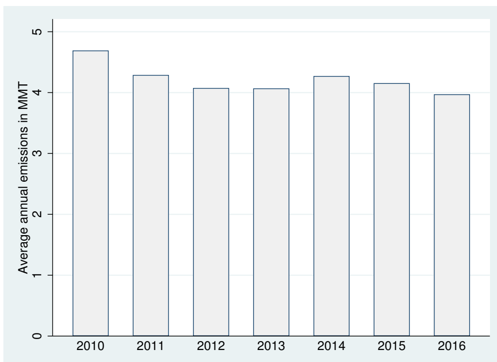


(a) Firms with any EPA data

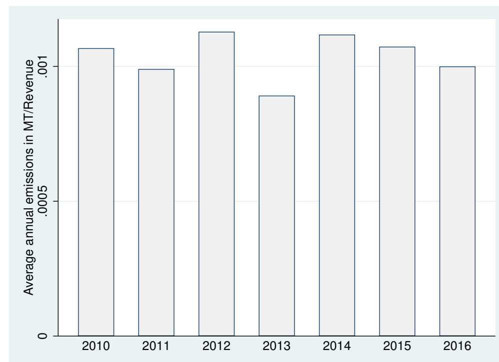


(b) Firms with CO_2 emissions data

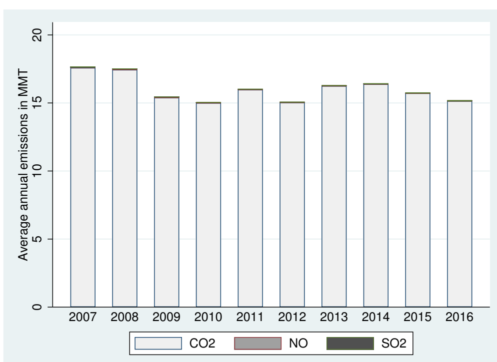
Figure 2: Firm types by year. Panel (a) presents the sample of firms that are monitored by the EPA. Panel (b) presents the subsample of firms that have CO_2 emissions data from either the GHGRP (2010-2016) or CAMD (2007-2015) emissions reporting programs.



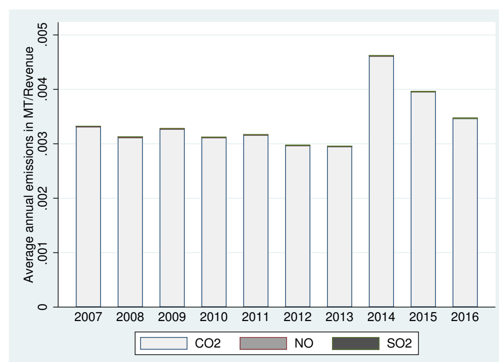
(a) CO2 Emissions - GHGRP



(b) CO2 Emissions/Revenue - GHGRP

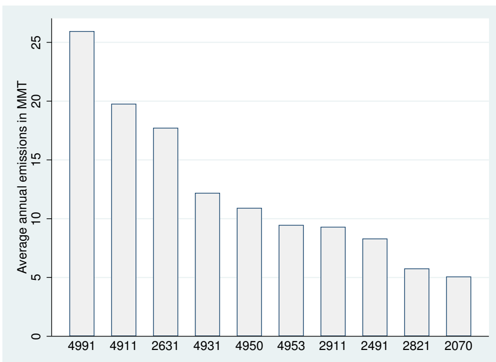


(c) CO2 Emissions - CAMD

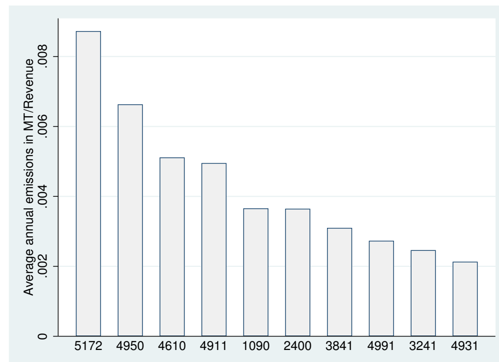


(d) CO2 Emissions/Revenue - CAMD

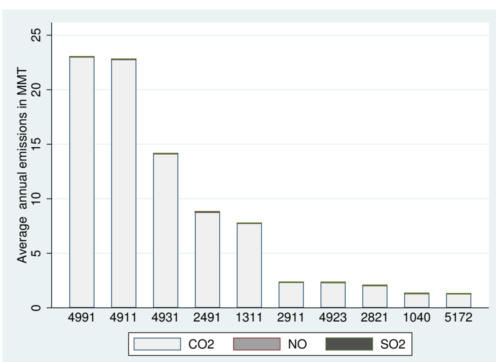
Figure 3: Emissions of greenhouse gases by year. Subfigures (a) and (b) present data from the GHGRP program and subfigures (c) and (d) present data from the CAMD. Emissions are in millions of metric tons of carbon-dioxide equivalent for subfigures (a) and (c), and in metric tons per dollar of revenue in subfigures (b) and (d).



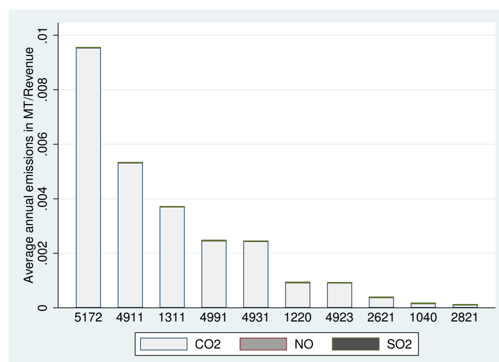
(a) Average emissions - GHGRP



(b) Average emissions/Revenue - GHGRP



(c) Average emissions - CAMD



(d) Average emissions/Revenue - CAMD

Figure 4: Emissions of greenhouse gases by SIC code for the top 10 SIC codes. Subfigures (a) and (b) present data from the GHGRP program and subfigures (c) and (d) present data from the CAMD. Emissions are in millions of metric tons of carbon-dioxide equivalent.

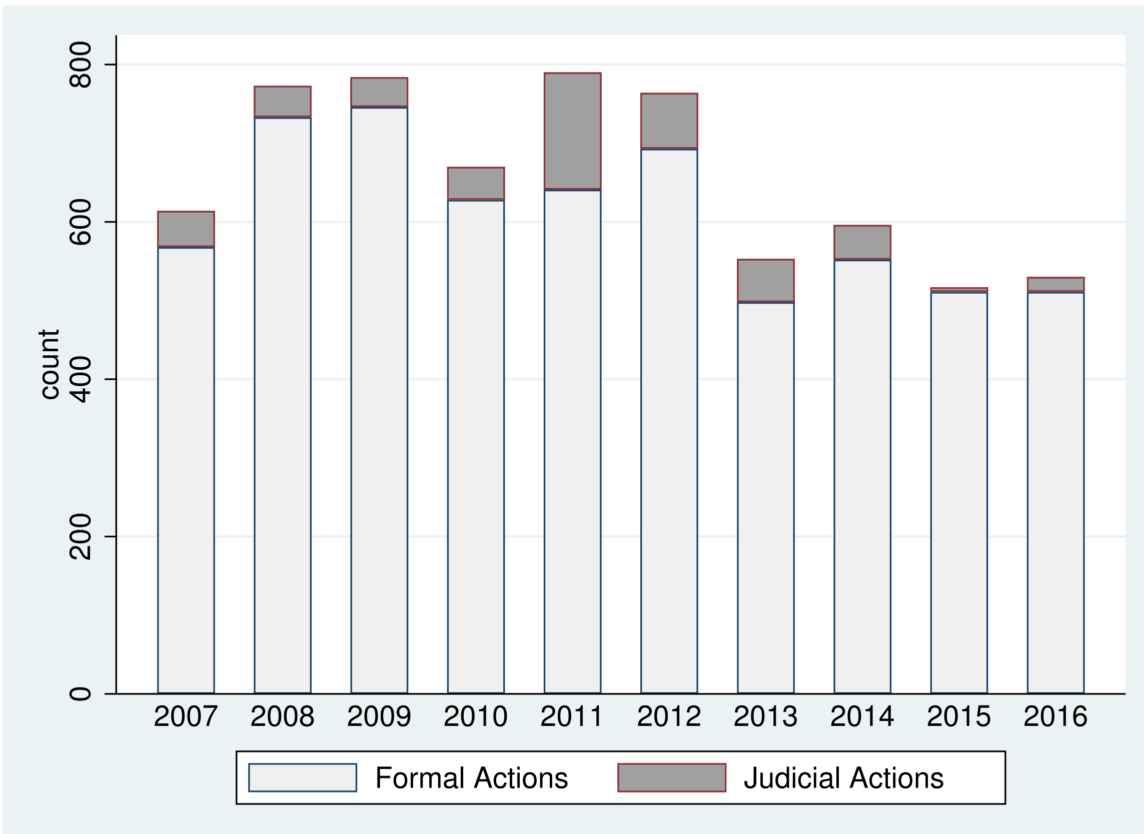
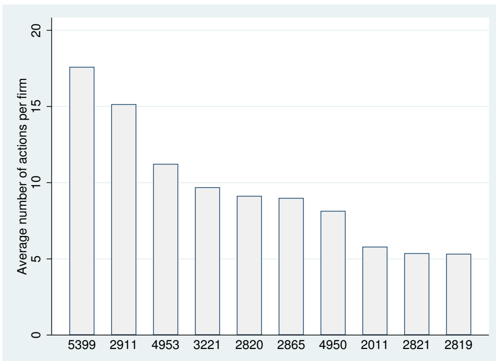
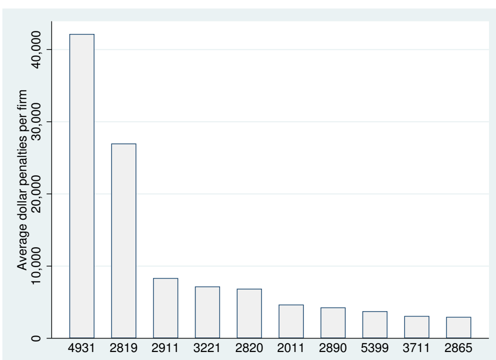


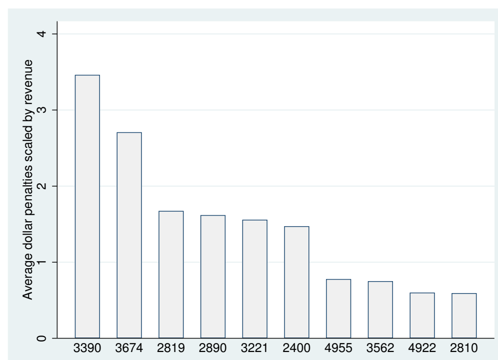
Figure 5: Number of informal actions, formal actions and judicial actions by year for our sample. Formal actions and informal actions are resolved within the agency. Judicial actions are resolved by the courts.



(a) Number of Actions



(b) Dollar penalties



(c) Dollar penalties/Revenue

Figure 6: Number of actions and total penalties by SIC code for the 10 top SIC codes for each value. Dollar penalties are in thousands and revenue is in millions.

Table 1: Variable descriptions

Variable	Description	Source
Private	An indicator variable for a firm that is not publicly traded in a given year. We define publicly traded firms as firms with equity ownership that trades on an exchange and that file 10-Ks with the SEC. We remove firms that are listed but to not file 10-Ks with the SEC.	EDGAR, company websites, news.
PrivateIndependent	Indicator variable for firms with equity ownership that is not traded on an exchange or controlled by a private equity firm.	SEC Edgar, company websites, news.
PrivateSponsor	Indicator variable for firms with equity ownership that is not traded on an exchange and that is controlled by a private equity firm.	SEC Edgar, company websites, news.
CO2eG	CO_2-equivalent emissions of carbon dioxide, methane, nitrous oxide and fluorinated greenhouse gasses, in millions of metric tons. The Greenhouse Gas Reporting Program includes data since since 2010.	EPA
CO2C	Pounds of carbon dioxide emissions as measured by the Clean Air Markets Division (CAMD)	EPA
NOC	Pounds of nitrogen oxide emissions as measured by the Clean Air Markets Division (CAMD). These are in CO2 equivalent.	EPA
SO2C	Pounds of sulphur dioxide emissions as measured by the Clean Air Markets Division (CAMD). These are in CO2 equivalent.	EPA
CO2e	Combined variable that is CO2C + NOC + SO2C when these exist, and CO2eG otherwise. We prioritize CAMD data because it is of the highest quality according to the EPA website, but prioritizing the GHGRP data does not affect our results.	EPA
NetGeneration	Net generation in megawatt hours (presented in millions of MWH in the summary statistics) aggregated from the generator level _GEN signifies that a variable is scaled by this variable.	EIA
Plant_age	Plant age computed by weighting generator ages by output	EIA
numAIF	The total number informal administrative actions against that facility or firm in a given year.	EPA
numAFR	The total number formal administrative actions against that facility or firm in a given year.	EPA

numAFR	The total number of judicial actions against that facility or firm in a given year. Judicial actions are resolved by the courts outside the EPA.	EPA
TotalPenalty	Total EPA penalty in thousands of dollars for a given facility or firm year	EPA
TotalRevenue	Annual total revenue. _R signifies that a variable is scaled by TotalRevenue.	Capital IQ
DA	The ratio of total debt to total assets	Capital IQ
TotalAssets	The total assets of the firm	Capital IQ
NetPPEA	Net property, plant and equipment scaled by total assets	Capital IQ
Edgar10K	Indicator variable for whether the firm files a 10K in the given year.	SEC EDGAR
CountGreenhouseGas	The count of the number of times that the word "greenhouse gas" appears in the 10-K.	SEC Edgar
ERC_suedecile	Earnings response coefficient: the coefficient on the regression of returns on the announcement date on the earnings surprise suescore.	IBES and CRSP
GParachute	An indicator for a golden parachute.	IRRC governance
CBoard	An indicator for a classified board.	IRRC governance
ActiveMFown	Mutual fund ownership: sum of shares owned by all mutual funds divided by shares outstanding, and capped at 1, minus the shares owned by passive funds.	CRSP mutual fund database
PassiveMFown	Mutual fund ownership by passive funds: funds with any index fund type flag in CRSP plus ETFs but not ETNs.	CRSP mutual fund database
Boardsize	The size of the board.	IRRC Directors
Age	Firm age based on firm founding date or IPO date if the former does not exist.	Jay Ritter's website

Table 2: Firm-level summary statistics

Firm-level summary statistics. Variable descriptions appear in Table 1. Panel A presents statistics for variables for public and private firms, and Panel B presents summary statistics for variables for public firms. In t-tests for differences with public firms, ***, ** and * signify significance at the 1, 5 and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public		Private Independent		Private Sponsor			
VARIABLES	mean	p50	mean	p50	mean	p50	sd	N
CO2eG	4.310	0.320	2.499*	0.174	5.412	0.151	12.26	2,579
CO2C	17.82	5.693	5.048***	1.176	13.52	1.092	25.23	732
NOC	0.0154	0.00363	0.00598***	0.000523	0.00781*	0.000189	0.0240	736
SO2C	0.0423	0.00625	0.0100***	0.00257	0.0418	2.10e-05	0.0821	689
CO2e	5.635	0.393	2.867**	0.195	6.437	0.217	15.06	2,794
logCO2eG	0.773	0.275	0.667	0.160	0.700	0.140	1.042	2,583
logCO2C	1.272	1.739	0.371**	0.162	0.490*	0.0878	2.370	732
logNOC	-6.098	-5.618	-6.883***	-7.556	-7.570***	-8.574	2.603	736
logSO2C	-6.399	-5.075	-7.853***	-5.964	-8.536***	-10.77	4.099	689
logCO2e	-0.717	-0.932	-1.055***	-1.633	-0.987	-1.527	2.329	2,797
CO2eG_R	0.000929	0.000113	0.00216***	0.000688	0.00178	0.000291	0.00437	2,579
CO2C_R	0.00323	0.00193	0.00452	0.00152	0.00327	0.000592	0.00739	732
NOC_R	2.82e-06	1.26e-06	5.33e-06***	1.74e-06	1.77e-06	1.05e-07	5.48e-06	736
SO2C_R	6.29e-06	2.45e-06	9.73e-06***	3.56e-06	6.74e-06	1.13e-08	1.10e-05	689
CO2e_R	0.00114	0.000130	0.00257***	0.000716	0.00182	0.000320	0.00475	2,794
logCO2eG_R	-9.148	-9.084	-7.409***	-7.283	-8.050***	-8.141	2.287	2,579
logCO2C_R	-7.252	-6.248	-6.398***	-6.491	-7.062	-7.431	2.302	732
logNOC_R	-14.62	-13.59	-13.60***	-13.26	-15.12	-16.07	2.635	736
logSO2C_R	-14.98	-12.92	-14.61	-12.55	-16.21	-18.30	4.188	689
logCO2e_R	-8.981	-8.947	-7.304***	-7.242	-8.018***	-8.047	2.357	2,794
CO2e_GEN	875.09	901.38	869.18	839.67	737.91**	618.34	308.53	738
logCO2e_GEN	6.71	6.800	6.725	6.733	6.513***	6.699	0.402	738
NetGeneration (M)	21.39	7.430	4.72***	1.076	15.10	1.678	28.34	738
PlantAge	26.69	28.39	24.01*	24.71	15.56***	13.78	12.34	723
numAFR	0.409	0	0.126***	0	0.306	0	2.229	15,543
numJDC	0.0352	0	0.00368	0	0.00759	0	1.025	15,543
TotalPenalty	1,151	0	3.657	0	310.3	0	46,906	15,543
TotalRevenue	6,543	1,131	3,321***	521.5	2,187***	1,069	21,417	15,543
lagDA	0.261	0.224	0.416***	0.367	0.601***	0.539	0.319	15,543
lagAssets	9,685	1,292	12,890**	686.5	3,910***	1,211	40,986	15,543
lagNetPPEA	0.298	0.217	0.392***	0.338	0.295	0.196	0.253	15,543
Edgar10K	1.001	1	0.361***	0	0.489***	0	0.223	15,543

Panel B

VARIABLES	(1) mean	(2) p50	(3) sd	(4) N
Age	32.83	23	30.26	925
CountGreenhouseGas	7.675	3	12.47	2,340
Maxinstown	0.0913	0.0760	0.0801	2,362
ActiveMFown	0.159	0.150	0.0983	2,328
PassiveMFown	0.102	0.102	0.0544	2,328
Boardsize	10.50	10	2.018	1,509
ERC_suedecile	0.00802	0.00674	0.00989	2,355
GParachute	0.831	1	0.375	1,564
CBoard	0.324	0	0.468	1,564

Table 3: Emissions

Regressions of measures of reported emissions on measures of ownership. Variable descriptions appear in Table 1. In Panel A, the dependent variables are unscaled emissions and $logTotalRevenue$ is included as a control variable. In Panel B, emissions data are scaled by total revenue. In both panels, Columns (1) and (5) present GHGRP data and the remaining columns present CAMD data. Columns (1)-(4) use firm-level data and columns (5)-(8) use facility-level data. Standard errors are clustered by industry and year and p-values are in parentheses.

Panel A

VARIABLES	(1) logCO2eG	(2) logCO2C	(3) logNOC	(4) logSO2C	(5) logCO2eG	(6) logCO2C	(7) logNOC	(8) logSO2C
PrivateIndependent	-0.399*	-1.276***	-2.132***	-4.585***	-0.0808*	-1.477***	-1.645***	-2.465***
	(0.08)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.136	0.610	0.323	0.622	0.0426	-0.400	-0.0872	0.182
	(0.50)	(0.51)	(0.67)	(0.59)	(0.49)	(0.32)	(0.83)	(0.77)
logTotalRevenue	0.182***	0.831***	0.775***	0.836	0.0165	-0.0495	0.0297	0.685***
	(0.00)	(0.00)	(0.00)	(0.12)	(0.25)	(0.89)	(0.92)	(0.00)
lagDA	0.0225	2.097***	2.260***	5.826***	0.0297	0.395	0.107	0.907
	(0.88)	(0.00)	(0.00)	(0.00)	(0.30)	(0.54)	(0.91)	(0.63)
loglagAssets	0.157**	0.232	0.167	0.229	0.0204	0.0648	-0.0505	-0.643**
	(0.02)	(0.47)	(0.52)	(0.65)	(0.34)	(0.84)	(0.87)	(0.02)
lagNetPPEA	0.569	1.940	0.685	-2.327	0.0937	-0.287	-0.210	-0.275
	(0.12)	(0.31)	(0.74)	(0.42)	(0.25)	(0.31)	(0.52)	(0.65)
Observations	2,579	732	736	689	18,132	5,411	5,539	4,481
R^2	0.686	0.675	0.719	0.727	0.243	0.185	0.251	0.317
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	logCO2eG_R	logCO2C_R	logNOC_R	logSO2C_R	logCO2eG_R	logCO2C_R	logNOC_R	logSO2C_R
PrivateIndependent	-0.588*	-1.294***	-2.155***	-4.609***	-0.401***	-1.511***	-1.681***	-2.501***
	(0.09)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.426	0.656	0.383	0.665	0.517**	0.130	0.402	0.320
	(0.29)	(0.48)	(0.62)	(0.57)	(0.02)	(0.61)	(0.22)	(0.58)
lagDA	0.0250	2.133***	2.304***	5.867***	0.0373	0.733	0.427	1.036
	(0.92)	(0.00)	(0.00)	(0.00)	(0.81)	(0.41)	(0.70)	(0.59)
loglagAssets	-0.172**	0.0764	-0.0408	0.0770	-0.766***	-0.917***	-0.964	-0.940***
	(0.02)	(0.69)	(0.72)	(0.53)	(0.00)	(0.00)	(.)	(0.00)
lagNetPPEA	1.389**	1.922	0.654	-2.360	0.322	-0.0541	-0.0113	-0.238
	(0.04)	(0.32)	(0.75)	(0.41)	(0.38)	(0.76)	(0.97)	(0.70)
Observations	2,579	732	736	689	18,132	5,411	5,540	4,482
R^2	0.711	0.655	0.725	0.739	0.452	0.262	0.317	0.339
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: Emissions

Regressions of measures of reported emissions on measures of ownership. Variable descriptions appear in Table 1. In Panel A, the dependent variables are unscaled emissions and $logTotalRevenue$ is included as a control variable. In Panel B, emissions data are scaled by total revenue. In both panels, columns (1) and (4) present the combined emissions variable; columns (2) and (5) present the adjusted dependent variable which divides by the mean from that industry-year, and column (3) and (6) present the matched sample. Columns (1)-(3) use firm-level data and columns (4)-(6) use facility-level data. Standard errors are clustered by industry and year and p-values are in parentheses.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logCO2e	logadjCO2e	logCO2e	logCO2e	logadjCO2e	logCO2e
PrivateIndependent	-0.737**	-0.732**	-0.769**	-0.515**	-0.507**	-1.088***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)
PrivateSponsor	0.255	0.370	0.561	0.0210	0.0202	-0.190
	(0.58)	(0.48)	(0.36)	(0.84)	(0.84)	(0.43)
logTotalRevenue	0.584***	0.625***	1.435***	0.109**	0.0994**	0.00248
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.99)
lagDA	0.0148	0.00403	0.160	0.0266	0.0382	-0.116
	(0.96)	(0.99)	(0.63)	(0.79)	(0.64)	(0.52)
loglagAssets	0.215*	0.175	-0.533***	0.0912*	0.0957**	0.142
	(0.05)	(0.16)	(0.00)	(0.05)	(0.04)	(0.33)
lagNetPPEA	1.506**	1.454**	-0.637	0.490	0.452	0.322
	(0.03)	(0.05)	(0.43)	(0.14)	(0.17)	(0.36)
Observations	2,794	2,125	465	19,828	19,356	1,755
R^2	0.703	0.469	0.778	0.228	0.160	0.317
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.809**	-0.738**	-0.685**	-0.934***	-0.869***	-1.230***
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.382	0.580	0.378	-0.128	0.0394	-0.00905
	(0.36)	(0.23)	(0.51)	(0.21)	(0.61)	(0.98)
lagDA	0.00834	-0.106	0.115	0.515	0.408	0.0690
	(0.98)	(0.73)	(0.72)	(0.13)	(0.21)	(0.79)
loglagAssets	-0.169**	-0.142*	-0.150	-0.243***	-0.218***	-0.160
	(0.02)	(0.05)	(0.48)	(0.00)	(0.00)	(0.29)
lagNetPPEA	1.540**	1.490**	-0.524	0.399	0.655	-0.286
	(0.02)	(0.03)	(0.50)	(0.46)	(0.16)	(0.65)
Observations	2,794	2,125	465	19,828	19,327	1,755
R^2	0.704	0.231	0.733	0.410	0.233	0.364
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Table 5: Emissions scaled by electricity generation for utilities

Columns (1)-(4) present unscaled emissions, and columns (5)-(8) present emissions scaled by electricity generation. from Form EIA-923, Part1. Control variables not shown are *loglagTotalAssets*, *lagDA*, and *lagNetPPEA*.Variable descriptions appear in Table 1. Columns (1), (2), (5) and (6) present firm-level data and columns (3), (4), (7), and (8) present facility-level data. Standard errors are clustered by industry and year and p-values are in parentheses.

VARIABLES	(1) logCO2e	(2) logCO2e	(3) logCO2e	(4) logCO2e	(5) logCO2e_GEN	(6) logCO2e_GEN	(7) logCO2e_GEN	(8) logCO2e_GEN
PrivateIndependent	-0.187*	-0.0952*	-0.271***	-0.170***	-0.188**	-0.0792	-0.235**	-0.125*
	(0.10)	(0.09)	(0.01)	(0.01)	(0.03)	(0.13)	(0.03)	(0.06)
PrivateSponsor	-0.0533	0.0339	-0.0287	-0.0639	-0.0540	0.0380	-0.0165	-0.0469
	(0.32)	(0.62)	(0.78)	(0.27)	(0.28)	(0.53)	(0.87)	(0.43)
logNetGeneration	1.001***	0.976***	0.973***	0.961***				
	(0.00)	(0.00)	(0.00)	(0.00)				
logPlantAge		0.269***		0.271***		0.250***		0.257***
		(0.00)		(0.00)		(0.00)		(0.00)
Observations	738	738	5,315	5,272	738	738	5,315	5,272
R^2	0.984	0.987	0.932	0.940	0.465	0.540	0.130	0.218
By	Firm	Firm	Facility	Facility	Firm	Firm	Facility	Facility
Controls	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 6: Actions and penalties

Regressions of measures of EPA enforcement activity on measures of ownership. Variable descriptions appear in Table 1. Panel A presents the original data, Panel B presents an adjusted sample, and Panel C presents a matched sample. In all panels, Columns (1)-(4) present firm-level data and columns (5)-(8) present facility-level data. Standard errors are clustered by industry and year and p-values are in parentheses.

Panel A

VARIABLES	(1) numAFR	(2) numJDC	(3) logTotalPenalty	(4) numAFR	(5) numJDC	(6) logTotalPenalty
PrivateIndependent	-0.227*	-0.0264**	-0.251*	-0.0209	-0.00227*	-0.0574**
	(0.05)	(0.05)	(0.08)	(0.12)	(0.05)	(0.03)
PrivateSponsor	0.0232	-0.0269*	-0.00473	0.0142	-0.000865	0.0111
	(0.90)	(0.09)	(0.95)	(0.49)	(0.40)	(0.70)
logTotalRevenue	0.124	0.00270	0.112**	-0.00655***	-0.000611	-0.00682***
	(0.13)	(0.66)	(0.02)	(0.00)	(.)	(0.00)
lagDA	-0.189	-0.00666	-0.0455	-0.0108	-0.00126	-0.0156
	(0.14)	(0.34)	(0.37)	(0.35)	(0.15)	(0.42)
loglagAssets	0.129*	0.00826	0.0713**	-0.00617	-0.000680	-0.0165
	(0.09)	(0.26)	(0.04)	(0.25)	(0.25)	(0.14)
lagNetPPEA	-0.144	-0.0146	-0.104	-0.0254	-0.000260	-0.0502
	(0.64)	(0.39)	(0.61)	(0.44)	(0.91)	(0.38)
Observations	13,186	13,186	13,186	217,373	217,373	217,373
R^2	0.218	0.136	0.261	0.014	0.007	0.016
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC FE	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) adjnumAFR	(2) adjnumJDC	(3) logTotalPenalty	(4) adjnumAFR	(5) adjnumJDC	(6) logadjTotalPenalty
PrivateIndependent	-0.0823	-0.675	-0.251*	-0.646	-2.691	-0.0420**
	(0.66)	(0.15)	(0.08)	(0.48)	(0.22)	(0.02)
PrivateSponsor	-0.0283	-0.219	-0.00473	0.401	0.529	0.0320
	(0.92)	(0.64)	(0.95)	(0.69)	(0.71)	(0.29)
logTotalRevenue	0.276***	0.573***	0.112**	-0.535**	-0.221	-0.00543***
	(0.00)	(0.01)	(0.02)	(0.01)	(0.28)	(0.01)
lagDA	-0.0733	-0.546	-0.0455	-1.064	-2.462**	-0.0312**
	(0.72)	(0.16)	(0.37)	(0.23)	(0.05)	(0.04)
loglagAssets	0.377***	0.0894	0.0713**	-0.507	-1.411	-0.0143
	(0.00)	(0.73)	(0.04)	(0.26)	(0.22)	(0.11)
lagNetPPEA	0.201	-1.628*	-0.104	-3.150	-9.343***	-0.0462
	(0.71)	(0.05)	(0.61)	(0.18)	(0.01)	(0.29)
Observations	7,491	2,059	13,186	203,214	108,517	201,069
R^2	0.105	0.063	0.261	0.005	0.002	0.013
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC FE	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) numAFR	(2) numJDC	(3) logTotalPenalty	(4) numAFR	(5) numJDC	(6) logTotalPenalty
PrivateIndependent	0.0183	-0.0272**	-0.0139	-0.0136	-0.00184	-0.0315
	(0.83)	(0.03)	(0.88)	(0.26)	(0.19)	(0.11)
PrivateSponsor	0.254	-0.0327*	0.143	0.0148	0.00174	0.0209
	(0.32)	(0.08)	(0.25)	(0.32)	(0.20)	(0.10)
logTotalRevenue	0.0123	0.0110*	0.0484	-0.00581	-0.000366	-0.00304
	(0.86)	(0.09)	(0.41)	(0.43)	(0.53)	(0.79)
lagDA	0.0812**	0.00205	0.113	-0.0132	-0.00219	-0.00758
	(0.05)	(0.75)	(0.13)	(0.10)	(0.29)	(0.73)
loglagAssets	0.136	-0.00515	0.107	-0.00532	-0.000978	-0.00335
	(0.16)	(0.51)	(0.11)	(0.30)	(0.29)	(0.62)
lagNetPPEA	-0.0987	0.0264	0.430	0.0309	0.00456	0.135**
	(0.66)	(0.51)	(0.12)	(0.30)	(0.24)	(0.03)
Observations	1,577	1,577	1,577	10,251	10,251	10,251
R^2	0.401	0.221	0.305	0.064	0.060	0.052
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC FE	YES	YES	YES	YES	YES	YES

Table 7: Correlates of emissions

The dependent variable is the log of emissions scaled by revenues. Column (2) uses only private firms, while the other columns, data is only available for public firms. Control variables not shown are *logTotalRevenue*, *loglagTotalAssets*, *lagDA* and *lagNetPPEA*. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses.

VARIABLES	(1) logCO2e	(2) logCO2e	(3) logCO2e	(4) logCO2e	(5) logCO2e	(6) logCO2e	(7) logCO2e	(8) logCO2e	(9) logCO2e	(10) logCO2e
logAge	0.0136									
	(0.90)									
Edgar10K		0.812*								
		(0.06)								
logCountGreenhouseGas			0.0998**							0.0752
			(0.04)							(0.34)
Maxinstown				-0.451						-4.153**
				(0.24)						(0.04)
ActiveMFown					-0.790**					-0.589
					(0.04)					(0.40)
PassiveMFown					-2.185					-7.566**
					(0.16)					(0.04)
Boardsize						-0.0747**				-0.0939**
						(0.02)				(0.02)
ERC_suedecile							16.05***			22.01
							(0.00)			(0.27)
GParachute								0.378**		0.394*
								(0.03)		(0.09)
CBoard									-0.0775	-0.0525
									(0.68)	(0.76)
Observations	912	287	2,336	2,358	2,325	1,507	2,344	1,562	1,562	1,303
R^2	0.778	0.864	0.715	0.738	0.747	0.803	0.739	0.802	0.800	0.829
By	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix A. Data collection

This Appendix provides additional detail about our sample and data collection methodology. We download Capital IQ data on all variables that we use in the paper for the years 2006-2017, accessing the terminal from January 30 though February 3 2018. This produces data on 13,393 U.S.-based firms and subsidiaries. Of these entities, 10,957 have more than one year of data with total assets, total debt and total revenue defined. We use this subsample to match with the EPA data.

Data from the publicly available EPA data download site only provide the current name of each facility. Through a Freedom of Information Act request with the EPA, we obtained the list of all historical facility names and associated first and last dates that these facility names were used in correspondence with the EPA. For example, the facility with registry_id number 110022482277 went by the name *KERR-MCGEE - COTTONWOOD COMPRESSOR* first on February 4 2006 and last on January 8 2009, and by the name *ANADARKO / KERRM-CGEE COTTONWOOD C.S.* from December 28 2009 to the time that the FOIA request was fulfilled, October 26 2017. Our contact person at the EPA cautioned that the dates are not extremely accurate prior to 2006. This dataset contains 7,623,443 lines and 6,326,404 unique registry_ids. The registry_id is the most commonly used identifier at the EPA uses for facilities, though most EPA programs produce data with their own set of identifiers.

We first regularize the names in the EPA data, replacing for example the strings *Corporation* and *Company* with *Co* and removing punctuation. Next, to match the EPA data to the Capital IQ data, we create a set of simple but unique keywords and matching rules for each Capital IQ firm. For example, the keyword for ExxonMobil would be simply *Exxon*, since this keyword is unique enough, but the keywords for Archer Daniels Midland would be the strings *Archer Daniels* or *ADM*. For other firms, such as Harry & David, we require the presence of the string *Harry* and that of the string *David* to generate a match. We execute these rules in Stata to produce a list of facility matches for each Capital IQ firm. Then, we examine each match by hand and delete the matches that are incorrect. For example, our hand check removed a facility named *RUFUS CLEAN UPS* from matches to United Parcel Service. When these names are not completely clear, we look up the firm to confirm that it has facilities in the city and state given for that facility by the EPA. When in doubt, the facility is omitted.

This matching process leaves many facility-date observations in the EPA data unmatched. We manually go through all of the the unmatched facility name-date combinations for the Clean Air Markets (2,547 lines) and GHGRP (15,256 lines) to look for missed matches or facilities that are listed under the names of subsidiaries that belong to the Capital IQ firms. For each facility name and associated date range, we determine whether it should be a match to our Capital IQ firms using a Google search of the name and/or of the facility's address if necessary. This check catches, for example, all of the spellings of *LA-Z-BOY INC* that we did not anticipate, facility name misspellings in the EPA data such as *PIONEER NATRUAL RESOURCES*, and also subsidiaries that do not appear as entities in our Capital IQ sample. For example, BFI Waste Systems is a subsidiary of Republic Services, Inc. (NYSE:RSG) throughout our sample period, but there is no Capital IQ entry for BFI Waste, so facilities with EPA data under the BFI name would have gone unmatched without this process.

In some cases, we find that facilities are joint ventures between two firms in our Capital IQ data. In this case, we attempt to determine the operator of the facility. If we cannot, we do not use the facility. Phillips 66 and Spectra Energy have multiple 50/50 joint ventures for which we cannot determine the operator, and we do not include these. Offshore facilities are especially difficult to attribute. These facility names are generally vague - for example *WD 143 A/B*, and there is of course no address associated with them except for *OFFSHORE* in the city field. Moreover, even identified offshore facilities are often found to be shared by several firms, so they are excluded from our data.

Facilities that remain unmatched after this process include firms headquartered outside the U.S. (*ARCELORMITTAL USA LLC*), universities (*UNIVERSITY OF NORTHERN IOWA - POWER PLANT*), hospitals (*THE JOHNS HOPKINS HOSPITAL*), prisons (*NYC-DOC - RIKERS ISLAND*), facilities for all levels of government (*PENTAGON*), Native American tribal facilities (*MOHEGAN TRIBE OF INDIANS OF CONNECTICUT*), and names that we cannot reliably attribute to a firm in our data (*ST. CLAIR*, with no address given).

In this sample, the number of public firms is not decreasing as it is, for example, in Doidge, Karolyi and Stulz (JFE 2017). Due to the labor intensity of manual lookups, we did not determine the status of the Capital IQ firms that did not match with EPA data in any year and are therefore not in the paper's data set. Thus, we cannot calculate the proportion of private firms in all of Capital IQ and whether it is increasing.
Like Doidge, Karolyi and Stulz (2017), we begin with all CRSP firms that have a match to Compustat and have share codes 10 and 11 and remove SIC codes 6722, 6798, and 6799. We then merge this with our data set using hand-collected gvkeys (CIKs are not always accurate and not always unique) and keep the matches and the CRSP/Compustat firm years that do not match to our data set. By matching our data set with CRSP/Compustat, we achieve comparability with Doidge, Karolyi and Stulz (2017) and match to a known comprehensive sample of public firms. Figure F1 presents the results annually. The dark bars represent the firms in CRSP/Compustat that do not match with our data, and the light bars represents the firms in CRSP/Compustat that match with our data. As you can see, the total number of public firms in this sample decreases, but the number of firms that match with our data does not decrease. Recall that to be in our data set, the firms must appear in Capital IQ and also have a match in the EPA data.

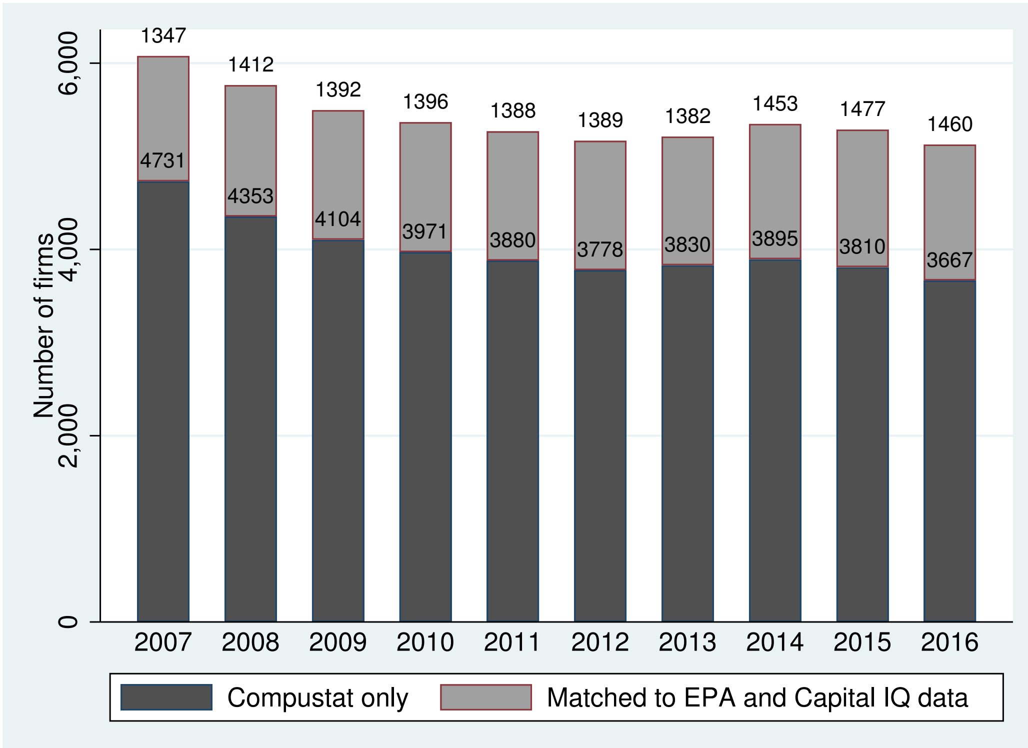


Figure F1: CRSP/Compustat merged data with share codes 10 and 11, excluding SIC codes 6722, 6798 and 6799.

One might ask whether this result is due to increased match rate of our data with EPA data in the later years coupled with a drop off in the number of public firms, or whether our matching public firms are simply not the ones disappearing. In some cases, like 1-800-Flowers, the firm exists in Capital IQ and in Compustat during the entire period, but the EPA data only has the firm from 2015-2016. Evidence points to the latter explanation, however. Each year, the rate of new matches entering the sample is between 0.5% and 2% of the sample, and the dropout rate is similar. Also, the median total assets of firms in the unmatched Compustat sample is $565M, while the median total assets of firms in the matched sample is $1,515M. This leads us to believe that the types of firms that are disappearing from Compustat are less likely to be in our sample than are the larger firms.

Appendix B. Endogeneity of the decision to be public

A firm's decision of whether to be public or private is not exogenous, and it could be the case that a factor that we have not considered is driving both the decision to be publicly traded and the decision of how much to pollute. The potential endogeneity of listed status is a well-known problem in the literature on public and private firms. We first present a list of studies with the same concern and the solutions that they have employed.

The literature's response to potential endogeneity between the listing decision and the effect studied.

Table B1: The literature's response to potential endogeneity

Paper	Paper's main findings	Data source	Period	Solution to potential endogeneity
Acharya and Xu (2017), JFE	Public firms in external finance dependent industries spend more on R&D and generate more patents, but results do not hold for internal finance dependent industries.	Capital IQ	1994-2004	(1) Predict public status and control for inverse Mills Ratio, and (2) Nasdaq delisting discontinuity fuzzy regression approach
Asker, Farre-Mensa, and Ljungqvist (2015), RFS	Compared to private firms, public firms invest less and are less responsive to changes in investment opportunities.	Sageworks	2001-2011	Within-firm variation in listing status for a sample of firms that go public without raising new capital and so change only their ownership structure. Also instrumenting a firm?s listing status with plausibly exogenous variation in the supply of start-up funding across U.S. states and time.
Bernstein (2005), JF	Quality of internal innovation declines following the IPO. Skilled inventors leave and there is a decline in the productivity of the remaining inventors.	Thomson SDC New Issues iPO filings	1985-2003	NASDAQ fluctuations during the book-building phase are used as an instrument for IPO completion.
Brav (2009), JF	Private firms have higher leverage ratios and their capital structures are more sensitive to performance.	UK FAME database	1993-2003	Use variation within sample in ownership dispersion and transparency
Gao, Harford, and Li (2013), JFE	Public firms pay higher dividends and smooth them more than private firms do.	Capital IQ	1995-2011	(1) treatment regression approach, (2) propensity score matching with industry-level underwriter concentration as in Liu and Ritter 2011 in Fama-French industries, 3) transition sample that do secondary offerings changing their listing status without receiving the proceeds.

Gilge and Taillard (2016), JF	Private firms respond less than public firms to changes in investment opportunities	Projects in the natural gas industry	1997-2012	"Because of the endogenous nature of the listing decision, we do not rule out the possibility that other factors could also affect the investment behavior of private and public firms. ...Although we do not have a randomized experiment, our empirical design and quasi-natural experiment limit the potential impact of confounding variables."
Maksimovic, Phillips, and Yang (2013), JF	Public firms participate in merger waves more than private firms and realize higher productivity gains.	Census	1977-2004	Predict public status using size and productivity at birth, use propensity score.
Michaely and Roberts (2012), RFS	Private firms smooth dividends less than public firms and pay lower dividends.	UK FAME database	1993-2002	(1) a propensity score matched sample (firm size, profitability, leverage, investment opportunities (sales growth), and industry); and (2) a sample of firms that undergo a transition from private to public status (or vice versa).
Mortal and Reisel (2013), JFQA	Public firms havee higher investment sensitivity to growth opportunities than private firms.	Europe: 2007 version of Amadeus by BvD	1996-2006	Self -selection model and a subsample of firms that changed status from private to public
Phillips and Sertsios (2016), RFS	Public firms find it easier to find financing.	Capital IQ	1998-2010	(1) Matched samples based on products, productivity and size (2) Compare public firms to a sample of private firms that have equity investments from financial institutions, since these have been shown to be more similar to public firms. (3) Compare firmst hat attempted an IPO to firms that did not.

We focus on the prescriptions of the studies that also use Capital IQ data, which oversamples the largest and most visible private firms. As in Acharya and Xu (2017) we estimate and control for the inverse mills ratio from a selection model that predicts private status.
Table B2 presents the first stage of the estimation of the models to predict private independent or private sponsor status. We use the same variables as Acharya and Xu (2017) except that we do not have access to their innovation variables. We then use the inverse mills ratios from this model as explanatory variables in Tables B3 and B4. We find that although they are often significantly related to the dependent variables, they do not change our results.

Table B2: First stage probit model

The probit model is of the decision to be an independent private firm or a sponsor-backed private firm for estimation of inverse mills ratio. WROA is the return on assets winsorized at the 1% level, TotalRevenueGrowth is the growth in total revenues since the prior year, and WPPEGrowth is the growth in property, plant and equipment since the prior year. All are from Capital IQ.

VARIABLES	(1) PrivateIndependent	(2) PrivateSponsor	(3) PrivateIndependent	(4) PrivateSponsor
WROA	0.128**	-0.161**	0.642***	-3.354***
	(0.02)	(0.01)	(0.00)	(0.00)
logTotalRevenue	-0.0574***	0.0101	-0.187***	-0.0966***
	(0.00)	(0.32)	(0.00)	(0.00)
WTotalRevenuegrowth	0.0354	0.0868*	-0.131***	0.0770***
	(0.33)	(0.06)	(0.00)	(0.00)
WPPEgrowth	-0.108*	-0.0475	-0.945***	0.125***
	(0.06)	(0.52)	(0.00)	(0.00)
Observations	16,403	16,403	592,427	592,427
By	Firm	Firm	Facility	Facility
Pseudo R^2	0.00982	0.00272	0.0929	0.128

Table B3: Controlling for the inverse mills ratio: emissions.

The dependent variable is the log of emissions scaled by revenues. Control variables not shown are *loglagTotalAssets*, *lagNetPPEA*, and *lagDA*. Variable descriptions appear in Table 1. Columns (1)-(4) present firm-level data and columns (5)-(8) present facility-level data. Standard errors are clustered by industry and year and p-values are in parentheses.

VARIABLES	(1) logCO2eG	(2) logCO2C	(3) logNOC	(4) logSO2C	(5) logCO2eG	(6) logCO2C	(7) logNOC	(8) logSO2C
PrivateIndependent	-0.427*	-1.210***	-2.074***	-4.561***	-0.0718	-1.483***	-1.630***	-2.411***
	(0.06)	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.131	0.585	0.301	0.633	0.0365	-0.385	-0.122	0.0703
	(0.49)	(0.53)	(0.69)	(0.58)	(0.53)	(0.31)	(0.76)	(0.90)
IMR_I	2.272**	3.298	2.141	-9.572	-0.0281*	-0.107	0.0120	-0.119
	(0.01)	(0.72)	(0.82)	(0.46)	(0.09)	(0.72)	(0.97)	(0.83)
IMR_S	-0.816	-8.945	-7.945	-4.490	-0.0782	0.101	-0.208	-0.628
	(0.42)	(0.22)	(0.28)	(0.73)	(0.12)	(0.49)	(0.54)	(0.31)
logTotalRevenue	0.123**	0.569	0.575	1.171	0.0369*	-0.0411	0.0455	0.756***
	(0.03)	(0.25)	(0.28)	(0.14)	(0.09)	(0.91)	(0.86)	(0.00)
lagDA	0.0143	1.959**	2.137***	5.780***	0.0184	0.419	0.0526	0.742
	(0.92)	(0.01)	(0.00)	(0.01)	(0.47)	(0.56)	(0.96)	(0.70)
loglagAssets	0.115*	0.350	0.277	0.362	0.0139	0.0617	-0.0483	-0.638**
	(0.10)	(0.27)	(0.32)	(0.51)	(0.51)	(0.85)	(0.88)	(0.02)
lagNetPPEA	0.673*	2.083	0.763	-2.870	0.0962	-0.347	-0.160	-0.191
	(0.08)	(0.36)	(0.75)	(0.41)	(0.29)	(0.35)	(0.65)	(0.74)
Observations	2,574	731	735	688	18,106	5,407	5,535	4,479
R^2	0.689	0.677	0.720	0.728	0.244	0.185	0.251	0.317
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	-0.624*	-1.259***	-2.123***	-4.538***	-0.266*	-1.505***	-1.654***	-2.430***
	(0.06)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.450	0.643	0.358	0.611	0.264*	-0.215	0.0333	0.0917
	(0.26)	(0.50)	(0.65)	(0.61)	(0.09)	(0.49)	(0.92)	(0.86)
IMR_I	0.537	-1.936	-3.023	-7.575	-1.893***	-1.844**	-1.587**	-0.547
	(0.80)	(0.68)	(0.52)	(0.42)	(0.00)	(0.01)	(0.02)	(0.36)
IMR_S	2.274	-5.543	-4.587	-5.816	-1.048***	-0.674***	-0.913**	-0.815
	(0.24)	(0.38)	(0.31)	(0.56)	(0.00)	(0.00)	(0.05)	(0.13)
lagDA	0.0235	2.058***	2.236***	5.734***	-0.0931	0.472	0.104	0.764
	(0.92)	(0.00)	(0.00)	(0.00)	(0.26)	(0.57)	(0.92)	(0.69)
loglagAssets	-0.198*	0.178	0.107	0.434	-0.388***	-0.607***	-0.665***	-0.794***
	(0.10)	(0.39)	(0.58)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)
lagNetPPEA	1.644**	1.770	0.455	-2.742	0.188	-0.628*	-0.432	-0.285
	(0.02)	(0.39)	(0.84)	(0.39)	(0.53)	(0.09)	(0.26)	(0.62)
Observations	2,574	731	735	688	18,106	5,407	5,536	4,480
R^2	0.713	0.657	0.726	0.740	0.463	0.265	0.319	0.339
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	-0.790**	-0.787**	-0.823**	-0.519***	-0.513***	-1.180***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
PrivateSponsor	0.260	0.385	0.695	0.0240	0.0349	-0.0294
	(0.55)	(0.44)	(0.26)	(0.81)	(0.73)	(0.89)
IMR_I	4.279*	4.272	4.573*	0.289**	0.291**	1.752***
	(0.07)	(0.13)	(0.07)	(0.03)	(0.02)	(0.00)
IMR_S	-0.977	-0.664	2.375	-0.0682	-0.0132	0.276
	(0.66)	(0.82)	(0.37)	(0.54)	(0.91)	(0.20)
logTotalRevenue	0.493***	0.531***	1.339***	0.101**	0.0904*	-0.0636
	(0.00)	(0.00)	(0.00)	(0.04)	(0.09)	(0.70)
lagDA	0.00159	-0.0180	0.117	0.0197	0.0390	-0.165
	(1.00)	(0.95)	(0.72)	(0.84)	(0.63)	(0.38)
loglagAssets	0.118	0.0790	-0.633***	0.0625	0.0620	-0.104
	(0.31)	(0.55)	(0.00)	(0.10)	(0.12)	(0.38)
lagNetPPEA	1.765**	1.700**	-0.274	0.597*	0.560	0.582**
	(0.02)	(0.03)	(0.74)	(0.10)	(0.11)	(0.04)
Observations	2,789	2,122	465	19,802	19,330	1,755
R^2	0.706	0.475	0.781	0.228	0.161	0.321
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.834***	-0.753**	-0.771**	-0.835***	-0.804**	-1.258***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
PrivateSponsor	0.406	0.593	0.566	-0.372***	-0.0903	-0.0218
	(0.34)	(0.22)	(0.33)	(0.01)	(0.27)	(0.95)
IMR_I	0.268	0.00546	5.986*	-1.940***	-2.160***	0.619
	(0.89)	(1.00)	(0.06)	(0.00)	(0.00)	(0.17)
IMR_S	2.044	1.552	1.081	-0.883***	-0.142	-0.230
	(0.30)	(0.42)	(0.72)	(0.00)	(0.77)	(0.44)
lagDA	0.0122	-0.104	0.0859	0.401	0.412	0.0101
	(0.96)	(0.73)	(0.80)	(0.12)	(0.13)	(0.97)
loglagAssets	-0.182	-0.144	-0.385**	0.123	0.106	-0.223
	(0.12)	(0.24)	(0.05)	(0.12)	(0.18)	(0.16)
lagNetPPEA	1.779***	1.626**	-0.123	0.233	0.378	-0.117
	(0.01)	(0.02)	(0.88)	(0.71)	(0.47)	(0.85)
Observations	2,789	2,122	465	19,802	19,301	1,755
R^2	0.707	0.234	0.738	0.419	0.241	0.365
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Table B4: Controlling for the inverse mills ratio: EPA actions and penalties.

Columns (1)-(4) present firm-level data and columns (5)-(8) present facility-level data. Control variables not shown are *loglagTotalAssets*, *lagNetPPEA*, and *lagDA*. Standard errors are clustered by industry and year and p-values are in parentheses.

VARIABLES	(1) numAFR	(2) numJDC	(3) logTotalPenalty	(4) numAFR	(5) numJDC	(6) logTotalPenalty
PrivateIndependent	-0.184	-0.0248**	-0.230	-0.0213*	-0.00194	-0.0568**
	(0.12)	(0.05)	(0.11)	(0.08)	(0.12)	(0.02)
PrivateSponsor	0.0229	-0.0237*	-0.0134	0.0185	-0.00118	0.0166
	(0.89)	(0.06)	(0.85)	(0.37)	(0.23)	(0.57)
logTotalRevenue	0.146*	0.00184	0.128***	-0.00877***	-0.000657	-0.0104***
	(0.09)	(0.76)	(0.01)	(0.00)	(.)	(0.00)
IMR_I	0.722*	0.0668	0.367	0.0203	0.00242	0.0376
	(0.08)	(0.11)	(0.14)	(0.16)	(0.23)	(0.18)
IMR_S	0.605	-0.0742	0.701	0.0131**	-0.00153	0.0147*
	(0.40)	(0.21)	(0.13)	(0.03)	(0.18)	(0.09)
Observations	15,339	15,339	15,339	218,044	218,044	218,044
R^2	0.221	0.136	0.269	0.014	0.007	0.016
By	Firm	Firm	Firm	Facility	Facility	Facility
Controls	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Appendix C

This Appendix contains additional summary statistics and tests . Table C1 presents facility-level summary statistics. Table C2 presents the effect of removing the years 2014-2016. Table C3 uses 2-digit SIC industries instead of 4-digit industries. Table C4 uses Compustat Industry revenue and fuel cost data to scale emissions data. Table **??** uses firm fixed effects to identify switchers, and Table C6 examines the proportion of minority residents in the 3-mile radius around the emitting facility. Tables B2, B3 and B4 present a probit model modeling the decision to be a private firm and controlling for the inverse mills ratio.

Table C1: Facility-level summary statistics

Facility-level summary statistics. Variable descriptions appear in Table 1. In t tests for differences with public firms, ***, ** and * signify significance at the 1, 5 and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public		Private Independent		Private Sponsor			
VARIABLES	mean	p50	mean	p50	mean	p50	sd	N
CO2eG	0.611	0.0691	1.009***	0.0935	0.927***	0.0606	1.816	18,132
CO2C	2.350	0.750	1.451***	0.138	2.766	0.369	3.760	5,411
NOC	0.00203	0.000210	0.00173	5.10e-05	0.00147*	0.000178	0.00393	5,540
SO2C	0.00618	5.00e-05	0.00409**	4.00e-06	0.00845*	6.00e-06	0.0152	4,482
CO2e	0.792	0.0746	1.107***	0.100	1.094***	0.0673	2.254	19,828
logCO2eG	0.277	0.0659	0.373***	0.0884	0.300	0.0587	0.501	18,266
logCO2C	-0.778	-0.287	-1.711***	-1.980	-0.658	-0.998	2.338	5,411
logNOC	-8.329	-8.468	-9.173***	-9.884	-8.434	-8.636	2.489	5,540
logSO2C	-9.041	-9.903	-10.13***	-12.43	-10.46***	-12.02	3.941	4,482
logCO2e	-2.198	-2.595	-2.118	-2.301	-2.194	-2.698	1.984	19,828
CO2eG_R	0.000125	8.39e-06	0.000872***	0.000153	0.000305***	3.10e-05	0.00104	18,132
CO2C_R	0.000399	7.64e-05	0.00130***	0.000141	0.000670***	0.000112	0.00133	5,411
NOC_R	3.42e-07	2.67e-08	1.55e-06***	6.59e-08	3.34e-07	2.95e-08	1.45e-06	5,540
SO2C_R	8.74e-07	7.31e-09	3.97e-06***	4.38e-09	1.36e-06*	1.17e-09	3.43e-06	4,482
CO2e_R	0.00223	0.000235	0.00490***	0.000480	0.00310	0.000488	0.0119	19,828
logCO2eG_R	-11.53	-11.69	-9.079***	-8.788	-10.01***	-10.38	2.297	18,132
logCO2C_R	-9.867	-9.479	-8.655***	-8.868	-9.119***	-9.101	2.471	5,411
logNOC_R	-17.42	-17.44	-16.07***	-16.53	-16.92**	-17.34	2.619	5,540
logSO2C_R	-18.18	-18.73	-17.05***	-19.25	-18.95**	-20.57	4.007	4,482
logCO2e_R	-8.446	-8.355	-7.682***	-7.642	-7.523***	-7.625	2.388	19,828
CO2e_GEN	907.41	813.00	833.51	726.32	725.04*	680.66	1,347.31	5,315
logCO2e_GEN	6.649	6.700	6.622	6.58	6.49***	6.523	0.633	5,315
NetGeneration (M)	2.699	1.043	1.485***	0.203	2.8739	0.565	3.751	5,315
PlantAge	28.31	28.77	18.74***	13	26.66	26.50	16.85	5,562
numAFR	0.0104	0	0.0106	0	0.0244***	0	0.221	582,768
numJDC	0.000896	0	0.000308*	0	0.000604	0	0.0315	582,768
TotalPenalty	29.06	0	0.306	0	24.67	0	4,302	582,768
TotalRevenue	93,623	22,138	6,229***	4,608	5,152***	5,370	143,731	582,768
lagDA	0.283	0.272	0.443***	0.428	0.646***	0.602	0.185	582,768
lagAssets	9,670	4,147	2,063***	668.1	8,833	1,543	39,523	218,281
lagNetPPEA	0.479	0.541	0.297***	0.195	0.319***	0.237	0.225	582,768
Edgar10K	1.000	1	0.228***	0	0.427***	0	0.141	582,768

Table C2: Emissions - removing years 2014-2016

In this section, we examine the effects of removing years 2014-2016 because Capital IQ has more missing data for private firms in those years. While there are more than 7% of private firms in the earlier years, there are 7%, 5.8% and 5% in 2014, 2015 and 2016. This table presents regressions of measures of reported emissions scaled by revenue on measures of ownership. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses. Columns (1) and (4) present the combined emissions variable; Columns (2) and (5) present the adjusted dependent variable which divides by the mean from that industry-year, and column (3) and (6) present the matched sample.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	logCO2eG	logCO2C	logNOC	logSO2C	logCO2eG	logCO2C	logNOC	logSO2C
PrivateIndependent	-0.255	-1.696***	-2.682***	-5.872***	-0.0698	-1.637***	-1.777***	-2.645***
	(0.28)	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.117	-0.188	-0.279	0.0294	0.0374	-0.593	-0.140	0.00639
	(0.62)	(0.87)	(0.77)	(0.99)	(0.59)	(0.18)	(0.76)	(0.99)
logTotalRevenue	0.128***	0.831	0.877	0.679	0.0172	0.0795	0.0598	0.521**
	(0.00)	(0.25)	(0.17)	(0.50)	(0.45)	(0.80)	(0.85)	(0.03)
lagDA	-0.246	3.818***	4.094***	10.24***	0.0459	0.818	0.227	0.998
	(0.18)	(0.00)	(0.00)	(0.00)	(0.23)	(0.43)	(0.87)	(0.70)
loglagAssets	0.215***	0.321	0.104	0.250	0.0240	-0.0372	-0.0678	-0.532*
	(0.00)	(0.66)	(0.86)	(0.76)	(0.39)	(0.90)	(0.84)	(0.06)
lagNetPPEA	0.483	2.276	0.906	-2.550	0.0571	-0.220	-0.105	-0.377
	(0.23)	(0.24)	(0.66)	(0.38)	(0.52)	(.)	(0.12)	(0.33)
Observations	1,441	519	520	485	9,564	3,723	3,801	3,010
R^2	0.698	0.711	0.727	0.739	0.250	0.186	0.244	0.317
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	-0.188	-1.719***	-2.700***	-5.940***	-0.193	-1.665***	-1.821***	-2.700***
	(0.60)	(0.00)	(0.00)	(0.00)	(0.34)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.370	-0.145	-0.249	0.103	0.567*	-0.186	0.266	0.187
	(0.41)	(0.90)	(0.80)	(0.95)	(0.06)	(0.58)	(0.54)	(0.78)
lagDA	-0.374	3.886***	4.143***	10.42***	0.0382	1.312	0.767	1.317
	(0.43)	(0.00)	(0.00)	(0.00)	(0.87)	(0.34)	(0.64)	(0.64)
loglagAssets	-0.172**	0.164	-0.0115	-0.0518	-0.755***	-0.883***	-0.938***	-0.974***
	(0.02)	(0.14)	(0.93)	(0.82)	(0.00)	(0.00)	(0.00)	(0.00)
lagNetPPEA	1.324	2.238	0.876	-2.660	-0.0198	-0.237	-0.148	-0.440
	(0.12)	(0.23)	(0.66)	(0.34)	(0.96)	(.)	(0.46)	(0.27)
Observations	1,441	519	520	485	9,564	3,723	3,802	3,011
R^2	0.726	0.680	0.730	0.751	0.450	0.245	0.292	0.339
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	-0.567	-0.550	-0.201	-0.499*	-0.488*	-0.988***
	(0.16)	(0.17)	(0.74)	(0.05)	(0.05)	(0.01)
PrivateSponsor	0.0822	0.255	0.458	-0.0266	-0.0269	-0.612
	(0.87)	(0.65)	(0.57)	(0.86)	(0.87)	(0.10)
logTotalRevenue	0.458***	0.532***	1.327***	0.0820**	0.0674	-0.0958
	(0.00)	(0.00)	(0.00)	(0.05)	(0.10)	(0.20)
lagDA	-0.417	-0.466	-0.957	-0.121	-0.109	-0.423
	(0.41)	(0.38)	(0.25)	(0.54)	(0.52)	(0.24)
loglagAssets	0.340***	0.291**	-0.232**	0.117**	0.128***	0.257*
	(0.00)	(0.04)	(0.02)	(0.02)	(0.01)	(0.08)
lagNetPPEA	1.668*	1.640*	-1.015	0.446	0.463	-0.0518
	(0.05)	(0.07)	(0.43)	(0.24)	(0.21)	(0.94)
Observations	1,658	1,267	303	11,145	10,866	1,073
R^2	0.717	0.507	0.816	0.243	0.174	0.378
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.622	-0.537	-0.0435	-0.939***	-0.884***	-1.251***
	(0.11)	(0.16)	(0.94)	(0.00)	(0.01)	(0.00)
PrivateSponsor	0.306	0.544	0.345	-0.0569	0.124	-0.0988
	(0.52)	(0.29)	(0.64)	(0.62)	(0.44)	(0.87)
lagDA	-0.398	-0.520	-1.075	0.389	0.423	-0.0433
	(0.43)	(0.35)	(0.24)	(0.34)	(0.28)	(0.93)
loglagAssets	-0.164**	-0.108	0.0645	-0.245***	-0.217***	-0.0908
	(0.03)	(0.13)	(0.80)	(0.00)	(0.00)	(0.66)
lagNetPPEA	1.604*	1.620*	-1.017	0.641	0.975*	-0.775
	(0.07)	(0.07)	(0.41)	(0.30)	(0.08)	(0.49)
Observations	1,658	1,267	303	11,145	10,840	1,073
R^2	0.715	0.305	0.782	0.415	0.232	0.385
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Table C3: Emissions - SIC 2-digit fixed effects instead of SIC 4-digit fixed effects

This table presents regressions of measures of reported emissions scaled by revenue on measures of ownership. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses. Columns (1) and (4) present the combined emissions variable; Columns (2) and (5) present the adjusted dependent variable which divides by the mean from that industry-year, and column (3) and (6) present the matched sample.

Panel A

VARIABLES	(1) logCO2eG	(2) logCO2C	(3) logNOC	(4) logSO2C	(5) logCO2eG	(6) logCO2C	(7) logNOC	(8) logSO2C
PrivateIndependent	0.0967	-1.117**	-1.832***	-4.190***	0.114	-1.469***	-1.449***	-1.769***
	(0.58)	(0.02)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.0979	0.679	0.330	1.186	0.0676	-0.299	0.150	0.944
	(0.63)	(0.49)	(0.67)	(0.43)	(0.50)	(0.40)	(0.75)	(0.31)
logTotalRevenue	0.0941	-0.102	-0.254	-0.723	-0.0719	-0.102	-0.141	0.131
	(0.12)	(0.75)	(0.47)	(0.21)	(0.16)	(0.77)	(0.62)	(0.49)
lagDA	0.106	2.444***	2.701***	5.130***	-0.0655	0.121	-0.642	-1.428
	(0.33)	(0.00)	(0.00)	(0.00)	(0.33)	(0.83)	(0.55)	(0.58)
loglagAssets	0.202***	0.971***	1.007***	1.446**	0.126**	0.118	0.132	-0.103
	(0.01)	(0.00)	(0.01)	(0.02)	(0.05)	(0.71)	(0.64)	(0.70)
lagNetPPEA	0.883***	3.236	2.240	0.154	0.588***	-0.0679	-0.148	-0.532
	(0.00)	(0.10)	(0.28)	(0.96)	(0.00)	(0.87)	(0.70)	(0.29)
Observations	2,579	732	736	689	18,132	5,411	5,539	4,481
R^2	0.503	0.591	0.630	0.640	0.107	0.184	0.247	0.305
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	0.186	-1.174	-1.883***	-4.292***	0.233	-1.405***	-1.388	-1.783***
	(0.51)	(.)	(0.00)	(0.00)	(0.39)	(0.00)	(.)	(0.00)
PrivateSponsor	0.482	1.036	0.727	1.832	0.712***	0.435***	0.911***	1.492***
	(0.28)	(0.13)	(0.23)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)
lagDA	0.196	2.750***	3.024***	5.572***	-0.230*	0.0891	-0.652***	-1.387***
	(0.49)	(0.00)	(0.00)	(0.00)	(0.09)	(0.66)	(0.00)	(0.00)
loglagAssets	-0.218**	-0.0321**	-0.134	-0.122***	-0.667***	-0.906***	-0.932***	-0.917***
	(0.05)	(0.05)	(.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lagNetPPEA	2.432***	3.500*	2.491	0.443	2.457***	0.241***	0.157	-0.371
	(0.00)	(0.07)	(0.19)	(0.89)	(0.00)	(0.00)	(0.46)	(0.37)
Observations	2,579	732	736	689	18,132	5,411	5,540	4,482
R^2	0.537	0.551	0.624	0.643	0.356	0.259	0.310	0.325
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC2 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	0.159	-0.170	-0.216	-0.0624	-0.733**	-0.301
	(0.63)	(0.75)	(0.61)	(0.80)	(0.02)	(0.45)
PrivateSponsor	0.262	0.706	-0.0410	0.135	-0.190	-0.616**
	(0.57)	(0.22)	(0.93)	(0.51)	(0.15)	(0.02)
logTotalRevenue	0.423***	0.653***	0.846***	0.224***	-0.183*	-0.0621
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.65)
lagDA	0.133	-0.283	0.521	-0.0517	0.211	0.0506
	(0.50)	(0.36)	(0.15)	(0.78)	(0.15)	(0.84)
loglagAssets	0.311**	0.0280	0.0225	0.0806	0.0704	0.331**
	(0.04)	(0.82)	(0.93)	(0.10)	(0.18)	(0.01)
lagNetPPEA	2.446***	1.832***	0.886	1.606***	-0.782***	0.325
	(0.00)	(0.01)	(0.19)	(0.00)	(0.01)	(0.50)
Observations	2,794	2,125	465	19,828	19,356	1,755
R^2	0.544	0.370	0.642	0.144	0.093	0.250
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC2 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	0.0947	-0.430	-0.241	-0.555	-1.198***	-0.773**
	(0.75)	(0.13)	(0.57)	(0.14)	(0.00)	(0.03)
PrivateSponsor	0.480	0.762*	0.0281	-0.0470	-0.154	0.278
	(0.28)	(0.09)	(0.95)	(0.80)	(0.50)	(0.43)
lagDA	0.167	-0.0863	0.544	0.772***	0.804**	0.498*
	(0.43)	(0.79)	(0.15)	(0.00)	(0.03)	(0.07)
loglagAssets	-0.209***	-0.0673	-0.114	-0.309***	-0.313***	-0.193**
	(0.00)	(0.34)	(0.57)	(0.00)	(0.00)	(0.02)
lagNetPPEA	2.560***	0.936	0.852	0.222	-1.323**	-0.0212
	(0.00)	(0.12)	(0.20)	(0.75)	(0.04)	(0.97)
Observations	2,794	2,125	465	19,828	19,327	1,755
R^2	0.541	0.186	0.575	0.332	0.165	0.248
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC2 FE	YES	YES	YES	YES	YES	YES

Table C4: Emissions scaled by utility-specific fuel cost and by measures of operating revenue

The Compustat Industry Specific database provides measures of output for utilities, which we use to scale their emissions. These output measures are *ufcostt* (fuel cost for electric generation provided by schedule USR), *uopereuct* (Operation Revenues Electric Ultimate Customers), and *uopre* (Operating Revenues Electric - Income Statement). As we do with total revenues in the body of the paper, for the facility-level data, we divide the firm-level revenue variable by the number of facilities that the firm has. As there is only one private independent firm (Old Dominion Electric Cooperative) that has Compustat Industry, Capital IQ and EPA emissions data, we use the Private identifier rather than distinguishing between private independent and private sponsor-backed firms. This table shows that emissions scaled by these more precise variables are lower for private firms. The economic significance of being private is roughly half of a standard deviation of these dependent variables. Panel A presents summary statistics for the new Compustat Industry variables at the firm level, Panel B presents summary statistics at the facility level, and Panel C presents regressions at the firm level (columns 1-3) and at the facility level (columns 4-6). Control variables not shown are *loglagTotalAssets*, *lagDA*, and *lagNetPPEA*. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses. There are 6 SIC codes in this data.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Public				Private		
	mean	p50	sd	N	mean	p50	sd	N
ufcostt	1,300	680.6	1,523	183	187.8	202.2	55.65	18
uopereuct	3,364	1,788	3,858	242	2,070	2,070	47.38	9
uopre	4,184	2,262	4,570	339	3,196	2,128	2,754	26
logCO2e_ufcostt	-4.285	-4.022	1.373	183	-5.504	-5.512	0.641	18
logCO2e_uopereuct	-6.252	-5.598	1.868	242	-7.485	-7.287	0.659	9
logCO2e_uopre	-6.393	-5.684	1.871	339	-6.738	-7.079	1.363	26

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Public				Private		
	mean	p50	sd	N	mean	p50	sd	N
ufcostt	2,561	2,312	1,855	2,157	208.1	212.3	52.08	81
uopereuct	6,409	5,909	4,975	2,042	2,076	2,070	43.61	57
uopre	7,605	6,521	6,090	3,090	4,865	5,636	2,818	201
logCO2e_ufcostt	-8.536	-8.467	2.695	2,157	-7.425	-7.210	1.281	81
logCO2e_uopereuct	-9.611	-9.500	2.545	2,042	-9.910	-9.884	1.375	57
logCO2e_uopre	-9.815	-9.681	2.592	3,090	-9.501	-9.627	1.992	201

Panel C

VARIABLES	(1) logCO2e	(2) logCO2e	(3) logCO2e	(4) logCO2e	(5) logCO2e	(6) logCO2e
Private	-1.050***	-1.142***	-1.059***	-0.665***	-0.896***	-0.340
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.18)
logufcostt	1.020***			0.603**		
	(0.01)			(0.05)		
loguopereuct		1.941			0.0690	
		(0.18)			(0.87)	
loguopre			0.646			-0.0506
			(0.21)			(0.41)
Observations	201	251	365	2,238	2,099	3,291
R^2	0.626	0.445	0.488	0.045	0.084	0.075
By	Firm	Firm	Firm	Facility	Facility	Facility
Controls	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_ufcostt	(2) logCO2e_uopereuct	(3) logCO2e_uopre	(4) logCO2e_ufcostt	(5) logCO2e_uopereuct	(6) logCO2e_uopre
Private	-1.059***	-1.208***	-1.173***	-0.528**	-1.037***	-0.958***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Observations	201	251	365	2,238	2,099	3,291
R^2	0.140	0.187	0.201	0.015	0.034	0.036
By	Firm	Firm	Firm	Facility	Facility	Facility
Controls	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Table C5: Firm fixed effects to identify switchers

We use firm fixed effects to identify firms that switch in and out of the three categories of firm: private independent, private sponsor-backed, and public. There are 151 firms that switch from public to private or vice versa and 14 of these have emissions data in the year prior to the switch and in the year of the switch. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses. p-values of the form (.) denote negative standard errors as computed by double clustering. As this is likely due to the small sample of switchers, we do not interpret these as ***.

VARIABLES	(1) logCO2eG	(2) logCO2C	(3) logNOC	(4) logSO2C	(5) logCO2eG	(6) logCO2C	(7) logNOC	(8) logSO2C
PrivateIndependent	-0.00591	-5.570	-1.916	-11.67***	-0.0317***	2.477***	-1.876***	-1.081
	(.)	(0.12)	(0.53)	(0.00)	(0.00)	(0.00)	(0.00)	(0.67)
PrivateSponsor	-0.0470	-0.0320	-0.133	0.184	-0.00409	0.129	0.0690	1.221**
	(0.37)	(0.92)	(0.70)	(0.77)	(.)	(0.46)	(0.75)	(0.03)
logTotalRevenue	-0.00844	9.17e-06	-0.136	0.291	-0.00152	-0.362***	-0.326**	-0.403**
	(0.86)	(1.00)	(0.54)	(0.56)	(0.84)	(0.01)	(0.04)	(0.04)
lagDA	0.0267	-0.226	0.430	0.245	0.0260	0.137	-0.306	0.550
	(0.39)	(0.76)	(0.66)	(0.88)	(0.26)	(0.58)	(0.34)	(0.25)
loglagAssets	0.0970**	-0.123	0.125	-0.314	0.0123**	0.158	0.117	-0.126
	(0.01)	(0.78)	(0.78)	(0.71)	(0.04)	(0.38)	(0.65)	(0.75)
lagNetPPEA	-0.166	-1.057	-1.786*	-2.106*	-0.0251	-1.503***	-1.436***	-1.797
	(0.14)	(0.40)	(0.09)	(0.08)	(.)	(0.01)	(0.00)	(0.30)
Observations	2,579	732	736	689	18,132	5,411	5,539	4,481
R^2	0.968	0.917	0.905	0.869	0.333	0.269	0.322	0.396
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	-0.402***	-4.600	-0.206	9.160***	-0.382***	2.801***	-0.556	0.0802
	(0.01)	(0.20)	(0.95)	(0.00)	(0.00)	(0.00)	(0.23)	(0.97)
PrivateSponsor	0.108	-0.167	-0.288	0.0892	0.180**	0.00677	-0.0489	1.101*
	(0.37)	(0.61)	(0.40)	(0.89)	(0.02)	(0.97)	(0.85)	(0.07)
lagDA	0.166*	-0.296	0.335	0.210	0.00794	0.0344	-0.403	0.526
	(0.09)	(0.77)	(0.79)	(0.90)	(0.96)	(0.95)	(0.48)	(0.49)
loglagAssets	-0.183	-0.818	-0.667	-0.815	-0.402***	-0.704***	-0.730***	-1.031**
	(0.14)	(0.19)	(0.30)	(0.45)	(0.00)	(0.00)	(0.00)	(0.02)
lagNetPPEA	-0.146	-0.825	-1.544	-1.983	0.227	-1.325***	-1.293***	-1.681
	(0.53)	(0.51)	(0.13)	(0.12)	(0.44)	(0.00)	(0.00)	(0.32)
Observations	2,579	732	736	689	18,132	5,411	5,540	4,482
R^2	0.932	0.908	0.903	0.873	0.544	0.340	0.383	0.413
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	-0.415***	-0.349*	-1.390***	-0.468	-0.512	-0.0531
	(0.00)	(0.05)	(0.01)	(.)	(.)	(0.82)
PrivateSponsor	-0.354	-0.218	0.0898	-0.0156	-0.0239	0.190
	(0.36)	(0.43)	(0.84)	(0.85)	(0.73)	(0.52)
logTotalRevenue	0.0600	-0.0266	0.584**	0.248***	0.187***	0.201
	(0.63)	(0.82)	(0.01)	(0.00)	(0.00)	(0.15)
lagDA	0.162	0.227**	0.123	0.0273	0.0716	0.155
	(0.11)	(0.03)	(0.69)	(0.83)	(0.41)	(0.49)
loglagAssets	0.317**	0.376**	-0.275	-0.0870	-0.0703*	-0.169*
	(0.02)	(0.02)	(0.36)	(0.37)	(0.08)	(0.06)
lagNetPPEA	-0.403	-0.374	-0.173	-0.429	-0.515	-0.596
	(0.24)	(0.37)	(0.77)	(0.25)	(0.11)	(0.17)
Observations	2,794	2,125	465	19,828	19,356	1,755
R^2	0.932	0.889	0.925	0.328	0.278	0.383
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.407***	-0.130	-1.573***	-0.620***	0.278	-1.316***
	(0.01)	(0.72)	(0.00)	(0.00)	(0.52)	(0.00)
PrivateSponsor	-0.198	0.187	-0.150	-0.246	0.174	-0.234
	(0.62)	(0.60)	(0.73)	(0.42)	(0.11)	(0.55)
lagDA	0.214**	0.101	0.0419	0.00433	-0.345	-0.0160
	(0.05)	(0.45)	(0.90)	(0.98)	(0.15)	(0.97)
loglagAssets	-0.169	0.0142	-0.487*	-0.271**	-0.110	-0.577***
	(0.16)	(0.91)	(0.06)	(0.02)	(0.31)	(0.00)
lagNetPPEA	-0.208	-0.249	-0.179	-0.332	1.089	-0.789
	(0.51)	(0.61)	(0.78)	(0.44)	(0.27)	(0.19)
Observations	2,794	2,125	465	19,828	19,327	1,755
R^2	0.928	0.778	0.911	0.529	0.369	0.447
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table C6: Including the percentage of minority residents in a 3-mile radius around the facility

The dependent variable is the log of emissions scaled by revenues. Variable descriptions appear in Table 1. Standard errors are clustered by industry and year and p-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	logCO2eG	logCO2C	logNOC	logSO2C	logCO2eG	logCO2C	logNOC	logSO2C
PrivateIndependent	-0.401*	-1.286***	-2.150***	-4.823***	-0.0829*	-1.530***	-1.719***	-2.525***
	(0.08)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.136	0.623	0.345	0.929	0.0404	-0.575	-0.321	-0.148
	(0.50)	(0.48)	(0.63)	(0.31)	(0.48)	(0.20)	(0.46)	(0.82)
fac_p_minority	-0.00122	-0.00226	-0.00404	-0.0576***	-0.000446	-0.0133***	-0.0164***	-0.0265***
	(0.59)	(0.87)	(0.73)	(0.01)	(0.74)	(0.00)	(0.00)	(0.00)
logTotalRevenue	0.183***	0.830***	0.774***	0.767**	0.0167	-0.0103	0.0849	0.791***
	(0.00)	(0.00)	(0.00)	(0.04)	(0.25)	(0.98)	(0.79)	(0.00)
lagDA	0.0230	2.071***	2.212***	5.098***	0.0294	0.385	0.0411	0.880
	(0.88)	(0.00)	(0.00)	(0.00)	(0.29)	(0.53)	(0.96)	(0.61)
loglagAssets	0.156**	0.231	0.165	0.258	0.0200	0.000780	-0.138	-0.787***
	(0.02)	(0.47)	(0.51)	(0.52)	(0.34)	(1.00)	(0.66)	(0.01)
lagNetPPEA	0.557	2.003	0.797	-0.631	0.0903	-0.319	-0.254	-0.249
	(0.12)	(0.23)	(0.66)	(0.77)	(0.27)	(0.27)	(0.41)	(0.69)
Observations	2,579	732	736	689	18,114	5,411	5,539	4,481
R^2	0.686	0.675	0.719	0.741	0.244	0.199	0.268	0.335
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B

VARIABLES	(1) logCO2eG_R	(2) logCO2C_R	(3) logNOC_R	(4) logSO2C_R	(5) logCO2eG_R	(6) logCO2C_R	(7) logNOC_R	(8) logSO2C_R
PrivateIndependent	-0.601*	-1.305***	-2.173***	-4.856***	-0.404***	-1.564***	-1.754***	-2.550***
	(0.08)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.423	0.669	0.405	0.988	0.513**	-0.0699	0.134	-0.0621
	(0.29)	(0.45)	(0.57)	(0.29)	(0.02)	(0.81)	(0.68)	(0.92)
fac_p_minority	-0.00637	-0.00226	-0.00403	-0.0574***	-0.000784	-0.0137***	-0.0167***	-0.0266***
	(0.20)	(0.87)	(0.73)	(0.01)	(0.84)	(0.00)	(0.00)	(0.00)
lagDA	0.0278	2.107***	2.256***	5.160***	0.0348	0.709	0.342	0.965
	(0.91)	(0.00)	(0.00)	(0.00)	(0.83)	(0.41)	(0.74)	(0.59)
loglagAssets	-0.170**	0.0753	-0.0429	0.0434	-0.766***	-0.945***	-1.001	-0.985***
	(0.03)	(0.71)	(0.72)	(0.75)	(0.00)	(0.00)	(.)	(0.00)
lagNetPPEA	1.328**	1.985	0.766	-0.684	0.315	-0.0953	-0.0692	-0.229
	(0.04)	(0.24)	(0.68)	(0.76)	(0.38)	(0.56)	(0.81)	(0.72)
Observations	2,579	732	736	689	18,114	5,411	5,540	4,482
R^2	0.712	0.655	0.726	0.752	0.452	0.275	0.333	0.357
By	Firm	Firm	Firm	Firm	Facility	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel C

VARIABLES	(1) logCO2e	(2) logadjCO2e	(3) logCO2e	(4) logCO2e	(5) logadjCO2e	(6) logCO2e
PrivateIndependent	-0.753**	-0.752**	-0.804**	-0.523**	-0.516**	-1.088***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)
PrivateSponsor	0.253	0.364	0.461	0.00892	0.00667	-0.186
	(0.58)	(0.48)	(0.45)	(0.93)	(0.95)	(0.44)
fac_p_minority	-0.00663	-0.00709	-0.0217	-0.00184	-0.00194	-0.00151
	(0.15)	(0.11)	(0.13)	(0.66)	(0.64)	(0.24)
logTotalRevenue	0.593***	0.635***	1.526***	0.110**	0.100**	0.00904
	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.95)
lagDA	0.0186	0.0103	0.226	0.0268	0.0376	-0.116
	(0.94)	(0.97)	(0.47)	(0.79)	(0.64)	(0.51)
loglagAssets	0.210*	0.166	-0.527***	0.0893**	0.0937**	0.137
	(0.06)	(0.18)	(0.00)	(0.05)	(0.04)	(0.35)
lagNetPPEA	1.445**	1.384*	-0.810	0.473	0.434	0.310
	(0.03)	(0.06)	(0.24)	(0.15)	(0.19)	(0.38)
Observations	2,794	2,125	465	19,810	19,338	1,755
R^2	0.704	0.471	0.782	0.228	0.161	0.317
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES

Panel D

VARIABLES	(1) logCO2e_R	(2) logadjCO2e_R	(3) logCO2e_R	(4) logCO2e_R	(5) logadjCO2e_R	(6) logCO2e_R
PrivateIndependent	-0.825***	-0.761**	-0.699**	-0.944***	-0.879***	-1.230***
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
PrivateSponsor	0.377	0.566	0.263	-0.143	0.0220	-0.000577
	(0.37)	(0.23)	(0.65)	(0.20)	(0.83)	(1.00)
fac_p_minority	-0.00738	-0.00939**	-0.0180	-0.00244	-0.00270	-0.00385**
	(0.11)	(0.03)	(0.13)	(0.57)	(0.53)	(0.04)
lagDA	0.0127	-0.0971	0.162	0.513	0.405	0.0656
	(0.96)	(0.74)	(0.59)	(0.13)	(0.21)	(0.79)
loglagAssets	-0.167**	-0.141*	-0.0793	-0.245***	-0.220***	-0.167
	(0.02)	(0.06)	(0.74)	(0.00)	(0.00)	(0.26)
lagNetPPEA	1.471**	1.397**	-0.649	0.380	0.633	-0.308
	(0.03)	(0.04)	(0.34)	(0.48)	(0.17)	(0.61)
Observations	2,794	2,125	465	19,810	19,309	1,755
R^2	0.705	0.236	0.737	0.410	0.233	0.365
By	Firm	Firm	Firm	Facility	Facility	Facility
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SIC4 FE	YES	YES	YES	YES	YES	YES