The Climate and Financial Consequences of Fossil Fuel Power Plant Divestitures in the US

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Abstract

Recent pressure on publicly traded firms to divest high greenhouse gas emitting assets have raised concerns that assets are flowing to more opaque, privately held firms that may be operating them in more emissions-intensive ways and are being financially rewarded for doing so. Whether this is likely to be an important concern depends on the climate and valuation consequences of such asset transfers. To provide evidence on these effects, I exploit M&A-induced divestments of fossil fuel power plants by publicly traded firms between 2002-2020 to estimate divestment effects on plant production and emissions at the unit level and announcement effects on sellers' market values. I find that post-divestment effects on units' emissions behaviors were statistically indistinguishable from zero, regardless of whether the buyer was publicly traded or privately held. I also reject the null that publicly traded sellers were rewarded more by the stock market when they announced divestments to privately held firms compared to when they announced divestments to public firms. To help think further about the climate impacts of pressuring public firms to decarbonize, I develop a model of firm production and emissions and study the effects on ownership and emissions of shocking publicly traded firms, but not privately held firms, with an increase to the cost of emitting. In some cases, there exists a "green-washing equilibrium" in which publicly traded firms sell to privately held firms and assets emit more than they would have without trade. There are also equilibria with no-trade and lowered emissions, and divestments of assets to publicly traded firms and lowered emissions. This paper suggests that ESG investor strategies that stress divestment as a way to reduce aggregate emissions may have near zero climate impacts.

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1 Introduction

> "If a corporation sells the dirtiest stuff to some private enterprise somewhere in the world and that private enterprise is doing exactly or even worse offenses to the environment, how do you define that? The company looks better...but the world is probably worse off."
>
> - Larry Fink, CEO of BlackRock

There has been accelerating interest in corporate contributions to climate change. Recent pressures on publicly traded firms to decarbonize and their decisions to sell dirty assets to privately held firms have sparked concerns that they are engaging in green-washing - taking actions that appear superficially green but in reality have zero, or negative climate effects - and are being rewarded for doing so.

The argument for the hypothesis that these sales have zero, or negative climate effects is that such sales reshuffle asset ownership to private firms who may have weaker incentives to operate assets in environmentally responsible ways. That could be because private firms a.) are relative more opaque (Bernstein, 2022), b.) subject to fewer regulatory reporting requirements[1], and/or c.) because they're immune to investor activism through the acquisition of voting shares (Gozlugol and Ringe, 2022; Deshmukh, 2023). Thus, when asset ownership shifts to those who may be less concerned about their emissions impacts, the argument is that assets will emit just as they would have before or more. These concerns gained renewed attention after a 2022 Environmental Defense Fund reports which documented hundreds of cases in which assets were sold by operators with public commitments to cut methane emissions to those with no such obligations and an instance in which the sale of a Nigerian oil gas field led to a near four-fold increase in average methane flaring (Malek et al., 2022).

The argument for the hypothesis that the stock market financially rewards such sales is that there are gains to trade when assets move from public to private ownership because private firms are more inclined to cut costs associated with maintaining or improving the environmental performance of assets, raising asset values under private firm ownership compared relative to those under public ownership. In a model in which gains to trade sometimes accrue to the seller, on average, there should exist a premium and thus incentive for selling to private firms over public firms.

If so, this would suggest that ESG investment strategies that target publicly traded firms and stress divestment may be ineffective or even counterproductive.

[1] For example, as noted in Duchin et al. (2023), "in 2022, the SEC enforced ESG disclosure requirements for investment funds and other investment companies, whose portfolios largely comprise publicly traded firms. In contrast, no regulations impose such disclosure requirements on privately held firms."

While plausible, there are also arguments in the other direction. One argument is that public firms may pollute more than private firms if public firms engage in short-term, myopic behavior (Stein, 1989; Graham et al., 2005) that manifests in higher discounting of future environmental liabilities.[2] Another is that private operators may be better at identifying and executing positive net present value projects that reduce the emissions intensity of production because firm ownership tends to be relatively more concentrated, leading to more efficient management control (Bolton and von Thadden, 1998). This would be consistent with the literature on operational improvements following private equity acquisitions (Davis et al., 2014; Bernstein and Sheen, 2016). If so, asset sales by public firms to private firms may lead to improved environmental outcomes.[3]

Whether shifting asset ownership from the hands of public to private firms is "innocuous"–that is, have near zero impacts on assets' emissions behavior–or "perverse"–that is, lead assets to become sharply more emissive, and rewards public firms through increased valuations are empirical questions that have not yet been explored.

This paper investigates these questions in context of the fossil fuel power plant sector and with respect to short-horizon emissions outcomes. What happens in this sector is important because of its

1. Aggregate importance to US emissions: it is the second largest source of U.S. greenhouse gas emissions, accounting for 25% of the U.S. total;

2. Similarity to industrial sectors that generate 20% of additional US annual emissions by combusting fossil fuels to generate heat and/or mechanical energy study.[4]

To answer questions about divestment effects on emissions, I combine power plant input, output, and emissions data from the Environmental Protection Agency (EPA), plant characteristics data from the Energy Information Administration (EIA), and ownership data

[2]For example, DellaVigna and Pollet (2007) find evidence suggesting that investors of publicly traded firms are short-sighted and neglect information beyond a horizon of four to eight years. Meanwhile, private equity and venture capital firms, which are important members of the class of private firms, raise funds in which investors commit to provide a certain amount of money to pay for investments in companies as well as management fees. They have fixed lives for 10 years, but can be extended for up to three (and often more) additional years (Kaplan, 2019).

[3]For example, consider assets that combust fossil fuels, an activity that accounts for 73% of total anthropogenic greenhouse gas emissions. A project that increases how efficiently the heat generated from fuel combustion is converted into useful energy would directly reduce fuel costs, and emissions since emissions in this context is primarily determined by the quantity and carbon content of the fuel burned. Because of costs, not all such projects will be positive net present value projects, but industry periodicals have identified projects that are, and cover case studies of implementing such projects (Nowling, 2015; Korellis, 2014).

[4]with a further 31% that is generated by assets that combust fossil fuels. A caveat is that there are also important differences, such as the fact that these assets operate in/interact with different input and final goods markets.

from S&P Capital IQ Pro to construct a virtually complete characterization of ownership, emissions, and production from this sector from 1998-2022 at the weekly frequency. Two key advantages of this dataset are

1. The coverage, accuracy, granularity of the emissions and production data. Data cover 96% of US fossil fuel generation. Reporting is federally audited, and the ability of firms to misreport is sharply bounded by the physics and chemistry of combustion (the process that generates emissions), which tightly links emissions with observable input and output quantities. Furthermore, the data are reported at the level of the power plant unit, which is the level at which operators make decisions that determine the emissions intensity of production;

2. Significant volume of assets sold by publicly traded firms. Focusing only on those sales that involved a transfer of a majority stake, in which the seller was a domestic, publicly traded company, and didn't involve a repeat sales, I am able to study 82 deals, 56% to public firms and 44% to private firms that transferred 601 power plant units. These sales transferred, in the years in which they were completed, a cumulative 616 million short tons of carbon dioxide, or 27% of annual 2022 sectoral emissions.

On the climate impacts, there are two main findings. First, using a difference in difference design, I find that in the eighteen months after sale, plants sold to private firms do not become more emissive. In fact, they become less emissive. But the effects are small and statistically insignificant. Thus, the narrative that private firms buy up dirty assets and ramp up emissions did not hold in this asset class and period. This suggests that "innocuous greenwashing" – the kind with near zero effects on asset emissions - may be a concern in this setting, but not "perverse greenwashing" –the kind with large negative effects. I also find that these effects were statistically indistinguishable from the effects of sales to public firms. Thus, the narrative that private firms always operate dirty assets in more emissive ways compared to public firms did not hold in this setting.

On the financial impacts, I use an event study methodology to estimate the effect of public to private sale announcements on sellers' market values. I find that on average, the stock market rewarded sales to private firms, but not above and beyond those to public firms in a statistically significant way. Thus, I am unable to reject the null that there is no premium, and thus no incentive, to sell to more opaque, private firms over public firms.

To help think further about the climate effects of ESG pressure on public firms, I develop a general equilibrium model that predicts what will happen to asset ownership and emissions when public, but not private, firms experience a positive shock to their cost of emitting when there is trade in assets. I find three qualitatively distinct equilibria, one of which is a "green-washing equilibrium." The public firm expresses the shock entirely through ownership decisions by selling to to private firms and assets emit more than they would have were trade suppressed. There are also equilibria with no-trade, and divestments of assets to public firms.

In sum, this paper suggests that ESG investor strategies that stress divestment by public firms as a way to reduce aggregate emissions may be ineffective. A caveat is that this paper only focused on changes in the short-horizon emissions behavior of operating units. Acquisitions may affect long-term decisions such as shut-down decisions or changes to the technology, which are important determinants of generators' long-term emissions, but low-frequency events not the focus of this paper. Furthermore, this paper did not evaluate whether or not sales were motivated by a green-washing motive.

The paper is organized as follows; Section 2 presents the literature review; Section 3 covers climate implications; Section 4 covers valuation implications; Section 5 covers the model; Section 6 concludes.

2 Literature Review

This paper is related to several strands of literature.

The first strand is the empirical literature on the environmental and financial effects of divestitures of pollutive assets. Duchin et al. (2023) find evidence consistent with greenwashing in assets that release chemical pollutants: following the divestiture of pollutive assets, changes in pollution are statistically indistinguishable from zero, but sellers earn positive announcement returns that are increasing in the pollutive level and intensity of divested assets. In the opposite direction, Jacqz (2021), using the same dataset, finds that toxic air releases, measured both in pounds of toxic releases and in the volume of releases adjusted for toxicity, fall dramatically in the ten years following divestment.[5] This paper complements these studies by quantifying the real and financial impacts of divestitures on a kind of pollution not covered by their dataset, but with climate relevance: carbon dioxide, which accounted for 79% of all U.S. greenhouse gas emissions from human activities in 2021. In contemporaneous work, Bai and Wu (2023) examine the effects of power plant acquisitions on the emissions intensity of operations when the acquirer is a private equity firm and find that acquired plants operate with a lower heat rate, which translates into reduced fuel consumption and reduced output-scaled emissions. This paper's contribution is to focus on the absolute and relative effects of divesting to a private firm, where relative is defined vis-à-vis the effects of divesting to a public firm. I also examine other margins by which new operators can affect the environmental operation of power plants such as by changing the likelihood of being on in a given week, generation levels and the fuel mix of generation, and also present a model.

The second strand is the empirical literature on how firm characteristics shape polluting behavior. Akey and Appel (2021) study the effects of limited liability on environmental outcomes and find that subsidiaries with parents that face strong limited liability protection are more likely to emit ground pollution. Bellon (2021) studies the effects of private-equity acquisitions on the environmental operations of an asset in oil and gas well transactions. He finds that acquisitions are associated with a 70% reduction in the use of toxic chemicals and a 50% reduction in satellite-based measures of carbon dioxide emissions from gas flaring vis-à-vis nearby, observationally equivalent wells, but that private-equity backed firms increase pollution in locations and periods where environmental liability risk is low. This paper complements these studies by studying whether private firms operate acquired assets differently than publicly traded firms. Andonov and Rauh (2023) study differences in plant retirement

[5] Jacqz (2021)focuses only on toxic air releases; Duchin et al. (2023) covers toxic releases without distinguishing by release type (e.g. air release, water release, land release, release to an off-site treatment or disposal facility).

and capacity factor decisions between public and private firms. They find that public firms have the highest probability of decommissioning a power plant conditional on plant age and capacity, followed by private firms and that private firms operate plants at slightly lower capacity factors, particularly natural gas power plants. They find that domestic corporations have a 0.28 percentage points higher probability to retire coal and petroleum power plants, and 0.19 percentage points lower probability to retire natural gas power plants compared to other owners after controlling for plant capacity, plant age, and fuel-state-time fixed effects. This paper complements this study by focusing on the short-horizon emissions decisions of plants beyond capacity factor decisions such as the choice the turn on, and the fuel mix to burn.

This third strand of literature is the theoretical and empirical literature on emissions leakage. When pressure is applied to only a subset of facilities contributing to the pollution problem, it has been long recognized that this pressure may be muted or wholly ineffective if it prompts a shift in production from pressured to unpressured producers (van Benthem et al., 2022; Fowlie, 2009). Existing studies, however, keep ownership fixed. This model focuses on emissions leakages mediated by changes in ownership.

The fourth strand is on the effect of divestitures on firm value. Hite et al. (1987) investigate the valuation consequences of announcements to sell part or all of a corporations' assets and find that successful sellers and buyers reap statistically significant abnormal returns. Wright and Ferris (1997) report significant and negative excess returns to the shares of companies announcing divestments of South African operations during a period in which there was a buildup of private and public pressure to divest US business interests in that country due to moral outrage over the treatment of black South Africans by the minority white South African government. Their results support the premise that noneconomic pressures may influence managerial strategies rather than value-enhancement goals that lead to a decline in firm values. This contributes by focusing on the divestment of fossil-fuel power plants.

The fifth strand is the empirical literature on how firm valuations and returns are related to the ownership of emitting assets. Bolton and Kacperczyk (2021) find that investors of publicly traded firms care about carbon risk: stocks of firms with higher total carbon dioxide emissions (and changes in emissions) earn higher excess returns, controlling for size, book-to-market, and other return predictors. The authors find that this premium cannot be explained by differences in unexpected profitability or other known risk factors. Berk and van Binsbergen (2022) find that given current levels of socially conscious capital, the fraction of targeted firms in the economy and the return correlation between targeted firms and the rest of the stock market, the likely impact of divestiture strategies on the cost of capital is very small.

3 Climate Implications

In this section, I describe how I estimate the effect of divestitures on units' decisions to produce, how much to produce, and the emissions intensity at which to produce.

3.1 Data

This study utilizes a detailed panel dataset of weekly operations and emissions of, and ownership of the US fossil-fuel power plant sector from 1998 to 2023.

Data on plant operations and carbon dioxide emissions, characteristics, and regulatory regimes are from the EPA's Clean Air Markets Division database. The database covers 96% of total fossil fuel generation in the United States and reports the following variables: gross generation, defined as the total amount of electric energy; heat input, defined as the energy supplied to produce heat; carbon dioxide emissions; the primary and secondary fuels burned; unit type (i.e. whether or not the unit was a part of a combined cycle system); and participation in an emission trading program or other air quality program at the unit level. A power plant is typically composed of many units. I conduct my analysis at the unit level because emissions are primarily determined by the quantity and carbon content of the fuel burned, and the unit is the level at which the choice of the type and quantity of fossil fuel combusted is determined. Though fossil fuel-burning power plants emit greenhouse gases besides carbon dioxide, such as methane and nitrogen dioxide, only carbon dioxide is reported in the EPA's emissions dataset. However, because carbon dioxide is the primary greenhouse gas emitted, this is a small concern. In fact, where they can be compared, plant carbon dioxide emissions and total greenhouse gas emissions are close and have a correlation coefficient of 0.98 (Shiver and Forster, 2020). Thus, in this paper, I will use the terms carbon dioxide emissions and emissions interchangeably.

From this data, following Demirer and Karaduman (2022), I estimated units' nameplate capacities, defined as the maximum rated electricity output at full power, by using the 99th percentile the generation as the capacity for the unit every year. Data are based on federally mandated emissions reporting. Advantages of this dataset are a) the strict standards for and auditing of emissions estimations and b) the chemistry and physics of fossil fuel combustion sharply bounds the ability of plants to misreport without detection.[6][7] The decision to burn fuels and thus, emit is unit specific (a unit typically consists of a boiler connected to a generator), which makes the unit the relevant level at which to conduct the analysis.

I then matched this data to the following plant characteristics data from the EIA's Form 860 "Annual Electric Generator Report": the plant's longitude, latitude, carbon capture technology, and the North American Electric Reliability Corporation (NERC) region. The NERC region gives a boundary of the regional electricity market, which tends to but does not always fall along state lines. Over the sample, there are instances of NERC regions consolidating; in such instances, I used the consolidated region for my whole sample.

Ownership data are from Standard and Poor's Capital IQ Pro. To my knowledge, this is the most complete and accurate dataset of power plant transactions in the US. Deals data include seller, buyer, and target identities and where available, stock tickers, the announcement date, the completion date, the deal type (e.g., involved a majority stake; percent owned by the buyer after the deal; percent acquired through the deal), deal summary, and the names and, for a subset, the EIA identifier known as the ORIS code of the power plants involved. For this dataset, I recognize a divestment by a publicly traded firm if (a.) the seller was listed on a major US trading exchange (i.e. NASDAQ, NYSE), (b.) the divestment involved an ownership transfer that changed the identity of the majority financial owner of the plant, defined as the owner of more than 50% of the asset's financial interest, and (c.) the buyer was a for-profit entity. This excludes municipalities, co-ops, federal agencies, etc. I only consider transactions that changed the identity of the majority financial owner under the assumption that the primary controller of plant operations is the owner with the majority financial share. I also only include the first instance of a plant acquired in my sample and impose the restriction that the plant could not have been divested within the event window. Additionally, I exclude divested, oil-fired units because of insufficient deals.

Power plants are matched to the operations and emissions data using, where available, the plant's ORIS code and with fuzzy matching on names, otherwise. I also used the deal

[6] The federal Acid Rain Program required all units over 25 megawatts and new units under 25 megawatts that use fuel with a sulfur content greater than 0.05 percent by weight to measure and report emissions. For carbon dioxide, all units can either use a mass balance estimation, carbon dioxide CEMS, or oxygen CEMS. All CEMS used for compliance are certified by the EPA, and undergo daily calibration tests, and annual reference test audits. It is typically composed of a Data Acquisition and Handling System which collects and stores data on the emissions intensity. For compliance, it must be in continuous operation even if no process is on and for valid measurement, must record at least one reading every 15 minutes for 3 out of 4 quarters and the readings are averaged quarterly. See https://web.archive.org/web/20090211082920/http://epa.gov/airmarkets/emissions/continuous-factsheet.html.

[7] Carbon dioxide emissions are primarily determined by the carbon and heat content of the fuel burned, both of which are quantities that can be measured well.

summary and google search to algorithmically and manually identify and correct cases in which a majority transfer was incorrectly recorded or when a majority transfer was not identified though it had occurred.

Table 3.1 presents summary statistics of the divested units analyzed in this paper and the deals they were a part of. This study covers the divestment of 601 units from 236 power plants. In the year they were acquired, these units generated electricity that equaled 27% of annual 2022 fossil-fuel power plant generation and emitted 27% of annual 2022 fossil-fuel power plant emissions. Of these, 160 were coal-fired units from 64 plants.[8] Though only 27% of divested units, these coal-fired units emitted, in the years in which they were acquired, the equivalent of 20% of annual 2022 fossil fuel power plant emissions, reflecting both the relative emissions intensity of coal generation, and the fact that some of the divested units were very large.[9]

[8]For context, there are currently 217 operational coal power plants in the US.

[9]Coal units release 1.8x more carbon dioxide per MBtu, and 2.3x more carbon dioxide per Mwh vis-à-vis gas units.

Table 3.1: Summary Statistics

Panel A: Counts				
	Buyer Type			Combined as % of Sector
	Public	Private	Combined	in 2022
# of Units	333	268	601	20
Coal-fired	144	16	160	5
Gas-fired	189	252	441	15
# of Plants	130	106	236	21
Coal-fired	56	8	64	6
Gas-fired	77	98	175	15
# of Deals	45	37	82	
# of Unique Sellers	30	26	33	
# of Unique Buyers	24	8	44	

Panel B: Sums using average characteristics/behavior before divestment				
	Buyer Type			% of Sector
	Public	Private	Combined	2022
Generation (bn. MWh)	0.39	0.22	0.62	24
Coal-fired	0.29	0.08	0.37	14
Gas-fired	0.10	0.15	0.25	10
Emissions (bn. short tons)	0.33	0.15	0.48	27
Coal-fired	0.28	0.08	0.36	20
Gas-fired	0.05	0.07	0.12	7
Emissions Intensity $(\frac{s.tons}{MWh})^*$	0.85	0.68	0.77	-
Nameplate Capacity (MW)	81,074	55,869	136,943	21
Coal-fired	50,584	11,618	62,202	8
Gas-fired	30,490	44,251	74,741	11

Notes:
* the average emissions intensity is reported, here.

Table 3.2 presents a tabulation of the industries of the seller and buyer. The majority of divestments to public buyers, around 90%, were by power firms to other power firms. The majority of divestments to private buyers, around 75%, were by power firms to financial firms, of which 60% were private equity (PE) firms and the remaining, non-PE financial firms, are a category which includes other investment firm types, family offices, etc.

Table 3.2: Seller Buyer Matrix

(a) Deals with Public Buyer

Seller/Buyer	Finance	Power	Total
Power	4	41	45
	(9%)	(91%)	(100%)
	4	41	45

(b) Deals with Private Buyer

Seller/Buyer	Finance - Non PE	Finance - PE	Power	Total
Finance - Non PE	2	0	0	2
	(100%)	(00%)	(00%)	(100%)
Power	17	11	7	35
	(49%)	(31%)	(20%)	(100%)
	19	11	7	37

3.2 Empirical Strategy

To estimate the effect of divestitures on units' decisions about (a.) whether or not to engage in emissions generating production, and conditional on producing, (b.) how much to produce, and (c.) at what emissions intensity to produce, I estimate the following DD model using ordinary least squares:

$$\begin{aligned} y_{it} = \quad & \beta_1 (Post \times Public\,Buyer)_{it} \\ + \quad & \beta_2 (Post \times Private\,Buyer)_{it} \\ + \quad & X_{it} + \alpha_i + \eta_{it}, \end{aligned} \tag{3.1}$$

where outcome y_{it} is for each unit i and week t includes: weekly "starts", defined as a dummy variable equal to one if gross generation was positive in week t;[10] the capacity factor, defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; and the natural log of the emission rate, defined as the ratio of carbon dioxide

[10] This is an approximation to starts since some units will cycle on and off at a higher frequency.

emissions to gross generation conditional on gross generation being positive:

$$y_{it} = \begin{bmatrix} Starts \\ Capacity\,Factor \\ ln(Emissions\,Intensity) \end{bmatrix}_{it} = \begin{bmatrix} Gross\,Generation > 0 \\ \frac{Gross\,Generation}{Nameplate\,Capacity}|_{Gross\,Generation>0} \\ ln(\frac{CO_2}{Gross\,Generation})|_{Gross\,Generation>0} \end{bmatrix}_{it} . \tag{3.2}$$

The dummy variable $(Post \times Public\,Buyer)_{it}$ is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable $(Post \times Private\,Buyer)_{it}$ is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. The post-divestment period is defined as the 18 months following divestment completion. I chose this horizon to balance the desire to capture short-term divestment effects, while respecting the fact that these effects may take more than a few months to materialize. Previous work has found divestment effects in the 8-month to 2-year horizon (Cicala, 2015; Demirer and Karaduman, 2022). Observations of treated units are dropped past this horizon so that the comparison for treated units is always with never-acquired or not yet acquired units. Time-varying trends or slow-moving processes within a state and NERC region are captured by X_{it} which is the interacted set of the following variables: state, NERC region, a combined cycle indicator equal to one if the unit was part of a combined cycle system, the types of fuel the unit can burn, the week, and year. Time-invariant unit fixed effects are denoted by α_i. Standard errors are clustered at the plant level. To ensure I am only capturing divested units for which I can obtain a DD treatment effect, I impose the condition that divested units included in the estimation must have observations in both the pre and post-divestment period and have had at least one control in both periods (i.e. another never-acquired or not-yet acquired unit that could be used to estimate X_{it}). The medium number of controls is 13; the mean, 20. [11]

This strategy compares changes in the behavior of treated units with controls, which are never-treated or not yet treated units in the same state and NERC region with the ability to burn the same kind of fuels, and, if a unit that can burn natural gas, of the same system type (i.e. combined cycle or not combined cycle). I include the state, NERC region in the interaction set to control for regional trends in demand that can arise from local economic conditions and population growth, as well as to control for regional trends in generation supply that can arise from state regulation of carbon dioxide and non-carbon dioxide pollutants released by power plants, such as mercury, sulfur dioxide, and nitrous oxides. I include the fuel set in the interaction set for two reasons. The first reason is that the set of fuels the unit can burn is a technological constraint that determines the means by

[11] This led to the loss of 17% of units.

which owners can change the emissions intensity of generation. For example, an owner can reduce the emissions intensity of generation by burning a cleaner fuel, but only if burning multiple fuels is technologically feasible. The second reason is that the ranking of fuel prices for the major fuel categories: coal, oil, and gas is the primary determinant of which fuels are burned to generate electricity and by extension, unit starts and generation and also a slow moving process.[12] Thus, when estimating the divestment effect on units' emissions intensities, I want treated units to be compared with control units with the same ability to change their emissions intensities and subject to the same factors that would influence their propensities to change their emissions intensities like relative fuel prices. I control for the system type because combined cycle systems can be 50-70% more efficient at converting fuel energy to electricity than non-combined cycle systems, which significantly impacts marginal operating costs and thus start probabilities and generation.[13]

One way to see whether the controls are good is to compare differences in means of the control and treated groups. Differences in the average annual generation, annual emissions, and emissions intensities of the two groups were statistically indistinguishable from zero. However, treated units were, on average, 221 MW and slightly larger than the control group by 23MW; they were also likely to be a part of plants that were younger by five years. I assume that the unit fixed effects absorb these differences.

A concern may be that divestment differentially affects coal and gas units and that aggregating divestment effects across unit types masks important heterogeneity in the divestment effect. For example, one may argue that new owners were unlikely to have changed coal-unit starts and generation because these units were, for a large fraction of the period covered, non-marginal electricity suppliers. Another argument is that new buyers may have greater opportunities to run coal-fired units in environmentally ruinous or beneficial ways vis-à-vis natural gas units because coal-fired operators have more room to alter emissions since they can switch from burning a dirtier to cleaner coal and vice versa. For example, coke, a kind of coal, releases 22% more carbon dioxide emissions per MMBtu than bituminous coal.[14][15] This

[12] The relative rank of fuel prices that determine the unit's location in the dispatch curve, which is typically ordered from the least to greatest marginal cost unit, determines the order in which the unit is "dispatched" to meet electricity demand. Because the time varying changes in the relative rank of fuel prices is slow-moving, it is important to control for the fuel set in this setting when I have a sizable, but modest number of treated units. Not controlling for these time varying changes in relative rank can impact point estimates, whereas I wouldn't have had to if I could assume (a.) orderings of relative fuel prices were uniformly distributed and (b.) I had many treatment units.

[13] In a combined cycle system, waste heat from combustion is often converted to steam, which is then used to drive an additional turbine to increase the plant's overall thermal efficiency.

[14] https://www.eia.gov/environment/emissions/co2_vol_mass.php

[15] Coal plants can burn blends of coal. Switching from one type of coal to another, entirely, however, can require large modification costs because different types of coal have different propensities to generate different amounts of slag on boiler and furnace surfaces.(McCartney, 2006)

is in contrast to gas units, the vast majority of which are made to burn pipeline natural gas, which is gas processed into a homogenous output according to standards fixed by gas transmission pipelines and local distribution companies, making substitution within natural gas less likely. Thus, I re-estimate the model with post-divestment dummy variables interacted with dummy variables of the divested unit's fuel type:

$$
\begin{aligned}
y_{it} = \quad & \Sigma_f \beta_1 \left(Post \times Public\, Buyer \times f\, Unit \right)_{it} + \\
+ \quad & \Sigma_f \beta_2 \left(Post \times Private\, Buyer \times f\, Unit \right)_{it} \\
+ \quad & X_{it} + \alpha_i + \eta_{it},
\end{aligned} \tag{3.3}
$$

where the dummy variable $(Post \times Public\, Buyer \times\ f - Unit)_{it}$ is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type $f \in \{Coal, Gas\}$ and the dummy $(Post \times Private\, Buyer \times\ f - Unit)_{it}$ is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f.

Identifying variation comes from average differences in the outcome variable from treated and never treated units and variation in treatment timing. Since the estimation strategy relies on comparing changes over time, it is important that pre-existing trends are not responsible for the subsequent differences between treatment and control units. In Section 7.3.8 Appendix shows the dynamic Sun and Abraham (2021) interaction weighted (IW) estimator, which is robust to heterogeneous treatment effects across time. It provides encouraging evidence that both treatment and control groups were following parallel paths before divestment.

3.3 Results

Table 3.3 presents estimated average treatment effects on the treated (ATT) that measure the average short-horizon impacts of divestments on starts, capacity factors, and emissions intensities, as well as the p-value of a Wald test of the null that effects are the same when units are sold to a public firm versus a private firm.

I find that following divestment to a private firm, starts decreased by 2.8 percentage points, or approximately two weeks a year. The effect is statistically insignificant and the difference in divestment effects by buyer type is statistically insignificant. Divestment effects on capacity factors, and emissions intensities are statistically indistinguishable from zero, and the difference in effects by buyer type are statistically insignificant.

Breaking effects out by fuel type, I find that no statistically significant divestment effects on coal-fired starts. Starts of gas-fired units decreased by an average, and statistically significant 3.1 percentage points after divestment to a private buyer, which implies that these units were less likely to engage in emissions generating production. Starts of coal-fired units increased by an average, and statistically insignificant 1.9 percentage points. Divestment effects on capacity factors at both coal-fired and gas-fired plants were near zero and statistically insignificant, implying that conditional on being on, on average, units did not change their levels of emissions generating production post-divestment relative to comparable units.

Turning to the divestiture effects on emissions intensities, I find that the divestiture of coal-fired units (but not gas-fired units) was associated with statistically significant effects. A caveat is that post-divestment effects when the unit was sold to a private buyer is estimated on sixteen units from eight unique plants. To put these numbers in context, there are currently 217 operational coal power plants. These units, however, were quite large, and in the year before sale completion had annual emissions that together were 4% of 2022 sectoral emissions. In divestitures of coal-fired units, units divested to private and public firms experienced an average decline in emissions intensities of 4.1% and 1.3%, respectively. The estimates are statistically significant and their magnitudes are broadly in line with estimates of divestment effects on heat rates, a primary component of the emissions intensity (Bushnell and Wolfram, 2005; Demirer and Karaduman, 2022; Bai and Wu, 2023), [16] as well as in the range of heat rate improvements estimated by the EIA at existing coal-fired plants (EIA, 2015). The implied impact on aggregate emissions, however, is modest: approximately 0.40% of sectoral emissions or about 0.11% of total US emissions in 2022. This does not support the extreme version of the green-washing story in which transfers to private firms lead to dramatic increases in emissions, but it does support the version in which they have near zero emissions impacts.[17] Even if private firms were to acquire all coal units and make an additional reduction of emissions intensities by 4.1%, at the 2022 level of emissions by coal-

[16] Since the choice to divest a particular asset is deliberate and unlikely random, one may be concerned that estimated effects on the emissions intensity is being driven by selection bias: sellers are divesting assets whose emissions intensities were on a trajectory to improve. This is unlikely to happen naturally as physical assets tend towards depreciation and increased inefficiency. The other possibility is that sellers divested assets with an existing pipeline of operational improvement project expected to come live upon acquisition. I cannot observe this and thus, cannot rule it out. I do, however, check to see if there were changes in the boiler type, which would change the heat rate, following the acquisition and find no change.

[17] At the average emissions intensity of coal units, which is $1.01\frac{CO_2}{MWh}$, the implied effect of divestment to public and private buyers on the level of the emissions intensity at the means is a decline of 0.014 $\frac{CO_2}{MWh}$ and 0.041 $\frac{CO_2}{MWh}$, respectively. Coal-fired units divested to public and private firms generated approximately 0.29 bn MWh and 0.08 bn MWh of electricity. This implies a decline of $0.014 \times 1.01 \times 0.29 + .041 \times 1.01 \times 0.08 \approx .007\,bn$ short tons of carbon dioxide. In 2020, fossil-fuel units generated 1.65 billion short tons of carbon dioxide. Thus, the implied decline is about 0.4% of sectoral emissions or about 0.11% of total US emissions in 2022.

fired units, the implied impact on aggregate emissions would be 2.4% of sectoral emissions or 0.6% of US emissions.[18] Furthermore, though the point estimate of the divestment effect when the buyer is private is nearly double the effect when the buyer is public, the difference is not statistically significant and I cannot reject the null that public and private firms decrease emissions intensities at coal-fired units by a similar amount.

[18]Coal firing emitted 0.957 short tons of emissions. All fossil fuel plants emitted 1.650 billion short tons. A 4.1% improvement would generate a 2.4% decline in sectoral emissions. Since the sector is about a quarter of total US emissions this translates to a decline of 0.6% of US emissions.

Table 3.3: Divestment Effects on Unit Starts, Capacity Factors, and Emissions Intensities

	All			By Fuel		
	Starts	Capacity Factor	$ln(Emissions\,Intensity)$	Starts	Capacity Factor	$ln(Emissions\,Intensity)$
	(1)	(2)	(3)	(3)	(4)	(5)
$Post \times Public\,Buyer$	-0.017	-0.005	-0.011			
	(0.013)	(0.008)	(0.010)			
$Post \times Private\,Buyer$	-0.028	-0.011	0.000			
	(0.017)	(0.013)	(0.017)			
$Post \times Public\,Buyer \times Coal\,Unit$				-0.026	-0.008	-0.013*
				(0.019)	(0.012)	(0.007)
$Post \times Private\,Buyer \times Coal\,Unit$				0.019	-0.007	-0.041**
				(0.029)	(0.022)	(0.020)
$Post \times Public\,Buyer \times Gas\,Unit$				-0.011	-0.003	-0.010
				(0.018)	(0.012)	(0.016)
$Post \times Private\,Buyer \times Gas\,Unit$				-0.031*	-0.011	0.003
				(0.019)	(0.014)	(0.018)
Sample						
Observations	356,704	273,278	273,278	356,704	273,278	273,278
R-squared	0.40	0.72	0.93	0.40	0.72	0.93
R-squared contribution	0.00	0.00	0.00	0.00	0.01	0.00
Wald Test P-value						
All	0.58	0.68	0.61			
Coal				0.19	0.99	0.18
Gas				0.39	0.62	0.64

Notes: This table uses OLS regressions to test the effect of divestment on starts, capacity factors, and the log of the emissions intensity by the primary fuel burned by the divested unit prior to divestment. Observations are at the unit level and weekly frequency. Starts is a dummy variable equal to one if gross generation is positive; the capacity factor is defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; the log of the emission rate is defined as the ratio of carbon dioxide emissions to gross generation conditional on gross generation being positive. Columns (1)-(3) present the effects of divestment on all units without distinguishing by unit fuel type. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Columns (4)-(6) present the effects of divestment on units by fuel type. The dummy variable ($Post \times Public\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type f and the dummy ($Post \times Private\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f. Two types of units exist: coal and gas units. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, the fuels the unit is able to burn, week, year. The table reports also the number of relevant observations used to identify the coefficients reported in that column only, the R-squared contribution of the post-divestment dummies, and the p-value of a Wald test of the null that the post-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

So far, the discussion has been limited to the effect of divestments on emissions at the individual unit level. But what are the impacts on aggregate emissions? Declines in the emissions intensities unambiguously decrease aggregate emissions. However, while individually divested units did not increase emissions-generating production relative to comparable units, the aggregate implications are generally ambiguous. Since electricity demand is inelastic in the short run, any change in generation from a change in starts is replacing, or will be replaced by other units. Thus, the effect of divestment on aggregate emissions depends on the emissions profile of the replaced or replacement generation. However, when the divested unit burns the most or least emissions intensive fuel type, the divestment effects of individual assets can tell us something about aggregate effects.

Burning coal generates the most carbon dioxide per MWh of electricity generated of all fuel types. Thus, electricity generated from burning coal is most likely to displace or be replaced by generation that is similarly emissions intense (i.e. other coal plants) or less emissions intense (i.e. other gas, oil plants). When I break out divestment effects by the type of fuel burned, I find that coal-fired units did not contribute to worse aggregate climate outcomes in a robust, and detectable way: divestment effects on starts by, and the capacity factors of coal-fired units are statistically indistinguishable from zero, regardless of buyer type.

One may wonder why I do not test for aggregate effects more directly. For example, by testing for whether post-divestment, more/less emissions-intense units start more frequently or produce more. This would be like estimating post-divestment effects on the electricity region's non-acquired units, or the buyer's pre-existing generation units. I do not do this because in cases in which one or few units were sold, the divestment effect on the behavior of the firm's pre-existing generation units will likely be close to zero. This is because the estimated, average offsetting effect will be the change in the divested unit divided by many, non-acquired units in a given electricity region and/or the pre-existing units of the buyer, which will approach zero as the number of non-acquired units and/or pre existing units increases.

Robustness As a robustness check, I re-estimate divestment effects using a ten-day symmetric window around the divestment date, and clustering standard errors by deal. Qualitatively, the results are unaffected.

3.4 Decomposing Changes in the Emissions Intensity

One question is whether or not changes in the emissions intensity are due to genuine reductions, or changes in reporting.

There are four ways to change the reported emissions intensity of generation:

1. Change the unit's primary or secondary fuel category. A unit able to burn multiple fuels can decrease its emissions intensity by using more of the cleaner fuel to generate electricity. This behavior, however, is constrained to units that are technologically equipped to burn multiple fuels. Table 3.4 reports on the emissions factors, defined as, emissions per unit of the fuel's heat input, of the three, dominant fossil fuels used to generate electricity: coal, oil, and gas. Coal and oil are about 1.8 times and 1.4 times more emitting than natural gas, respectively.

Table 3.4: Emissions Factor by Fuel

	Emissions	
Fuel Type	Scaled by heat input ($\frac{kg\,CO_2}{MBtu}$)	Relative to Gas
Coal	95.92	1.8
Oil	74.14	1.4
Gas	52.91	1

Source: Carbon dioxide emissions coefficients, EPA

2. Change the fuel subtype (e.g. shift from burning a dirtier coal to a cleaner coal). There are weaker technological constraints to doing this than changing the unit's fuel mix, but substantial, possible emissions gains since the most emitting coal type coke emits 22% more emissions per heat input than the least emitting coal type bituminous coal.

3. Change the way emissions are estimated and reported.

4. Change the heat rate, which is the physical efficiency at which the energy in the fossil fuel is converted into electricity, known as the heat rate. Note that increasing physical efficiencies implies that less fuel is being combusted per unit of electricity generated. Since emissions are primarily determined by the quantity and carbon content of fuel burned, this mechanically implies a decline in the emissions intensity.

In this section, I show that the decline in the emissions intensity appears to be genuine and driven primarily by improvements in the heat rate.

3.4.1 Fuel-switching and Co-firing

There are units that are technologically able to fuel-switch (i.e. units running on one fuel can replace that fuel in its entirety with a substitute fuel) and, or co-fire (i.e. units can simultaneous use two or more fuels). In such units, new buyers can reduce the emissions intensity of electricity generation by switching completely to a cleaner fuel or by tilting the fuel mix towards a cleaner fuel.

I identify units with fuel-switching and co-firing abilities using their historical behavior.[19] In my estimation sample, none of the units were able to fuel switch,[20] but some were able to co-fire. As reported in Table 3.5, of divested units sold to public buyers, 33% of coal-fired units and 49% of gas-fired units were able to co-fire; of those divested to private buyers, 13% of coal-fired units and 29% of gas-fired units were able to co-fire.

Table 3.5: Type of Divested Units

Co-Firing Type of Divested Unit					
Coal-firing			Gas-firing		
Type	Public Buyer	Private Buyer	Type	Public Buyer	Private Buyer
Coal Only	96	14	Gas Only	101	186
Coal, Oil	30	0	Gas, Oil	96	76
Coal, Gas	18	2	Gas, Coal	0	0
Coal, Gas, Oil	0	0	Gas, Coal, Oil	0	0
Total	144	16	Total	197	262

To study whether divestment leads to changes in co-firing decisions, I estimate the effects of divestiture on coal and gas units separately to estimate linear probability models with intuitive, and easily interpretable coefficients.

[19] Identification is not perfect, but an approximation based on discussions with EIA staff. The Appendix goes into greater detail.

[20] Fuel switching is not technologically feasible in all units, especially the dirtiest: coal units. As of January 2021, 18% of US electric power generating capacity could functionally switch fuels, 27% of utility scale electric generation that could potentially use multiple energy sources could functionally switch fuels; less than 20% of coal capacity could fuel switch; 19% of natural gas-fired combined-cycle applications can fuel switch; 45% of natural gas combustion turbines can fuel switch (Source: EIA, 2022). Furthermore, transforming the asset to go from burning one fuel to many fuels is so costly that the EPA does not include fuel switching as part of the "best system of emissions reduction." For example, "although the EPA acknowledged in the GHG Abatement Measures TSD that some coal plant owners are engaging in repowering projects, the agency concluded that this kind of fuel switching will be on average more expensive than other available options, such as constructing a new natural gas combined-cycle unit. Because gas and biomass cofiring options were found to be relatively expensive when national average cost data were used, the EPA declined to include fuel switching as part of the "best system of emissions reduction" in its proposed emissions guidelines" (NACAA, 2015).

Empirical Strategy To estimate the effect of divestitures on fuel switching in units able to burn coal, I estimate Eq. 3.2

$$
\begin{aligned}
y_{it} = \quad & \beta_1(Post \times Public\,Buyer)_{it} \\
+ \quad & \beta_2(Post \times Private\,Buyer)_{it} \\
+ \quad & X_{it} + \alpha_i + \eta_{it},
\end{aligned}
$$

using observations of units able to co-fire with coal and using coal as the primary fuel that week. The dependent variable y_{it} is a dummy variable equal to one if the unit burned a secondary fuel:

$$y_{it} = Burned\,Secondary\,Fuel_{it}.$$

Time-varying trends or slow-moving processes within a state and NERC region are captured by X_{it} which is the interacted set of the following variables: state, NERC region, a combined cycle indicator equal to one if the unit was part of a combined cycle system, week, and year. Time-invariant unit fixed effects are equal to α_i. Standard errors are clustered at the plant level. Since for coal-fired units, alternative fuels (i.e. oil or gas) are cleaner than coal, a positive coefficient on the post-divestment dummy variables would imply that post-divestment, new buyers were co-firing units to make generation cleaner vis-à-vis comparable units.

To estimate the effect of divestitures on co-firing in units able to burn natural gas, I estimate Eq. 3.2 using observations of all units able to co-fire with natural gas and using natural gas as a primary fuel that week. The dependent variable is a dummy variable equal to one if the unit burned a secondary fuel. Everything is as before except that the interaction set X_{it} includes a combined cycle indicator equal to one if the unit was part of a combined cycle system. Since in our divested gas-fired units, the alternative fuels with which they could co-fire are dirtier, a positive coefficient on the post-divestment dummy variables would imply that new buyers are fuel-switching and co-firing units in ways that would make generation dirtier.

Results Table 3.6 present the main results as ATT estimates to measure the short-horizon impact of divestments on units' co-firing behavior.

Table 3.6: Co-firing

Dependent Variable: Burned Secondary Fuel	Coal (1)	Gas (2)
$Post \times Public\,Buyer$	0.014	0.004
	(0.014)	(0.003)
$Post \times Private\,Buyer$	0.000	-0.044
	0.000	(0.039)
Observations	15,493	88,685
R-squared	0.59	0.80
R-squared contribution	0.00	0.01
Wald Test P-value	0.32	0.23

Notes: This table uses OLS regressions to estimate the effects of divestment on co-firing by the fuel type of the unit divested. Observations are at the unit level and weekly frequency. The dependent variable is equal to one if the unit burned a secondary fuel, while burning coal as the primary fuel. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, primary and secondary fuel type burned, week, year. The table reports also the R-squared contribution of the pre-divestment dummies, and the p-value of a Wald test of the null that the pre-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In coal-fired units, divestments to public buyers lead to an average 1.4 percentage point decline in the probability of burning a cleaner secondary fuel; divestments to private buyers lead to no decline in the probability of burning a cleaner secondary fuel. In gas-fired units, divestments to public buyers lead to a 0.4 percentage point increase in the probability of burning a dirtier secondary fuel; divestments to private buyers lead to a 4.4 percentage point decline in the probability of burning a dirtier secondary fuel. None of these point estimates are statistically indistinguishable from zero.

3.4.2 Reporting, Fuel Subtype, and Heat Rate

Empirical Strategy. Here, I study whether divestment leads to changes in the emissions intensity via (a.) changes in the fuel type within the major fuel categories of coal, oil, and gas, and reporting method changes, and/or (b.) changes in the heat rate.

Before proceeding, I briefly touch on how owners can change emissions factors and heat rates.

The reported emissions factor can change by (a.) changing the unit's methodology for reporting carbon dioxide emissions, (b.) changing parameters used to estimate carbon dioxide emissions, (c.) changing the fuel sub-type. Depending on the fuel type, the EPA decides the methodologies allowed for reporting carbon dioxide emissions. For solid fuels like coal, the EPA requires emissions to be estimated by a continuous emissions monitoring system (CEMS). These systems measure pollutant concentration and stack gas flow at least every 15 minutes to estimate emissions. While owners have some latitude in the choice of the exact CEMS system to install, variation in estimates across CEMS systems is bounded by stringent system guidelines.[21][22] For oil or natural gas, carbon dioxide emissions may be estimated using CEMS, continuous monitoring of the fuel flow rate and periodic sampling of the fuel characteristics, or fuel-specific default emission rates and hourly heat inputs.

The heat rate can change by improving the technology, or changing dispatch to more frequently operate at levels at which the unit is the most efficient. For example, heat rates at coal plants can be improved by implementing processes such as rank coal drying, intelligent or neural network soot blowing. Heat rates at gas units can be improved by coating turbine blades and conductor components, repairing steam leaks, adding or restoring insulation, and implementing an effective steam-trap maintenance program.

To decompose changes in the emissions intensity, I estimate the baseline equation broken out by fuel type. Equation 3.2, where the outcome y_{it} is for each unit i and week t, the vector of the natural log of the emissions intensity, defined as the ratio of emissions to gross generation, the natural log of the emissions factor, defined as the ratio of emissions to the heat input, and the natural log of the heat rate, defined as the ratio of the heat input to gross generation:

$$y_{it} = \begin{bmatrix} ln(Emissions\,Intensity) \\ ln(Emissions\,Factor) \\ ln(Heat\;Rate) \end{bmatrix}_{it} = \begin{bmatrix} ln(\frac{CO_2}{MWh}) \\ ln(\frac{CO_2}{MMBtu}) \\ ln(\frac{MMBtu}{MWh}) \end{bmatrix}_{it}. \tag{3.4}$$

All other variables are as before, except X_{it}, which here is the interacted set of the variables included in the baseline specification but with one change: the interaction set does not include the type of fuels the unit can burn, but the actual primary and secondary fuel type burned. Thus, the control are units that actually burned the same primary and secondary

[21] CEMs must be certified by the EPA, and undergo daily calibration tests, and annual reference test audits For compliance, it must be in continuous operation even if no process is on and for valid measurement, must record at least one reading every 15 minutes for 3 out of 4 quarters and the readings are averaged quarterly.

[22] The EPA provides an CEMS Cost Modeler spreadsheet on its website https://www.epa.gov/emc/emc-continuous-emission-monitoring-systems. A single carbon dioxide analyzer would cost $114,988 initially and $37,549 a year with capital recovery (10 years, 7% interest rate).

fuel type that week, not units that could have burned the same primary and secondary fuel type. This prevents any effects on the emissions intensity coming from fuel mixing and thus, isolates changes in emissions intensities coming from changes in the emissions factor or heat rate.

Note that in this setting, mechanically, post-divestment effects on the emissions intensity can only come through changes in the emissions factor and the heat rate. The emissions intensity is the product of the emissions factor and the heat rate

$$\underbrace{(\frac{CO_2}{Generation})_{it}}_{Emissions\,Intensity} = \underbrace{(\frac{CO_2}{Heat\,Input})_{it}}_{Emissions\,Factor} \times \underbrace{(\frac{Heat\,Input}{Generation})_{it}}_{Heat\,Rate}.$$

Taking log changes,

$$\Delta ln(Emissions\,Intensity)_{it} = \Delta ln(Emissions\,Factor)_{it} + \Delta ln(Heat\,Rate)_{it}.$$

Thus, the coefficient on the dummy for post-divestment to a buyer of type b in the emissions intensity regression will be the sum of coefficients on the same dummy variable from the emissions factor and heat rate regressions.

Results Table 3.7 present the main results as ATT estimates to measure the short-horizon impact of divestments on the emissions intensity through changes in reporting, fuel subtype and the heat rate. Note that the point estimates of the divestment effect on the emissions intensity will differ from the benchmark specification, which controlled for the type of fuel the unit could burn, not the actual primary and secondary fuel burned as in this specification. The point estimates from the benchmark specification aggregated the effects of changes in reporting, fuel subtype, heat rate, and co-firing. Here, I separate the divestment effects on the emissions intensity through changes in reporting, fuel subtype and heat rate, from divestment effects through changes in co-firing.

Table 3.7: Decomposition of the Change in the Emissions Intensity By Fuel Type

	$ln(Emissions\,Rate)$ (1)	$ln(Emissions\,Factor)$ (2)	$ln(Heat\,Rate)$ (3)
$Post \times Public\,Buyer \times Coal\,Unit$	-0.016**	0.000	-0.015**
	(0.007)	(0.001)	(0.007)
$Post \times Private\,Buyer \times Coal\,Unit$	-0.043**	-0.005	-0.038*
	(0.021)	(0.003)	(0.021)
$Post \times Public\,Buyer \times Gas\,Unit$	-0.013	0.002	-0.015
	(0.017)	(0.002)	(0.017)
$Post \times Private\,Buyer \times Gas\,Unit$	0.007	-0.001	0.008
	(0.018)	(0.001)	(0.018)
Sample			
Observations	270,629	270,629	270,629
R-squared	0.94	0.993	0.849
R-squared contribution	0.00	0.00	0.00
Wald Test P-value			
Coal	0.23	0.14	0.33
Gas	0.47	0.23	0.42

Notes: This table uses OLS regressions to test the effect of divestment on starts, capacity factors, and the log of the emissions intensity by the primary fuel burned by the divested unit prior to divestment. Observations are at the unit level and weekly frequency. Starts is a dummy variable equal to one if gross generation is positive; the capacity factor is defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; the log of the emission rate is defined as the ratio of carbon dioxide emissions to gross generation conditional on gross generation being positive. Columns (1)-(3) present the effects of divestment by fuel type. The variable $(Post \times b - \ Buyer)$ is a dummy variable equal to one if the unit was divested by a public firm to a buyer of type b, where b is either a public firm or a private firm, and t is in the post-divestment period. The variable $(Post \times b - \ Buyer \times \ f - Unit)$ is a dummy variable equal to one if the unit was divested by a public firm to a buyer of type b, where b is either a public firm or a private firm, whose primary fuel before the acquisition was of type f, where f is either coal or gas, and if t is in the post-divestment period. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, the primary and secondary fuel type burned that week, week, year. The table reports also the number of relevant observations used to identify the coefficients reported in that column only, the R-squared contribution of the post-divestment dummies, and the p-value of a Wald test of the null that the post-divestment dummies for public buyers and private buyers are equivalent by divested unit fuel type. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The divestment of coal-fired units through changes in reporting, fuel subtype, and heat rate is associated with statistically significant 1.6% and 4.3% average decline in emissions intensities when sold to public and private buyers, respectively. However, the difference is not statistically significant across buyer types.

Point estimates in Columns (2) and (3) decompose this decline into two components: the change in the emissions factor and the change in the heat rate. I find that 88-100% of the decline in the emissions intensity of coal-fired units is due to statistically significant declines in the heat rate, which corresponds to an increase in the physical efficiency at which fuel energy is converted into electricity. The remaining decline can be attributed to statistically insignificant changes in the emissions factor. As noted earlier, because all coal-fired units must use CEMS to estimate emissions, the most likely lever by which owners can change the emissions factor is by changing the coal type used. I obtain annual data on plants' primary coal and secondary coal types from S&P Capital IQ Pro. Of the 56 plants that were divested to a public firm, none changed their primary coal type and four changed their secondary fuel types at some point in the post-divestment period. Of the eight plants that were divested to a private firm, none changed their primary coal type and one began burning a secondary fuel type that tilted its fuel mix to be cleaner in the post-divestment period.[23] In all, this suggests "tuning" type improvements, like sootblowing and turbine upgrades.

As noted earlier, post-divestment declines in the emissions intensity of gas-fired units are statistically indistinguishable from zero.

Another question is whether new owners are pushing the boundary on emissions intensity and heat rate improvements, or picking units that have lagged behind comparable units in efficiency improvements and bringing them in line with the average. To distinguish between the two, I estimate the baseline equation broken out by fuel type Equation 3.2, but with pre-divestment dummies and without unit fixed effects:

$$
\begin{aligned}
y_{it} = \quad & \Sigma_f \beta_1 \, (Pre \times Public\,Buyer \times f\,Unit)_{it} + && (3.5)\\
+ \quad & \Sigma_f \beta_2 \, (Post \times Public\,Buyer \times f\,Unit)_{it} && (3.6)\\
& \Sigma_f \beta_3 \, (Pre \times Private\,Buyer \times f\,Unit)_{it} + && (3.7)\\
+ \quad & \Sigma_f \beta_4 \, (Post \times Private\,Buyer \times f\,Unit)_{it} \\
+ \quad & X_{it} + \alpha_i + \eta_{it},
\end{aligned}
$$

where the dummy variable $(Pre \times Public\,Buyer \times f - Unit)_{it}$ is equal to one if unit i is in the pre-divestment period at time t, was divested by a public buyer and of type$f \in \{Coal, Gas\}$; and the dummy $(Pre \times Private\,Buyer \times \ f - Unit)_{it}$ is equal to one if unit i is in the pre-divestment period at time t, was divested by a private buyer, and of type f. Let y_{it} denote

[23] In particular, a plant that primarily burned lignite started to burn subituminuous coal as its secondary fuel, which is around 0.5% cleaner per MMBtu cleaner than lignite.

the vector of the natural log of the emissions intensity and the natural log of the heat rate

$$y_{it} = \left[\begin{array}{c} ln(Emissions\, Intensity) \\ ln(Heat\, Rate) \end{array} \right]_{it}. \tag{3.8}$$

Table 3.8 reports the pre-divestment dummies, which parameterizes the average unit fixed effects of divested units in the pre-divestment period, defined as the eighteen month period before divestment. The coefficient on the pre-divestment dummies of coal-fired units divested to public buyers and private buyers in the log emissions intensity regression are 0.008 and 0.057, respectively. The coefficients on the pre-divestment dummies of gas-fired units divested to public and private buyers in the regression of the log of the emissions intensity are similarly positive. This raises the possibility that acquired coal-fired units, which experienced an average 1.4% and 4.1% decline in the emissions intensity when divested to public and private buyers, respectively, were units that had been lagging behind comparable units being brought into line with the average. The results from the log heat rate regression are qualitatively similar. With the caveat that these are very imprecisely estimated coefficients, this leans against the idea of new owners pushing the boundary on emissions intensity and heat rate improvements and favors the idea of new owners bringing inefficient units to the standard baseline.

One puzzle this raises, however, is why natural gas units that are acquired do not also experience post-divestment declines in the heat rate and emission intensity. One possibility is that heat rate improvements in coal units are particularly attractive because they deliver extra benefits beyond cost savings. For instance, coal combustion also generates other pollutants such as sulfur dioxide, nitrogen oxides, and mercury, which are either directly or indirectly taxed; improving the heat rate thus reduces the costs of regulatory compliance.[24]

This suggests that divestments have a positive, aggregate climate impact through improvements in the physical efficiency of units, which in this context, directly translates to reduced emissions intensity of generation, but that divestments to private firms are not particularly better than those to public firms.

[24]See the cap-and-trade Acid Rain Program (ARP), mercury emissions limits imposed by the Mercury and Air Toxics Standards (MATS).

Table 3.8: Average Emissions Intensity of Treated Units vis-à-vis Control Units in the Pre-divestment Period

	$ln(Emissions\, Intensity)$ (1)	$ln(Heat\, Rate)$ (2)
$Pre \times Public\, Buyer \times Coal\, Unit$	0.008	0.008
	(0.015)	(0.015)
$Pre \times Private\, Buyer \times Coal\, Unit$	0.057	0.029
	(0.055)	(0.047)
$Pre \times Public\, Buyer \times Gas\, Unit$	0.016	0.031
	(0.023)	(0.022)
$Pre \times Private\, Buyer \times Gas\, Unit$	0.043	0.048*
	(0.026)	(0.026)
Sample		
Observations	273,278	273,278
R-squared	0.80	0.54
R-squared contribution	0.00	0.01
Wald Test P-value		
Coal	0.41	0.67
Gas	0.43	0.59

Notes: This table uses OLS regressions to test for selection. Observations are at the unit level and weekly frequency. The dependent variable in Column (1) is the natural log of the emissions intensity: the ratio of emissions to gross generation. The dependent variable in Column (2) is the natural log of the heat rate: the ratio of the heat input to gross generation. The dummy variable ($Post \times Public\, Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type f and the dummy ($Post \times Private\, Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f. Two types of units exist: coal and gas units. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, primary and secondary fuel type burned, week, year. The table reports also the R-squared contribution of the pre-divestment dummies, and the p-value of a Wald test of the null that the pre-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

So far, I have said nothing about the social welfare implications of the drop in the emissions intensity. If the social objective is to minimize short-horizon emissions at whatever cost, the drop in the emissions intensity is good for social welfare. The reality is that there are competing objectives both at a particular point in time, and across time. For example, by dropping the emissions intensity via the heat rate of coal-fired units, new owners may be reducing the path of expected, future fuel costs and extending the economic lifespan and thus, expected, future long run emissions of the units. This could reduce social welfare. Or, if emissions intensity improvements were made but the costs were passed onto consumers, the value of the drop in emissions might be too small to compensate for the loss of consumption value. A welfare analysis would require information about the private net present value of projects implemented to achieve reductions in the emissions intensity and an assumption about the social cost of carbon. If these projects had positive net present values, the emissions intensity reductions would be behavior that I would expect to observe in an equilibrium in which social welfare was being maximized. Because I do not observe projects implemented, their cash flows, I am unable to do this.

3.5 External Validity

A natural question is whether these results generalize to other asset classes that are high emitters of greenhouse gases. The challenge here is that other asset classes do not publish high quality and high frequency input, output, and emissions data, barring the kind of analysis done so far. However, the EPA publishes the Greenhouse Gas Reporting Program (GHGRP) dataset, which provides annual emissions and ownership data at the facility level from 2011-2020, which I can use in a coarser analysis on the climate effects of divesting high greenhouse gas emitting facilities in four industries that accounted for approximately 42% of total US emissions in 2020 (17% exlcuding power plants): power plants, petroleum and natural gas systems, chemicals, and waste. In this analysis, I recognize a divestment by a public firm if a facility whose parent company was a publicly traded firm sold the facility to a different parent company that was private. I find that divestment is not associated with any statistically significant effects on emissions levels in all four industries. Data construction, the empirical strategy, and estimates can be found in the Appendix.

4 Valuation Implications

If investors expect negative consequences for public firms with high emissions, the announcement of an unanticipated divestiture might generate positive abnormal returns to shareholders. In this section, I measure the effect of power plant divestment announcements on the value of the public seller by conducting an event study of abnormal returns around divestment announcements.

The approach rests on the idea that events that affect a firm's future value are reflected immediately in asset prices because of the forward looking nature of asset prices; thus, the event's economic impact can be measured using asset prices observed over a relatively short time period, whereas direct measures may require many months or years of observation MacKinlay (1997).

4.1 Data

To estimate the valuation effects of divestment announcements on the seller, I assemble a dataset of power plant sale announcement dates from S&P Capital IQ Pro, buyer and seller names, and, where available, tickers and listed exchanges. I then pair this with stock price data from WRDS's CRSP. This allows me to consider 153 sales in the sample: 62 that were to a publicly traded firm and 91 that were to a private firm (see Table 4.1).

Table 4.1: Generator and Deal Counts by Study

	Deal Count
Divestment Type	Asset Purchases Only
Public to Public	62
Public to Private	91
All	153

Notes: This table reports on number of events over which average cumulative abnormal returns were computed, by divestment type.

4.2 Empirical Strategy

To assess the event's impact, a measure of abnormal returns is required. It is defined as the actual ex-post return of the security over the event window minus the expected return of the firm over the event window:

$$AR^i_{t-1,t} \equiv r^i_{t-1,t} - \mathbb{E}_{t-1}(r^i_{t-1,t}), \tag{4.1}$$

where $AR^i_{t-1,t}$ is stock i's abnormal return over $t-1$ to t, $r^i_{t-1,t}$ is stock i's ex-post realized return over $t-1$ to t, and $\mathbb{E}_{t-1}(r^i_{t-1,t})$ is stock i's expected return at time $t-1$ over $t-1$ to t.

Here, the expected return is the Fama-French Plus Momentum Model. This model assumes a stable linear relationship between the security's excess return, the risk-free rate, and four factors, which are the three Fama-French factors: the excess return on the market, size of firms, and book-to-market values; and the momentum factor. I can thus express abnormal returns as

$$\begin{aligned} AR^i_{t-1,t} &\equiv r^i_{t-1,t} - \mathbb{E}_{t-1}(r^i_{t-1,t}) && (4.2)\\ &= (r^i_{t-1,t} - r^{Risk-free}_{t-1,t}) && (4.3)\\ &- (\alpha^i + \beta_1 f^{Market}_{t-1,t} + \beta_2 f^{SMB}_{t-1,t} + \beta_3 f^{HML}_{t-1,t} + \beta_4 f^{Mom}_{t-1,t}), && (4.4) \end{aligned}$$

where $r_{t-1,t}^{Risk-free}$ is the risk-free rate over $t-1$ to t estimated by the one-month T-bill rate, the factors $f_{t-1,t}^{Market}$, $f_{t-1,t}^{SMB}$, $f_{t-1,t}^{HML}$, and $f_{t-1,t}^{Mom}$ are the value-weighted aggregate market return on the CRSP US. stock universe, and returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns, respectively over $t-1$ to t. The factors $f_{t-1,t}^{SMB}$, $f_{t-1,t}^{HML}$ are obtained from Ken French's website; the factor $f_{t-1,t}^{Mom}$ is the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month. The portfolios include all NYSE, Amex, and Nasdaq stocks and are re-formed monthly.

The parameters of the model are estimated using the 100 days of trading data that are 50 days before the start of the event window. Having estimated the parameters, I compute abnormal returns and cumulative abnormal returns over the window. I then aggregate these returns across events on a nameplate weighted basis, where the nameplate for a given event is the total nameplate fossil fuel generation capacity that changed hands.

4.3 Result

Average The results suggest that sellers were not rewarded financially for selling to private firms compared to public firms.

Figure 7.10 plots the nameplate-weighted average cumulative abnormal returns over the eleven-day symmetric window surrounding the announcement of a power plant divestment by a publicly traded firm, by buyer type. In public to public transactions, sellers' stocks have cumulative abnormal returns of 0.6%; in public to private transactions, 1.4%. The point estimates and their difference are not statistically significant. Thus, I reject the null that publicly traded sellers were rewarded more by the stock market when they announced divestments to privately held firm compared to when they announced divestments to public firms. This suggests that in my period, there was no detectable financial incentive for sellers to divest high greenhouse case emitting assets to private firms in particular. This result is robust to using smaller and larger windows for the event study, to averaging CARs using nameplate weights, to inluding mergers and acquisitions (see Appendix).

Table 4.2: Cumulative Abnormal Returns (-5,5)

	CAR (Percent)
	Equally-weighted
Public to Public: Seller	
Mean	0.56
Standard Error	0.82
Count	62
Sharpe Ratio	0.09
Public to Private: Seller	
Mean	1.44**
Standard Error	0.67
Count	91
Sharpe Ratio	0.23
Comparison of Two Means Test[1]	
P-value	0.41

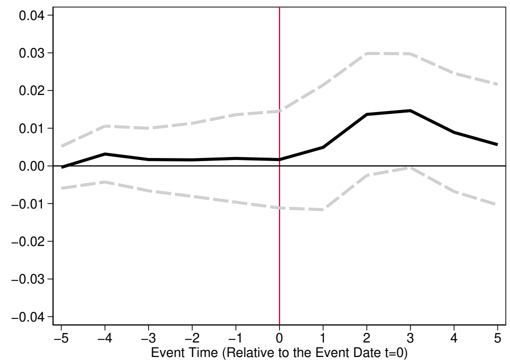
Notes:
*, **, *** denotes statistical significance at the 1%, 5%, 10% levels, respectively.
1) I test the comparison of the mean of the seller CAR in public to private transactions with the mean of the seller CAR in public to public transactions. In the setting in which means and standard deviations are unknown, we can use the two-sample t statistic:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

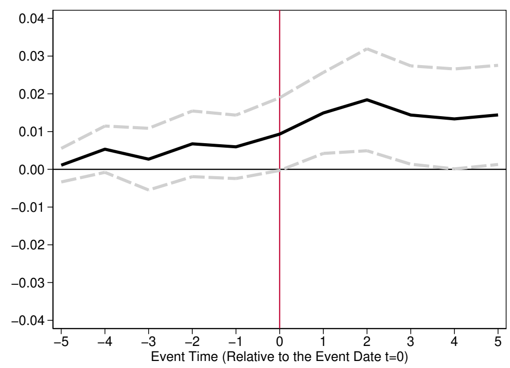
Conservative p-values may be obtained using the $t(k)$ distribution where $k = min(n_1 - 1, n_2 - 1)$, which is what I report.

Figure 4.1: Average Cumulative Abnormal Returns Around Plant Sale Announcements (Equally-Weighted): Eleven Day Window

(a) Public to Public: Seller



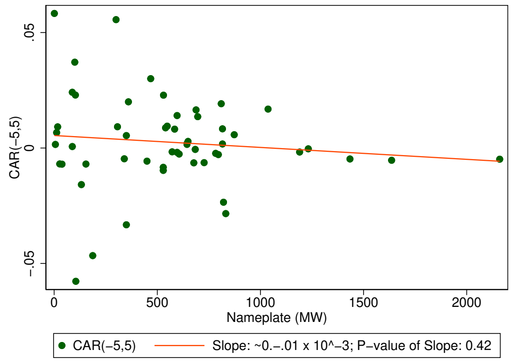
(b) Public to Private: Seller



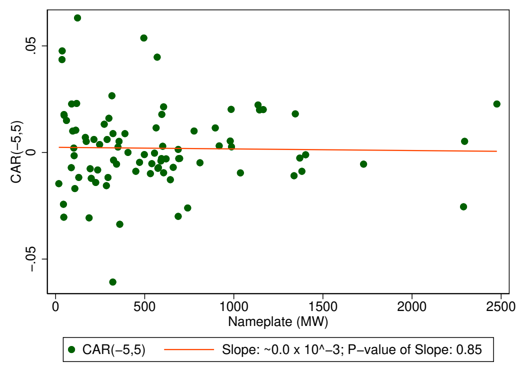
Notes: This figure shows the average cumulative returns (CARs) around plant sale announcements by sale type: Public to Public and Public to Private, and party: Buyer and Seller. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The CARs averaged across firms are plotted on the y-axis; daily CARs are based on expected return estimates generated using the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

Cross-section Figure 4.2 displays CARs around divestment announcements by the total nameplate capacity of fossil fuel power plants involved. Cumulative abnormal returns do not appear to have a statistically robust, linear relation to nameplate capacity. In public to public transactions, cumulative abnormal returns are weakly decreasing in nameplate capacity for the seller, weakly decreasing in nameplate capacity for the buyer. For public to private transactions, they are weakly increasing in nameplate capacity for the seller. The results are similar when we plot CARs by the plant emissions in the year prior to the announcement.

Figure 4.2: Cross section of CARS



(a) Public to Public: Seller



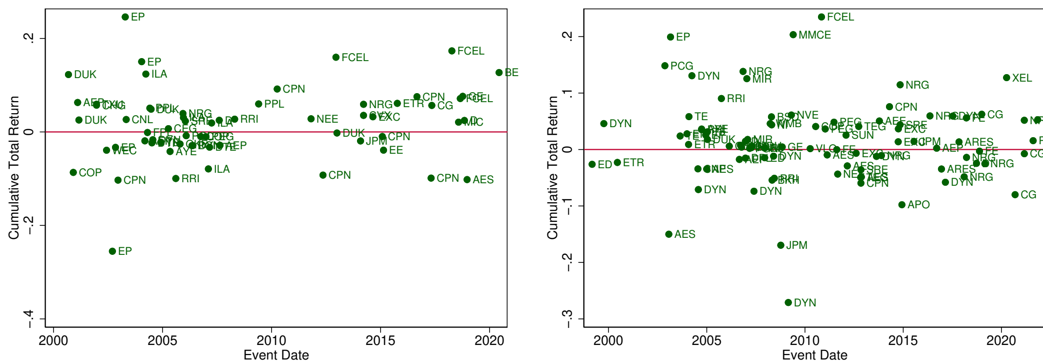
(b) Public to Private: Seller

Figure 4.3 displays CARs around divestment announcements by the year of the announcement date. Data points are labeled by seller tickers. Returns largely straddle zero. Positive abnormal returns are not surprising, as they suggest selling firms are taking a positive NPV action. Negative abnormal returns require more explanation. This could be noise associated with the event study - that is, that there was a downward short-term trend in the underlying stock not absorbed by the factors, but orthogonal to the divestment announcement; they could be instances of miscalculation of the benefits and costs of the trade by publicly traded firms or large internal private benefits from divestments not reflected in state prices, which encode preferences of the marginal investors.

Notably, in the plot, there are very large observations for El Paso Corp (NYSE: EP), Dynegy (NYSE:DYN), MMC Energy (NASDAQ:MMCE), which close examination reveals occurred during sharp price trends that spanned many months. All three companies were also penny stocks around the time of these large observations, and large swings are not uncommon for such stocks.

Figure 4.3: Time Series of CARs

(a) Public to Public (b) Public to Private



Notes: This plot displays the cumulative abnormal returns of divestment announcements by the year of the announcement date. Data points are labeled by seller tickers. The very large observations of El Paso Corp (NYSE: EP) occurred during a period of a sharp upward trend in price; this stock was also a penny stock with very high variation at low prices.

5 Model

In this section, I present a static, general equilibrium model of firm production and emissions in two settings: trading in assets and no trading in assets. The model provides intuition for the mechanisms by which a positive shock to the cost of emissions for public firms can have an emissions impact.

5.1 Framework

Firms There are two firm types: public and private firms. Each type exists in unit continuum. The two types have the same endowment of production technologies but differ in their cost of emissions. Denote private firm variables with a tilde; public firm variables without a tilde. Each firm is endowed with two types of assets–a clean asset and a dirty asset, where asset type is denoted by $f \in \{C, D\}$. The dirty asset produces emissions as a byproduct of production; the clean asset does not. There is no firm entry or asset creation. Hence, total productive assets in this industry are fixed.

Asset$f$ takes input x_f and generates y_f of the final good. Its production function is

$$y_f \equiv min(x_f^{1/2}, \bar{np}_f) \tag{5.1}$$

where np_f is the asset's capacity constraint. Emissions generated by the dirty asset are

$$e_D = x_D. \tag{5.2}$$

The emissions generating function captures the fact that the emissions level of fossil fuel-burning units is primarily determined by the quantity and carbon content of the fuel burned. The concavity of the production function captures the fact that more efficient assets have lower marginal costs than less efficient ones and thus are used first.[25]

I assume no fuel switching[26] and no opportunity to adopt technologies that will make the asset more or less clean.[27] By shutting down these two channels, emissions levels are solely determined by production decisions. It will be true in equilibrium that asset sales between firms are at the unit level; there is no fractional retention of ownership.

Firms take the final goods price p given. Inputs to the clean asset have zero marginal

[25] Fuel costs are approximately 70-80% of electricity generation. More efficient assets use less fuel to generate electricity thus have lower marginal costs and will be dispatched earlier.

[26] This is consistent with reality as noted in the earlier empirical section on fuel-switching.

[27] Making assets less emitting will primarily be through production decisions. Carbon capture technology is in its infancy and has generally been implemented only at pilot scale with government support (Howard, 2022).

costs (e.g. wind and solar). Inputs to the dirty asset (e.g. ga, oil, coal) are in perfectly elastic supply at exogenous cost c_D.

The optimization problem of firm i is as follows. Each firm chooses its input demands for its clean and dirty assets x_C^i, x_D^i to maximize the following objective function subject to its individual rationality constraint

$$x_C^{i*}, x_D^{i*} \equiv arg \max_{\{x_C, x_D\}} py_C^i + py_D^i - (\phi + c)x_D^i \tag{5.3}$$
$$s.t.\ py_C^i + py_D^i - (\phi^i + c)x_D^i \geq 0,$$

where ϕ^i denotes the firm's cost to emitting.

Representative Consumer Aggregate demand d is linear in the price of the final good. The demand function is

$$d = np_C + a - bp, \tag{5.4}$$

where $np_C, a, b > 0$. [28] There is no short selling.

I assume demand is sufficiently high so that clean assets are always operating at maximum capacities. Since clean assets have zero marginal costs, this assumption is equivalent to the restriction that the equilibrium price of the final good is greater than zero

$$p^* = \frac{2a}{\frac{1}{\phi + c} + \frac{1}{\tilde{\phi} + c} + 2b} > 0.$$

Emissions cost shock Initially, the final goods price is such that supply and demand are in equilibrium. That equilibrium is disrupted when public firms experience an unanticipated positive shock Φ to their cost of emitting

$$\Phi \equiv \frac{\phi}{\tilde{\phi}} > 0.$$

The shock will affect equilibrium output, emissions, and price, and it may cause a desired reallocation of dirty assets between public and private firms.

Within a firm type, firms have symmetric beliefs and strategies: each firm believes that if its type finds it individually profitable to buy or sell assets, all firms of its type will do the same. Thus, there are three possible ownership outcomes post-shock: (1) both public

[28] In the electricity sector, this is a common modeling assumption. For example, Holland et al. (2022) assume linear demand for short-term electricity consumption of the form $d(p) = \underline{b} - bp$, where the two parameters are $b = 0.15q_0/p_0$ and $\underline{b} = 1.15q_0$ where p_0 and q_0 are the observed price and demand.

and private firms retain ownership of their initial dirty assets; (2) private firms own all dirty assets; and (3) public firms own all dirty assets.

The relative bargaining power of public firms is fixed and parameterized by $\lambda \in (0, 1)$. After any trading has occurred, firms choose inputs demands, production and emissions. The final goods price clears the final goods market.

5.2 Pre-shock and No-trade Equilibrium

Pre-shock For the dirty assets, the pre-shock equilibrium output and input quantities by firm type are

$$y_D^{i*} = \frac{p^*}{2(\phi^i + c)}, \tag{5.5}$$

$$x_D^{i*} = \left[\frac{p^*}{2(\phi^i + c)}\right]^2. \tag{5.6}$$

Market clearing in the final goods market

$$y_D^* + \tilde{y}_D^* = a - bp \tag{5.7}$$

pins down the equilibrium output price

$$p^* = \frac{2a}{(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}) + 2b}. \tag{5.8}$$

Notice that for larger b, i.e. higher sensitivity of demand to price, the influence of changes in production costs $(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c})$ on p^* will diminish. This is a property of the fact that $f(x) = \frac{1}{x}$ is highly convex, especially near $x = 0$.

Substituting Eq. (**??**) into Eq (**??**), we see that the price is a linear function of aggregate production with sensitivity b

$$p^* = \frac{a - (y_D^* + \tilde{y_D}^*)}{b}. \tag{5.9}$$

When b is very small, a small change in aggregate production will produce avery large change in the price.

Post-shock with no asset trading If trading in assets between public and private firms is either not desired or not permitted, Eqs. 5.5, 5.6, 5.8 continue to hold, but with $\tilde{\phi}$ replaced by $\tilde{\phi}' = \Phi \times \phi$.

Post-shock with trading in assets Before characterizing the equilibrium in which there is trading in assets, I define new notation. Let ξ^* be the private cost of emitting of the equilibrium owner of the public firm's dirty asset, and $\tilde{\xi}^*$be the private cost of emitting of the equilibrium owner of the private firm's dirty asset. Eqs. 5.5, 5.6, 5.8 continue to hold, but with $\phi, \tilde{\phi}$ replaced by $\xi^*, \tilde{\xi}^*$, respectively.

5.3 Trading in Assets

When post-shock trading in assets is permitted there exist three qualitatively distinct, possible equilibria. Which one will prevail depends on b, the sensitivity of demand to price.

The first equilibrium is the "Green-washing Equilibrium" in which public firms sell their dirty assets to private firms. Private firms then own all dirty assets. They operate those assets more intensively than would public firms that have a higher cost of emissions and hence aggregate production is higher, emissions are higher, and the final goods price is lower than if no sales had occurred. Note that the increased output from the units previously owned by public firms reduces the value of private firms' existing assets. However, because the market is competitive, that effect is only indirectly taken into account through price effects in the final goods market, and the dominant effect is the private firms' relatively low cost of emitting. In the range of demand elasticities that support this equilibrium, there is a net increase in the value of dirty assets when they move from public to private ownership. The increase is so large that there are gains to trade and the equilibrium sale of assets from public firms to private firms.

What happens in comparison to the pre-shock equilibrium depends on the pre-shock emissions costs for both types of firms. An interesting case is when pre-shock the private and public cost of emitting is the same and equal to the post-shock cost to private firms of emitting. In that case production and emissions will be unchanged because private owners will operate assets as the public owner would have in the pre-shock equilibrium. Another interesting comparison is the case of public owners initially having a higher cost of emitting than private firms, but not sufficiently higher for them to have already sold the assets. Post-shock, the new, private owners will produce more with the acquired assets, and at a higher, average emissions intensity since the emissions function is convex in the production level. However, because aggregate production increases, the final goods price will decline. Consequently, private firms' existing assets will produce less and at a lower average emissions intensity. Which effect dominates will determine the aggregate emissions impact.

This possible equilibrium outcome highlights the fact that activist pressure for the divestiture of dirty asset may cause changes in ownership that are ineffective at reducing aggregate emissions or that even increase them. Lemma 1 formally establishes this results.

Lemma 1. ***Green-washing Equilibrium*** - *Given a positive shock to the public firm's private cost to emitting of size Φ, the public firm will sell its assets to the private firm if the demand sensitivity to price b is sufficiently high. Production and emissions of the divested assets, as well as aggregate production and emissions, will be unchanged from or higher than in the pre-shock equilibrium.*

Proof. See Lemma 10 in the Appendix. □

The second possibility is an "Impact Equilibrium" in which private firms sell their dirty assets to public firms. In this equilibrium, a positive emissions cost shock has "impact" because aggregate emissions go down, but counterintuitively, dirty assets are all owned by public firms. This equilibrium only exists when demand is sufficiently inelastic. The increase in the cost of emitting causes public firms reduce output, and given very inelastic demand, this generates a large increase in the final goods price and asset values. That output price increase, and hence the value of the assets, is greatest when public rather than private firms hold the dirty assets. Intuitively, in this equilibrium, the shock to the cost of emitting acts to commit all public firms to output reductions when they own all assets. In the range of demand elasticities that support this equilibrium, this substantially raises the final goods price and asset values when they move from private to public ownership.

The existence of this equilibrium requires that the production function be concave; it would not exist for a linear production function. With a linear production function, post-shock, the public firm's dirty assets will earn zero profits and the private firm's dirty assets will earn positive profits. Because marginal and average production costs are equal, the acquisition of additional assets by the public firm generates no profits, and they would not pay any premium to buy them. Hence, private firms have no incentive to sell their profit-making assets.

Lemma 2. ***Impact Equilibrium*** - *Given a positive shock to the public firm's private cost to emitting of size Φ, the private firm will sell dirty assets to the public firm if the demand sensitivity to price b is sufficiently small. Production and emissions of the divested assets, as well as aggregate production and emissions, will decline relative to the pre-shock equilibrium.*

Proof. See Lemma 11 in the Appendix. □

The third possibility is a "No Trade Equilibrium." This equilibrium exists in an intermediate range for the sensitivity of demand to price.[29] This equilibrium exists because when

[29] A more mathematical, mechanical explanation is that the Green-washing Equilibrium exists when $\{t :$

public firms sell to public firms, the increased output from the units previously owned by public firms reduces the value of private firms' existing assets. This creates a wedge in the cut-off point for the Green-washing Equilibrium and Impact Equilibrium. This is more formally stated in the Appendix. The existence of this equilibrium makes clear that increased pressure on public firms to reduce emissions is insufficient to generate trade in assets. It provides one way to contextualize my empirical findings that though the pressure to decarbonize has increased dramatically, changes in the parent ownership of high greenhouse gas emitting facilities have been very low.

Lemma 3. ***No Trade Equilibrium*** - *Given a positive shock to the public firm's cost to emitting of size Φ, there will be no trade in assets if the demand sensitivity to price is neither too small or too large. The public firms reduce emissions and aggregate emissions decline.*

Proof. See Lemma 12 in the Appendix. ☐

The emissions implications are then identical to the case in which no trade was allowed: the assets of the public firms generate less emissions, as does the system as a whole.

5.4 No Trading in Assets

When there is no trading in assets, for instance because it is expensive to undertake such transactions, there is no Green-washing equilibrium. Pressure on public firms has the intended result on their assets' emissions levels: they decline. Without trading in assets, public firms must internalize the positive shock to their emissions through production and emissions decisions.

Lemma 4. *With no trading in assets, there is no green-washing equilibrium. The public firms reduce emissions and aggregate emissions decline.*

Proof. See Appendix.

The result on aggregate emissions, however, is sensitive to the functional form of the production function assumed. One can easily generate an increase in aggregate emissions by having output reductions by public firms replaced (even if only in part) by output increases by private firms at very high emissions intensities, or in this case, at a very inefficient, flat region of the production function ☐

$2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) - V(\phi, \phi) > 0\}$ is non zero. The Impact Equilibrium exists when $\{t : V(\phi, \phi) - \tilde{V}(\phi, \tilde{\phi}) > 0\}$. The wedge exists because the marginal, portfolio value of a new asset to the public firm $2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi})$ is not equal to the value of the asset to the public firm if it retains the asset $\tilde{V}(\phi, \tilde{\phi})$.

5.5 Discussion

The model predictions are particularly sensitive to these key assumptions:

No new dirty assets A critical assumption is that there is that the aggregate stock of dirty assets in this industry are fixed. This is a plausible assumption if the technology becomes illegal or its production highly taxed. For example, Green and Vallee (2023) find that size weighted, most banks active in commercial bank lending and bond underwriting are implementing coal exit policies and that bank intermediation of credit to coal companies drops significantly after a bank adopts a coal policy. In particular, the total amount of bank loans and corporate bonds issued by a firm drops when it is more exposed to bank exit policies.[30]

Relaxing this assumption and allowing for new firms with the same cost to emitting as existing private firm to enter freely creates a setting with perfect competition and zero profits. An increase to the cost of emitting by public firms will make operating dirty assets unprofitable, and those assets will be sold to private firms.

Homogeneity of assets With assets that are heterogeneous with regard to how efficiently they convert inputs to the final good and in the relation between their inputs and emissions, the effects of a shock that changes the production of public firms' assets will depend on the technological and emissions profile of these other assets. For example, if the shock causes public firms' assets to decrease production and thus, emissions, the aggregate emissions implications depend on the emissions profile of replacement generation. This point has been repeatedly made in the empirical literature about the aggregate emissions consequences of various policies that affect the production of a subset of emitting facilities (Mansur, 2007).

No trading costs This paper assumed no significant trading costs. As long as trading costs are sufficiently low, all three equilibria will continue to exist. As the cost of trade increases, the set of bs in which there will be a no-trade equilibria will expand.

Concavity of the production function In a given regional electricity market, there are generators that use different fuels. The dispatch curve is then ordered by the relative

[30]It is also reasonable if I am only interested in the short-term climate response, and if adding productive capacity is expensive and requires a lot of time. For example, if I were interested in the consequence of a cost shock like the one described on one to two year horizon environmental outcomes, this assumption is reasonable given that plant construction takes years (e.g. combined cycle plants take 2 years to construct, and coal plants take 3-4 years). However, for larger horizons, I would want to relax this assumption.

price of fuels. Within fuels, the curve is ordered by the efficiency of the generators, with the least efficient and thus, more emissions-intense generators having higher marginal costs and therefore being dispatched later. The concavity of the production function can be rationalized by assuming that marginal assets that are of a single fuel type. Infra-marginal assets are assumed to be supplying at maximum capacity and so who holds them is irrelevant to production, emissions, and emissions intensities unless the asset is shut down. I am assuming that the shock to private costs of emitting is not sufficiently high to cause a shut down.

Fuel switching By assuming homogenous technologies, the only margin along which production can become more/less emissions intensive is if production moves to a more/less efficient level. That is, I do not allow for jumps in emissions intensities through decisions like fuel switching. Suppose, however, that it is technologically feasible for assets to switch fuels. If the cleaner fuel is the more expensive fuel, if the shock is large enough to overcome fuel price differentials this will induce fuel switching by the public firm. The aggregate emissions impact will depend on the relative magnitude of the decline in emissions from this channel versus the increase in emissions from the private firm from increasing production at a higher emissions intensity.

With these caveats in mind, this simple model highlights features of a setting in which we might expect green-washing to occur. It also makes clear what would be needed to prevent green-washing: apply pressure on firms while blocking divestments, forcing firms to express increased costs of emitting through production and emissions decisions. There are two major caveats. The first is that if demand is very inelastic, reductions in emissions coming primarily through reductions in production will generate a near symmetric increase in production elsewhere. If that replacement production is more emissions intensive, aggregate emissions will increase on net. The second is that I did not allow firms to alter their assets. If there are differences in firm abilities to make assets more, or less emissions intensive, screening trades to find and allow only those trades that would facilitate the flow of assets towards firms that would make assets less emissions intensive would be good for the climate.

Symmetric beliefs and trading strategies Individual firms will not deviate from symmetric beliefs and trading strategies. To illustrate by example, consider the second equilibrium in which private firms sell to public firms. On the surface, it may appear that individually, public firms might deviate because the private firms will be willing to operate the asset more intensely, and thus have higher valuations for the asset. However, this assumes the private buyer believes it will operate the acquired asset in a world in which all other assets are owned by public firms who operate assets less intensely and thus, support a higher final goods price. Said another way, it assumes the private buyer doesn't think through the equilibrium implications of a single public firm deviating. This paper assumes they do. If a private firm is offered the opportunity to buy the asset from a public firm, it will assume that all other public firms will make the same offer. Thus, if it accepts the offer, it does so assuming that in equilibrium, all assets will be owned by private firms.

Note that this assumption means that if there are trade flows, they will only be across firm types. Public to public sales can be generated in this model by extending the number of time periods from one to two. In the first period, public firms are shocked as described in the original model. In the second period, firms are randomly sorted into two unit intervals of firms. Each unit interval is shocked with cost shocks that equalize the marginal cost of fuel inputs within the unit interval. If I drive the marginal cost differential between the unit intervals to infinity, there will be an aggregate transfer of assets from firms in the high marginal cost interval to the low marginal cost interval, and in some realizations of unit interval segments, there will be public to public sales. This highlights that to see public to public and public to private sales, differences in the cost of emitting for public and private firms have to be small enough that they can be overwhelmed by period two shocks. Furthermore, it also highlights that the public to private distinction is only relevant to the extent that public firms and private firms are sets of firms that are or are not shocked.

6 Conclusion

This paper empirically studied whether in my sample of fossil fuel power plant divestments in 2002-2020, shifting asset ownership from the hands of publicly traded firms to those of privately held firms a.) leads assets to be operated in ways that are more emitting in absolute terms and relative to what we might expect if they were sold to another publicly traded firm and b.) rewards publicly traded firms through increased valuations.

Estimated short-horizon, defined here as eighteen months, divestment effects on unit starts, capacity factors, fuel switching and co-firing behaviors, and emissions intensities suggest that in my sample, such ownership transfers did not lead assets to individually be operated in ways that were more emitting, either in absolute or relative terms. This favors the green-washing narrative that asset divestments are unlikely to have a meaningful effect on emissions.

One question is whether we expect these results to hold in the future. The nature of emissions generation from this sector implies that the change in emissions from ownership changes is likely to be limited, especially on the side of emissions dramatically increasing. This is because unlike other kinds of pollution, like ground pollution or even sulfur dioxide or nitrous oxide pollution from this sector, power plants cannot choose whether or not they will "dump" emissions into the air. This is because carbon capture technology is in its infancy and has generally been implemented only at pilot scale with government support (Howard, 2022). Thus, at existing technological constraints, the only margin along which firms can change emissions is by changing how much they produce, which is bounded above by capacity constraints, and constrained by ordinary economic forces like final goods demand–which is highly inelastic in this sector–and marginal costs.

To study the valuation implications of divestitures by publicly traded firms, I estimated cumulative abnormal returns around divestment announcements and found that divestments to private firms did not command a premium to divestments to public firms, suggesting the absence of large and systematic financial incentives to divest these highly emitting assets to private firms over public firms.

Both the empirics and model contribute to the growing literature suggesting that divestments are likely to have near zero, or negative climate impacts and encouraging engagement through the exercise of rights of control (Broccardo et al., 2022; Berk and van Binsbergen, 2022; Hartzmark and Shue, 2023; Krueger et al., 2020) over exit.

References

Akey, P. and I. Appel (2021): "The Limits of Limited Liability: Evidence from Industrial Pollution," *Journal of Finance*.

Andonov, A. and J. D. Rauh (2023): "The Shifting Finance of Electricity Generation," Working paper.

Bai, X. and Y. Wu (2023): "Private Equity and Gas Emissions: Evidence from Electric Power Plants," Working paper.

Bellon, A. (2021): "Does Private Equity Ownership Make Firms Cleaner? The Role Of Environmental Liability Risks," Working paper.

Berk, J. B. and J. H. van Binsbergen (2022): "The Impact of Impact Investing," Working paper.

Bernstein, S. (2022): "The effects of public and private equity markets on firm behavior," *Annual Review of Financial Economics*.

Bernstein, S. and A. Sheen (2016): "The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry," *The Review of Financial Studies*.

Bolton, P. and M. T. Kacperczyk (2021): "Do Investors Care About Carbon Risk," *Journal of Financial Economics*.

Bolton, P. and E.-L. von Thadden (1998): "Blocks, Liquidity, and Corporate Control," *The Journal of Finance*.

Broccardo, E., O. Hart, and L. Zingales (2022): "Exit versus Voice," *Journal of Political Economy*.

Bushnell, J. and C. D. Wolfram (2005): "Ownership Change, Incentives and Plant Efficiency: The Divestiture of US Electric Generation Plants," Working paper.

Cicala, S. (2015): "When Does Regulation Distort Costs? Lessons from Fuel Procurement in US Electricity Generation," *American Economic Review*.

——— (2022): "Imperfect Markets Versus Imperfect Regulation in US Electricity Generation," *The American Economic Review*, 112, 409–441.

Davis, S., J. Haltiwanger, K. Handley, R. Jarmin, J. Lerner, and J. Miranda (2014): "Private equity, jobs, and productivity," *American Economic Review*.

DellaVigna, S. and J. M. Pollet (2007): "Demographics and Industry Returns," *American Economic Review.*

Demirer, M. and O. Karaduman (2022): "Do Mergers and Acquisitions Improve Efficiency: Evidence from Power Plants," Working paper.

Deshmukh, A. (2023): "All Eyes on Brown Spinning: Do Banks Have a Net Zero Duty to Act," Tech. rep., Net Zero Investor.

Duchin, R., J. Gao, and Q. Xu (2023): "Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution," Working paper.

EIA (2015): "Analysis of Heat rate Improvlement Potential at Coal-fired Power Plants," Tech. rep., Energy Information Administration.

Fowlie, M. L. (2009): "Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage," *American Economic Journal: Economic Policy.*

Goodman-Bacon, A. (2021): "Difference-in-Differences with Variation in Timing Treatment," *Journal of Econometrics.*

Gozlugol, A. and W.-G. Ringe (2022): "Private Companies: The Missing Link to The Path to Net Zero," Working paper, European Corporate Governance Institute.

Graham, J. R., C. R. Harvey, and S. Rajgopal (2005): "The Economic Implications of Corporate Financial Reporting," *Journal of Accounting and Economics.*

Green, D. and B. Vallee (2023): "Can Finance Save the World? Measurement and Effects of Bank Coal Exit Policies," Working paper.

Gupta, A. and S. T. Howell (2023): "The Role of Private Equity in the U.S. Economy and Whether and How Favorable Tax Policies for the Sector Need to be Reformed," Tech. rep.

Hartzmark, S. M. and K. Shue (2023): "Counterproductive Sustainable Investing: Impact Elasticity of Brown and Green Firms," Working paper.

Hite, G. L., J. E. Owers, and R. C. Rogers (1987): "The Market for Interfirm Asset Sales: Partial Sell-offs and Total Liquidations," *Journal of Financial Economics.*

Holland, S. P., E. T. Mansur, and A. J. Yates (2022): "Decarbonization and Electrification in the Long Run," Working paper, NBER.

Howard, K. L. (2022): "Decarbonization: Status, Challenges, and Policy Options for Carbon Capture, Utilization, and Storage," Tech. rep., United States Government Accountability Office.

Jacobson, M. Z. (2019): "The Health and Climate Impacts of Carbon Capture and Direct Air Capture," *Energy and Environmental Science*.

Jacqz, I. (2021): "Pollution and Acquisition: Emissions and Distributional Effects of Mergers," Working paper.

Kaplan, S. (2019): "Are US Companies Too Short-Term Oriented? Some Thoughts," *Journal of Applied Corporate Finance*.

Korellis, S. (2014): "Coal-Fired Power Plant Heat Rate Improvement Options, Part 1," Power Magazine.

Krueger, P., Z. Sautner, and L. T. Starks (2020): "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*.

MacKinlay, A. C. (1997): "Event Studies in Economics and Finance," *Journal of Economic Literature*.

Malek, G., A. Baxter, D. Watson, A. Howell, C. Staib-Kaufman, M. Davis, G. Sagingaliyev, and G. Swartzwelder (2022): "Transferred Emissions: How Risks in Oil and Gas Mergers and Acquisitions Could Hamper the Energy Transition," Tech. rep., Environmental Defense Fund.

Mansur, E. T. (2007): "Do Oligopolists Pollute Less? Evidence From a Restructured Electricity Market," *The Journal of Industrial Economics*.

McCartney, R. H. (2006): "Designing and Upgrading Plants to Blend Coal," Tech. rep., Power Magazine.

NACAA (2015): "Implementing EPA's Clean Power Plans A Menu of Options," Tech. rep.

Nowling, U. (2015): "Understanding Coal Power Plant Heat Rate and Efficiency," Power Magazine.

Shiver, S. A. and M. M. Forster (2020): "Corporate Governance and Pollution Externalities of Public and Private Firms," *The Review of Financial Studies*.

Staff (2019): "Natural Gas Flaring and Venting: State and Federal Regulatory Overview,Trends, and Impacts," Tech. rep., https://www.energy.gov/sites/prod/files/2019/08/f65/Natural

Stein, J. C. (1989): "Efficient Capital Markets, Inefficient Firms: A Model of Myopic Corporate Behavior," *Quarterly Journal of Economics*.

Sun, L. and S. Abraham (2021): "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*.

van Benthem, A. A., E. Crooks, S. Giglio, E. Schwob, and J. Stroebel (2022): "The effect of climate risks on the interactions between financial markets and energy companies." *Nature Energy*.

Wright, P. and S. P. Ferris (1997): "Agency Conflict and Corporate Strategy the Effect of Divestment on Corporate Value," *Strategic Management Journal*.

7 Appendix

7.1 Climate Implications: Robustness Checks

7.2 Omit unit fixed effects

When we have unit fixed effects, one might be concerned by estimates of divestment effects when the dependent variable is a binary variable and thus, can be a constant in the sample. I re-estimate divestment effects without unit fixed effects and find qualitatively similar results.

7.2.1 Robustness Checks: Cross Section

One may be interested in divestment effect heterogeneity. Below, I consider several stories that motivate cross-sectional analysis with the note of caution that some of these estimates were on very small sample sizes.

For example, one might think that divestment effects may exist in the following settings:

1. When divestment is to an owner with stronger incentives to reduce fuel costs. For example, when ownership is transferred from a rate-regulated to non-rate regulated firm.

   (a) Results on Emissions Intensity

      i. Qualitatively the same. Whether or not divestment was from a regulated to a deregulated firm doesn't matter.

   (b) Other Results

      i. Point estimates broadly tell the same story except that when divestment is from a regulated to a deregulated firm, post-divestment, the capacity factor increases on average by 14.6%. However, this was only estimated with 4 divested units.

      ii. Differences by buyer type are not statistically significant except when looking at divestments from regulated to deregulated entities.

2. When divestment is to an owner with more concentrated ownership or higher powered incentives to maximize firm value. For example, when ownership is transferred to a private equity firm. This is because the general partners are compensated with a call-option-like share of the profits, employ leverage, typically aim to liquidate investments and do not have existing relationships with target firms' other stakeholders, such as employees, customers, or suppliers (Gupta and Howell, 2023).

(a) Results on Emissions Intensity

    i. Qualitatively the same. Whether or not divestment was to a private equity buyer doesn't matter.

(b) Other Results

    i. Point estimates broadly tell the same story.

    ii. Differences by buyer type are not statistically significant.

3. When divestment is by an owner that may be under greater environmental scrutiny, such as power firms whose entire portfolios are essentially emissions generating. This assumes that scrunity scales with the importance of emissions generating activity as a percent of the company portfolio.

    (a) Results on Emissions Intensity

        i. When the seller wasn't a power firm, divestment to a private firm was associated with a 2.8% increase in emissions intensity. This was estimated on 7 divested units, however. When the seller was a power firm, divestment to a private firm was associated with a 0.2% decrease in emissions intensity.

    (b) Other Results:

        i. Point estimates show that when the seller wasn't a power firm, divestment to a private firm was associated with a 13.8% decrease in start probability. When the seller is a private firm, divestment is associated with a 3.4% decrease in start probability. That is, power firms selling is associated with a relatively lower decrease in starts when the sale is to a private firm.

        ii. The point estimates of coefficients when the seller wasn't a power firm, however, is based on a very small sample size. 0 units were divested in a Public to Public transaction where the seller was not a power firm. 7 units were divested in a Public to Private transaction where the seller was not a power firm.

4. When divestment was on or after 2015 (post Paris)

    (a) Emissions Intensity

        i. Post-Paris, drop in emissions intensity at coal units greater by 9.6% compared to the pre-Paris baseline decline of 1.9% , but the point estimate of the marginal effect is based on two units.

    (b) Other Results:

i. Divestments to private firms doesn't make units operate in ways that are more emissions-intense.

One might think divestment effects exist in the following settings

1. Where there aren't common, and strong incentives to reduce carbon dioxide emissions. One way to test for this is to compare divestment effects by cap and trade and non cap and trade states. A unit is in a cap and trade state if it was a part of RGGI or in the state of California and in years 2013+.

   (a) Emissions Intensity

      i. Divestment to private firms in non-cap and trade states is associated with 0.5% decline in the emissions intensity; in cap and trade states, divestment to a private firm was associated with an additional 4.1% increase in the emissions intensity, an effect estimated with 56 units and significant at the 10% level.

   (b) Other Results:

      i. Divestments to private firms doesn't make units operate in ways that are more emissions-intense.

7.2.2 Robustness Checks: Longer Window

One might be concerned that results may change if regressions are run at higher frequencies. I re-estimate the results using a 5 year horizon. There were 49 Public to Public deals and 50 Public to Private deals.

Table 7.1: Co-firing

Dependent Variable: Burned Secondary Fuel	Coal (1)	Gas (2)
$Post \times Public\,Buyer$	0.002	0.008
	(0.004)	(0.006)
$Post \times Private\,Buyer$	0.000	-0.013
	0.000	(0.021)
Observations	175,585	541,243
R-squared	0.99	0.99
R-squared contribution	0.00	0.00
Wald Test P-value	0.68	0.41

Notes: This table uses OLS regressions to estimate the effects of divestment on co-firing by the fuel type of the unit divested. Observations are at the unit level and weekly frequency. The dependent variable is equal to one if the unit burned a secondary fuel, while burning coal as the primary fuel. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, primary and secondary fuel type burned, week, year. The table reports also the R-squared contribution of the pre-sale dummies, and the p-value of a Wald test of the null that the pre-sale dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7.2: Divestment Effects on Unit Starts, Capacity Factors, and Emissions Intensities

	All			By Fuel		
	Starts	Capacity Factor	$ln(Emissions\,Intensity)$	Starts	Capacity Factor	$ln(Emissions\,Intensity)$
	(1)	(2)	(3)	(3)	(4)	(5)
$Post \times Public\,Buyer$	0.002	0	-0.001			
	(0.012)	(0.011)	(0.012)			
$Post \times Private\,Buyer$	0.002	0.006	0.019			
	(0.014)	(0.013)	(0.019)			
$Post \times Public\,Buyer \times Coal\,Unit$				0.031*	0.006	-0.013
				(0.018)	(0.012)	(0.009)
$Post \times Private\,Buyer \times Coal\,Unit$				0.059	0.01	-0.031*
				(0.036)	(0.021)	(0.016)
$Post \times Public\,Buyer \times Gas\,Unit$				-0.015	-0.005	0.008
				(0.017)	(0.018)	(0.020)
$Post \times Private\,Buyer \times Gas\,Unit$				-0.006	0.005	0.025
				(0.015)	(0.014)	(0.021)
Sample						
Observations	754,101	571,215	571,215	754,101	571,215	571,215
R-squared	0.39	0.71	0.93	0.39	0.71	0.93
R-squared contribution	0.00	0.00	0.00	.	0.00	0.00
Wald Test P-value						
All	0.97	0.71	0.41			
Coal				0.48	0.84	0.34
Gas				0.64	0.66	0.57

Notes: This table uses OLS regressions to test the effect of divestment on starts, capacity factors, and the log of the emissions intensity by the primary fuel burned by the divested unit prior to divestment. Observations are at the unit level and weekly frequency. Starts is a dummy variable equal to one if gross generation is positive; the capacity factor is defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; the log of the emission rate is defined as the ratio of carbon dioxide emissions to gross generation conditional on gross generation being positive. Columns (1)-(3) present the effects of divestment on all units without distinguishing by unit fuel type. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Columns (4)-(6) present the effects of divestment on units by fuel type. The dummy variable ($Post \times Public\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type f and the dummy ($Post \times Private\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f. Two types of units exist: coal and gas units. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, the fuels the unit is able to burn, week, year. The table reports also the number of relevant observations used to identify the coefficients reported in that column only, the R-squared contribution of the post-divestment dummies, and the p-value of a Wald test of the null that the post-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.2.3 Nameplate-Weighted Results

One might be concerned that results may change if we weight results by nameplate.

Table 7.3: Co-firing

Dependent Variable: Burned Secondary Fuel	Coal (1)	Gas (2)
$Post \times Public\,Buyer$	0.001	0.005
	(0.004)	(0.004)
$Post \times Private\,Buyer$	0.000	-0.008
	0.000	(0.007)
Observations	71,742	272,498
R-squared	0.99	1.00
R-squared contribution	0.00	0.00
Wald Test P-value	0.84	0.22

Notes: This table uses OLS regressions to estimate the effects of divestment on co-firing by the fuel type of the unit divested. Observations are at the unit level and weekly frequency. The dependent variable is equal to one if the unit burned a secondary fuel, while burning coal as the primary fuel. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, primary and secondary fuel type burned, week, year. The table reports also the R-squared contribution of the pre-sale dummies, and the p-value of a Wald test of the null that the pre-sale dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7.4: Divestment Effects on Unit Starts, Capacity Factors, and Emissions Intensities

	All			By Fuel		
	Starts	Capacity Factor	$ln(Emissions\,Intensity)$	Starts	Capacity Factor	$ln(Emissions\,Intensity)$
	(1)	(2)	(3)	(3)	(4)	(5)
$Post \times Public\,Buyer$	0.000	0.001	-0.012			
	(0.012)	(0.010)	(0.009)			
$Post \times Private\,Buyer$	-0.041***	-0.015	-0.008			
	(0.015)	(0.014)	(0.016)			
$Post \times Public\,Buyer \times Coal\,Unit$				0.003	0.003	-0.009
				(0.015)	(0.012)	(0.008)
$Post \times Private\,Buyer \times Coal\,Unit$				-0.004	-0.015	-0.049**
				(0.024)	(0.031)	(0.023)
$Post \times Public\,Buyer \times Gas\,Unit$				-0.006	-0.001	-0.014
				(0.020)	(0.016)	(0.019)
$Post \times Private\,Buyer \times Gas\,Unit$				-0.050***	-0.016	0.002
				(0.017)	(0.016)	(0.018)
Sample						
Observations	359,053	276,535	276,535	359,053	276,535	276,535
R-squared	0.35	0.61	0.95	0.35	0.61	0.95
R-squared contribution	0.00	0.00	0.00	0.00	0.00	0.00
Wald Test P-value						
All	0.84	0.29	0.88			
Coal				0.78	0.56	0.12
Gas				0.09	0.49	0.59

Notes: This table uses OLS regressions to test the effect of divestment on starts, capacity factors, and the log of the emissions intensity by the primary fuel burned by the divested unit prior to divestment. Observations are at the unit level and weekly frequency. Starts is a dummy variable equal to one if gross generation is positive; the capacity factor is defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; the log of the emission rate is defined as the ratio of carbon dioxide emissions to gross generation conditional on gross generation being positive. Columns (1)-(3) present the effects of divestment on all units without distinguishing by unit fuel type. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Columns (4)-(6) present the effects of divestment on units by fuel type. The dummy variable ($Post \times Public\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type f and the dummy ($Post \times Private\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f. Two types of units exist: coal and gas units. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, the fuels the unit is able to burn, week, year. The table reports also the number of relevant observations used to identify the coefficients reported in that column only, the R-squared contribution of the post-divestment dummies, and the p-value of a Wald test of the null that the post-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.2.4 Including Oil Transactions

In the main paper, I excluded transactions involving oil fired units because they were not many (26 Public to Public divestments, and 34 Public to Private divestments).

Table 7.5: Divestment Effects on Unit Starts, Capacity Factors, and Emissions Intensities

	All			By Fuel		
	Starts	Capacity Factor	$ln(Emissions\,Intensity)$	Starts	Capacity Factor	$ln(Emissions\,Intensity)$
	(1)	(2)	(3)	(3)	(4)	(5)
$Post \times Public\,Buyer$	-0.018	-0.006	-0.011			
	(0.013)	(0.008)	(0.010)			
$Post \times Private\,Buyer$	-0.028	-0.011	0.000			
	(0.017)	(0.013)	(0.017)			
$Post \times Public\,Buyer \times Coal\,Unit$				-0.026	-0.008	-0.013*
				(0.019)	(0.012)	(0.007)
$Post \times Private\,Buyer \times Coal\,Unit$				0.019	-0.007	-0.041**
				(0.029)	(0.022)	(0.020)
$Post \times Public\,Buyer \times Gas\,Unit$				-0.015	-0.003	-0.009
				(0.018)	(0.012)	(0.016)
$Post \times Private\,Buyer \times Gas\,Unit$				-0.031*	-0.011	0.003
				(0.019)	(0.014)	(0.018)
$Post \times Public\,Buyer \times Oil\,Unit$				0.035	-0.044	-0.009
				(0.076)	(0.033)	(0.016)
$Post \times Private\,Buyer \times Oil\,Unit$				0.008	-0.025	-0.046**
				(0.037)	(0.025)	(0.020)
Sample						
Observations	359,064	274,625	274,625	359,064	274,625	274,625
R-squared	0.40	0.72	0.93	0.40	0.72	0.93
R-squared contribution	0.00	0.00	0.00	0	0.00	0.00
Wald Test P-value						
All	0.64	0.71	0.62			
Coal				0.19	0.99	0.18
Gas				0.49	0.64	0.65
Oil				0.75	0.64	0.17

Notes: This table uses OLS regressions to test the effect of divestment on starts, capacity factors, and the log of the emissions intensity by the primary fuel burned by the divested unit prior to divestment. Observations are at the unit level and weekly frequency. Starts is a dummy variable equal to one if gross generation is positive; the capacity factor is defined as the ratio of gross generation to nameplate capacity conditional on gross generation being positive; the log of the emission rate is defined as the ratio of carbon dioxide emissions to gross generation conditional on gross generation being positive. Columns (1)-(3) present the effects of divestment on all units without distinguishing by unit fuel type. The dummy variable ($Post \times Public\,Buyer$) is equal to one if unit i was divested by a public firm to a public firm, and t is in the post-divestment period and the dummy variable ($Post \times Private\,Buyer$) is equal to one if unit i was divested by a public firm to a private firm, and t is in the post-divestment period. Columns (4)-(6) present the effects of divestment on units by fuel type. The dummy variable ($Post \times Public\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a public buyer, and of type f and the dummy ($Post \times Private\,Buyer \times f - Unit$) is equal to one if unit i is in the post-divestment period at time t, was divested by a private buyer, and of type f. Two types of units exist: coal and gas units. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, the fuels the unit is able to burn, week, year. The table reports also the number of relevant observations used to identify the coefficients reported in that column only, the R-squared contribution of the post-divestment dummies, and the p-value of a Wald test of the null that the post-divestment dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.2.5 Including Private-Private and Private-Public

While sales by private firms were not the focus of this paper, I estimate divestment effects and find the following results:

- Private-Private divestments
  - No statistically significant change in co-firing behavior
  - No statistically significant change in starts
  - Statistically significant increase in the capacity factor by 4.6% (driven by gas units)
  - No statistically significant change in the emissions intensity
- Private to Public divestments
  - No statistically significant change in co-firing behavior
  - Statistically significant increase in starts by 11.6% (driven by gas units)
  - No statistically significant change in capacity factor
  - No statistically significant change in the emissions intensity

7.3 Climate Implications

7.3.1 Comparison of Treated Units and Controls

Table 7.6 presents the average operations and emissions behavior of treated and control units, as well as their unit characteristics: their nameplate capacities and the ages of associated plants, across the entire sample. Treated units were, on average, 221 MW and slightly larger than the control group by 23MW; they were also likely to be a part of plants that were younger by five years. When means are compared within fuel groups, the difference in nameplate capacities and age are statistically significant for gas-fired units only.

Table 7.6: Comparison of Control and Treated Units, Full Sample

	Treated Units	Control Units	Difference
	(1)	(2)	(3)
Annual Generation (MWh)			
Mean (MW)	938,291	876,716	61,574
Std. Dev./Std. Error	(1,268,854)	(1,227,594)	(61,066)
Annual Emissions (s. tons)			
Mean	734,039	653,970	80,068
Std. Dev./Std. Error	(1,249,113)	(1,126,822)	(58,058)
Emissions Intensity ($\frac{s.tons}{MWh}$)			
Mean	0.70	0.69	0.01
Std. Dev./Std. Error	(0.23)	(0.21)	(0.01)
Nameplate (MW)			
Mean	221	198	23**
Std. Dev./Std. Error	(201)	(197)	(10)
Age (Years)			
Mean	37	41	-5***
Std. Dev./Std. Error	(21)	(24)	(1)

Notes: Means and standard deviations reported in columns (1)-(2). Means and standard errors reported in column (3).
*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Tables 7.7 and 7.8 in the Appendix present similar results for treated units broken out by buyer identity and the fuel type of divested units.

In the sample used, the average coal-fired unit acquired by public buyers was smaller, generated less, and emitted less than those acquired by private buyers. They also tended to be a part of older plants. Differences in average emissions intensities are not statistically significant.

The average gas-fired unit acquired by public buyers tended to be a part of older plants than those acquired by private buyers. Differences in average generation levels, emissions, emissions intensity, and nameplate capacity are not statistically significant.

7.3.2 Comparison Among Treated Units and Controls by Buyer Type

Table 7.7: Comparison Among Treated Coal-fired Units, Year of Sale

	Public Buyer	Private Buyer	Difference
	(1)	(2)	(3)
Annual Generation (MWh)			
Mean (MW)	1,953,444	4,232,072	-2,278,628***
Std. Dev./Std. Error	1,819,261	2,522,803	436,534
Annual Emissions (s. tons)			
Mean	1,898,567	4,393,694	-2,495,127***
Std. Dev./Std. Error	1,668,923	2,585,083	410,582
Emissions Intensity ($\frac{s.tons}{MWh}$)			
Mean	1.03	1.07	-0.04
Std. Dev./Std. Error	0.13	0.18	0.03
Nameplate (MW)			
Mean	351	669	-318***
Std. Dev./Std. Error	277	366	66
Age (Years)			
Mean	52	36	15***
Std. Dev./Std. Error	15	13	3

Notes: Means and standard deviations reported in columns (1)-(2). Means and standard errors reported in column (3).
*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7.8: Comparison Among Treated Gas-fired Units, Year of Sale

	Public Buyer	Private Buyer	Difference
	(1)	(2)	(3)
Annual Generation (MWh)			
Mean (MW)	599,274	555,372	43,902
Std. Dev./Std. Error	663,811	621,191	59,955
Annual Emissions (s. tons)			
Mean	306,301	276,767	29,534
Std. Dev./Std. Error	298,659	276,069	26,795
Emissions Intensity ($\frac{s.tons}{MWh}$)			
Mean	0.60	0.58	0.01
Std. Dev./Std. Error	0.12	0.12	0.01
Nameplate (MW)			
Mean	172	167	5
Std. Dev./Std. Error	100	100	9
Age (Years)			
Mean	24	16	8*
Std. Dev./Std. Error	23	16	2

Notes: Means and standard deviations reported in columns (1)-(2). Means and standard errors reported in column (3).
*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.3.3 Averages of Divested Coal and Gas Units

Table 7.9: Averages of Divested Coal and Gas Units

	Coal	Gas
	(1)	(2)
Weekly Starts		
Mean	0.82	0.76
Std. Dev.	0.38	0.43
Capacity Factor (MWh/Nameplate)		
Mean	0.72	0.48
Std. Dev.	0.24	0.32
Emissions Intensity (short tons/MWh)		
Mean	1.01	0.58
Std. Dev.	0.13	0.15
Carbon Factor (short tons/MMBtu)		
Mean	0.10	0.06
Std. Dev.	0.00	0.01
Heat Rate (MMbtu/MWh)		
Mean	9.81	9.55
Std. Dev.	1.18	2.17

7.3.4 Heat Rate Improvements

In its May 2015 report "Analysis of Heat Rate Improvement Potential at coal-fired Power Plants", the EIA identified heat rate improvements at existing plants ranging from 0.8% - 10% through such methods. Drying low-rank coal prevents heat energy from being lost to evaporate moisture in coal. "Sub-bituminous and lignite coals contain relatively large amounts of moisture (15 to 40%) compared to bituminous coal (less than 10%). A significant amount of the heat released during combustion of low-rank coals is used to evaporate this moisture, rather than generate steam for the turbine. As a result, boiler efficiency is typically lower for plants burning low-rank coal. The technologies include using waste heat from the flue gas and/or cooling water systems to dry low-rank coal prior to combustion." Intelligent sootblowing can help maintain boiler efficiency. "Sootblowers intermittently inject high velocity jets of steamor air to clean coal ash deposits from boiler tube surfaces in order to maintain adequate heat transfer. Proper control of the timing and intensity of individual sootblowers is important to maintain steam temperature and boiler efficiency. The identified technologies include intelligent or neural network sootblowing (i.e., sootblowing in response to real-time conditions in the boiler) and detonation sootblowing."

In its October 2017 report "Improving Heat Rate on Combined Cycle Power Power Plants" delivered to the Environmental Defense Fund, clean energy consulting firm Andover Technology Partners identified possible heat rate improvements in gas plants through such processes. Coating turbine blades can improve a turbine's heat resistance, fouling resistance, corrosion resistance, and reduce the turbine's surface friction. Repairing steam leaks and adding or restoring insulation, and effective steam-trap maintenance program prevents the loss of the heat energy being converted to electricity. Heat rate improvements were estimated to be around 0.5-3%.

7.3.5 Pre-post-divestment, Full Results

Note that the difference between the pre and post dummies do not equal the post dummy in the benchmark specification. This is because in the regression with the pre and post dummies, the pre dummies is the average unit fixed effects weighted by sample shares and the post dummies is the average of unit fixed effects weighted by sample shares plus the divestment effect. In the regression with just the post dummies, the post dummy is divestment effect after individual unit fixed effects have been taken out.

Table 7.10: Average Emissions Intensity of Treated Units vis-à-vis Control Units in the Pre-divestment Period

	ln(Emissions Rate) (1)	*ln(Heat Rate)* (2)
$Pre \times Public\,Buyer \times Coal\,Unit$	0.008	0.008
	(0.015)	(0.015)
$Post \times Public\,Buyer \times Coal\,Unit$	0.001	(0.006)
	(0.017)	(0.017)
$Pre \times Private\,Buyer \times Coal\,Unit$	0.057	0.029
	(0.055)	(0.047)
$Post \times Private\,Buyer \times Coal\,Unit$	0.027	0.005
	(0.062)	(0.052)
$Pre \times Public\,Buyer \times Gas\,Unit$	0.016	0.031
	(0.023)	(0.022)
$Post \times Public\,Buyer \times Gas\,Unit$	0.036	0.047**
	(0.022)	(0.022)
$Pre \times Private\,Buyer \times Gas\,Unit$	0.043	0.048*
	(0.026)	(0.026)
$Post \times Private\,Buyer \times Gas\,Unit$	0.019	0.022
	(0.027)	(0.026)
Sample		
Observations	273,278	273,278
R-squared	0.80	0.54
R-squared contribution	0.00	0.01
Wald Test P-value		
Coal	0.41	0.67
Gas	0.43	0.59

Notes: This table uses OLS regressions to test for selection. Observations are at the unit level and weekly frequency. The dependent variable is the natural log of the emissions intensity: the ratio of emissions to generation. The variable $Pre \times Public\,Buyer$ is a dummy variable that takes the value of one before a unit has been divested by a public seller to a public buyer. The variable $Pre \times Private\,Buyer$ a dummy variable that takes the value of one before the unit has been divested by a public seller to a private buyer. Standard errors are clustered at the plant level and reported in parentheses. Fixed effects are unit fixed effects and interactions of the following variables: state, NERC region, a combined cycle indicator equal to one if the boiler was part of a combined cycle system, primary and secondary fuel type burned, week, year. The table reports also the R-squared contribution of the pre-sale dummies, and the p-value of a Wald test of the null that the pre-sale dummies for public buyers and private buyers are equivalent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.3.6 Logit

Description: This table estimates a logit model of the conditional probability of being sold to a private buyer in our sample, with the condition being, being sold by a public firm. The data are the unit characteristics of sold units the year before sale. The dependent variable takes a value of one when the outcome is being acquired by a private buyer, and a value of zero when the outcome is being acquired by a public buyer. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The table reports McFadden's pseudo R-squared, defined as one minus the ratio of the log likelihood of the full model to the log likelihood of the model with just the intercept: $1 - \frac{ln(\mathcal{L}_{Full})}{ln(\mathcal{L}_{intercept})}$.

Table 7.11: Selection

Dependent Variable: $P(Sold\, to\, Private\, Firm \mid Sold\, by\, Publicly\, Traded\, Firm)$	All (1)	Coal (2)	Gas (3)
Is gas unit	1.462***		
	(0.402)		
Combined cycle plant	-0.024	1.915	0.180
	(0.273)	(9,533.749)	(0.291)
Nameplate quartile	0.129	-0.176	-0.012
	(0.141)	(0.414)	(0.170)
Age quartile	-0.449***	-2.102***	-0.289**
	(0.133)	(0.709)	(0.143)
In regulated state	-3.022***	-17.204	-2.757***
	(0.536)	(1,443.629)	(0.547)
In deregulated retail electricity state	0.393*	0.576	0.360
	(0.225)	(0.768)	(0.237)
In cap and trade program state	1.119***	0.399	1.094***
	(0.382)	(1.275)	(0.415)
Constant	-0.616	4.571*	0.790*
	(0.630)	(2.725)	(0.406)
Pseudo R-squared	0.33	0.48	0.16

Notes: The indicator function for deregulation was omitted in the second column because of collinearity.

7.3.7 Diff-in-Diff Goodman-Bacon critique

Goodman-Bacon (2021) decomposes did estimator into the weighted average of all possible two-group/two-period did estimators in the data, where the groups are earlier treated, later treated, and never treated. The paper also shows that the coefficient can have the wrong sign if treatment induces a trend shift. Because I only use never-treated units as controls, our did estimator is the average of the 2x2 estimator comparing the treated with the never treated. Because I use never-treated, or not yet acquired units as controls, our coefficient will always have the right sign as the never-treated units will never experience a treatment-related trend-shift. Thus, the concerns about identification and interpretation in Goodman-Bacon (2021) are not issues in this setting.

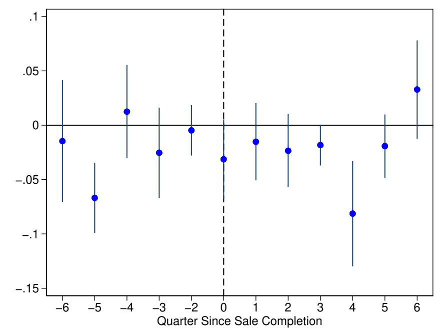
7.3.8 Sun and Abrahams Estimator

The Sun and Abraham (2021) IW estimator is formed by estimating cohort specific average CATT, and then weighing them by sample shares of each cohort in the relevant period.

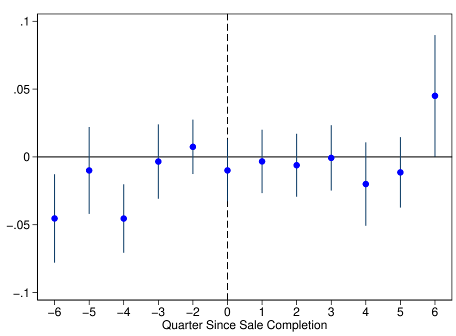
In our setting, each cohort is a singleton. Therefore, the sample share of each cohort in the relevant period is equal to $\frac{1}{\#\,cohorts}$, and the IW estimator reduces to a simple average of deal-generator CATTs.

Sun and Abraham show that the IW estimator is consistent and with a few standard assumptions (there are observations from at least two cohorts not treated in $t = 0$, cross sectional observations are independent, and identically distributed, large outliers are unlikely, and that the matrix whose rows consist of the vector of double demeaned data for cohort i in time t is full rank), is asymptotically normal.

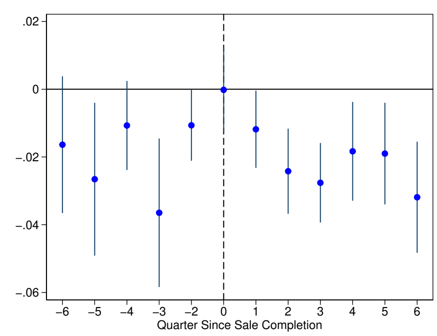
Figure 7.1: Sun and Abrahams Estimator for Dynamic Divestment Effects of Coal Units Sold to Public Firms



(a) Starts*



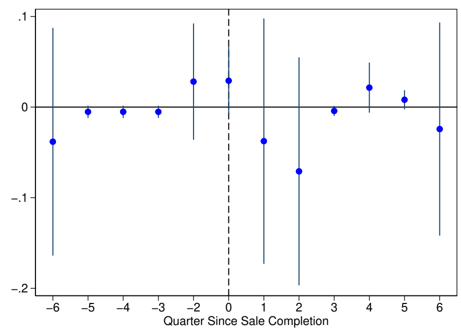
(b) Capacity Factor



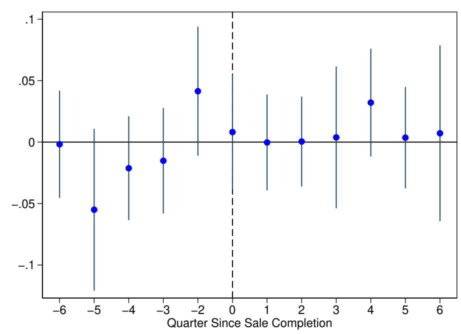
(c) Emissions Intensity

Note: For computational reasons, I aggregated to the quarterly frequency. This means that "starts", here, is a dummy variable equal to one if the unit was on at any point in a given quarter, in contrast to the main paper where "starts" was a dummy variable equal to one if the unit was on in a given week. Units that were always "on" at this frequency would drop out of the estimation because the dependent variable would be collinear with unit fixed effects. Thus, the results of this plot and the results of divestments on starts in the simple DD regression in the paper will differ.

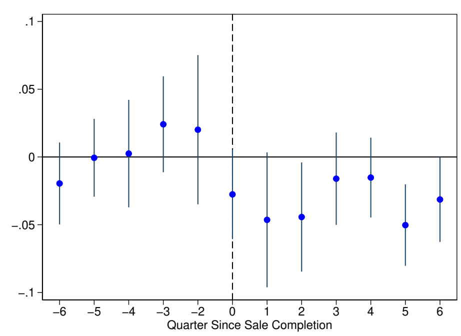
Figure 7.2: Sun and Abrahams Estimator for Dynamic Divestment Effects of Coal Units Sold to Private Firms



(a) Starts*



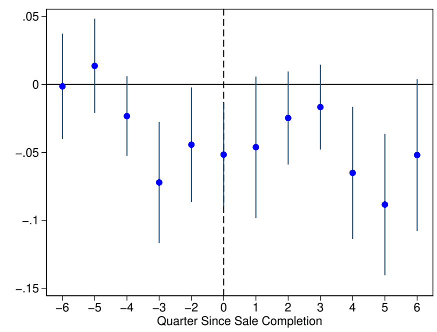
(b) Capacity Factor



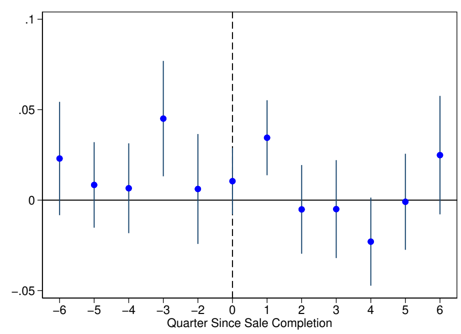
(c) Emissions Intensity

Note: For computational reasons, I aggregated to the quarterly frequency. This means that "starts", here, is a dummy variable equal to one if the unit was on at any point in a given quarter, in contrast to the main paper where "starts" was a dummy variable equal to one if the unit was on in a given week. Units that were always "on" at this frequency would drop out of the estimation because the dependent variable would be collinear with unit fixed effects. Thus, the results of this plot and the results of divestments on starts in the simple DD regression in the paper will differ.

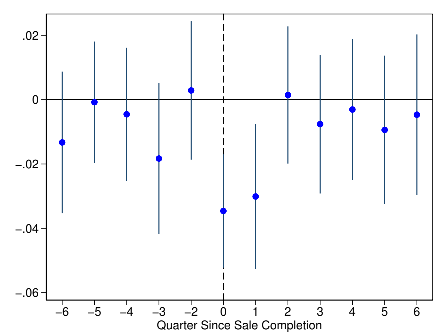
Figure 7.3: Sun and Abrahams Estimator for Dynamic Divestment Effects of Gas Units Sold to Public Firms



(a) Starts*



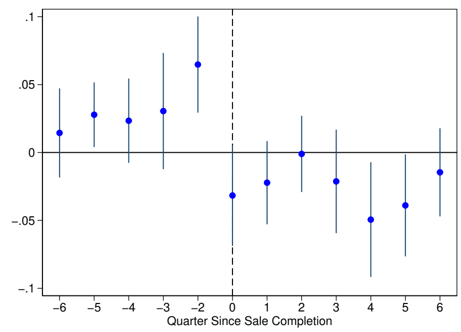
(b) Capacity Factor



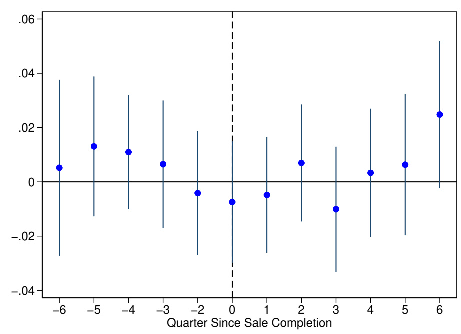
(c) Emissions Intensity

Note: For computational reasons, I aggregated to the quarterly frequency. This means that “starts”, here, is a dummy variable equal to one if the unit was on at any point in a given quarter, in contrast to the main paper where “starts” was a dummy variable equal to one if the unit was on in a given week. Units that were always “on” at this frequency would drop out of the estimation because the dependent variable would be collinear with unit fixed effects. Thus, the results of this plot and the results of divestments on starts in the simple DD regression in the paper will differ.

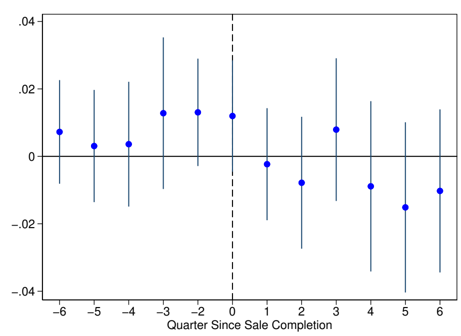
Figure 7.4: Sun and Abrahams Estimator for Dynamic Divestment Effects of Gas Units Sold to Private Firms



(a) Starts*



(b) Capacity Factor



(c) Emissions Intensity

Note: For computational reasons, I aggregated to the quarterly frequency. This means that "starts", here, is a dummy variable equal to one if the unit was on at any point in a given quarter, in contrast to the main paper where "starts" was a dummy variable equal to one if the unit was on in a given week. Units that were always "on" at this frequency would drop out of the estimation because the dependent variable would be collinear with unit fixed effects. Thus, the results of this plot and the results of divestments on starts in the simple DD regression in the paper will differ.

7.3.9 Institutional Background

Balancing Load In the aggregate, electricity demand is short-term inelastic and production simply clears demand. At the plant level, production decisions are more nuanced. A plant's choice to produce is the joint decision between the plant operator and the balancing authority that controls the transmissions system and dispatches power plants within the power control areas (PCAs) in its territory.

Balancing authorities take one of two approaches to dispatch power plants: a "command and control approach", and a "market dispatch approach." Under a "command and control approach", balancing authorities have their own algorithms for calling on plants to meet demand based on the authority's modeling of plants under its control. This was the traditional approach. The Energy Policy Act of 1992, however, sought to make the wholesale market for electricity more competitive by requiring the separation of transmission system owners and power marketers. The Act was codified in 1996 by the Federal Energy Regulatory Commission (FERC) orders 888 and 889, which required open-access, nondiscriminatory tariffs for wholesale electricity transmission. These acts precipitated a wave of deregulation that saw many, though not all, balancing authorities move to a "market dispatch" model in which generators would submit bids to provide capacity the day before, and the day of, the independent system operator calls upon different generators to meet demand based on its bid schedule. Generators could either meet the demand, or buy back one's allocated output at the real time price (Cicala, 2022).

Fossil Fuel Combustion Fossil fuels are formed from the fossilized, buried remains of plants and animals. Over time, layers of these remains were buried under sand, silt, and rock. Pressure and heat caused carbon and hydrogen from these materials to bond together and create fossil fuels. The chemical bonds holding carbon and hydrogen together effectively became stores of energy that are released when fossil fuels could be combusted by contact with heat and oxygen.

Fossil-fuel power power plants generate electricity by combusting a primary energy source, such as coal, gas and oil, to generate heat. This heat is converted into the mechanical energy of a rotating turbine that is linked by an axle to a generator. The generator is a large magnet that rotates around coils, and in doing so, induces an alternating current in the coil - a flow of electrons, which I call electricity. During the combustion process, primarily carbon dioxide is released.

Combustion is the rapid combination of a substance with oxygen involving the production of heat and light. In the case of fossil fuel combustion, the heat generation from combustion causes elements in the fossil fuel and air to combine and form greenhouse gases. To illustrate by example, in the case of most natural gas boilers, natural gas and oxygen in the air combusts on contact with an ignition source, such as an open flame. Natural gas contains many compounds, the largest of which is the carbon compound methane CH_4. Nearly all the fuel carbon is converted to CO_2 in the process. High temperatures during the combustion process also cause nitrogen, and sulfur to react with oxygen and create sulfur and nitrogen oxides. (Note: Air contains nitrogen. Natural gas contains both nitrogen and sulfur, although is smaller quantities than natural as most of it must be removed before it can be transported, and sold (https://www.eia.gov/energyexplained/natural-gas/)). These however, while toxic to human health, are not greenhouse gases and therefore, not the object of our study. In this paper, I will use the term CO_2 emissions and emissions interchangeably.

Regulation Regulation of plant operations and ownership falls into two categories: wholesale sales and interstate electric transmission, and local sales and local electric distribution. The former is regulated by Federal Energy Regulatory Commission (FERC); the latter, by states, and sometimes, self-regulated municipalities and electric co-operatives.

Regulation of plant emissions is largely at the federal and state level.

At the federal level, the EPA regulates greenhouse gas emissions from power plants under Section 111 of the Clean Air Act. Monitoring occurs through its Clean Air Markets Division.

In January, 1993, Congress passed the Part 75 rule, which established established a continuous emission monitoring (CEM) program in support of EPA's Acid Rain Program (ARP), which was instituted in 1990 under Title IV of the Clean Air Act. Part 75 requires continuous monitoring and reporting of carbon dioxide (CO2) mass emissions (among other emissions) of electric generating units (EGUs) that burn fossil fuels such as coal, oil and natural gas and that serve a generator greater than 25 megawatts. The program is run by the EPA's Clean Air Markets Division programs.

However, few federal efforts to regulate the carbon dioxide emissions of all power plants have survived legal review. At the state level, some states have their own, or are members of market-based programs to reduce greenhouse gas emissions. For example, Massachusetts has its own allowance trading program for carbon dioxide emissions from electricity generation, with planned declines in total allowances in the future.[31] It is also involved in the Regional Greenhouse Gas Initiative which is an allowance trading program involving several states.[32]

[31] Allowance at present, however, exceed actual emissions. See https://www.mass.gov/doc/fact-sheet-massdep-electricity-sector-regulations/download and https://www.potomaceconomics.com/wp-content/uploads/2021/06/774-q4report20.pdf

[32] At the state level, twelve states have active carbon-pricing programs: California and the eleven Northeast states — Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont, and Virginia — that make up the Regional Greenhouse Gas Initiative (RGGI). RGGI is the first mandatory cap-and-trade program in the United States to limit carbon dioxide emissions from the power sector. California's program was the first multi-sector cap-and-trade program in North America. Massachusetts has also implemented regulations to establish an additional cap-and-trade program for its power sector that runs in parallel with RGGI but extends out to 2050. Washington state recently enacted new cap-and-invest legislation to take effect beginning in 2023.

Concerns that policy variations will bias our empirical results is mitigated by our empirical strategy, which implicitly controls for time variation at the state level.

Efforts to Regulate Emissions Most federal efforts to regulate carbon emissions has met legal challenge. A notable exception is the the August 3, 2015 Final Rule "Carbon Pollution Standard for New Power Plants" (CPP) which contains a rule limiting GHG emissions from new fossil fuel-fired utility boilers and from natural gas-fired stationary combustion turbines that remain in place today. More common are legal challenges. For example, in the recent 2022 Supreme Court Case West Virginia v. EPA, the Court ruled that the EPA does not have the authority to substantially restructure the energy industry to limit emissions, and that agency action with large economic and political significance falls under the "major questions doctrine"- that is, Congress cannot defer significant issues of national policy to an administrative authority unless such intent is clearly expressed - and therefore requires clear Congressional authorization. However, the Court still retains significant practical authority to regulate plant emissions at the individual level.

New natural gas power plants can emit no more than 1,000 pounds (lbs) of carbon dioxide per megawatt-hour (MWh) of electricity produced, which is achievable with the latest combined cycle technology. New coal power plants can emit no more than 1,400 lbs CO2/MWh, which almost certainly requires the use of carbon capture and storage (CCS) technology (https://www.c2es.org/document/epa-regulation-of-greenhouse-gas-emissions-from-new-power-plants/).

Recent efforts to regulate carbon dioxide emissions from existing power plants have failed legal review. On October 23, 2015, the EPA Clean Power Plan, which established emission guidelines for states to follow in limiting carbon dioxide emissions from existing power plants, but the agency determined that it exceeds the EPA's statutory authority under the Clean Air Act and it was repealed. On June 19, 2019, this was replaced by the Affordable Clean Energy rule (ACE), which on January 19, 2021, was vacated by the D.C. Circuit and remanded to the Environmental Protection Agency for further proceedings consistent with its opinion. On June 30, 2022 the Supreme Court ruled in West Virginia v. EPA that the Clean Power Plan and its enactment of the replacement ACE rule was unconstitutional. The Court ruled that the EPA does not have the authority to substantially restructure the energy industry to limit emissions, and that agency action with large economic and political significance falls under the "major questions doctrine"- that is, Congress cannot defer significant issues of national policy to an administrative authority unless such intent is clearly expressed - and therefore requires clear Congressional authorization. However, the Court still retains significant practical authority to regulate plant emissions at the individual level by setting standards.

7.4 External Validity

7.4.1 Summary Statistics of Divestments

Table 7.12 reports on the number of facilities that were divested only once in the sample by industry and new owner. Of the twelve industries in the sample, all but the onshore oil and gas production and local distribution industries had facilities that changed ownership. The industries with a sufficient number of divestments by public firms to other public and private firms in my sample to reasonably estimate post-divestment effects are: power plants, which has 98 divestments by a public firm, petroleum and natural gas systems, which has 130 divestments by a public firm, chemicals, which has 31 divestments by a public firm, waste, which has 30 divestments by a public firm.

Table 7.12: Number of Facilities Divested Once in Sample

Industry	Emissions (GHGRP) (1)	Transaction Type: Public to Public (2)	Public to Private (3)	Private to Public (4)	Private to Private (5)	Total (6)
Power Plants	1.39	57	41	28	21	147
Petroleum and NG Sys.	0.13	95	35	17	10	160
Chemicals	0.07	26	5	9	3	43
Refineries	0.1	11	2	1	6	20
Other	0.27	76	32	31	27	166
Waste	0.09	21	9	5	12	47
Minerals	0.08	35	3	12	8	58
Metals	0.04	14	4	5	4	27
Pulp And Paper	0.01	12	4	5	10	31
Electrical Equipment Use	0	1	0	1	0	2

Note: This table tabulates the facilities transferred once by deal type, and the sold facility's industry. The first column reports the emissions from that industry in my sample. Columns (2)-(5) report the number of facilities transferred once by deal type. Column (6) reports totals by industry.

7.4.2 Empirical Strategy

To estimate divestment effects on the level of emissions, I estimate the following model using ordinary least squares

$$ln(Emissions)_{it} = \alpha + \beta \begin{bmatrix} Post \times Public \\ Post \times Private \end{bmatrix}_{it} + X_{it} + \alpha_i + \epsilon_{i,t} \tag{7.1}$$

where $ln(Emissions)_{it}$ is the natural log of emissions of facility i in year t, $Post \times Public_{it}$ denotes a dummy variable equal to one if facility i was divested to a public firm and is in the two-year post-divestment period at time t, $Post \times Private_{it}$ denotes a dummy variable equal to one if facility i was divested to a private firm and is in the post-divestment period at time t, X_{it} denotes the controls which are the interactions of the following variables: state, emissions size, industry, and year, α_i denotes facility fixed effects. Size is measured by the emissions quartile of the facility when it entered the dataset.

I include the state and year in the interaction set to control for regional trends in demand and supply that can arise from local economic conditions, population growth, and state regulation. I include the emissions size, industry, and year, together in the interactions set to control for industry trends that may differentially impact larger/more emitting firms, as well as to control for changes in the EPA's reporting requirements for facilities in that industry. I control for facility fixed effects to take into account time invariant differences in facilities' average emissions levels.

The model is estimated for the following four industries: power plants, petroleum and natural gas systems, chemicals, and waste, which had a sufficient number of divestments by public firms to justify model estimation. I estimate the model for all industries, and then for each industry.

In a subsequent subsection, I cover each industry's emissions profile and the which emissions they are asked to report in the GHGRP. The latter constrains the margins along which reported emissions may change and the interpretation of the model's point estimates. For example, in the waste industry, facilities are required to report gross emissions implied by waste volume, not emissions net of gases captured or otherwise not emitted into the atmosphere. Therefore, the margins along which reported emissions may change are (1) the volume of degradable waste and (2) changes in the two equation given to calculate annual methane emissions, the latter of which should uniformly impact all waste facilities. On the other hand, the petroleum and natural gas industry is required to report carbon dioxide and methane releases from the combustion of fossil fuel, and process emissions, which is a net measure that includes vented emissions (i.e. intentional or designed releases of gas), equipment leaks, and flaring.

7.4.3 Results

Since the facility data are at a lower frequency, and not matched with granular information about the facility's technological characteristics, production functions, and output data, the analysis is much more coarse and necessarily restricted by the availability of data. I include power plants to see if this specification yields the same qualitative results as in the previous analysis which used higher frequency data. Table 7.4.3 reports the estimated coefficients.

I find that post-divestment, facilities do not emit more vis-à-vis comparable facilities, regardless of buyer type. The p-value of a Wald test with the null that the difference in post-divestment effects by buyer type is zero fails to be rejected in the regression aggregating all industries, as well as in the industry specific regressions. Qualitatively, these results hold when I break down divestment effects by industry type. Some of the statistically insignificant point estimates are large. For example, in the waste facilities regression, the point estimate of the post-divestment effect when a facility is sold to a private firm is 0.18. Since the EPA asks waste facilities to report emissions in such a way that emission levels are essentially equivalent to levels of waste volume, which is exogenous, one hypothesis for why the point estimate is this large is that divested facilities are poaching waste processing contracts from other facilities.

Table 7.13: Greenhouse Gas Reporting Program Dataset: Other Industries

	Industry				
	All	Power Plants	Petroleum and Natural Gas Systems	Chemicals	Waste
	(1)	(2)	(3)	(4)	(5)
Post × *Public*	-0.030	-0.010	-0.040	0.120	-0.070
	(0.030)	(0.070)	(0.050)	(0.090)	(0.080)
Post × *Private*	0.060	0.010	0.080	0.050	0.180
	(0.050)	(0.090)	(0.070)	(0.150)	(0.140)
Observations	19,881	6,413	4,426	1,166	7,876
R^2	0.37	0.45	0.28	0.30	0.33
Adj. w/in R^2	0.00	0.00	0.00	0.00	0.00
Test	0.12	0.16	0.69	0.11	0.12

Notes: This table uses OLS regressions to test the effect of an acquisition on a facility's subsequent emissions. The sample is of facilities that were sold by publicly traded firms (to other publicly traded firms, and to private firms) and facilities that were never sold. The dependent variables are the log of greenhouse gas emissions. *Post* × *Public* is a dummy variable equal to one in the four year period after a facility has experienced a change in parent ownership. *Post* × *Private* is an indicator that takes the value of one in the four year period after after a facility has experienced a change in parent ownership in which the facility changed hands from a publicly traded firm to a private firm. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7.4.4 Data

Facility-level emissions data is from the EPA's Greenhouse Gas Reporting Program (henceforth referred to as GHGRP), which is a federal program that requires facilities that emit more than 25,000 metric tons of carbon dioxide equivalents per year, and engage in activities that fall under highly emitting source categories to report their annual greenhouse gas emissions.[33] While the program began in 2010, the set of reporting categories was expanded in 2011. Thus, to ensure comparability of emissions data across years, I use data from 2011 to 2020 only.

Two types of emissions are reported: direct and indirect. direct emissions are those directly emitted by the facility from the processes covered by the program. Indirect emissions are those that would result from the complete combustion, oxidation or use of the supplied products covered, such as fossil fuel products like petroleum, natural gas, and industrial gases. Indirect emissions may result in direct emissions that are also reported in our database; thus, I restrict the dataset to the set of direct emitters to avoid double counting. Based on the reporting requirements, I know that indirect emissions not reported in direct emissions in our dataset are ultimately emitted by a large collection of small emitters, such as drivers, individual offices, homeowners.[34] Facilities emit a variety of greenhouse gases with differing implications for global warming. To make data on gas emissions directly comparable, emissions are reported in terms of carbon dioxide equivalents (or CO_2e), defined as the quantity of emissions that traps as much heat on earth over a hundred year horizon as

[33] 25,000 metric tons of CO_2e is the emissions equivalent of burning 136 rail cars of coal.

[34] Using the language of emissions scopes, direct emissions would be Scope 1 emissions, which are defined as "emissions that occur from sources that are controlled or owned by an organization." Indirect emissions would be Scope 3 emissions, because they do not occur due at the site of the entity's operations but is enabled (for example, by the supply of fossil fuels) by the entity. Scope 2 emissions, defined as indirect emissions associated with the purchase of electricity, steam, heat, or cooling do not correspond to any category here.

a metric ton of carbon dioxide. [35][36][37] Reported emissions are then validated by the EPA using logic checks, statistical checks, and cross-validation with other datasets such as those held by the Department of Energy.

I subset the GHGP dataset two times. As mentioned earlier, I include direct emissions only. Second, I impose a balanced panel restriction so that our analysis of aggregate and individual records reference the same underlying dataset. These restrictions bring our dataset's emissions coverage to 37-42% of total U.S. greenhouse gas emissions. To measure our dataset's coverage as a fraction of all U.S. emissions I compare our dataset's annual emissions series with the EPA's annual emissions series for the entire U.S. The EPA estimates come from its annual *Inventory of U.S. Greenhouse Gas Emissions and Sinks* reports, which estimates emissions across all sectors of the economy using national-level data. It is a superset of the GHGRP dataset, which, as a facility-level emissions dataset, trades off breadth for granularity. Thus, while our dataset is not the universe of U.S. emissions, as a whole, it captures a majority of the aggregate dynamics. It covers between 37-42% of total U.S. emissions in a given year, has a 91% correlation with EPA's total U.S. emissions series, and captures 70% of the of the total decline in U.S. emissions in sample: the total U.S. emissions series drops by 0.86 bn. CO_2e and our dataset captures 0.60 bn of that change.[38][39]This is

[35]A single carbon dioxide equivalent is equal to a single global warming potential (GWPs). A primer on this measurement unit can be found on the EPA's website."Greenhouse gases warm the Earth by absorbing energy and slowing the rate at which the energy escapes to space; they act like a blanket insulating the Earth. Different GHGs can have different effects on the Earth's warming. Two key ways in which these gases differ from each other are their ability to absorb energy (their 'radiative efficiency'), and how long they stay in the atmosphere (also known as their 'lifetime'). The GWP was developed to allow comparisons of the global warming impacts of different gases. Specifically, it is a measure of how much energy the emissions of 1 ton of a gas will absorb over a given period of time, relative to the emissions of 1 ton of carbon dioxide." There are four principal classes of gases: Carbon Dioxide, Methane, Nitrous Oxide, and high-GWP gases like Chlorofluorocarbons, hydrofluorocarbons, hydrochlorofluorocarbons, perfluorocarbons, and sulfur hexafluoride. The first, by definition has a GWP of 1. Methane has a GWP of 28-36 over 100 years. Nitrous Oxide has a GWP of 265-298 for a 100 year time scale. High gases can have GWPs in the thousands or tens of thousands.Carb

[36]GWPs of gases are updated according to the latest scientific evidence; the GHGRP updated many of the GWP values used to calculate reporters' emissions in carbon dioxide equivalent in the reporting year 2013. As described in the FAQ associated with the GHGRP database "These GWP values were updated from values provided in Intergovernmental Panel on Climate Change's (IPCC) Second Assessment Report (SAR) to those in the Fourth Assessment Report (AR4). See Table A-1 for the complete list of gases and their updated GWPs. To present a consistent time-series, EPA has provided re-calculated prior year GHG totals, which were calculated using SAR values, using the revised AR4 GWP values. The raw data submitted by facilities for reporting years prior to 2013 remains as submitted using SAR GWPs."

[37]Conversion factors are published, and occasionally revised by the Intergovernmental Panel on Climate Change (IPCC). The EPA produces a series that uses constant factors across the sample and so the impact of factor revisions on the consistency of reported emissions is not a concern.

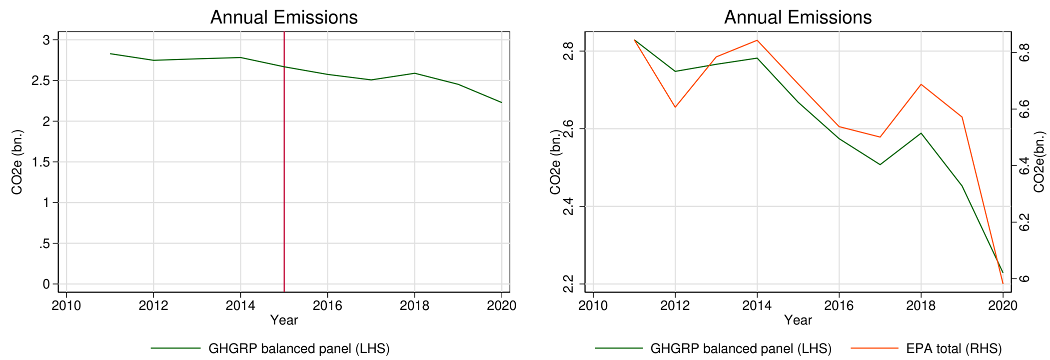
[38]In the aggregate U.S. emissions dataset, a decline of 0.14 bn CO_2e or 16% of the decline in our sample, can be attributed to transportation, which is a very large collection of relatively small emitting agents that would not report.

[39]I miss emissions due to gathering and boosting, transmission pipelines, geological sequestration, because

illustrated in the sub-figure on the right in Figure 7.4.4.

Figure 7.5: Total Emissions by Year

(a) GHGRP Dataset (b) GHGRP v. EPA Totals



Notes: This figure displays our dataset's annual emissions in levels on the right. The same series is plotted alongside the EPA's total U.S. emissions series; scales differ but are marked at identical interval lengths for comparability of the series in changes.

In Table and Figure 7.4.4, I disaggregate emissions by the industry/activity that generated it. Twelve industries/activities are represented in my sample: power plants, minerals, waste, chemicals, metals, petroleum and natural gas systems, onshore and gas production, pulp and paper, local distribution, refineries, electrical equipment use, and other. The largest industry by direct emissions is power plants, which accounts for 62% of total emissions in our sample. The next largest category is the other category, which accounts for 18% of sample emissions and include entities involved in one or more of the following industries: petroleum product suppliers and refineries, power plants and waste, natural gas and natural gas liquids suppliers, petroleum and natural gas systems.

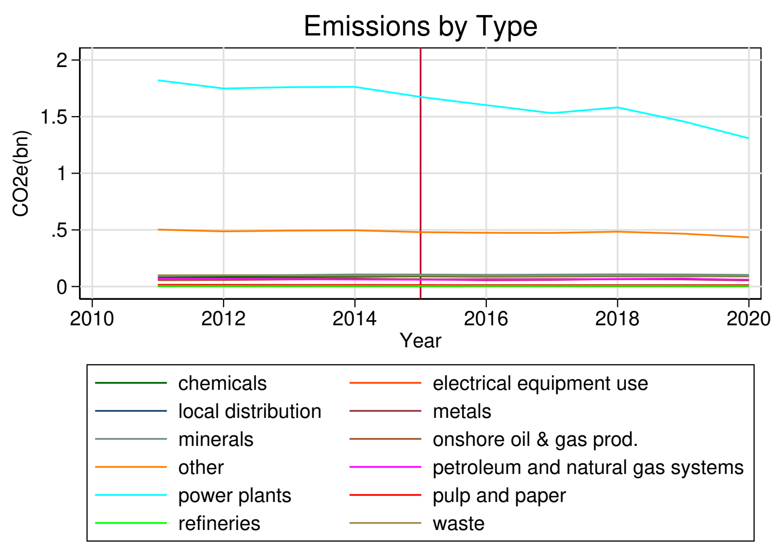
the data reporting began in 2016. I miss confidential data on suppliers, CO2 injections. These are protected from Freedom of Information Act requests by Exemption 4: "trade secrets and commercial or financial information obtained from a person [that is] privileged or confidential."

Figure 7.6: Shares of Emissions by Source Activity

(a) Table

Industry	Share
Power Plants	0.62
Other	0.18
Minerals	0.04
Waste	0.04
Chemicals	0.03
Metals	0.02
Petroleum and Natural Gas Systems	0.02
Onshore Oil and Gas Production	0.02
Pulp and Paper	0.01
Local Distribution	0.00
Refineries	0.00
Electrical Equipment Use	0.00

(b) Time series



Note: This table and plot reports GHG emissions by industry/activity source.

To create a facility-level ownership database, I begin with the GHGRP companion ownership dataset with self-reported records of the names, addresses, and ownership shares of parent companies that own the reporting facilities at the annual and facility-level.The Code of Federal Regulations delineates clear and specific guidelines for GHGRP reporting on a facility's parent company (40 CFR 98.3). The reported parent company should be the highest-level company in the ownership hierarchy with caveats for foreign companies, and joint ventures. However, reporting is inconsistent and the dataset requires extensive cleaning.

The first stage of cleaning involved standardizing string names and addresses of parent companies in the dataset and reconciling reporting differences within and across years. I standardized parent company names by enforcing uniform entity references (for example, Corp and Corporations are recognized as the same entity type), fixing spelling errors, imposing uniform rules for punctuation use in names. I standardized parent company addresses by enforcing common abbreviations for cardinal directions, and address unit designators. For missing company addresses, I populated the record with the most common address in the dataset under that parent company's name; for those I could not populate in this way, I manually searched and populated the address. I then used Google Maps's GeoLocation API to validate and convert string addresses into GPS coordinates. Once I did this, I enforced a single name for groups of entities with similar names and identical address. The second stage of cleaning, involved mapping companies to their ultimate parents. Some facilities in our sample are recorded under wholly owned company subsidiaries, or under temporary entities such as those created to facilitate a merger. Some facilities in our sample are companies in which there are a few dominant firm owners. I designate the ultimate parent as the majority owner at that time (owned >50% shares in the subsidiary) by fuzzy matching the facilities records with a time-dependent record of parent-subsidiary relationships from CorpWatch API, a public and free service that uses automated parsers to extract the subsidiary relationship information from Exhibit 21 of companies' 10-K filings with the SEC across time, and Open Corporates API, the largest, private open database of companies in the world which graciously extended access to their database for this project. In cases in which I was unable to match parent companies to a legal entity in the CorpWatch or Open Corporates database, I programmatically retrieved the closest legal corporate entity from Wikipedia and/or Google's Knowledge Graph. If the ownership share was unknown, I used the parent referenced in the news or the parent that prominently listed the company as a subsidiary on its website. I also adjusted the record for corporate restructuring events using Zephyr, a database of mergers and acquisitions, initial public offerings, and venture capital deals, with pan-European transactions dating back to 1997 and US deals from 2001, and manual searches of restructuring deals.[40] Finally, I manually corrected for name changes by checking records of apparent changes in ownership identified off of changes in the parent company's name. I then augmented ownership data with securities data through a combination of programmatic fuzzy matching to WRDS's Compustat/CRSP, Wikipedia and/or

[40]The coverage is comprehensive: the universe of deals in which the target, acquirer and seller are U.S. based for an approximately twenty year period is around 600,000 which averages out to 30,000 deals a year. This number is more than the usual 10,000-20,000 annual number for M&A because deals include not just merger and acquisitions, but other restructuring events such as spinoffs and significant investments.

Google's Knowledge Graph and manual search.

I class entities as one of three types: publicly traded firms, private firms, and other. Publicly traded firms are those that are publicly listed for at least a portion of that year. Within our sample, a firm can change from being a public firm to a private firm because it has been delisted. Reasons include going private, merging with or being acquired by another company and acquiring a new ticker, failure to meet standards of the exchange on which it is listed, or bankruptcy. Private firms are entities that are in the private sector but not listed on a public exchange; these can include entities that are listed in the over-the-counter (OTC) markets. Other includes federal, state, and municipal governments, and colleges and universities and were identified by substring searches of the parent name (e.g. "county", "city", "university", "municipal", etc.).

I match the emissions dataset with ownership dataset using the EPA's Facility ID, a unique identifier of facilities subject to the GHGRP. In cases of joint ownership, I assigned a given owner emissions proportional to its ownership share in the facility. I windsorized the top and bottom 10% observations.[41] The dataset follows 5,390 unique facilities owned by, on average, 508 publicly traded firms and 931 private firms. Because of joint ownership, a single facility may be owned by a public and private firm. On average, between 2011 and 2020, facilities emitted between .10 and 22 million tons of carbon dioxide equivalents, with the average being 471,670 tons. Table 7.4.4displays a table of the average share of emissions owned by three types of owners: publicly traded firms, private firms, and other (which includes federal, state, municipal governments, universities) as well as a time series of those shares. Across our entire sample, publicly traded firms own 64% of emissions, private firms, 22%, and other firms, 14%.

Table 7.14: Average Share of Emissions by Owner Type

Owner type	Average Across Sample	2011	2020
Publicly traded firms	0.64	0.64	0.62
Private firms	0.22	0.21	0.24
Other firms	0.14	0.15	0.14

Notes: The table reports the average share of emissions attributed to facilities owned by owner type.

Figure 7.4.4 displays the total share of emissions owned by owner type as well as the share of privately owned emissions (i.e. excluding the other category) by owner type. Figure 7.4.4 displays emissions in levels by owner type. After the Paris Accords in 2015, which is denoted in the figure by a vertical line, there is a decline in the share of emissions owned

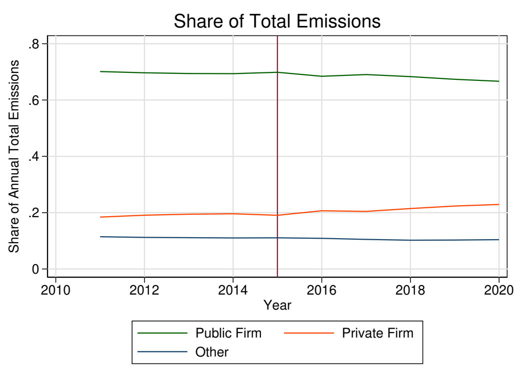
[41] The results are qualitatively similar without windsorizing. Results in the Appendix.

by publicly traded firms, and a corresponding and near symmetric increase in the share of emissions owned by private firms. This is due to the combination of sharp declines in the level of emissions by publicly traded firms, which in the absence of any change in the level of emissions by private and other would generate the time series pattern in shares, as well as a slight increase in the level of emissions owned by private firms and an even slighter offsetting decline in the level of emissions owned by other.

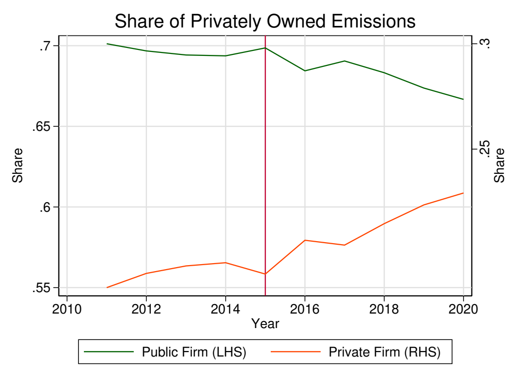
The increase in the level of emissions by private firms should not be interpreted to mean that individually, private firms on average have been polluting more post-Paris. Changes in the level of emissions across time arise not only due to changes in emissions of facilities already owned, but also due to the acquisition or sale of new facilities.

Figure 7.7: Share of Emissions by Owner Type

(a) Time series

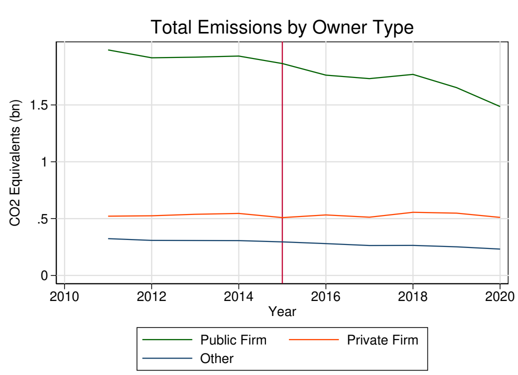


(b) Public v. Private



Notes: The figure is a time series of the share of annual emissions by owner type. The figure on the left displays shares by all owner types. The figure on the right displays shares only for public and private firms and with two axes to better observe changes.

Figure 7.8: Total Emissions by Owner Type



I identify a divestment as having occurred if there was a change in the parent company. Table 7.4.4 reports on the facilities that were divested, and the number of times they were divested in the sample. The majority of facilities in our sample, around 72%, never changed parent companies; 21% changed parent companies once; the residual 7% changed parent companies multiple times.

Table 7.15: Transactions

# of Transactions in Sample	Count	Percent of facilities
0	3,997	72%
1	1,170	21%
2	315	6%
3	49	1%
4	8	0

Note: This table tabulates the # of facilities involved in zero, one, and repeat transactions.

7.4.5 Ownership Data Cleaning

The first stage of cleaning involved standardizing string names and addresses of parent companies in the dataset and reconciling reporting differences within and across years. I standardized parent company names by enforcing uniform entity references (for example, Corp and Corporations are recognized as the same entity type), fixing spelling errors, imposing uniform rules for punctuation use in names. I standardized parent company addresses by enforcing common abbreviations for cardinal directions, and address unit designators. For missing company addresses, I populated the record with the most common address in the dataset under that parent company's name; for those I could not populate in this way, I manually searched and populated the address. I then used Google Maps's GeoLocation API to validate and convert string addresses into GPS coordinates. Once I did this, I enforced a single name for groups of entities with similar names and identical address. The second stage of cleaning, involved mapping companies to their ultimate parents. Some facilities in our sample are recorded under wholly owned company subsidiaries, or under temporary entities such as those created to facilitate a merger. Some facilities in our sample are companies in which there are a few dominant firm owners. I designate the ultimate parent as the majority owner at that time (owned >50% shares in the subsidiary) by fuzzy matching the facilities records with a time-dependent record of parent-subsidiary relationships from CorpWatch API, a public and free service that uses automated parsers to extract the subsidiary relationship information from Exhibit 21 of companies' 10-K filings with the SEC across time, and Open Corporates API, the largest, private open database of companies in the world which graciously extended access to their database for this project. In cases in which I was unable to match parent companies to a legal entity in the CorpWatch or Open Corporates database, I programmatically retrieved the closest legal corporate entity from Wikipedia and/or Google's Knowledge Graph. If the ownership share was unknown, I used the parent referenced in the news or the parent that prominently listed the company as a subsidiary on its website. I also adjusted the record for corporate restructuring events using Zephyr, a database of mergers and acquisitions, initial public offerings, and venture capital deals, with pan-European transactions dating back to 1997 and US deals from 2001, and manual searches of restructuring deals.[42] Finally, I manually corrected for name changes by checking records of apparent changes in ownership identified off of changes in the parent company's name. I then augmented ownership data with securities data through a combination of programmatic fuzzy matching to WRDS's Compustat/CRSP, Wikipedia and/or Google's Knowledge Graph and manual search.

7.4.6 Industry Emissions Profiles

Carbon dioxide makes ups the vast majority of greenhouse gas emissions In this section, I cover each industry's emissions profile and the margins along which reported emissions may change.

- Waste:[43] The waste sector includes municipal solid waste landfills, industrial waste landfills, industrial wastewater treatment systems, and facilities that operate combustors or incinerators for the disposal of non-hazardous wastes.
  - Emissions and Emissions Reporting: This sector primarily produces landfill gas (LFG), which is composed of roughly 50% methane and 50% carbon dioxide, when organic wastes such as food scraps, wood and paper decompose. The largest contributors to the waste sector are municipal solid waste (MSW) landfills, which generate 80% of sector emissions. MSW landfills report gross emissions implied by waste volume, not emissions net of gases captured or otherwise not emitted into the atmosphere.
  - Emissions Abatement: Because of reporting on a gross basis, in this dataset, the margins along which emissions may change are (1) the volume of degradeable

[42] The coverage is comprehensive: the universe of deals in which the target, acquirer and seller are U.S. based for an approximately twenty year period is around 600,000 which averages out to 30,000 deals a year. This number is more than the usual 10,000-20,000 annual number for M&A because deals include not just merger and acquisitions, but other restructuring events such as spinoffs and significant investments.

[43] https://www.epa.gov/system/files/documents/2022-01/waste_profile_01-10-2022.pdf

waste (2) changes in the two equations they are given to calculate annual methane emissions.[44][45]

- Demand: MSWs face approximately inelastic demand in the short-horizon. Municipal solid waste landfills, as implied by their name, are operated by municipalities as a public good. Private landfill operators charge municipalities by waste tonnage; however, the waste is generated by households in the municipalities, and these households are not charged by waste volume. In the long-run, municipalities can manage waste costs by encouraging recycling, and composting.

- Petroleum and NG Systems[46]: Petroleum and natural gas systems includes facilities involved in production, gathering and boosting, processing, transmission, and distribution.

  - Emissions and Emissions Reporting: This sector produces carbon dioxide and methane as a result of the combustion of fossil fuels, and from the process itself. In this sector, process emissions include vented emissions (i.e. intentional or designed releases of gas), equipment leaks, and flaring.

  - Emissions Abatement: Emissions intensity abatement can occur through (1) operational changes (e.g., increased venting/flaring), (2) changes in production quantity, (3) changes in monitoring requirements. A note about venting/flaring, which receives much attention in the news. Venting can occur because a well need to unload fluids that have accumulated as the well pressure has declined; there are alternatives such as using sufactants, plunger lifts, to move liquids that accumulate in well tubing to the surface.[47] Venting also can occur to deal with the extraction of associated petroluem gas (a form of raw natural gas) that accompanies petroleum extraction from oil wells. As noted in the Department of Energy's June 2019 Natural Gas Flaring and Venting Report, "commercial alternatives to flaring include compressing natural gas and trucking it short distances for use as a fuel for oil field activities; extracting natural gas liquids from the flare gas stream before flaring the remaining methane (a partial solution); converting the gas to electric power using small-scale generators, small-scale gas-to methanol or gas-to-liquids conversion plants; and converting captured gas to LNG and trucking it short distances for use as a fuel for oil field activities"(Staff, 2019).

[44]For example, starting in 2013, MSWs were allowed to assume a higher percentage of methane generated by the landfill was oxidized to CO_2 as it passed through the landfill soil cover.

[45]Source: https://ccdsupport.com/confluence/pages/viewpage.action?pageId=189038672

[46]Source: https://www.epa.gov/system/files/documents/2021-10/subpart_w_2020_sector_profile.pdf

[47]https://www.epa.gov/sites/default/files/2016-06/documents/ll_options.pdf

- Regulation: Every oil and gas producing state has regulations to limit the "waste" of gas resources; limits vary from state to state and there exists no national standard. For example, the Texas Railroad Commission (TRRC) allows operators to flare gas while drilling a well for up to 10 days after a well's completion to conduct well potential testing. Requests to flare can also be submitted. The majority are requests to permit flaring of casinghead gas (a type of natural gas that is found in a liquid form along with crude oil and produced at the top of an oil well) from oil wells. This may be necessary if the well is drilled in areas new to exploration where pipeline connects are not available until after a well is completed and a determination is made about the well's productive capability. Other acceptable reasons for flaring include processing plant shutdowns, downstream repairs or maintenance, or existing gas pipelines reaching capacity(Staff, 2019).
- Demand: Oil and natural gas have low, short-horizon elasticities of demand. At the two year horizon, the EIA estimates it at -.04 for oil and -.01 for natural gas.[48]

- Power Plants[49]
  - Emissions and Emissions Reporting: This sector primarily produces CO_2 from combusting fuel to convert energy in chemical bonds to electricity. In general, if a unit is coal-fired or combusts any type of solid fuel, emissions are reported using a CEMS. If a unit is classified as an oil or gas-fired unit, it may qualify for an alternative calculation methodology that are based on (a.) company records of fuel usage and periodic fuel sampling and analysis (to determine the percent of carbon in the fuel), (b.) heat input rate measurements, and fuel-specific, carbon-based "F-factors", or (c.) heat inputs and fuel specific default emissions factors.
  - Emissions Abatement: Emissions abatement can be through (a.) decreases in the heat rate through operational changes, keeping the generator technology fixed (i.e. improvements in the efficiency at which fuel is converted to electricity keeping fixed the technology), (b.) decreases in the heat rate through changes to the generator's technology (i.e. changing the generator to run on a cleaner fuel, changing the generator system from single cycle to combined cycle). While commercial carbon capture technologies exist, these technologies are "too expensive to deploy across the energy sector because they have not been proven at full scale, and the capital operating costs are too expensive when compared to the limited

[48] https://www.eia.gov/outlooks/steo/special/pdf/elasticities.pdf
[49] https://www.epa.gov/system/files/documents/2021-10/power_plants_2020_sector_profile.pdf

revenue generating applications for CO_2 that are currently available" (?). Existing, major carbon capture projects have been federally supported, and with true emissions captures less than what headline results might imply. For example, in a study of emissions from a retrofitted pulverized coal boiler connected to a steam turbine at the W.A. Parish coal power plant near Thomsons, Texas, Jacobson (2019)finds that CC equipment captured an average of only 55.4% coal combustion CO_2 rather than 90%, and 33.9% of coal plus gas combustion CO_2. The low net capture rates are due to uncaptured combustion emissions from the natural gas used to power the equipment, Furthermore, in a sign that the technology is in its infancy, in February, 2023, the U.S. Department of Energy announced the Carbon Capture Demonstration Program to develop six carbon capture facilities that can be replicated and deployed.[50]

  – Regulation: California and twelve Eastern states that participate in the Regional Greenhouse Gas Initiative (RGGI) require emitting facilities/power plants to acquire tradeable, and costly permits to emit greenhouse gases.

- Minerals:[51] The waste sector includes the following subsectors: Cement Production, Glass Production, Lime Manufacturing, Soda Ash Production, and Other Minerals production facilities that operate under NAICS codes beginning with 327. Facilities under this sector transform mined or quarried nonmetallic minerals into intermediate or final goods.

  – Emissions and Emissions Reporting: This sector primarily produces CO_2, and report process emissions from the calcination of carbonate-based raw materials and from stationary combustion sources, referred to as process and combustion emissions, respectively. Facilities are required to report facilities and process emissions separately, unless they use a CEMS, in which they case they can report a single number. In the former case, gross emissions are reported; thus, for the small number of facilities that collect CO_2 for such in other production processes, such as in sugar refining, or to sequester and inject underground, emissions will be gross, not net emissions.[52] In the latter case, if carbon capture is deployed

[50] https://www.energy.gov/oced/carbon-capture-demonstration-projects-program

[51] https://www.epa.gov/system/files/documents/2021-11/minerals_sector_profile_2020.pdf

[52] Approximately 60% of emissions from this sector are from Cement Production, and about 88-94% of facilities monitor emissions using CEMS. The residual reports process and fuel combustion emissions separately. For process emissions, carbon mass balance is used; for fuel combustion, facilities use the default emissions factor to estimate CH_4 and N_2O emissions from fuel combustion. As noted in the GHGRP's 2020 Mineral Sector Profile, "In carbon mass balance, process CO_2 emissions are based on measurements of the annual mass of process inputs or outputs, or both, and periodic analyses of the weight fraction of carbon in

before gases produced from combustion travel through the flue-gas stack where the CEMS is installed, emissions will be at the net level; otherwise, emissions will be at the gross level.

  - Emissions Abatement: Because reporting is on a gross basis, and because carbon capture technology is in its infancy, likely margins along which emissions abatement will occur are (1) fuel changes, or (2) changes in production quantity.

- Chemicals[53]
  - Emissions: Emissions are produced from the chemical production process, as well as combustion emissions from the production facilities. Of these the production of Petrochemicals, Hydrogen, Ammonia, and Adipic Acid, accounted for 82.3% of total reported emissions from this sector. CO_2 is the primary GHG emitted from all chemical production sub-sectors, with the exception of Adipic Acid production. N_2O is the primary GHG emitted from that sub-sector.
  - Emissions Intensity Abatement: In Adipic Acid[54] production, implementation of Nitrous oxide abatement devices.
  - Emissions Intensity Increases: In Petrochemicals[55], increases in flaring. Flaring occurs as part of the start-up and shutdown of the production process, and is a safety measure designed to prevent pressure in the installations from becoming too high. Residual gasses are discharged via the flare and are burnt off.[56]

inputs and outputs."

[53]Source: https://www.epa.gov/system/files/documents/2021-11/non-fluorinated_chemicals_sector_profile_2020.pdf

[54]Adipic acid is one of the most important monomers in the polymers industry. It is used in the manufacture of nylon, plasticizers, adhesives, food additives.

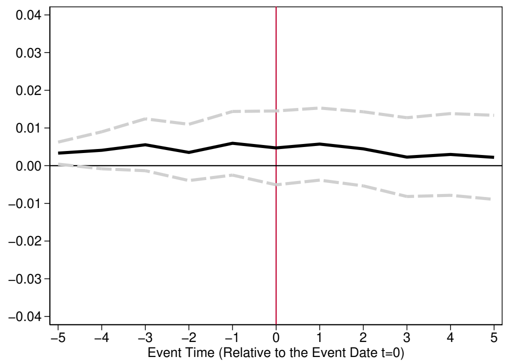
[55]Petrochemicals are the chemical products obtained from petroleum by refining.

[56]Source: https://ducorchem.com/future-proof/what-is-flaring/

7.5 Event Study

7.5.1 Event-study of Buyer

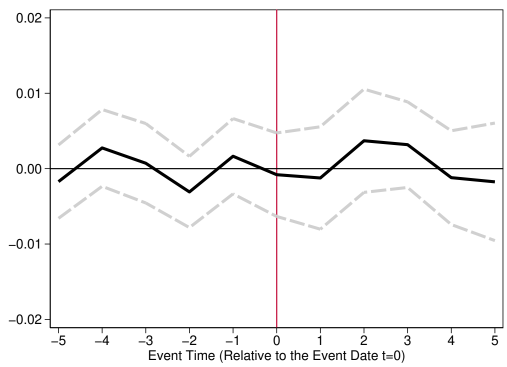
Figure 7.9: Public to Public: Buyer



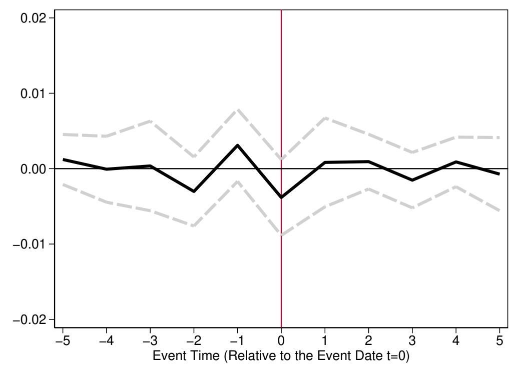
7.5.2 Robustness Check: Equally Weighted

Figure 7.10: Average Cumulative Abnormal Returns Around Plant Divestment Announcements

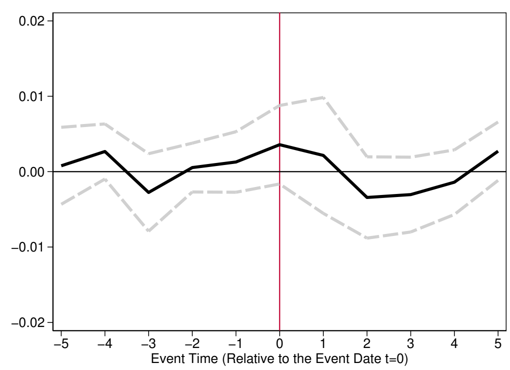
(a) Public to Public: Seller



(b) Public to Public: Buyer



(c) Public to Private: Seller



Notes: These figures shows the average cumulative returns (CARs) over an eleven-day window surrounding announcement of a plant divestment. Figures are distinguished by divestment type: Public to Public and Public to Private. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The average CAR displayed is nameplate weighted average of firm CARs across firms. The return model is the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

Table 7.16: Generator and Deal Counts by Study

	Deal Count
Divestment Type	Asset Purchases Only
Public to Public	62
Public to Private	91
All	153

Notes: This table reports on number of events over which average cumulative abnormal returns were computed, by divestment type.

Table 7.17: Cumulative Abnormal Returns (-5,5)

		CAR (Percent)	
		Equally-weighted	Nameplate-weighted
Public to Public			
Seller	Mean	0.56	-0.23
	Standard Error	0.82	0.35
	Count	62	62
	Sharpe Ratio	0.09	–0.08
Buyer	Mean	0.22	-0.07
	Standard Error	0.57	0.18
	Count	62	62
	Sharpe Ratio	0.05	-0.05
Public to Private			
Seller	Mean	1.44**	0.27
	Standard Error	0.67	0.17
	Count	91	91
	Sharpe Ratio	0.23	0.17
Comparison of Two Means Test[1]			
P-value		0.41	0.20

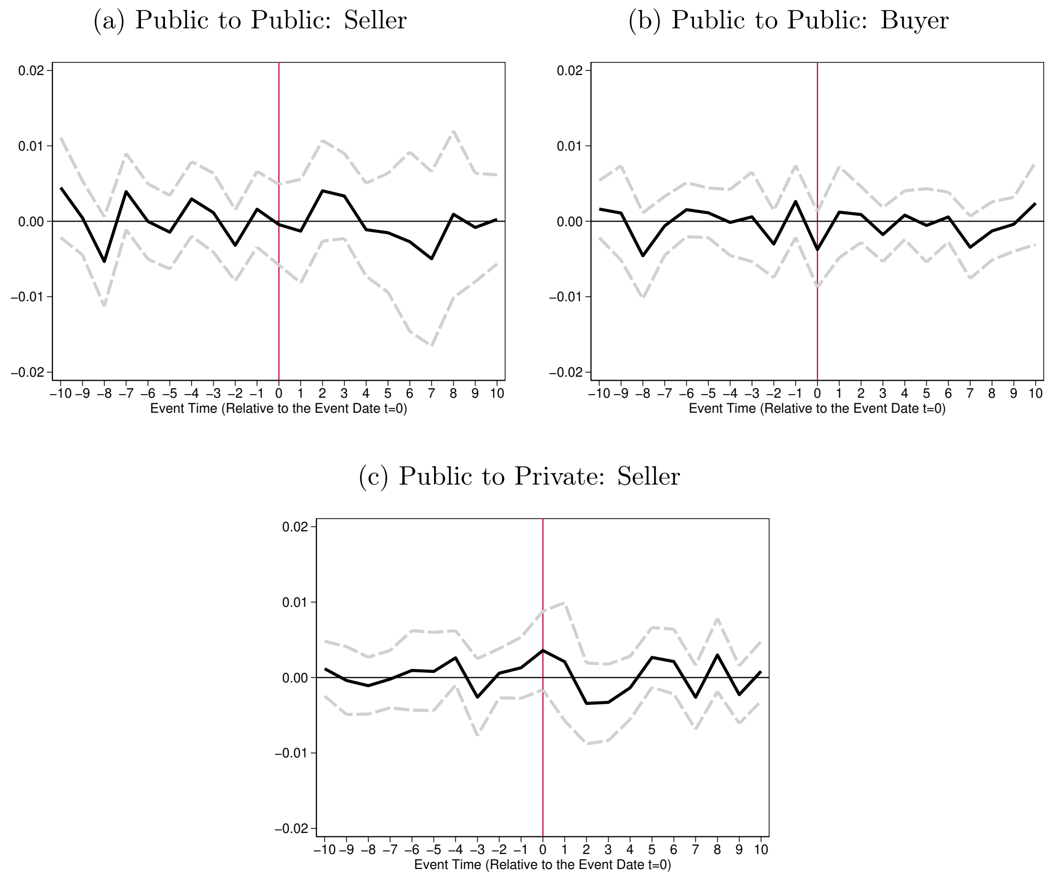
Notes: *, **, *** denotes statistical significance at the1%, 5%, 10% levels, respectively.
1 Here, I test the comparison of the mean of the seller CAR in public to private transactions with the mean of the seller CAR in public to public transactions. In the setting in which means and standard deviations are unknown, we can use the two-sample t statistic:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Conservative p-values may be obtained using the $t(k)$distribution where $k = min(n_1 - 1, n_2 - 1)$, which is what I report.

7.5.3 Different Window Sizes: Nameplate-weighted

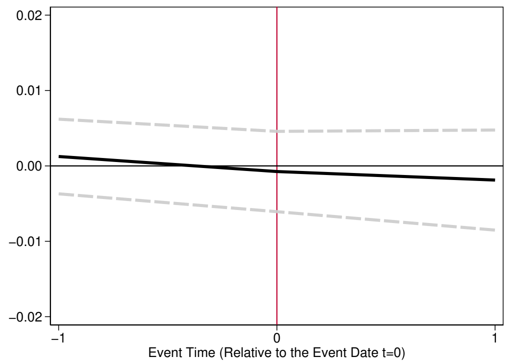
Figure 7.11: Average Cumulative Abnormal Returns Around Plant Sale Announcements: 21-Day Window



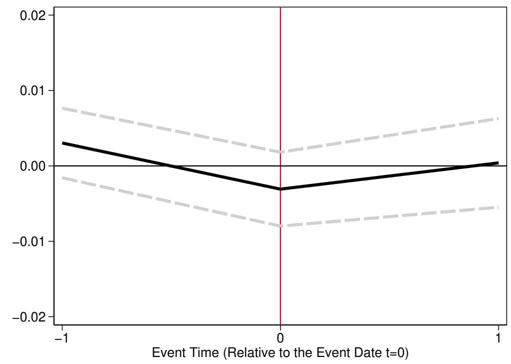
Notes: This figure shows the average cumulative returns (CARs) around plant sale announcements by sale type: Public to Public and Public to Private, and party: Buyer and Seller. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The CARs averaged across firms are plotted on the y-axis; daily CARs are based on expected return estimates generated using the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

Figure 7.12: Average Cumulative Abnormal Returns Around Plant Sale Announcements: Three Day Window

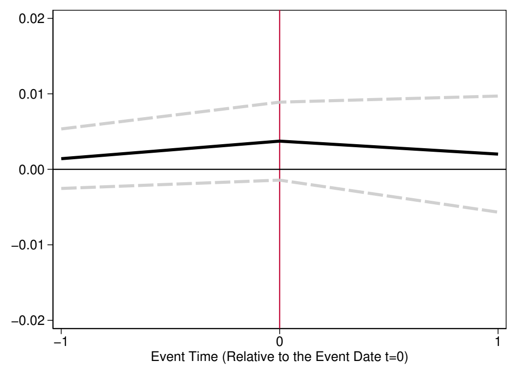
(a) Public to Public: Seller



(b) Public to Public: Buyer



(c) Public to Private: Seller

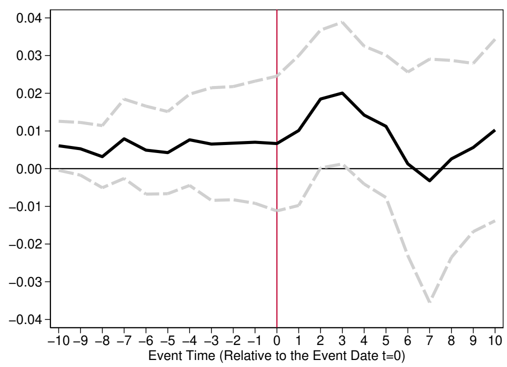


Notes: This figure shows the average cumulative returns (CARs) around plant sale announcements by sale type: Public to Public and Public to Private, and party: Buyer and Seller. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The CARs averaged across firms are plotted on the y-axis; daily CARs are based on expected return estimates generated using the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

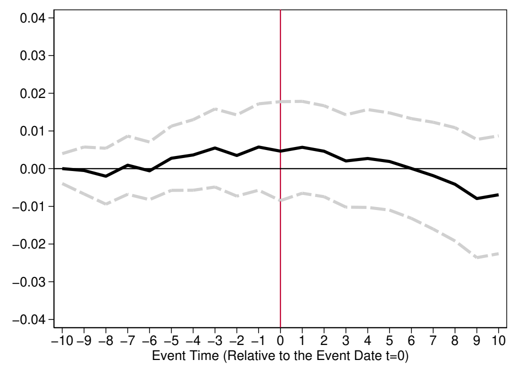
7.5.4 Different Window Sizes: Equally-weighted

Figure 7.13: Average Cumulative Abnormal Returns Around Plant Sale Announcements: 21-Day Window

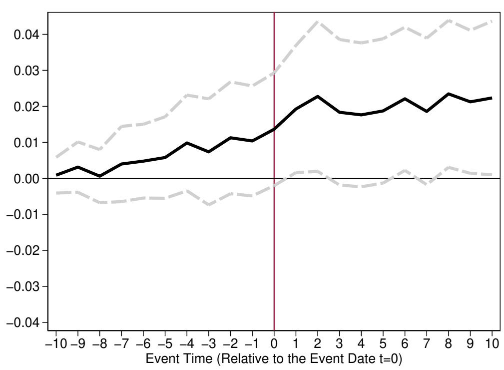
(a) Public to Public: Seller



(b) Public to Public: Buyer



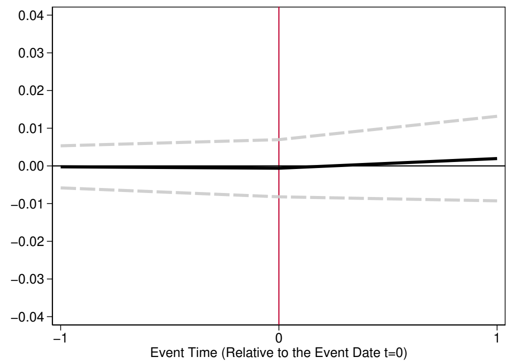
(c) Public to Private: Seller



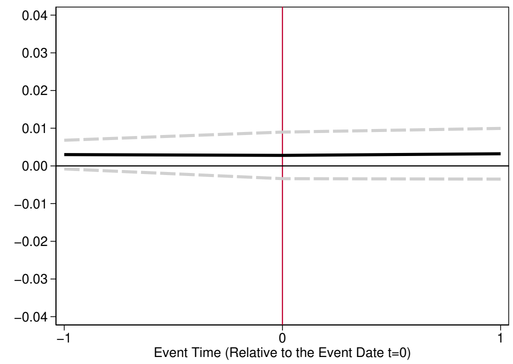
Notes: This figure shows the average cumulative returns (CARs) around plant sale announcements by sale type: Public to Public and Public to Private, and party: Buyer and Seller. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The CARs averaged across firms are plotted on the y-axis; daily CARs are based on expected return estimates generated using the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

Figure 7.14: Average Cumulative Abnormal Returns Around Plant Sale Announcements: Three Day Window

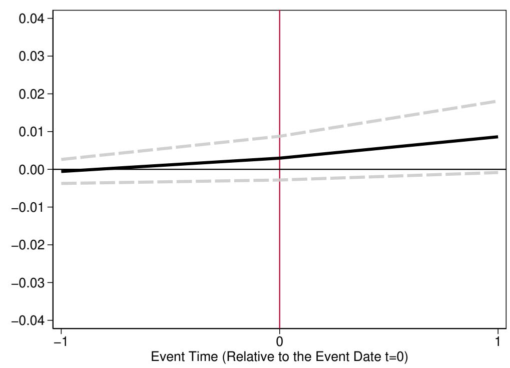
(a) Public to Public: Seller



(b) Public to Public: Buyer



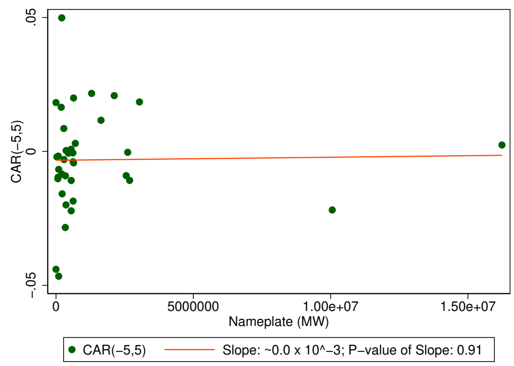
(c) Public to Private: Seller



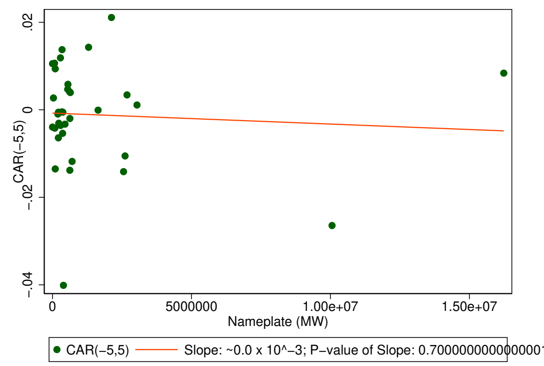
Notes: This figure shows the average cumulative returns (CARs) around plant sale announcements by sale type: Public to Public and Public to Private, and party: Buyer and Seller. The event window is plotted on the x-axis and starts five business days before the event, and ends five business days after the event. The CARs averaged across firms are plotted on the y-axis; daily CARs are based on expected return estimates generated using the Fama-French factor plus Momentum model. Dashed lines indicate the 95% confidence interval.

7.5.5 Cross section using Emissions

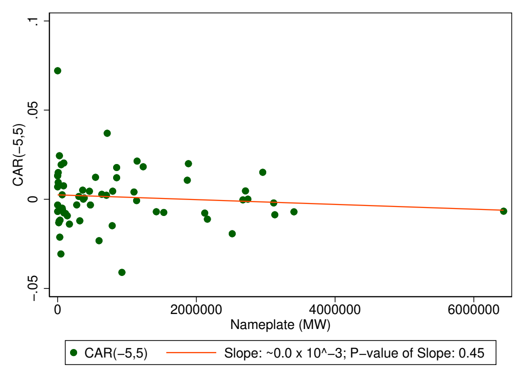
Figure 7.15: CARs and Emissions



(a) Public to Public: Seller



(b) Public to Public: Buyer



(c) Public to Private: Seller

7.5.6 Standard errors on the stock event study

Standard errors for weighted averages assume that individual abnormal returns are drawn from identical distributions (i.e. drawn from distributions with the same population variances) and are computed according to the formula

$$SE = \sqrt{\frac{\frac{\Sigma_i w_i (x_i - \bar{x})^2}{\Sigma_i w_i} \frac{n_{eff}}{n_{eff}-1}}{n_{eff}}} \tag{7.2}$$

$$n_{eff} = \frac{\Sigma(w_i)^2}{\Sigma_i(w_i^2)}. \tag{7.3}$$

Qualitatively, the results are the same as when variances are assumed to be of the form $\sigma_i = \sigma/\sqrt{w_i}$. This assumption would lead to the same standard error as taking the simple standard errors of unweighted abnormal returns. This assumption implies that large deviations from the null, if they occur in transactions that involved the ownership transfer of a very large quantity of nameplate capacity, will lead more towards rejecting the null than if they occurred in transactions that involved the ownership transfer of a very small quantity of nameplate capacity.

8 Theory

Notation Before proceeding, I introduce simplifying notation and auxiliary functions.

Denote the state by s, which is a pair of parameters that specify the equilibrium owners of the asset originally owned by the public firm and the asset originally owned by the private firms, in that order. Owner identity is represented by the owner's private cost of emitting. Since each firm believes that if its type finds it individually profitable to sell all firms of its type will sell, there are three possible states:

$$S \equiv \{(\phi, \tilde{\phi}), (\phi, \phi), (\tilde{\phi}, \tilde{\phi})\}.$$

The first corresponds to the state in which both public and private firms own assets; the second corresponds to the state in which public firms own all assets; the third corresponds to the state in which private firms own all assets.

Denote the ratio of the public and private firms' costs by

$$k \equiv \frac{(\phi + c)}{(\tilde{\phi} + c)}.$$

Note that there is a one-to-one mapping between $\Phi = \frac{\phi}{\tilde{\phi}}$ and k and that as Φ increases, so does k.

Let $V(s), \tilde{V}(s)$ denote the value of an asset owned in state $s \in S$ by a public firm and private firm, respectively.$V(s)$ can take on the following values:

$$V(\phi, \tilde{\phi}) = \frac{1}{4k(\tilde{\phi} + c)} \left(\frac{2a}{\frac{1+k}{k}(\frac{1}{\tilde{\phi}+c}) + 2b} \right)^2, \tag{8.1}$$

$$V(\phi, \phi) = \frac{k}{4(\tilde{\phi} + c)} \left(\frac{a}{\frac{1}{\tilde{\phi}+c} + kb} \right)^2, \tag{8.2}$$

$$V(\tilde{\phi}, \tilde{\phi}) = 0. \tag{8.3}$$

$\tilde{V}(s)$ can take on the following values:

$$\tilde{V}(\phi,\tilde{\phi}) = \frac{1}{4(\tilde{\phi}+c)}\left(\frac{2a}{\frac{1+k}{k}(\frac{1}{\tilde{\phi}+c})+2b}\right)^2, \tag{8.4}$$

$$\tilde{V}(\phi,\phi) = 0, \tag{8.5}$$

$$\tilde{V}(\tilde{\phi},\tilde{\phi}) = \frac{1}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+b}\right)^2. \tag{8.6}$$

Denote the total value function, which specifies the total value of all assets in the equilibrium state s by $W(s)$. $W(s)$ can take on the following values:

$$W(\phi,\phi) = \frac{k}{2(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+kb}\right)^2, \tag{8.7}$$

$$W(\tilde{\phi},\tilde{\phi}) = \frac{1}{2(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+b}\right)^2, \tag{8.8}$$

$$W(\phi,\tilde{\phi}) = \frac{1}{4}\frac{1+k}{k}\frac{1}{\tilde{\phi}+c}\left(\frac{2a}{\frac{1+k}{k}\frac{1}{\tilde{\phi}+c}+2b}\right)^2. \tag{8.9}$$

8.1 Equilibrium

Given the assumptions that the clean assets will always produce to capacity, a public firm solves the following optimization problem

$$x^* \equiv arg\, \max_x py - (\phi+c)x \tag{8.10}$$
$$s.t.\, py - (\phi+c)x \geq 0,$$

taking p as given. First order conditions give the following equilibrium output and input demands from a public firm[57]

$$p\frac{1}{2}x^{\frac{-1}{2}} - (\phi+c) = 0$$

[57] where I have invertibility of the production function under the particular functional form I assumed. The derivative of f is $0.5x^{-0.5}$ which is strictly monotonic, and therefore injective.

$$y^* = \frac{p^*}{2(\phi + c)}, \tag{8.11}$$

$$x^* = \left[\frac{p^*}{2(\phi + c)}\right]^2. \tag{8.12}$$

By symmetry, the equilibrium output and input demands of a private firm are:

$$\tilde{y}^* = \frac{p^*}{2(\tilde{\phi} + c)}, \tag{8.13}$$

$$\tilde{x}^* = \left[\frac{p^*}{2(\tilde{\phi} + c)}\right]^2. \tag{8.14}$$

Note that because emissions scale one to one with input, a firm's equilibrium input demand is equal to the firm's equilibrium emissions. Market clearing in the final goods market pins down the equilibrium price.

Market clearing in the final goods market pins down the equilibrium final goods price:

$$\begin{aligned} y^* + \tilde{y}^* &= a - bp^* \\ \frac{p^*}{2(\phi + c)} + \frac{p^*}{2(\tilde{\phi} + c)} &= a - bp^* \\ \frac{1}{2}\left(\frac{1}{\phi + c} + \frac{1}{\tilde{\phi} + c}\right) &= \frac{a - bp^*}{p^*} \\ y^* + \tilde{y}^* &= \frac{a}{p^*} - b \end{aligned} \tag{8.15}$$

Solving for the equilibrium final goods price yields

$$p^* = \frac{2a}{\left(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}\right) + 2b}. \tag{8.16}$$

Note for the future that

$$\begin{aligned} \frac{\partial p^*}{\partial \phi} &= \frac{2a\left(\frac{1}{\phi+c}\right)^2}{\left(\left(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}\right) + 2b\right)^2} \\ &= p^* \frac{\frac{1}{(\phi+c)^2}}{\left(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}\right) + 2b} > 0. \end{aligned}$$

8.2 Lemmas

Lemma 5. *The equilibrium price satisfies the following inequality*

$$p(\tilde{\phi}, \tilde{\phi}) < p(\phi, \tilde{\phi}) < p(\phi, \phi). \tag{8.17}$$

Proof. By definition

$$\begin{aligned} p(\tilde{\phi}, \tilde{\phi}) &= \frac{2a}{(1+1)\frac{1}{\tilde{\phi}+c} + 2b} \\ p(\phi, \tilde{\phi}) &= \frac{2a}{(1+\frac{1}{k})\frac{1}{\tilde{\phi}+c} + 2b} \\ p(\phi, \phi) &= \frac{2a}{(\frac{1}{k}+\frac{1}{k})\frac{1}{\tilde{\phi}+c} + 2b}. \end{aligned}$$

Since $\frac{1}{k} + \frac{1}{k} < 1 + \frac{1}{k} < 1 + 1$, I have that $p(\tilde{\phi}, \tilde{\phi}) < p(\phi, \tilde{\phi}) < p(\phi, \phi)$. □

Lemma 6. *The value functions satisfy the following inequalities*

$$V(\phi, \tilde{\phi}) < V(\phi, \phi) \tag{8.18}$$

$$\tilde{V}(\tilde{\phi}, \tilde{\phi}) < \tilde{V}(\phi, \tilde{\phi}) \tag{8.19}$$

Proof. By definition,

$$\begin{aligned} V(\phi, \phi) &= \frac{p(\phi, \phi)^2}{4(\phi + c)} \\ V(\phi, \tilde{\phi}) &= \frac{p(\phi, \tilde{\phi})^2}{4(\phi + c)} \end{aligned}$$

Since $p(\phi, \tilde{\phi}) < p(\phi, \phi)$, $V(\phi, \tilde{\phi}) < V(\phi, \phi)$.

By definition,

$$\begin{aligned} \tilde{V}(\tilde{\phi}, \tilde{\phi}) &= \frac{p(\tilde{\phi}, \tilde{\phi})^2}{4(\tilde{\phi} + c)} \\ \tilde{V}(\phi, \tilde{\phi}) &= \frac{p(\phi, \tilde{\phi})^2}{4(\tilde{\phi} + c)} \end{aligned}$$

Since $p(\tilde{\phi}, \tilde{\phi}) < p(\phi, \tilde{\phi})$, $V(\tilde{\phi}, \tilde{\phi}) < \tilde{V}(\phi, \tilde{\phi})$.

□

Lemma 7. *If*

$$b > \frac{(k^2-2k)+\sqrt{4(k+k^2-2)(k^2-k)}}{k^2-k}\frac{1}{\tilde{\phi}+c}$$

then

$$\tilde{W}(\tilde{\phi},\tilde{\phi}) - \tilde{V}(\phi,\tilde{\phi}) - V(\phi,\phi) > 0.$$

Proof. By definition

$$2\tilde{V}(\tilde{\phi},\tilde{\phi}) - \tilde{V}(\phi,\tilde{\phi}) = \frac{1}{2(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+b}\right)^2 - \frac{1}{4(\tilde{\phi}+c)}\left(\frac{2a}{(1+\frac{1}{k})\frac{1}{\tilde{\phi}+c}+2b}\right)^2.$$

This quantity is bounded below by

$$\frac{1}{2(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+b}\right)^2 - \frac{1}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{k}\frac{1}{\tilde{\phi}+c}+b}\right)^2.$$

Thus, the set of bs that satisfy the following inequality will also satisfy the inequality $V(\phi,\phi) < 2\tilde{V}(\tilde{\phi},\tilde{\phi}) - \tilde{V}(\phi,\tilde{\phi})$

$$\begin{aligned}
\frac{k}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+kb}\right)^2 &< \frac{1}{2(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+b}\right)^2 - \frac{1}{4(\tilde{\phi}+c)}\left(\frac{a}{(\frac{1}{k})\frac{1}{\tilde{\phi}+c}+b}\right)^2 \\
k\left(\frac{1}{\frac{1}{\tilde{\phi}+c}+kb}\right)^2 &< 2\left(\frac{1}{\frac{1}{\tilde{\phi}+c}+b}\right)^2 - k^2\left(\frac{1}{\frac{1}{\tilde{\phi}+c}+kb}\right)^2 \\
k\left(\frac{1}{1+kN}\right)^2 &< 2\left(\frac{1}{1+N}\right)^2 - k^2\left(\frac{1}{1+kN}\right)^2, where\, b \equiv N\frac{1}{\tilde{\phi}+c} \\
0 &< (k^2-k)N^2 + (2k-k^2)N + (2-(k+k^2)).
\end{aligned}$$

Since $\forall k$, $(k^2-k) > 0$ and $(2-(k+k^2)) < 0$ and $g(x) \equiv (k^2-k)N^2 + (2k-k^2)N + (2-(k+k^2))$, $g(x)$ will have only one positive root, which I can bound above

$$\begin{aligned}
N_{pos} &= \frac{-(2k-k^2)+\sqrt{(2k-k^2)^2-4(k^2-k)(2-(k+k^2))}}{2(k^2-k)} \\
&< \frac{(k^2-2k)+\sqrt{4(k+k^2-2)(k^2-k)}}{k^2-k}.
\end{aligned}$$

Since $g(x)$ faces up, this in turn implies that the inequality holds for

$$b > \frac{(k^2-2k)+\sqrt{4(k+k^2-2)(k^2-k)}}{k^2-k}\frac{1}{\tilde{\phi}+c}.$$

□

Lemma 8. *If and only if*

$$b < b_1,$$

where $b_1 \equiv \frac{(\sqrt{k}\frac{1+k}{k}-2)\frac{1}{\tilde{\phi}+c}}{2(k-\sqrt{k})}$ *, then*

$$\tilde{V}(\phi,\tilde{\phi}) < V(\phi,\phi)$$

with inequality if $b = b_1$.

Proof. To see this, note that by definition

$$\begin{aligned}
\tilde{V}(\phi,\tilde{\phi}) &< V(\phi,\phi)\\
\frac{1}{4(\tilde{\phi}+c)}\left(\frac{2a}{\frac{1+k}{k}(\frac{1}{\tilde{\phi}+c})+2b}\right)^2 &< \frac{k}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{\tilde{\phi}+c}+kb}\right)^2\\
\sqrt{4\left(\frac{1}{\tilde{\phi}+c}+kb\right)^2} &< \sqrt{k\left(\frac{1+k}{k}(\frac{1}{\tilde{\phi}+c})+2b\right)^2}\\
2\left(\frac{1}{\tilde{\phi}+c}+kb\right) &< \sqrt{k}\left(\frac{1+k}{k}(\frac{1}{\tilde{\phi}+c})+2b\right)\\
2(k-\sqrt{k})b &< (\sqrt{k}\frac{1+k}{k}-2)\frac{1}{\tilde{\phi}+c}\\
b &< \frac{(\sqrt{k}\frac{1+k}{k}-2)\frac{1}{\tilde{\phi}+c}}{2(k-\sqrt{k})}.
\end{aligned}$$

Where the upper bound is greater than zero since $\sqrt{k}\frac{1+k}{k} > 2$ and $k-\sqrt{k} > 0, \forall k > 1$. The proof in the opposite direction is identically obtained if one replaces the less than sign with a greater than equal sign; the proof for the equality is identically obtained if one replaces the less than sign with an equality. □

8.3 Main Propositions

Lemma 9. *With no trading in assets, there is no Green-washing equilibrium. The public firm reduces emissions, and aggregate emissions decline.*

Proof. Derive partials of the output. I keep things in terms of p^*, which is itself a function of the cost to emitting for the public and private firms types $(\phi, \tilde{\phi})$, to make clear where changes in the partial are arising through changes in the price.

The partial of the final goods output of the private firms with respect to the public firm's cost to emissions is

$$\begin{aligned}
\frac{\partial y^*}{\partial \phi} &= \frac{\partial}{\partial \phi} \frac{p^*}{2(\phi + c)} \\
&= \frac{2(\phi + c)\frac{\partial p}{\partial \phi} - 2p^*}{(2(\phi + c))^2} \\
&= \frac{\frac{\partial p^*}{\partial \phi}}{2(\phi + c)} - \frac{p^*}{2(\phi + c)^2} \\
&= \frac{p^*\left[\frac{\frac{1}{\phi+c}}{(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}) + 2b} - 1\right]}{2(\phi + c)^2} < 0,
\end{aligned}$$

since $\frac{1}{\phi+c} < (\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}) + 2b$.

The partial of the final goods output of the public firm with respect to its cost to emissions is:

$$\begin{aligned}
\frac{\partial \tilde{y}^*}{\partial \phi} &= \frac{\partial}{\partial \phi} \frac{p^*}{2(\tilde{\phi} + c)} \\
&= \frac{2(\tilde{\phi} + c)\frac{\partial p^*}{\partial \phi}}{(2(\tilde{\phi} + c))^2} \\
&= \frac{\frac{\partial p^*}{\partial \phi}}{2(\tilde{\phi} + c)} \\
&= \frac{p^* \frac{\frac{1}{(\phi+c)}}{(\frac{1}{\phi+c} + \frac{1}{\tilde{\phi}+c}) + 2b}}{2(\phi + c)(\tilde{\phi} + c)} \\
&> 0,
\end{aligned}$$

since $\frac{\partial p}{\partial \phi} > 0$.

Finally, the partial of the total final goods output with respect to its cost to emissions is

$$\begin{aligned}\frac{\partial Y^*}{\partial \phi} &= \frac{\partial}{\partial \phi}(a - bp^*)\\ &= -b\frac{\partial p^*}{\partial \phi}\\ &< 0.\end{aligned}$$

Partials for the inputs are

$$\begin{aligned}\frac{\partial \tilde{x}^*}{\partial \phi} &= \frac{\partial}{\partial \phi}(\tilde{y}^*)^2\\ &= 2\tilde{y}^*\frac{\partial \tilde{y}^*}{\partial \phi}\\ &= 2\tilde{y}^*\frac{p^*\frac{\frac{1}{(\phi+c)}}{(\frac{1}{\phi+c}+\frac{1}{\tilde{\phi}+c})+2b}}{2(\phi+c)(\tilde{\phi}+c)}\\ &> 0\\ \frac{\partial x^*}{\partial \phi} &= \frac{\partial}{\partial \phi}(y^*)^2\\ &= 2y^*\frac{\partial y^*}{\partial \phi}\\ &= 2y^*\frac{p^*\left[\frac{\frac{1}{\phi+c}}{(\frac{1}{\phi+c}+\frac{1}{\tilde{\phi}+c})+2b}-1\right]}{2(\phi+c)(\phi+c)}\\ &< 0\\ \frac{\partial X^*}{\partial \phi} &= \frac{\partial \tilde{x}^*}{\partial \phi}+\frac{\partial x^*}{\partial \phi}\\ &= 2\tilde{y}^*\frac{p^*\frac{\frac{1}{(\phi+c)}}{(\frac{1}{\phi+c}+\frac{1}{\tilde{\phi}+c})+2b}}{2(\phi+c)(\tilde{\phi}+c)}+2y^*\frac{p^*\left[\frac{\frac{1}{\phi+c}}{(\frac{1}{\phi+c}+\frac{1}{\tilde{\phi}+c})+2b}-1\right]}{2(\phi+c)(\phi+c)}\\ &= \frac{2y_0^*p^*}{2(\phi_0+c)^2}\left(\frac{\frac{1}{(\phi_0+c)}}{(\frac{1}{\phi_0+c}+\frac{1}{\phi_0+c})+2b}+\frac{\frac{1}{\phi_0+c}}{(\frac{1}{\phi_0+c}+\frac{1}{\phi_0+c})+2b}-1\right)\\ &= \frac{y_0^*p^*}{(\phi_0+c)^2}\left(\frac{\frac{1}{(\phi_0+c)}}{\frac{1}{(\phi_0+c)}+b}-1\right)\\ &< 0\end{aligned}$$

The equilibrium input demands of the public firms $\frac{\partial x^*}{\partial \phi}$ and the equilibrium aggregate input demand $\frac{\partial X^*}{\partial \phi}$ are less than zero. Thus, the assets of the public firm generate less emissions, as does the system as a whole. The result on aggregate emissions however, is sensitive to the functional form of the production function assumed. One can easily generate an increase in aggregate emissions by having output reductions by public firms replaced (even if only in part) by output increases by private firms at very high emissions intensities, or in this case, at a very inefficient, flat region of the production function. $\square$

Lemma 10. ***Green-washing Equilibrium*** - *Given a positive shock to the public firm's cost to emitting of size* Φ*, the public firm will sell its assets to the private firm if the demand sensitivity to price is sufficiently high. Production and emissions of the divested assets as well as aggregate production and emissions will be unchanged vis-à-vis the initial equilibrium.*

Proof. Let t denote the transaction price of the asset. The public firm sells if the payoff from not trading is dominated by the payoff from selling (IR Constraint)

$$V(\phi, \tilde{\phi}) < t$$

and the payoff from buying is dominated by the payoff from selling (IC constraint)

$$\begin{aligned} W(\phi, \phi) - t &< t \\ V(\phi, \phi) &< t. \end{aligned}$$

By Lemma 6, $V(\phi, \tilde{\phi}) < V(\phi, \phi)$, which implies the latter condition is more restrictive and therefore, that the lower bound of the public firm's asking price is the marginal value of an asset in the equilibrium in which the public firms own all assets:

$$\underbrace{V(\phi, \phi)}_{Value\, of\, New\, Asset\, in\, (\phi,\phi)} < t.$$

For trade to occur, the price must also satisfy the conditions required for the private firm to buy. The private firms buy the asset if the payoff from not trading is dominated by the payoff from buying (IR Constraint)

$$\begin{aligned} \tilde{V}(\phi, \tilde{\phi}) &< 2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - t \\ t &< 2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) \end{aligned}$$

and if the payoff from selling is dominated by the payoff from buying (IC constraint)

$$\begin{aligned} t &< 2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - t \\ t &< \tilde{V}(\tilde{\phi}, \tilde{\phi}). \end{aligned}$$

Note that by Lemma 6, $2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) - \tilde{V}(\tilde{\phi}, \tilde{\phi}) = \tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) < 0$. Thus, the IR constraint is more restrictive and the upper bound of the private firms's bid is the value of an asset under the equilibrium in which it owns all assets plus the decline in the value of the asset it already owns

$$2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) = \underbrace{\tilde{V}(\tilde{\phi}, \tilde{\phi})}_{Value\, of\, New\, Asset\, in\, (\tilde{\phi}, \tilde{\phi})} - \underbrace{(\tilde{V}(\phi, \tilde{\phi}) - \tilde{V}(\tilde{\phi}, \tilde{\phi}))}_{\downarrow Value\, of\, Existing\, Assets}.$$

Therefore, the set of prices that support this equilibrium is

$$\{t : V(\phi, \phi) < p < 2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi})\}. \tag{8.20}$$

This set is non-zero if

$$2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) - V(\phi, \phi) > 0,$$

which, by Lemma 7, is satisfied if demand sensitivity to price is sufficiently high

$$b > \frac{(k^2 - 2k) + \sqrt{4(k + k^2 - 2)(k^2 - k)}}{k^2 - k} \frac{1}{\tilde{\phi} + c}.$$

The transaction price t is pinned down by λ, which parameterizes the relative bargaining power of the public firm:

$$t = V(\phi, \phi) + \lambda(2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - \tilde{V}(\phi, \tilde{\phi}) - V(\phi, \phi)).$$

Since all assets will be owned by owners with a cost of emitting equal to ϕ, production and thus, emissions will be unchanged vis-à-vis the initial equilibrium.

□

Lemma 11. ***Impact Equilibrium*** - *Given a positive shock to the public firm's cost to emitting of size* Φ*, the private firm will sell its assets to the public firm if the demand sensitivity to price is sufficiently small. Production and emissions of the divested assets as well as aggregate production and emissions will decline vis-à-vis the initial equilibrium.*

Proof. Let t denote the transaction price. The private firms sells if the payoff from not trading is dominated by the payoff from selling

$$\tilde{V}(\phi, \tilde{\phi}) < t$$

and if the payoff from buying is dominated by the payoff from selling

$$\begin{aligned} 2\tilde{V}(\tilde{\phi}, \tilde{\phi}) - t &< t \\ \tilde{V}(\tilde{\phi}, \tilde{\phi}) &< t. \end{aligned}$$

By Lemma 6, $\tilde{V}(\tilde{\phi}, \tilde{\phi}) < \tilde{V}(\phi, \tilde{\phi})$. Thus, the former is more restrictive

$$\underbrace{\tilde{V}(\phi, \tilde{\phi})}_{Value\,of\,Existing\,Asset\,in\,(\phi,\tilde{\phi})} < t.$$

When a pressured firm experiences a positive shock to its cost to emitting and retains its asset because there is no buyer for it, aggregate production declines and the equilibrium price increases. The firms that did not experience this shock benefit from an increase in firm profits and asset valuations, since they produce at quantities at least greater than the baseline but sell at a higher price.

The public firms buy if the payoff from not trading is dominated by the payoff from buying:

$$\begin{aligned} V(\phi, \tilde{\phi}) &< 2V(\phi, \phi) - t \\ t &< 2V(\phi, \phi) - V(\phi, \tilde{\phi}) \end{aligned}$$

and if the payoff from selling is dominated by the payoff from buying:

$$\begin{aligned} t &< 2V(\phi, \phi) - t \\ t &< V(\phi, \phi). \end{aligned}$$

By Lemma 6, $V(\phi, \tilde{\phi}) < V(\phi, \phi)$. Thus, $2V(\phi, \phi) - V(\phi, \tilde{\phi}) > V(\phi, \phi)$ and the latter condition is more restrictive

$$t < \underbrace{V(\phi, \phi)}_{Value\,of\,New\,Asset\,in\,(\phi,\phi)}.$$

To see this note that

$$\begin{aligned}
&V(\phi,\phi) < 2V(\phi,\phi) - V(\phi,\tilde{\phi}) \\
&V(\phi,\tilde{\phi}) < V(\phi,\phi).
\end{aligned}$$

Therefore, the set of prices that support this equilibrium is

$$\{t : \tilde{V}(\phi,\tilde{\phi}) < p < V(\phi,\phi)\}. \tag{8.21}$$

This set is non-zero if

$$V(\phi,\phi) - \tilde{V}(\phi,\tilde{\phi}) > 0.$$

which is satisfied when the demand sensitivity to price is sufficiently small

$$b < \frac{(\sqrt{k}\frac{1+k}{k} - 2)\frac{1}{\tilde{\phi}+c}}{2(k-\sqrt{k})},$$

by Lemma 7. The transaction price t is pinned down by $(1-\lambda)$, which parameterizes the bargaining power of the private firm:

$$t = \tilde{V}(\phi,\tilde{\phi}) + (1-\lambda)(V(\phi,\phi) - \tilde{V}(\phi,\tilde{\phi})).$$

If the private firms sell their assets to the public firms, aggregate production and emissions will decline vis-à-vis the pre-shock equilibrium. Let post-shock equilibrium variables be denoted by an apostrophe. Since assets are identical and have concave production functions, if a firm owns two assets, it will operate the assets identically. Hence,

$$\begin{aligned}
Y^{*'} &= 2y^{*'} \qquad & Y^* &= 2y^* \\
X^{*'} &= 2x^{*'} \qquad & X^* &= 2x^*.
\end{aligned}$$

Since $x^{*'} = (y^{*'})^2$, demonstrating that aggregate production and emissions decline vis-à-vis the pre-shock equilibrium, it is sufficient to show that

$$\begin{aligned}
y^{*'} &< y^* \\
\frac{p^*(\tilde{\phi},\tilde{\phi})}{2k(\tilde{\phi}+c)} &< \frac{\frac{a}{z+b}}{2(\tilde{\phi}+c)} \\
\frac{\frac{a}{\frac{1}{\tilde{\phi}+c}+kb}}{2(\tilde{\phi}+c)} &< \frac{\frac{a}{\frac{1}{\tilde{\phi}+c}+b}}{2(\tilde{\phi}+c)}
\end{aligned}$$

which holds since $k > 1$.

$\square$

Lemma 12. ***No Trade Equilibrium*** - *Given a positive shock to the public firm's cost to emitting of size* Φ*, there will be no trade in assets if the demand sensitivity to price is neither too small or too large.*

Proof. In the no trade equilibrium, the conditions required for the two other equilibria should be jointly violated.

The condition for the Green-washing Equilibrium is violated if

$$V(\phi,\phi) - 2\tilde{V}(\tilde{\phi},\tilde{\phi}) + \tilde{V}(\tilde{\phi},\phi) > 0.$$

Since $\tilde{V}(\tilde{\phi},\tilde{\phi}) < \tilde{V}(\tilde{\phi},\phi)$ by Lemma 6, it follows that if

$$\begin{aligned} V(\phi,\phi) - 2\tilde{V}(\tilde{\phi},\tilde{\phi}) + \tilde{V}(\tilde{\phi},\tilde{\phi}) &> 0 \\ V(\phi,\phi) - \tilde{V}(\tilde{\phi},\tilde{\phi}) &> 0, \end{aligned}$$

then the condition for the Green-washing Equilibrium will also have been violated. The set of bs that satisfy this inequality are

$$\begin{aligned} \tilde{V}(\tilde{\phi},\tilde{\phi}) &< V(\phi,\phi) \\ \frac{1}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{(\tilde{\phi}+c)}+b}\right)^2 &< \frac{k}{4(\tilde{\phi}+c)}\left(\frac{a}{\frac{1}{(\tilde{\phi}+c)}+kb}\right)^2 \\ b &< \frac{\sqrt{k}-1}{k-\sqrt{k}}\frac{1}{\tilde{\phi}+c} \equiv b_2. \end{aligned}$$

The condition for the Impact Equilibrium is violated if

$$b > b_1 \equiv \frac{(\sqrt{k}\frac{1+k}{k} - 2)\frac{1}{\tilde{\phi}+c}}{2(k-\sqrt{k})}$$

which follows directly from the proof of the Impact Equilibrium. Note that $\forall k$, $b_1 < b_2$. Hence, if $b \in (b_1, b_2]$ there will be no trade.

Note that the reason the no-trade equilibrium exists is because in the greenwashing equilibrium, increased output from the units previously owned by public firms reduces the value of the private firm's existing assets.

In the Green-washing Equilibrium,

$$\underbrace{\tilde{V}(\tilde{\phi},\tilde{\phi})}_{Value\,of\,New\,Asset\,in\,(\tilde{\phi},\tilde{\phi})} - \underbrace{V(\phi,\phi)}_{Value\,of\,New\,Asset\,in\,(\phi,\phi)} > \underbrace{(\tilde{V}(\phi,\tilde{\phi}) - \tilde{V}(\tilde{\phi},\tilde{\phi}))}_{Change\,in\,Value\,of\,Existing\,Assets} > 0$$

In the Impact Equilibrium,

$$\underbrace{\tilde{V}(\tilde{\phi},\tilde{\phi})}_{Value\,of\,New\,Asset\,in\,(\tilde{\phi},\tilde{\phi})} - \underbrace{V(\phi,\phi)}_{Value\,of\,New\,Asset\,in\,(\phi,\phi)} < 0.$$

Note that the wedge in the cut-off point for the Green-washing Equilibrium and Impact Equilibrium is $\tilde{V}(\phi,\tilde{\phi}) - \tilde{V}(\tilde{\phi},\tilde{\phi})$, which is the change in the value of existing assets under private ownership. $\square$

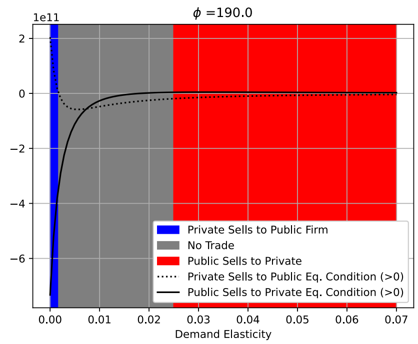
8.4 Equilibrium Visualization

To visualize the equilibria, I numerically solve for and present the cut-off points for a set of parameterizations (see Figure 5.1). I let the initial cost of emitting equal 7 for both shocked and unshocked firms, which corresponds to the upper range of the social cost of carbon under the Trump Administration. I examine the equilibria to shocks that make $\varphi = 190$, the EPA's 2023 social cost of carbon.

In Figure 8.1, to visualize the equilibria, I numerically solve for and present the cut-off points for a set of parameterizations. I let the initial cost of emitting equal 7 for both shocked and unshocked firms, which corresponds to the upper range of the social cost of carbon under the Trump Administration. I examine the equilibria to shocks that make $\phi = 190$, the EPA's 2023 social cost of carbon.

Figure 8.1: Equilibria

(a) EPA 2023 Shock



Notes: This figure illustrates how equilibria change as the sensitivity of demand to price b varies. To generate these figures, parameter values are defined as follows: $a = 101,200$, $b = 203$, $y^* = \tilde{y}^* = 44,000MWh$ and $x^* = \tilde{x}^* = 1,936,000,000$.

I take the demand functions coefficients to be

$$a = 1.15Q_0$$
$$b = 0.15\frac{Q_0}{P_0}$$

so that the elasticity of demand of 0.15. Let $Q_0 = 88,000MWh$ and $P_0 = \$65/MWh$, which corresponds to the average load and price in the PJM Interconnection, a regional transmission organization in 2021. Then,

$$a^{Electricity} = 101200$$
$$b^{Electricity} = 203.$$

Assuming competitive generation and homogeneity, the price is the marginal cost of generation c. At the initial symmetric equilibrium, for the value of Q_0 chosen, market clearing implies $y^* = \tilde{y}^* = 44,000MWh$ and $x^* = \tilde{x}^* = 1,936,000,000$. The derivative of the production function at this point is $\frac{1}{2}x^{-1/2} = 0.00001136363$ - that is, it is nearly flat.