Using Consumer Demand to Limit Climate Risk: Evidence from the U.S. Electric Utility Sector

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Abstract

Using comprehensive data on U.S. power plant emissions and generation from 2004 to 2020, I explore the environmental outcomes of the transfer of power plant control. Transacted plants, while more carbon-intensive than the originating firm's average plants, were less pollutive than those of the acquiring firm. Following the transaction, plants located in the non-competitive market experienced worse environmental performance. Results suggest that firms divest pollutive assets to entities facing less environmental pressure, leading to worsened environmental performance. On the other hand, plants located in the competitive market have seen no worsening, and sometimes even improved, environmental performance. The results are sustained when I examine transactions between different ownership types, specifically incumbent regulated utility (RU) and independent power producers (IPP). I propose a demand-side mechanism to explain the findings: power users' demand for clean energy motivates all power producers to prioritize their environmental footprint, leading to no worse environmental performance following asset divestitures.

Keywords: emission, utilities, regulation, externalities, ownership structure

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1 Introduction

Considerable evidence has shown that Greenhouse Gas (GHG) emissions by human activities are causing climate change that threatens the long-run stability of the earth (Rosa and Dietz (2012), UNCCC (2015)). The United States (U.S.), as the leading economy, sets long-term environmental objectives to achieve net-zero emissions across Federal operations by 2050.[1], where the electric utility industry is a key target. Recently the U.S. Security Exchange Commission (SEC) proposed disclosure of Scope 1 and Scope 2 GHG emissions in the annual 10-K form, making the electric utility sector strategically vital to firms' overall environmental impact because the most important component of Scope 2 emissions is those associated with power purchase.[2] Meanwhile, the electric utility industry is also the most GHG-polluting industry in the U.S., accounting for 32% of total U.S. greenhouse gas emissions in 2000. Figure 1 shows that the total amount of CO_2 equivalent emission[3] and the amount of GHG emissions produced from the electric utility industry as compared to other pollutive industries, and it was only until recent years that the utility sector has seen a reduction in total GHG emission. However, the electric utility sector is understudied by the finance literature because it is a highly regulated industry where the regulatory constraint, oftentimes through limiting a firm's rate of return, will result in different investment behavior as compared to unregulated firms.[4] Nevertheless, given the important role that electric power plants play in the country's emission landscape, a better understanding of power plant owners' environmental decisions and how they connect to the organizational structure will inform more fruitful discussions of environmental policy.

Over the past three decades, the U.S. utility industry has experienced considerable changes and evolution, particularly changes in ownership of electric power producers, and the evolution of the competition faced by power producers. In regards to ownership, the biggest change has been a relative decline in the importance of the incumbent vertically integrated utilities which are

[1]The plan is referred to as *The Federal Sustainability Plan* Details of the plan can be found at https://www.sustainability.gov/federalsustainabilityplan/carbon.html.

[2]SEC news see https://www.sec.gov/news/press-release/2022-46; https://www.spglobal.com/esg/solutions/getting-ready-for-the-sec-climate-disclosure-rule. Figure 4 provides information and examples regarding scope 1, 2, and 3 emissions.

[3]This measure includes emissions for carbon dioxide (CO_2), methane (CH_4), and nitrogen dioxide (NO_2), and is calculated based on global warming potential (GWP). GWP is a value assigned to a greenhouse gas so that the emissions of different gases can be assessed on an equivalent basis to the emissions of the reference gas.

[4]An early economics literature studies rate-based regulation in particular, including but not limited to Averch and Johnson (1962), Klevorick (1971), and Joskow and MacAvoy (1975).

mostly publicly traded firms and are regulated through state regulatory bodiesAndonov and Rauh (2022). Traditionally, the utility sector is dominated by these regulated utilities (RUs), serving as monopolies in power generation, distribution, and transmission at the state level. Following the 1990s' restructuring wave that promoted competition in the U.S. electric utility sector, existing plants of vertically integrated firms have been sold to new owners, known as independent power producers (IPP), including both domestic and foreign publicly traded firms as well as new private entities including private equity (PE) owners and other private companies. Meanwhile, IPPs also expand by creating new facilities. Since 2003 there has been no significant state-level restructuring of utility markets. As a result, the US is divided into areas with significantly more liberalization, and areas where RUs still remain dominant.

Given the significant shifts in ownership structure within the industry, and the important role that power producers play in the country's emission landscape, it is natural to ask what will be the impact of the changes in ownership and competition on the environmental footprint associated with power production? In this paper, I examine the transfer of control of power facilities among various types of owners and estimate the associated environmental consequences, by comparing plant carbon emission rates before and after the transfer. To evaluate the environmental consequences of asset transfer, I propose two hypotheses that generate competing predictions.

The first view, known as the leakage hypothesis, captures the fear that ownership change will lead to pollutive power plants being transferred from owners with greater attention to public pressure concerns to those with fewer, with predictably worse environmental outcomes (Duchin, Gao and Xu (2022); Andonov and Rauh (2022); Copeland, Shapiro and Taylor (2021)). This leakage hypothesis has been developed regarding concerns about outsourcing pollution in international trade and firms' greenwashing behavior, and can also be tested in my setting. More specifically, I conjecture that the incumbent RUs put more weight on generating environmental externalities than IPPs, for the following reasons. First, given that the government has put considerable effort into limiting emissions from power generation over the past two decades [5], and the incumbent RUs are still embedded in a regulatory process [6], RUs face the pressure of environmental performance

[5]Over the past decades, due to the rise of clean energy technology and government efforts to limit emissions at the state level, the share of emissions produced by the electric utility industry has reduced over time. Yet, the electric utility industry is still the second largest polluter in the U.S. by 2021.

[6]The company is vertically integrated and has divisions that continue to be regulated along with power production that is deregulated in certain states or area

from regulators more than the IPPs. Second, RUs are mostly publicly traded firms[7] that are subject to enhanced environmental disclosure requirements and pressures from pro-environmental stakeholders.[8] On the other hand, IPPs can be public firms, PE (investment) firms, and private firms. Private owners and PE owners are not subject to the level of oversight as an RU does and thus may care less about the environmental footprint. Lastly, RUs may have long-time horizons and more incentive to generate goodwill with stakeholders while private and PE owners are generally more profit-oriented.[9]

According to the leakage hypothesis, if a power plant is transferred from the incumbent firm to new owners, the new owners will put less weight on environmental externalities, leading to worse environmental performance. In the case the new owners are new publicly traded IPPs, they may have comparable incentives due to public pressure and the result may be weakened. In the case of PE owners or private firms, the prediction of less weight on environmental externalities should be stronger thus resulting in stronger results. Given that generating environmental externalities is costly to firms, the negative consequences of ownership change on environmental performance can be amplified in competitive markets because acquirers' incentive to pay attention to environmental goodwill can be weakened under heightened competition.

I contrast the leakage hypothesis with a view, known as the power user hypothesis. The power user hypothesis emphasizes the preference of end power users in affecting power producers' environmental choices. While power users, which include most publicly traded firms, in the past may not have cared about the environmental footprint associated with their power usage, they have many reasons to pay more attention over time. First, survey of institutional investors, and studies of institutional investors, shows institutional owners prefer higher environmental performance (Krueger, Sautner and Starks (2020), Dyck et al. (2019), Dyck et al. (2023)). Therefore, as Scope 2 emissions are becoming a valuable component of the overall environmental footprint in many industries, firms are likely to disclose Scope 2 emissions, viewing it as a highly relevant part of

[7] 1) A few regulated utilities are regional and private (for example, the major electricity provider in Alaska, Alaska Power & Telephone Co); 2) No RU in my sample is PE-owned in the starting year 2004 (but some of them experienced buyouts later but failed). 3) There are also a few cases where the control firm of regulated entities is a foreign utility firm (mainly from Canada and Europe).

[8] As Baron (2007), Bénabou and Tirole (2010), and Hart and Zingales (2017) point out, different prosocial outcomes are expected in equilibrium when some investors are prosocial and when firms have a comparative advantage in creating prosocial outcomes.

[9] On the other hand, existing literature also debates whether PE ownership leads to better prosocial outcomes (Bellon (2020), Gupta et al. (2021), and Howell et al. (2022)).

firms' environmental positioning, climate risk mitigation strategies, and strategies to engage with institutional investors.[10] If end users have a strong demand for emission performance from power usage, the power user hypothesis predicts contrasting results to the leakage hypothesis – even if a pollutive plant is divested, the plant's environmental performance would not be worsened after the transaction because on average all producers will deliver low carbon intense electricity. The power user hypothesis is less applicable in the non-competitive markets where incumbent RUs still dominate because customers have few choices and user preferences are less important to power producers.[11] In competitive environments where customers have more freedom to choose electricity providers, power users' preference is accentuated and hence provide an appropriate setting for testing the power user hypothesis. Meanwhile, it is also the setting where the predictions of the two hypotheses strongly diverge.

I use comprehensive plant-level data that covers 99% of U.S. electricity generation from 2004 to 2020 and focus on power plant output emission rate[12] as the proxy for the environmental outcome. After controlling for plant size, plant age, plant utilization, and plant regulatory status, cross-sectional analysis shows that while RU plants do provide less carbon emission per unit of output in the non-competitive market, they rely more on coal and petroleum for generation than IPP plants, indicated by higher total emissions from these plants. Then I examine the incentives and outcomes of all transactions by comparing the set of transferred plants to the seller's plants and the acquirer's plants pre- and post-transaction. The seller divests larger plants and plants that are more carbon-intense, while the buyer acquires smaller plants and plants that emit less carbon and are less carbon-intense. This observation is consistent with the leakage hypothesis that firms divest pollutive assets to owners who do not mind pollutive assets. Nevertheless, I only observe superior environmental performance to acquirers' plants among those located in the non-competitive markets, while those in the competitive markets exhibit no difference. After the transactions,

[10] The growing importance of disclosing such emissions is evident in the requirement for such reporting in IFRS sustainability standards issued in 2023, by the SEC, and is one of the very few disclosures agreed to by the private equity ESG Data Convergence Initiative.

[11] Here is an anecdote. In Nevada, consumer demand for cleaner energy is driving the state to deregulate retail electricity. The Energy Choice Initiative bill, also known as "Question 3," seeks to break up NV Energy's monopoly and establish an "open, competitive retail electric energy market" (State of Nevada 2016). A few customers (including MGM and Wynn, which represent 6% of NV Energy's customer base) have left NV Energy despite hefty exit fees in pursuit of an alternative energy provider to meet their corporate sustainability goals and obtain lower prices.

[12] Output emission rate (lb/MWh or lb/MWh) is a plant's total output emission scaled by net generation. An advantage of using power plant data is that I can obtain the unit emission per production output, an accurate measure for carbon emissions intensity.

transferred plants are less utilized and are downsized compared to both the acquirer's and seller's plants. Meanwhile, plants are increasingly aligning with the acquirers in terms of environmental performance: transferred plants located in the non-competitive markets are experiencing an increase in pollution levels, but the effect is offset by those located in the competitive market, where I do not observe a change in total emission and emission rate after the transaction. The result supports the power user hypothesis that in the competitive state, power producers' incentives are aligned and ownership change is less likely to affect environmental outcomes.

Next, I investigate the transfer of power plants between different types of owners. Figure 3 shows the amount of generating capacity between the transferred and untransferred plants. Few capacity is transacted from IPPs to RUs but comparable capacity is transferred from RUs to IPPs, between RUs, or between IPPs.[13]. To test my hypotheses, I start with the change of parent owner from an RU to an IPP versus another RU. Transfer of control can be attributed to divestiture and mergers.[14] In my baseline model, I employ a staggered Difference-in-Difference (DiD) with two-way fixed effects (TWFE) to control for time-invariant heterogeneity across power plants as well as the tendency to reduce emission over time, thus attributing the effect to solely the owner change. I employ a staggered adoption design by removing plants that are transacted multiple times from my analysis, taking into account the possibility that TWFE estimators can be biased when there are multiple instances of treatment and heterogeneity in treatment timing. I further address potential selection into treatment by plotting carbon emission rate dynamics around the event time to test the parallel trend assumption, and by implementing a propensity score weighting method as a robustness check. These methods effectively alleviate some concerns about selection bias. Finally, I show that my baseline result is robust to using alternative estimators proposed by De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), and Gardner (2022).

I compare plants transferred to IPPs to those transferred to another RU, and to untransferred plants owned by RUs. I find that plants transferred from RUs to IPPs experienced an increase in carbon intensity, but from RUs to another RU did not. Those that transferred to an IPP emit 57.15 lbs more CO_2 per one MWh generation, representing 9% of the unconditional mean. This

[13]The documented pattern is consistent new firms expand by purchasing old capital from existing firms (Ma, Murfin and Pratt (2022), Beaumont, Hebert and Lyonnet (2022))

[14]An empirical observation is that plants are transferred from RUs to IPPs through divestitures, and between IPPs or between RUs through mergers.

value results in an additional 5.1 million tons of carbon emissions, which represents 0.2% of total emissions from the sector per year.[15] This finding is robust to using a propensity score matched sample based on lagged carbon emission rates, lagged power plant capacity, size of the prior owner, calendar year, and plant opening year.[16] Next, I decompose IPPs into different types: publicly traded IPPs, investment/PE firms, and private firms, and find that emission rates increase if a plant is transferred to either investment firms or private firms, but not publicly traded firms, further supporting the leakage hypothesis.

To test the power user hypothesis, I conduct cross-sectional tests on transactions in the competitive and non-competitive markets respectively. In a competitive state, RUs directly compete with IPPs for electricity end customers, and catering to customers' preferences is much more important than in a non-competitive market where RUs still obtain monopolistic power. While plants located in non-competitive markets always see rising emission rates post-transaction, regardless of the IPP acquirers' type, plants located in competitive markets see barely any change in emission rates. My results strongly support the power user hypothesis that customer preferences allow firms with different ownership to have comparable incentives in delivering environmental externalities, overriding the effect brought by investors and regulators. Furthermore, I investigate transactions between IPPs and from IPPs to RU. First, I do not observe worsened environmental performance in either case and only better outcomes when plants located in the competitive market are transferred to another IPP. Considering that IPPs are predominantly new and small-scale owners, they may fiercely compete for customers, potentially resulting in improved environmental outcomes. This finding suggests that competition can yield even better results by enhancing power owners' customer outreach efforts.

To understand the driving force behind the increased carbon intensity, I propose three mechanisms. First, the carbon emission rate can increase if plants burn more fuel but generate less electricity. Second, increased carbon intensity may be driven by reduced total emissions because marginal emissions can be higher when total production is low. Third, power owners are reluctant to invest in abatement technology, thus leading to higher emission rates. Following the conjecture,

[15]The average annual generation of plants transferred to IPPs is 1,260,019 MWh, and on average I observe 141 treated units per year including both newly treated and already treated, so the additional carbon emission is $57.15 * 1260019 * 141/2000 = 5,076,711$ tons.

[16]The matched treated sample represents 45% of observations among the entire treated sample, while the matched control represents 34% of observations among the entire control sample.

I examine the total amount of emissions and plant inefficiencies after the transaction. I find that plant heat rate (BTUs/kWh) [17], a proxy for plant inefficiency, increases after it is transferred to an IPP only in the competitive state, but remains unchanged if it is transferred to another RU. Furthermore, I observe a strong positive correlation between inefficiency and carbon intensity (See Appendix A.3), suggesting that the increased carbon emission rate can potentially be driven by inefficiencies in the production process. In terms of the total amount of carbon emission, I document a reduction in total emission among plants transferred from RU to RU in the non-competitive market, and those transferred from IPP to IPP in the competitive market. Neither case is associated with an increase in carbon intensity; rather, they are only associated with reducing carbon intensity, if any. Overall, my results suggest that the rise in carbon intensity can be partly attributed to lowered combustion efficiency.

Lastly, I conducted a case study based on available data on abatement investment, abatement operating costs, and plant revenue. The abatement data is matched with the eGRID database. I can reproduce the pattern that emission rates increase if a plant is transferred to either investment IPPs or private IPPs using the subset of data, where the obtained results can provide some implications for the entire sample. While abatement investments do not change, plants transferred to IPPs experienced significant reductions in operating expenses, particularly those transferred to investment IPPs supporting the idea that investment owners are skilled at managing assets in a more cost-efficient way. On the other hand, I do not observe any cost savings at the expense of higher emission intensity among plants transferred to private IPPs, suggesting bad management of private owners. More importantly, I do not observe plants reducing abatement investment significantly after the transaction, rejecting the abatement investment mechanism.

I conduct additional tests as robustness checks. First, I used alternative estimators proposed by proposed by De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), and Gardner (2022). Second, I examined the features of plants transferred to different types of IPPs, in terms of plant primary fuel.[18] The distribution of plants (combust vs. non-combust) is very similar across

[17] It represents the amount of heat used to produce one kWh of power. A higher heat rate implies that the plant uses more heat to generate the same amount of electricity, and thus less efficient

[18] The primary fuel of a plant is determined solely by the fuel that has the maximum heat input, or the fuel with the highest nameplate capacity for plants that do not consume any combustible fuel. A combustion plant means that the plant's primary fuel is one of the following: coal, gas, oil, biomass, and other fossil fuels. These plants generate electricity from heat produced by the combustion process of fuels and are more likely to generate carbon emissions. A non-combustion plant uses one of the following primary fuels: nuclear, wind, solar, hydro, geothermal, and other

different types of IPP acquirers, and coal plants seem to drive the increase in carbon intensity the most. Third, my main conclusion is also robust to using alternative measures of competitive vs. non-competitive markets. Fourth, one can argue that when firms are making abatement investments, they trade off the importance of different gases. For example, power plants also generate SO_2 and NO_x – two toxic gases that risk people's health and are closely monitored by regulators under the implementation of the Clean Air Act 1967. Power plant owners might invest heavily in reducing other types of emissions while accidentally causing plant carbon intensity to increase. Therefore, I examined the performance of SO_2 and NO_x emission rates around the transaction and found no reduction in emission rates post-transaction.

In this paper, I shed light on the environmental consequences of asset divestitures by examining the transfer of assets between different types of owners within an industry that contributes significantly to the nation's GHG emissions. Overall, this paper makes three contributions. First, I provide new evidence for the leakage hypothesis by showing that the transferred asset is on average more pollutive the the sellers' assets but less pollutive than the buyers'. Following the prediction of the leakage hypothesis, I also show worse environmental performance following the change in asset ownership, particularly when buyers are more profit-oriented and receive less pressure from investors and regulators regarding their environmental footprint. Third, I highlight an novel mechanism that works against the leakage hypothesis in evaluating environmental consequences of divestitures. Given the important role that emissions from power usage play in a firm's environmental disclosure, power producers in the competitive markets must face higher environment pressures from end users. Empirical results have shown that such incentives counteract the effect provided by the leakage hypothesis and lead to no worse outcome following divestitures, suggesting that consumer preference can serve as an effective mechanism for disciplining a firm's environmental footprint and limiting environmental risk.

This paper contributes to the literature studying asset divestitures and M&A in the utility industry by focusing on environmental consequences following divestitures. Braguinsky et al. (2015) studies how changes in ownership affect the productivity and profitability of producers using plant-level data from the Japanese cotton spinning industry. Becher, Mulherin and Walkling (2012) show that M&A in the utility sector creates wealth through synergy rather than collision, and Shen

source.

(2018) studies change happens to power plants as a result of horizontal mergers between utility firms. Duchin, Gao and Xu (2022) uncovers a potential incentive behind plant divestitures: firms divest pollutive plants and enjoy higher ESG ratings and lower compliance costs while the sold plants do not reduce pollution after divestiture. Moreover, this paper provides additional evidence supporting engagement rather than divestment in providing desirable environmental outcomes by documenting worse environmental performance after divestitures. (Dimson, Karakaş, & Li (2015) Dimson, Karakaş and Li (2015), Barko, Cremers, & Renneboog (2021) Barko, Cremers and Renneboog (2021), Broccardo, Hart, & Zingales (2022) Broccardo, Hart and Zingales (2022), Edmans, Levit, & Schneemeier (2022) Edmans, Levit and Schneemeier (2022), Hoepner et al. (2018) Hoepner et al. (2018)).

Second, this paper provides additional evidence to support the notion that catering to environmentally, socially, and governance-conscious consumers is a valid mechanism for limiting a firm's risk, by focusing on environmental risk at the asset level. Lins, Servaes and Tamayo (2017) and Albuquerque et al. (2020) have shown how high customer loyalty helps firms survive crises. Servaes and Tamayo (2013) and Dai, Liang and Ng (2021) find that customers exert influence on firms' CSR and help improve operational efficiency and firm valuation. Aghion et al. (2023) demonstrates that exposure to environmentally concerned customers can foster clean innovation by firms.

Third, the paper complements the literature on ownership structure and the relevant incentives that influence environmental and social outcomes. Shive and Forster (2020) provide evidence that independent private firms are less likely to pollute and incur EPA penalties than public firms. Bartram, Hou and Kim (2022) and Xu and Kim (2022) both show that financial constraints distort managers' incentives and lead to undesirable environmental outcomes. Akey and Appel (2019) find that hedge fund activism campaigns are associated with a drop in emissions at plants of targeted firms. Dyck et al. (2019) documents a global pattern that institutional ownership increases environmental and social performance. Bellon (2020) shows that private equity (PE) ownership reduces pollution when the target company faces high environmental enforcement or political risks, while Gupta et al. (2021) shows that PE ownership lowers patient welfare at nursing homes. Heitz, Wang and Wang (2021) find that politically connected firms experience less regulatory enforcement and lower penalties, suggesting that certain firms can have weakened incentives for emission reduction. Grinstein and Larkin (2019) document evidence that cost-cutting incentives behind high product market competition can improve environmental footprint.

Lastly, my work is also relevant to the literature that studies energy economics and the utility sector specifically. While existing literature has studied 1) the environmental decisions of power producers in response to environmental regulations (Fowlie (2010), Fowlie, Reguant and Ryan (2016)); 2) changes in market concentration, costs, consumer markets resulted from electricity market deregulation (Borenstein (2002), Greer (2010), Cicala (2015), and Cicala (2022)); and 3) the evolution of ownership concentration following deregulation and innovation (Andonov and Rauh (2022)), I provide additional insights by showing how ownership of power producers and related incentives can influence the environmental performance of power plants.

2 Institutional Background

The US electric utility industry is a complicated landscape with different regulations across states and distinct ownership structures. There are five major types of plant owners[19] : (1) Rural Electric Cooperative: not-for-profit member-owned entities; (2) Municipal Utility: municipal utility board/company; (3) Other Public Utility: state-owned, federal-owned, or army-owned power agencies, and irrigation district; (4) Regulated Utility (RU); and (5) Independent power producer (IPP). Regulated utility[20] are for-profit utility holding companies that own subsidiaries with rate-based regulation exposure[21] as well as deregulated affiliates[22] operating in the deregulated market.[23] Most regulated utilities are publicly traded firms like Duke Energy, American Electric Power, and

[19]Non-utility purposed entities also own power plants. For example, manufacturers such as International Paper Co. and oil companies like Exxon Mobile own power plants for production use. Some universities and hospitals also operate their own power plants for service purposes. I exclude the non-utility entities from my analysis. They account for around 10,000 plant-year observations (1/8 of the sample size).

[20]Every state has at least one major regulated utility, or a regulated subsidiary of a utility holding company, that operates power plants, transmission, and distribution within the state. RUs are vertically-integrated firms and are mostly publicly traded companies

[21]Rate base refers to the assessed value of the property on which a public utility is authorized to earn a predetermined rate of return, following guidelines established by a regulatory agency. Essentially, it encompasses the value of property used by the utility to deliver its services.

[22]Rating agencies rate the deregulated affiliates of a regulated utility in the same way as an IPP.

[23]A deregulated, or competitive electricity market is a state that allows entry of competitors to engage in buying and selling electricity by enabling market participants to invest in power plants and transmission lines. In such a market, generation owners sell wholesale electricity directly to retail suppliers. States went over restructuring towards competition during the 1990s and stabilized in 2004. My sample period avoids the massive restructuring periods thus reverse causality problem is alleviated. Restructured states are Oregon, California, Texas, Illinois, Michigan, Ohio, Georgia, Virginia, Pennsylvania, New York, Maine, Connecticut, Rhode Island, New Hampshire, New Jersey, Maryland, Delaware, Massachusetts, and Washington DC. Different states went over different levels of restructuring, which I do not consider in my main test.

Exelon Corp, and they own power plants in multiple states. On the other hand, independent power producer (IPP) [24] is for-profit companies that operate power generation assets for a profit and is not subject to rate-based regulation. Publicly traded IPPs are standalone firms that only operate generation assets, like NRG Energy and Calpine Corp. Other IPPs are investment firms like Energy Capital Partner and Brookfield Asset Management, and private power generation firms like Calpine and Clean Energy Systems.

The reasons to study these two types of firms are twofold. First, Figure 2 shows that RUs and IPPs account for 80% of shares in both electricity production and carbon emission and they are also owners more frequently involved in asset substitutions and creation. Moreover, PE IPPs grow the fastest with a three-fold increase in market share from 2004 to 2020, consistent with the results shown in Andonov and Rauh (2022). Figure 6 shows state ownership concentration based on annual generation in 2004 and 2020. It is evident that IPPs are gaining market share from regulated utilities in the northeast and south-central, and shares of other owners are diluted overall. The states where IPPs expand the most are states that are open for retail competition. Second, this categorization of ownership type is widely used in the literature studying the utility industry and by practitioners in the finance industry[25], and the fundamental reason is the regulatory constraint that RUs face. Regulatory uncertainty and the ability to recover costs in a timely manner often take up heavy weights in an RU's risk consideration. For example, according to Moody's rating methodology for regulated electric and gas utilities in 2009, each of the aforementioned criteria has 25% (and together 50 %) of the risk factor weighting, outweighing financial strength.

In the 1990s, the U.S. experienced deregulation in the utility industry. Figure 5 summarizes the planned transition under deregulation. In the past, vertically integrated utility firms held a monopoly in the market and provided generation, transmission, and distribution services. Due to their monopoly status, these companies were regulated on the amount of risk involved and rate of return by the state Public Utility Commission (PUC) and FERC. However, in the 1990s, deregulation took place in the power generation, wholesale, and retail sales markets. Within the restructured landscape, formerly regulated utilities now operate as monopolies in transmission and distribution while also competing with new players in power generation and retail sales. This has

[24] Use interchangeably with independent owner.

[25] For example, Moody's design different rating standards for regulated utilities and IPPs.

led to a corporate structure where a publicly traded holding company oversees several operating subsidiaries, including regulated utility segments, and deregulated affiliates that operate power generation business in the deregulated market. New players in the generation sector are mostly independent power producers or merchant generators, both are known as independent power producers in my sample. They are independent for-profit entities that own and operate generation assets outside of the regulated landscape (Greer (2012)). Over the past two decades, independent power producers have gradually taken up the market share from regulated utilities, while the share of non-profit public utilities remains stable. Figure 6 shows the geographic dispersion of market share evolution. New players in the sales market are electric power marketers. They purchase electricity from generators and sell them to utilities, end users, and other market players – adding value by bringing buyers/sellers together, arranging for transmission and other services, and accepting market risk. My paper focuses on the power generation landscape, which is now dominated by regulated utilities and independent power producers.

Figure 7 shows the U.S. deregulation landscape. The primary purpose of deregulation is to reduce state-level electricity prices by encouraging more competition. During the wave of state-level restructurings in the 1990s and early 2000s, the electricity wholesale market was formed and was managed under independent system operators (ISOs) as the balancing authorities. The wholesale market restructurings are generally associated with production cost reductions (Fabrizio, Rose and Wolfram (2007); Davis and Wolfram (2012); Cicala (2015)). Plants operating in the retail electricity markets usually face higher competition than in wholesale markets, as shown in Figure 5. As a result of deregulation, the concentration of plant ownership differs between regulated vs. deregulated states. If a plant operates in a regulated state "s1" with a major state-regulated utility firm "f1", the plant can be owned by: 1) the regulated segment of "f1" that operates regulated plants; 2) the deregulated affiliate of "f1" and that operate deregulated plants; 3) an independent power company that operates deregulated plants. If a plant operates in an unregulated state "s2" with a major state-regulated utility firm "f2", a plant can be owned by: 1) the regulated segment of "f2" that operates regulated plants; 2) the deregulated segment of "f2" that operate deregulated plants; 3) the deregulated segment whose regulated operation is in other states (unregulated segment of "f1", for example) that operate deregulated plants; 4) an independent power company that operates deregulated plants. My data sample starts in 2004 when deregulation was stabilized, alleviating concerns about reverse causality. And the proxy for market competitiveness is provided as to whether a state is deregulated or not.

Starting 2000s, policymakers shifted attention to renewable generation.[26] Figure 8 shows that generation from coal and oil plants is reduced while the share of gas plants increases.[27] as well as a rapid expansion of solar and wind plants.[28] Despite the rapid growth of generation, the level of generation provided by wind and solar plants is still half of the amount from coal in 2020, and way below the amount produced from all fossil fuels.

3 Data

3.1 Power Plant Admin and Emission Data

I compile a database that covers almost all US power-generating plants that report to US Energy Information Administration (EIA), US Environmental Protection Agency (EPA), and Federal Energy Regulatory Commission (FERC). I collect plant location, owner, generation, emission, and administrative information from EPA's Emissions & Generation Resource Integrated Database (eGRID).[29] eGRID is usually released once every two years and is composed of data one to two years later than the reporting year indicated in eGRID. For example, part of the environment data, and plant operation and generation data of eGRID2004 is from government reports in 2005, rather than in 2004, and the plant ownership data is acquired from EIA's Electric Power Monthly Report, table *Electric Utility Plants That Have Been Sold and Reclassified as Nonutility Plants*, from 2004

[26]Nonrenewable fuels include coal, oil, gas, other fossil, nuclear power, and other unknown/purchased fuel. Renewable fuels include biomass, wind, solar, geothermal, and hydro.

[27]Coal has the most damaging emissions content, followed by oil and natural gas. For example, burning coal to generate one billion British Thermal Units (BBTU) of heat is associated with approximately 103 lb of CO_2. A typical power plant uses 22,000 BBTU per year, resulting in approximately 2.3 million lb of CO_2. In contrast, generation of the one BBTU of heat by burning petroleum is associated with 82 lb of CO_2. Finally, burning natural gas is associated with 58 lb of CO_2 for one BBTU.

[28]In addition to policy incentives, renewable energy technologies (RETs) have experienced a massive decline in their costs over the last two decades (Ray (2019); IRENA (2020)). The rapid decline in costs might have also played a significant role in the expansion of renewable plants.

[29]eGRID is a comprehensive source of data on the environmental characteristics of almost all electricity generating plants that provide power to the electric grid and report data to the U.S. government. Data reported include net generation (MWh); resource mix for renewable and nonrenewable generation (%); emissions in lb for nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon dioxide (CO_2); emissions in pounds for mercury (Hg); emission rates for CO_2, NO_x, and SO_2 (lb/MWh) and for Hg (lb/GWh); nameplate capacity in megawatts (MW); capacity factor, that is total generation scaled by nameplate capacity; and other administrative information like location (county, state, longitude, and latitude), ISO region, owner/operator name, fuel, etc.. eGRID reports this information on an annual or bi-annual basis at different levels of aggregation (unit, generator, plant, companies, and grid regions of the country).

to 2006. For simplicity, I use eGRID reporting year as the time indicator.

I collect plant abatement investment and expenses (2008-2020) and deregulated plant disposition (2004-2020) information from EIA's mandatory disclosure form: EIA-906, EIA920, and EIA-923. These data are available on a yearly basis, and I match this data with eGRID using a unique plant identifier. eGRID data report plant owners from 2004 to 2012, and starting in 2014 the category of owner was removed, and the plant operator category becomes the distribution and transmission system owner that the power plant is connected to. The only variable that possibly states the plant owner is the utility name. Using plant owner identifiers in 2009, 2010, and 2012 as benchmarks, I find plant utility overlaps 80% to 85% of the time with the plant owner among deregulated plants and overlaps 70% of the time with the plant owner among regulated plants. Given that the matching rate is not bad, accounting for the possibility of plant transactions between firms and between subsidiaries within a firm, I use plant utility as the plant owner.[30] For plants that I could obtain ownership share of each owner, I drop those (and their associated observations) that the owner with the highest stake has less than 50% share.[31]

Plant owner is recorded as a subsidiary or affiliate of a larger holding company, rather than the parent owner. Therefore, I match a plant owner to its highest parent company using the subsidiary file provided by WRDS. For the unmatched plant owner, I manually identify the plant's parent owner through various sources provided by Google search.[32] I record plant parent owner GVKEY if available on Compustat and Employment Insurance Number (EIN) if available on NCCS (not-for-profit financial data).

I track changes in the ownership of eGRID plants as follows. First, I flag all cases in which a plant's parent owner name changes, and label the parent name before the change as the seller and the name after the change as the buyer. Each plant is assigned a unique plant id and each owner is assigned a unique owner id. Owner name changes will not change the owner id. Then I look into each ownership change case. Ownership changes from a regulated utility to another regulated are mostly driven by M&A activities at the parent level, therefore, I verify all M&A occurred

[30] I obtain annual EIA-860A/860B filing of generator owner from https: //www.eia.gov/electricity/data/eia860/, the original file that eGRID used to construct the plant owner category.

[31] For example, if a plant has an owner split 40-30-30 once, all of its observations will not appear in the sample. I drop 3004 plant-year observations due to this adjustment.

[32] Sources include web page form of state government filings, business newswires, OpenCorporate, gem wiki, and power technology. Due to time limitations.

during the sample period that reflects the change of parent owner. Plants are transferred from regulated utilities to IPPs mainly through divestitures, and I verified the transactions through a search of news articles on Factivia and company press releases and finally obtained 303 such plant transactions. Lastly, I match power plant parent owner with Compustat data if it is a public company, and construct a set of firm-level control variables.

The major outcome variables are CO_2 equivalent emission rates (lb/MWh). While previous studies use either total emission or emission scaled by revenue as the outcome variable, this paper uses precisely the emission per unit productive output, providing an accurate "emission intensity" measure. Moreover, according to Shive & Foster (2020), emissions intensities are highly variable across industries. Since I only focus on the utility industry, this should be less of a concern. Other plant-level relevant variables include power plant nameplate capacity (MW), plant capacity factor [33], plant combustion efficiency [34], plant age [35] and plant primary fuel.

I further explore abatement investment and expenses of a subset of plants that report to the EIA.[36] Starting in 2008, these plants report three abatement-related financial variables: abatement capital expenditure, which is the investment for new structures and equipment during the year, excluding land and interest expense; operations and management expense, which is the operation and maintenance expenditure for old equipment during the year; byproduct sales revenue, which is the revenue from selling by-product generated from the power generation process during the year. Plant revenue from resales of electricity generation is obtained from the plant disposition information form and is only available starting in 2011.[37]

[33] This value is calculated in a standard way:= $\frac{NetGeneration}{Capacity*8760}$

[34] Known as heat ratio or heat rate, in Btu/kWh. It is calculated as follows: heat ratio = 1000 * (Plant annual heat input for combustion units / Plant annual net generation).

[35] Plant age is computed as reporting year minus plant opening year. Plant opening year is assigned to be the year when the plant operated its first power generator.

[36] The abatement expense is the cost of an intervention that will reduce pollutive gas emissions. For example, a plant manager can install a flue-gas desulfurization unit (FGD), or a scrubber, to remove flue gases generated from the combustion process. While I focus on the total costs, in the literature that studies abatement cost specifically, researchers scale the additional costs by avoided emissions to get the abatement cost per tonne of carbon not emitted.

[37] Revenue from retail sales is not reported. This is less of an issue because the quantity of retail sales is tiny compared to resales (see Appendices Figure 20)

3.2 Summary Statistics and Preliminary Analysis

3.2.1 Summary Statistics

I start my analysis by comparing the portfolio of power plants owned by regulated utilities and IPPs. Table 1 presents the summary statistics of power plant features across different owner types. Regulated utilities tend to own more pollutive plants like coal, gas, and oil plants, while IPPs own considerably more solar plants. Thus on average regulated utilities have higher unconditional emission rates than IPPs. Looking at proxies for plant size and age, regulated utilities operate both bigger and older plants. Lastly, while only 26% IPP owned plants have publicly traded parent owners, nearly all regulated utility-owned plants have publicly traded parent owners.

3.2.2 Differences between Regulated Utilities and IPPs

To observe whether different types of owners emit more, I conduct plant-level analysis and examine whether regulated owners generate better environmental outcomes among certain types of plants, in terms of fuel type and location, using the following specifications:

$$y_{iust} = \beta * RUOwned_{iust} + \gamma * Controls_{iust} + \xi_{ust} + \epsilon_{iust} \tag{1}$$

$$y_{iust} = \beta * RUOwned_{iust} + \theta * RUOwned_{iust} \times Competitive_s + \gamma * Controls_{iust} + \xi_{ust} + \epsilon_{iust} \tag{2}$$

i represents a unique plant, s represents the state a plant locates, u represents a plant's primary fuel type, and t represents the year. The outcome variables are carbon emission rates and the logarithmic total carbon emissions at the plant level. *RU_Owned* is an indicator variable of the parent owner type. *Competitive* is an indicator of states and regions deregulated successfully. Controls include plant capacity, plant utilization, plant age, and three regulatory-based measures. The three measures indicate whether a plant is subject to rate-based regulation, is a FERC-granted small power producer, or can engage in the wholesale sale of electricity without having to comply with certain regulations that would typically apply to larger utilities and power producers. Three measures control the regulatory-driven incentives for environmental performance at the asset level, allowing the main independent variable to capture incentives solely from ownership. I include State $\times$ Year $\times$ Fuel fixed effect to capture time-invariant and varying differences in pollution levels across states and among different fuel types. Table 3 presents the result. On average, plants owned by RUs are more carbon-intensive and release a higher quantity of carbon than those owned by IPPs. Higher carbon intensity is mainly attributed to plants that use fuels other than coal or petroleum while larger quantities of carbon release are mostly concentrated in coal and petroleum plants. On the other hand, RU plants in the competitive market, even though experience higher emission rates, have lower total emissions.[38] At a glance, RU plants perform no better in both metrics than IPP plants in the competitive markets. While RU plants do provide less carbon emission per unit of output in the non-competitive market, they rely more on coal and petroleum for generation than IPP plants, indicated by higher total emissions from these plants. The cross-section results indicate that the association of ownership and environmental performance is more prominent in the non-competitive market. In the next section, I present an empirical analysis of the transfer of control of power plants and the subsequent environmental performance.

4 Empirical Analysis

Table 2 presents a detail description of ownership change cases. On average, 6.7% of power plants change parent owners per year during my sample, attributing to transactions of a portfolio of plants, mergers of two firms, and divestiture of subsidiaries, with an emphasis on the first two cases. Moreover, the types of plants transacted in different markets are comparable and similar in size. In the first section, I present an analysis of all transferred plants by comparing them with the acquirer's incumbent plants and the seller's incumbent plants before and after the transactions, following the method proposed by Braguinsky et al. (2015). In the second section, I explore plant transfer between different types of owners, with more focus on plants originating from a regulated utility. I do not consider serial transfer and only retain power plants that changed parent owner once.[39]. This setting resembles a staggered adoption design, where the treatment of a group is weakly increasing over time.

[38]Appendix A.7 provides a more detailed examination of how RU plants perform in each type of fuel relative to IPP plants.

[39]There are two reasons for doing so: first, by looking at how frequently a plant is transferred multiple times, and given that my sample is bi-annually, the data period is not long enough for studying serial transfers that constitute a significant sample; second, the DiD tests struggle with the classification of repeat divestiture targets as treatment vs. control plants.

4.1 All Transactions

As asset divestitures are a firm's endogenous decision, I expect to observe some systematic differences between a divested plant as compared to other comparable plants owned by the same seller. The same intuition applies to the buyer as well. Therefore, I first observe whether transferred plants are different from both seller's and acquirer's average plant using the following specifications:

$$\bar{y}_{ifust} = \beta * Transferred_{ifust} + \gamma * Controls_{ifust} + \xi_{ust} + \xi_f + \epsilon_{ifust} \tag{3}$$

, where $\bar{y}_{ifust}$ is the outcome variable of plant i at time t if it is a transferred plant, while the outcome variables of incumbent plants are collapsed to $\sum_{i \in I_{fust}} y_{i,t} * \frac{NetGeneration_{i,t}}{\sum_{i \in I_{fust}} NetGeneration_{i,t}}$ where I_{fust} is the plant portfolio of firm *f*, fuel u, state s, and year t. The observation of transferred plants is only retained at -2 to -1 periods relative to the event year. Where For capacity and total carbon emissions, I employ a log transformation. Results are presented in Table 4. In panel A, the sample is restricted to 1) plants whose parent firm had divested at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. In panel B, the sample is restricted to 1) plants whose parent firm had acquired at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. Originator FE is a firm fixed effect applied for firms that divested the plants, and Acquirer FE is a firm fixed effect applied for firms that acquired the plants. Overall, the seller divests larger plants and plants that are more carbon-intense, while the buyer acquires smaller plants and plants that emit less carbon and are less carbon-intense. This observation is consistent with the leakage hypothesis that firms divest pollutive assets to owners who do not mind pollutive assets. Nevertheless, the difference between transferred plants to acquirers' plants is more concentrated in the non-competitive markets.

Next, I compare the performance of plants post transactions, as compared to incumbent plants of the buyer and the seller, by employing a TWFE specification as follows:

$$\bar{y}_{i,t} = \beta * Transferred_{i,t} \times Post_{i,t} + \xi_i + \xi_t + \epsilon_{i,t} \tag{4}$$

Here, the observation of transferred plants is only retained from -2 to +2 periods relative to the event year. The outcome variable and the sample composition are the same as in the previous test. Table

5 presents the results. After the transactions, transferred plants are less utilized and are downsized compared to both the acquirer's and seller's plants. Plants become more carbon-intensive compared to the seller's plants but are not emitting more. Meanwhile, plants are increasingly aligning with the acquirers in terms of environmental performance: transferred plants located in the non-competitive markets are experiencing an increase in pollution levels, but the effect is offset by those located in the competitive market, where I do not observe a change in total emission and emission rate after the transaction. The result is consistent with the implications from the cross-sectional analysis that change of ownership is more likely to influence environmental outcomes in the non-competitive market rather than in the competitive market.

4.2 Transactions between Different Owner Types

In this section, I explore asset transfers from RU to IPP versus to another RU, as well as from IPP to IPP versus RU, with an emphasis on the prior. According to Table 2 and Figure 3, the transactions between RUs, from RU to IPP, and between IPPs are more prominent. This observation is consistent with the documented pattern that new firms expand by purchasing old capital from existing firms.[40]. As RUs are active sellers of assets, I start my analysis with asset transfers from RUs and then provide some additional evidence by analyzing transactions between IPPs and from IPP to RU.

4.2.1 Empirical Design

Among all plants transferred from a regulated utility, 44.6% went to an IPP and 55.4% went to another regulated utility. To test the leakage hypothesis, I test whether the carbon emission intensity of plants changes when they are transferred from an RU to an IPP versus those transferred to another RU, as compared to the untransferred plants owned by an RU. Since transfer is not an exogenous occurrence and could be correlated with unobserved variables that potentially affect post-acquisition results, OLS estimators can be biased or even have the wrong sign due to omitted variable bias. As is typical in this literature, I do not have a source of random assignment of transfer.[41] To tackle the identification challenge, I implement a staggered DiD model with a two-

[40] Ma, Murfin and Pratt (2022), Beaumont, Hebert and Lyonnet (2022)

[41] A quasi-random assignment, however, is to compare transferred plants with those that were intended to transfer initially but failed to due to uncontrollable force (Seru (2014)). This method requires me to find out additional

way fixed effect (TWFE) to control for observed, unobserved, persistent, and time-sensitive factors. I test the parallel trend assumption and use propensity score matching (PSM) as an alternative robustness check. My results survive the parallel trend and are robust to using PSM reweighting.

A key identifying assumption when using the DID approach is the parallel trends. It requires that, in the absence of a transfer, the difference in carbon emission rates between treated and control plants would be constant over time. To provide support for this assumption, I estimate the following equation:

$$EmissionRate_{i,t} = \sum_{t \neq -1} \theta_t Periods_t * Transferred_i + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{5}$$

In this specification, I compare the outcomes of plants transferred to IPPs directly to the untransferred plants. I interact the post-transaction indicator with multiple indicators for event time: *Period* is an indicator that equals one if the observation corresponds to event period t and I use one period before the transaction as the reference period. For the parallel trends assumption, I am interested in whether the coefficients associated with the interactions between ownership change and pre-transaction event times are significantly different from zero. Figure 9 (a) and (b) plot estimates of differences in emission rate trends of plants transferred to IPPs and plants transferred to regulated, relative to the untransferred plants around event time. All pre-transaction θ coefficients are statistically indistinguishable from zero, consistent with parallel trends.

To test the leakage hypothesis, the main empirical specifications for my analysis are as follows:

$$\begin{aligned} EmissionRate_{i,t} = {} & \beta \times Transferred_i \times Post_{i,t} \times ToIPP_i \\ & + \theta \times Transferred_i \times Post_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} EmissionRate_{i,t} = {} & \beta \times Transferred_i \times Post_{i,t} \times ToRU_i \\ & + \theta \times Transferred_i \times Post_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{7}$$

where the first specification applies to transactions from RUs, while the second specification applies to transactions from IPPs. The dependent variable $EmissionRate_{i,t}$ is CO_2 equivalent emission

information about failed transactions of power plants. Unfortunately, the current version of my data is insufficient for running such a test and will require further data collection and verification.

rates (lb/MWh). *Transferred* indicates whether a plant experiences a change of parent owner, *Post* indicates whether the plant-year (i, t) observation is after the plant is transferred [42], *ToIPP* indicates whether the plant is transferred to an IPP owner, and *ToRU* indicates whether the plant is transferred to an RU owner. I control for potential confounding effects using plant fixed effects α_i and year fixed effects α_t, and standard errors are clustered at the plant level. In this panel specification, the interaction term $Transferred_i \times Post_{i,t}$ captures the change in emission rates for plants transferred to another RU in the years after the transaction. The key term for my test is the triple interaction $Transferred_i \times Post_{i,t} \times ToIPP_i$, which captures the additional change in emission rates for plants transferred to an IPP. I use plant fixed effect and year fixed effect in every regression. This specification removes any effects of selection into transfer on persistent plant attributes, like location and primary fuel type, and any industry-wide emission rate shifts over the sample period. One last accommodation is to keep observations where I can retain information from -2 to +2 relative to the event year, so dropping events and the associated observations occurred in the earliest and latest periods. This adjustment is made for enough period for the parallel trend assumption and the treatment effect to be realized. The resultant transactions are those that happened in 2007, 2009, 2010, 2012, 2014, 2016, and 2018. My baseline result is robust to the inclusion and exclusion of periods at the beginning and the end, and using alternative windows.

Furthermore, I apply a propensity score reweighted estimation method which alleviates the selection issue. Following Guadalupe, Kuzmina, and Thomas (2012), this allows me to further account for observable differences in the probability of being transferred. To calculate the propensity score for each plant, I conducted the following analysis. For each year, I consider plants transferred in that year as treated and plants that are never transferred as control observations. I pool treated and control observations across all years to estimate the probability (or propensity), p, that a plant is transferred as a function of lagged one-period emission rates and plant capacity, origin firm size (the total number of operable plants), plant vintage, and a year trend. I then transform p into weights (weighting each treated plant by $\frac{1}{p}$ and each control firm by $\frac{1}{1-p}$) and restrict the analysis to plants that fall within the common support.[43] Appenxix Figure 16 shows similar propensity distributions for transferred and untransferred projects after weighting.

[42] I do not drop the acquisition year and set *Post*=1 in year zero, considering that my data are mostly bi-annual.

[43] One caveat about the matching process is that I lost more than half of my sample.

The main result is also robust to using alternative estimators (see Appendix A.1), using an alternative definition of regulated vs. deregulated markets (see Appendix A.2), and using only transferred plants (see Appendix A.4).

4.3 Baseline Result

Now I provide a detailed description of my empirical analyses. Looking at Figures 9 (a) and (b), I observe a positive and significant rise in plant carbon emission rate right after the event period among plants transferred from RU to IPPs, and such a trend disappears over time; I find barely any significant change in carbon emission rates among plants transferred between RUs and between IPPs. I separate plants into two buckets according to their location: regulated states vs. deregulated states, and plot event graphs on these two samples respectively. According to Figure 10, plants transferred to IPPs and located in the regulated states experience significant and persistent increases in carbon emission rates, while those located in the deregulated states do not experience such change. Looking at plants transferred to another RU, I find that those located in regulated states tend to decrease emission rates.

If the leakage mechanism works, I should not expect to see increased carbon emission intensity among plants transferred from IPPs to RUs, as compared to the untransferred plants owned by IPPs. I test this hypothesis using the same method as for transfers from RUs. Figure 9 (c) and (d) shows that plants transferred from IPPs to RUs do not increase carbon intensity post-transaction. On the other hand, plants transferred between IPPs experienced reduced carbon intensity only in the competitive market. More interestingly, I observe targeting behavior when IPPs sell plants to another IPP – they sell off more pollutive plants. To summarize, I did not find contradicting evidence for the leakage hypothesis and even strengthened evidence for the power user hypothesis.

Table 6 presents the regression results from models (6) and (7). I narrow the comparable plants to those otherwise similar except for differences in transfer status by using fixed effect controls. Consistent with the event graphs (Figure 9), model (6) predicts a positive coefficient β, and the coefficient θ is statistically indistinguishable from zero. Moreover, the positive treatment effect is mainly driven by transactions happening in the regulated market. Similarly, model (7) predicts a negative coefficient θ, and the coefficient β is statistically indistinguishable from zero. Moreover, the positive treatment effect is mainly driven by plants in the non-competitive market, while the negative treatment effect is mainly driven by plants in the competitive market. Specifically, Table 6 column (1) shows the result of CO_2 emission rates using a full sample. Columns (3) and (5) show the treatment effect using samples of plants located in the non-competitive and competitive market respectively, while columns (2), (4), and (6) are results under PSM reweighting. Overall, I observe that plants transferred from RUs to IPPs suffer from worse environmental performance compared to 1) those transferred between RUs and the untransferred ones. My main results are robust under propensity score reweighting. On the other hand, plants transferred between IPPs or from IPPs to RUs experience no worse outcomes, and potentially better outcomes for plants located in the competitive market. Again the results support the power user hypothesis without fully rejecting the leakage hypothesis.

4.4 Acquirer Ownership Structure

To further test both hypotheses and understand whether ownership structure and associated incentives are driving the change of environmental performance post-acquisition, I verify the type of IPP buyers and divide them into three mutually exclusive categories: publicly traded IPPs [44], investment IPPs [45], and private IPPs [46]. Next, I obtain estimates of equation (6) using three sub-samples, shown in Table 7. Plants transferred to investment IPPs and private IPPs see a significant increase in carbon intensity post-transaction, while those transferred to public IPPs do not. These results are consistent with predictions under the leakage hypothesis. Nevertheless, results are mainly driven by plants located in the non-competitive market and are offset by those located in the competitive markets. More importantly, in the competitive market, transferred plants see no worsened performance, regardless of the acquirer's type, strongly supporting the power user hypothesis. Figure 11 plots the dynamics of CO_2 emission rates around the transaction year for plants transferred from RU to different types of IPPs, by dividing transferred plants into six buckets.[47] This plot excludes plants transferred to another RU and thus compares the plants transferred to IPPs directly to the untransferred ones.

[44] Use interchangeably with public IPPs

[45] They are mainly PE firms and asset management firms that own infrastructure funds, and take a direct stake in power plants

[46] IPPs that are not publicly traded and are not investment firms. They may be controlled by PE firms, for which I am not able to observe

[47] Based on a 2×3 dimensions: two markets and three types of acquirers.

Figures in the first row show that plants transferred to publicly traded IPPs emitted more in the two periods after the transaction and then started to reduce the emission rates. Plants transferred to investment IPPs, however, have seen persistent higher emission rates relative to the untransferred plants post-transaction. Plants transferred to private IPPs even experienced increasingly higher emission rates over time compared to the untransferred ones, further supporting that different ownership structures can explain the worsened emission outcomes.

Nevertheless, Figures in the second row show that the observed trending up in carbon intensity is mainly driven by plants located in the regulated state, regardless of the ownership structure of the acquirer type. Such a result implies that the power user channel overrides the leakage channel in the competitive market. In other words, ownership structure matters for green outcomes only if product market competition is low.[48] Information provided by the event graph is consistent with statistical estimates of the treatment effect in Table 7.

4.5 Additional Results

In this section, I explore three explanations for the observed increase in carbon intensity when plants are transferred from RU to IPP. First, the carbon emission rate can increase if plants burn more fuel but generate less electricity, represented by inefficiencies in the production process. Second, increased carbon intensity may be driven by reduced total emissions because marginal emissions can be higher when total production is low. Third, power owners are reluctant to invest in abatement technology, thus leading to higher emission rates.

Figure 15(a) shows a strongly positive correlation between carbon intensity and heat rate (BTUs/kWh), a proxy for how efficiently the generated heat is used to produce electricity. A higher heat rate means that more heat is used to generate the same amount of electricity, while more heat means burning more fuels and generating higher emissions. Therefore, if a plant uses more heat to generate the same amount of electricity as last year, I should observe a rise in both heat rate and carbon emission intensity. Mechanically, a higher emission rate can be attributed to lower utilization of the generated heat. Indeed, I find that transferring a plant from RUs to IPPs also leads to an increase in heat rate, but from RUs to another RU does not (see Figure 12). More

[48] The result also speaks to a literature that studies the relationship between product market competition and corporate governance: Schmidt (1997), Chhaochharia et al. (2017)

interestingly, this pattern is documented in only the non-competitive market, consistent with the baseline results that carbon intensity only increases in the non-competitive markets.

Next, I explore whether total carbon emission changes around the transaction. According to Table 8, I document a reduction in total emission among plants transferred from RU to RU in the non-competitive market, and those transferred from IPP to IPP in the competitive market. Neither case is associated with an increase in carbon intensity; rather, they are only associated with reducing carbon intensity, if any. The finding rejects reduced total emission as a valid explanation for the observed increase in carbon emission rate.

4.5.1 A Case Study about Abatement Investment

Lastly, to explore the third explanation that is related to abatement investment, I conducted a case study on a subset of plants for which I could obtain abatement investment, expenses, and revenue information In this case study, I specifically study two abatement-related financial metrics: abatement investment (CAPEX) and abatement technology operating costs (OME), because firms can either reduce abatement investment or replace existing abatement technologies with more cost-efficient options, while the prior will be reflected by a change in CAPEX, while the latter can be reflected on the OME. Both actions can lead to increased carbon intensity. Using a subsample of plants for which I can obtain abatement information (around 10% of the eGRID sample), I examine how abatement investment changes around the transfer of plant control, using model (6) and replacing outcome variables with the logarithm of CAPEX and OME.

To deploy the randomness in the sample of plants that disclose their abatement financials, I repeat the baseline test on this subset of plants that I can observe abatement investment. I can reproduce the pattern that emission rates increase if a plant is transferred to IPPs that are either investment firms or private firms using this subsample (see Table 10), which again strengthens my baseline results. Table 10 presents a plant-level analysis of the sample and shows that on average RU plants invest more in abatement technology and also have higher operating costs than IPP plants. Because the total amount of abatement investment and costs is highly correlated with the size and total production of the plant, I created two proxies: abatement CAPEX scaled by the previous year's total production, and scaled by the previous year's revenue from resale. And the same applies to abatement OME. Table 11 presents the result. Panel A shows that abatement CAPEX does not change while Panel B shows that both public and investment IPPs reduce abatement OME with investment IPPs reducing the most. Overall, mixed evidence supports that IPP acquirers do not reduce abatement investment but can save operating costs, especially the investment IPPs, consistent with the notion that PE owners are skilled at increasing operation efficiency. On the other hand, I do not observe any cost savings at the expense of higher emission intensity among plants transferred to private IPPs. The mixed evidence does not provide compelling support for the abatement channel. Overall, my results suggest that the rise in carbon intensity can be partly attributed to lowered combustion efficiency.

5 Conclusion and Discussion

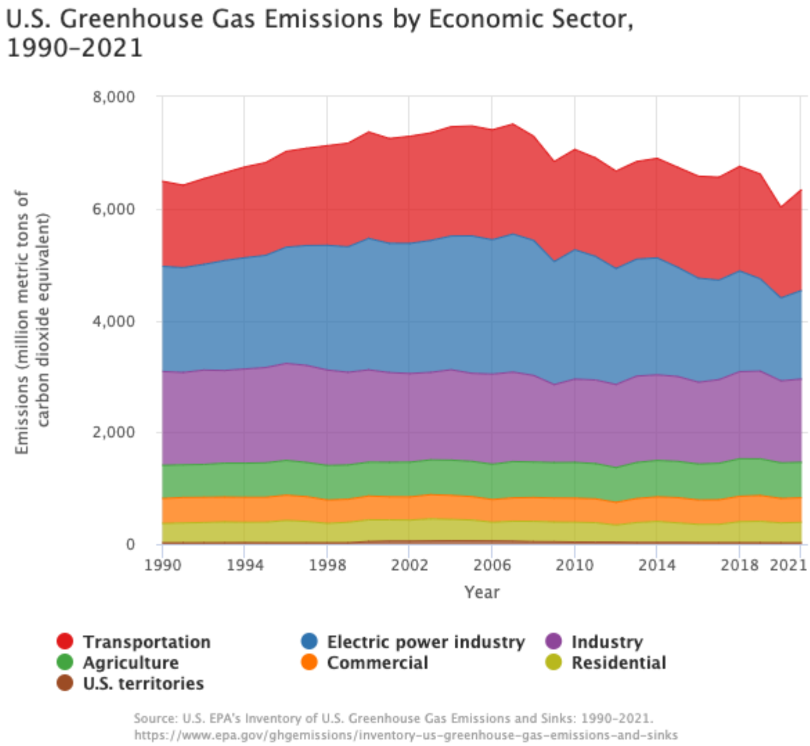
5.1 Conclusions

I use detailed plant-level emission and generation data that covers almost all power plants in the U.S. electric utility industry to investigate how the transfer of power plant control affects green outcomes. Specifically, I study the change of CO_2 emission rates when the parent owner of a plant changes, and focuses on transactions between and within different owner types: the incumbent vertically-integrated regulated utility (RU) versus an independent power producer (IPP). I consider two hypotheses when evaluating the environmental consequences of transactions: the leakage hypothesis which predicts worse environmental outcomes post transactions and for which the negative impact will be stronger in the competitive market because the acquirer prioritizes profit over environmental externalities. Contrasting the leakage hypothesis is the power user hypothesis. The power user hypothesis is motivated by the situation that emission generation from power usage is the biggest contributor to scope 2 emissions of all publicly traded firms and thus is closely related to the firm's strategies for environmental footprint. Power producers in the competitive market will for sure experience greater demand for cleaner energy from the consumer end. Catering to such demand predicts no worse environmental outcomes following divestitures because all power producers have no incentive to perform worse, regardless of their ownership structure.

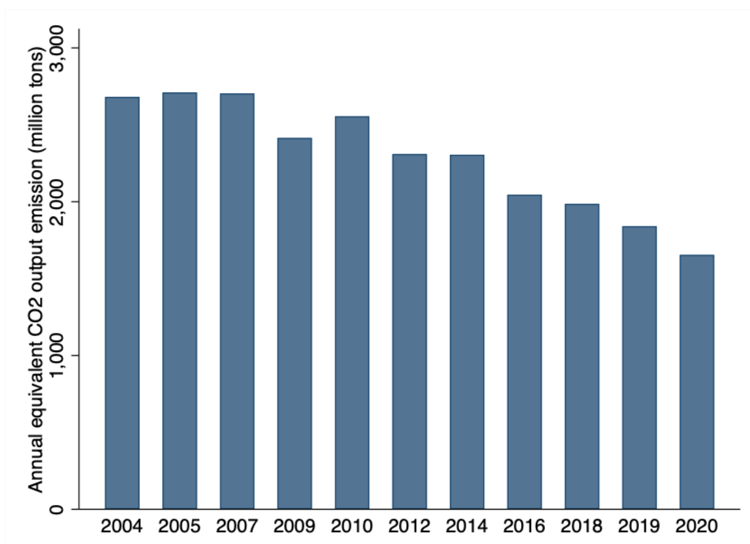
Empirically, I find evidence consistent with the leakage hypothesis in the non-competitive market, while results from the competitive market strongly support the power user hypothesis. My results survive the parallel trend test and are robust to using multiple specifications and propensity score reweighting. Furthermore, I propose three possible explanations for the observed increase in carbon intensity among transferred plants located in the non-competitive market: inefficiencies in the power generation process, a decrease in total carbon emissions, and a reduction in abatement investment. My results speak to inefficiencies as the only valid explanation for the observed rise in carbon intensity.

To the best of my knowledge, this is the first paper that studies the environmental consequences of asset transactions between different types of owners that are unique to the utility sector. While the study is concentrated in one industry, I believe the patterns documented in this industry have broader implications. I established a stylized fact that divestiture decisions can lead to worse environmental outcomes when the acquirer is less concerned about environmental footprint than the seller. Further, I document a demand-side mechanism that can mitigate the negative impact of divestitures on the environmental footprint. More specifically, my findings highlight the benefit of using customer demand for environmental footprint as a mechanism to incentivize firms to mitigate climate risks inherent in their operations. This mechanism can have broader policy implications for addressing environmental externalities across various industries.

Figures

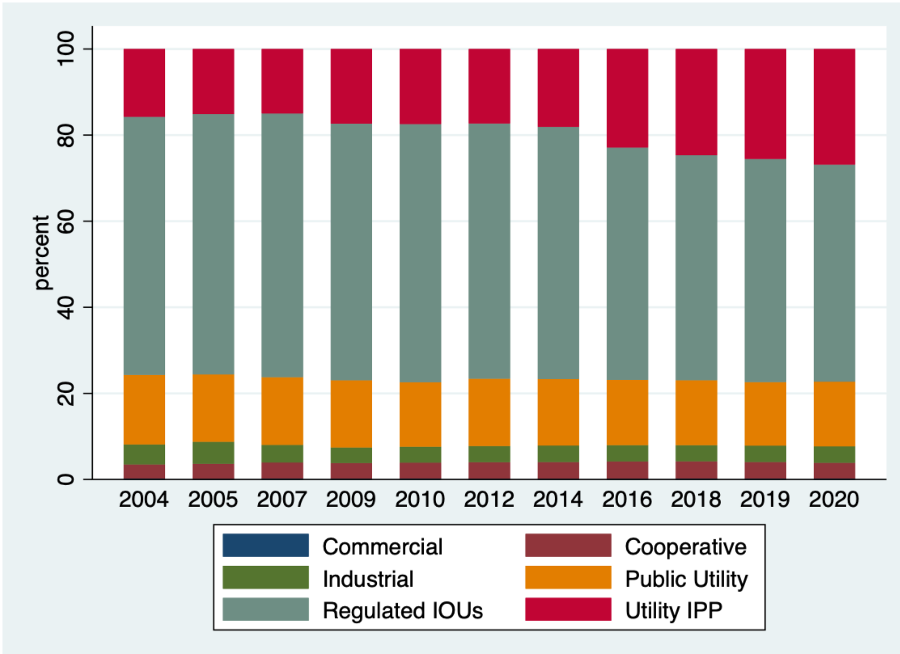


(a) U.S. Greenhouse Gas Emissions by Sector

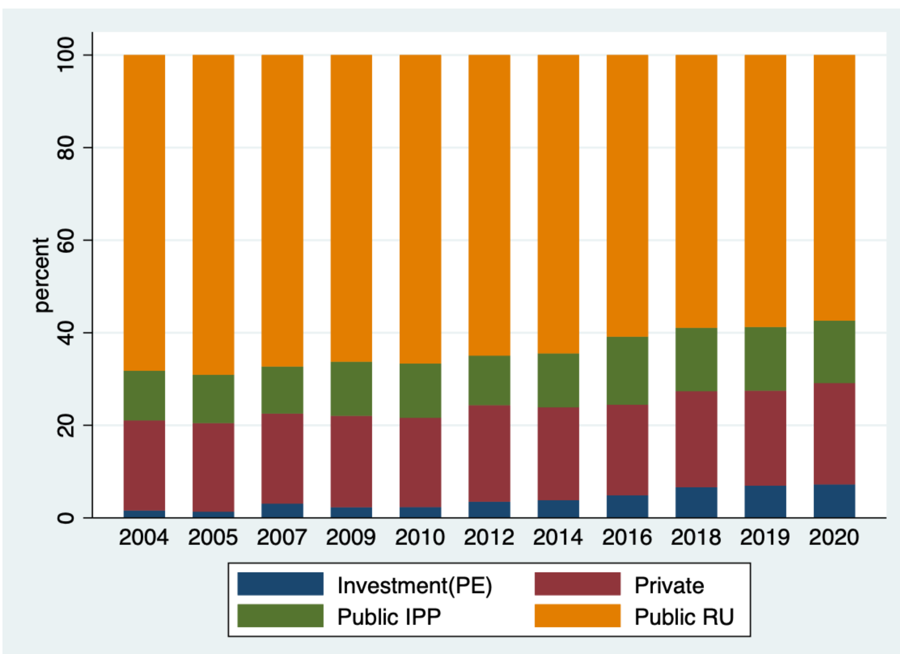


(b) U.S. Total CO_2 Emission Trend

Figure 1: Emission in the U.S electric utility industry over Time



(a) All Types of Owner



(b) For-profit Utility Only

Figure 2: Share of Total Net Generation by Ownership over Year

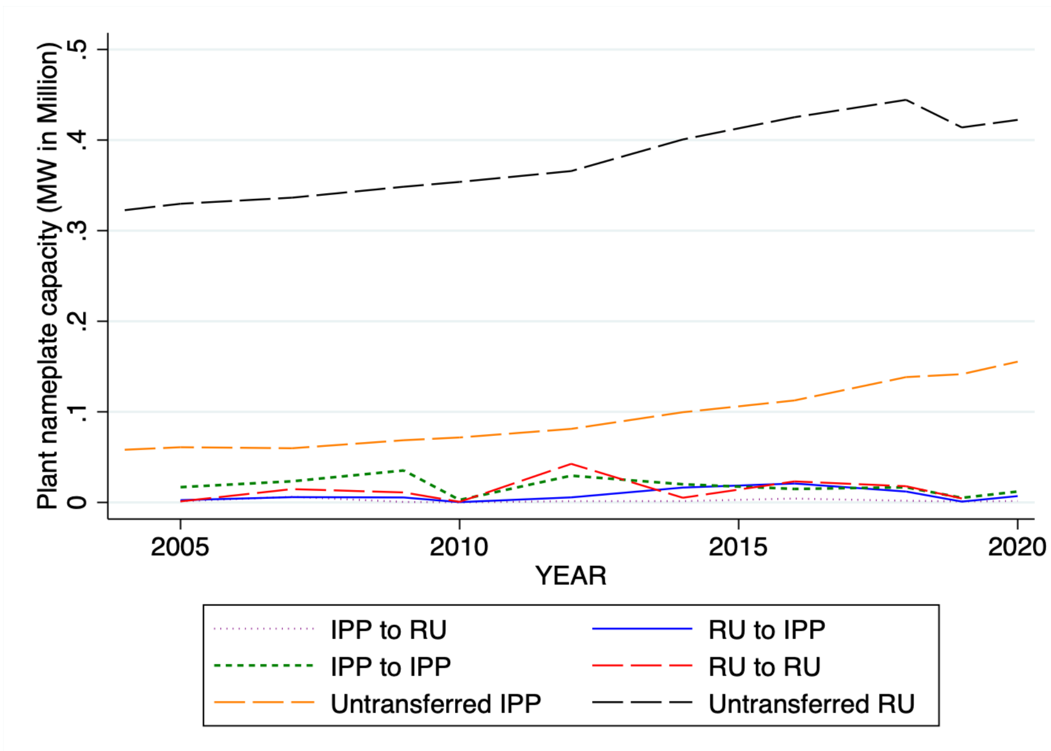


Figure 3: Total Generation Capacity (MW) of Incumbent and Entrant over Time

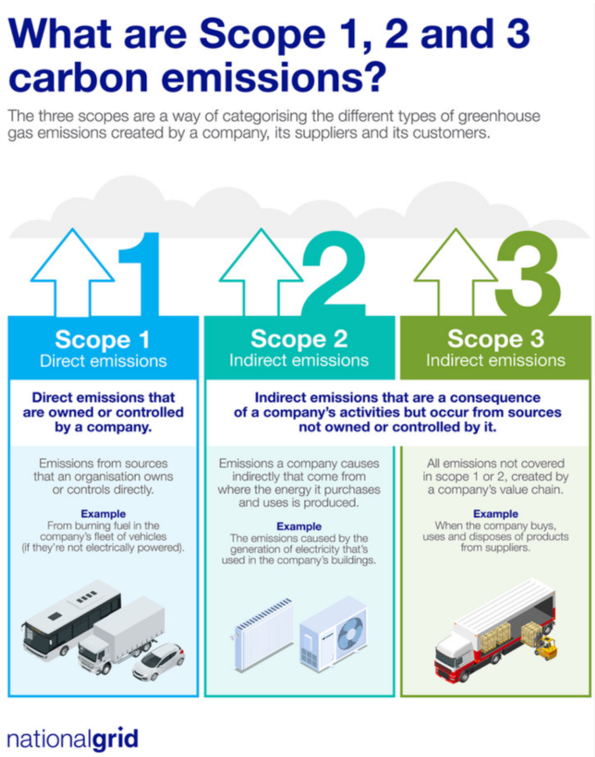


Figure 4: Information about Scope 1, Scope 2, and Scope 3 Emission. Source: National Gird.

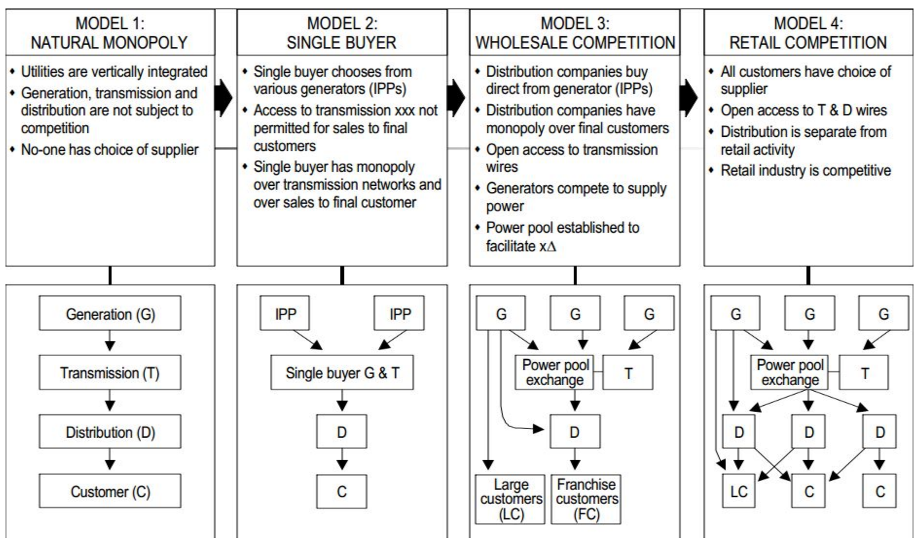
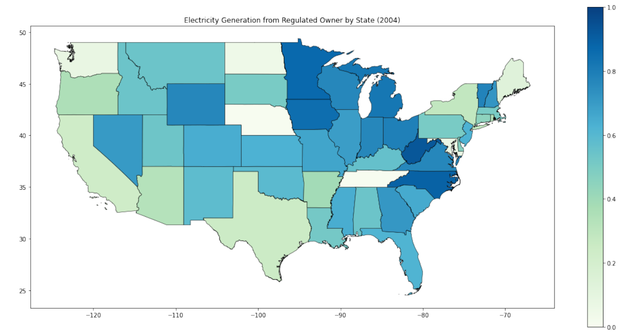
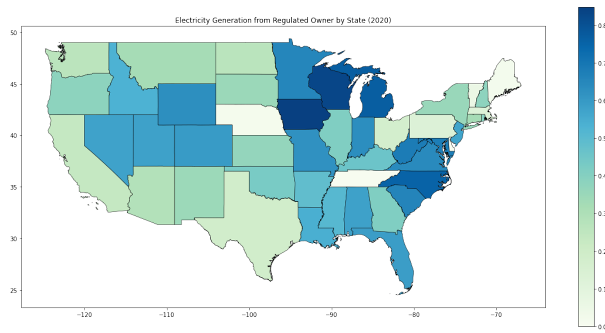


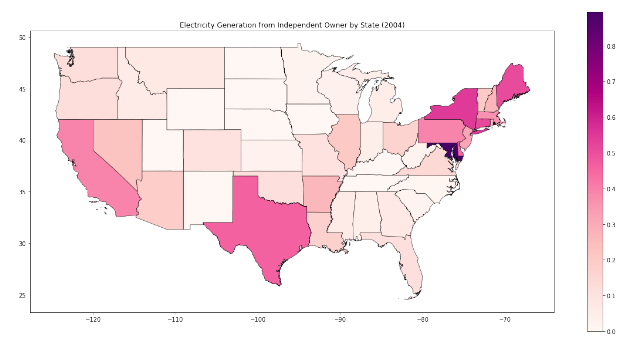
Figure 5: Shift of Business Model under Deregulation. Source: Eberhard, A. (2014), *Independent Power Producers and Power Purchase Agreements: Frontiers of International Experience.*



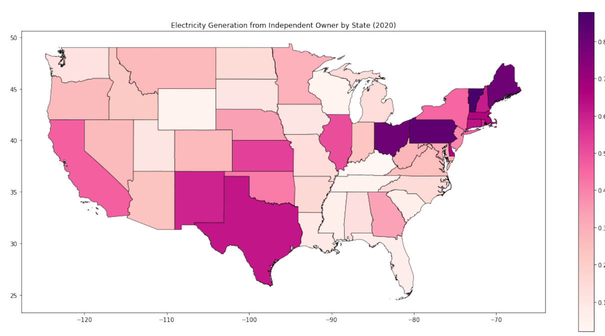
(a) Regulated Owner 2004



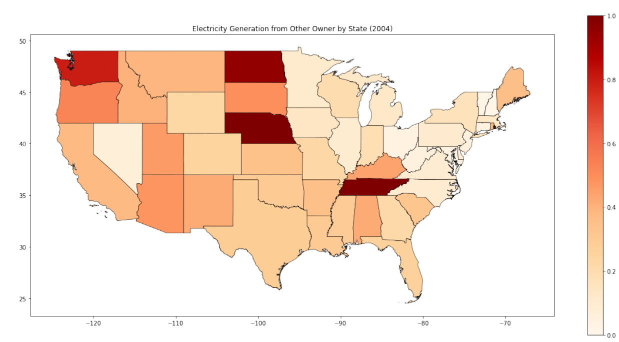
(b) Regulated Owner 2020



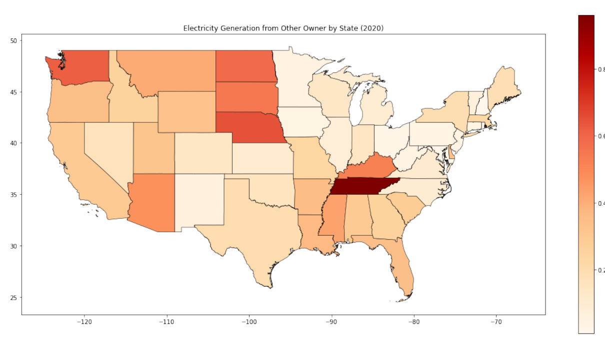
(c) Independent Owner 2004



(d) Independent Owner 2020

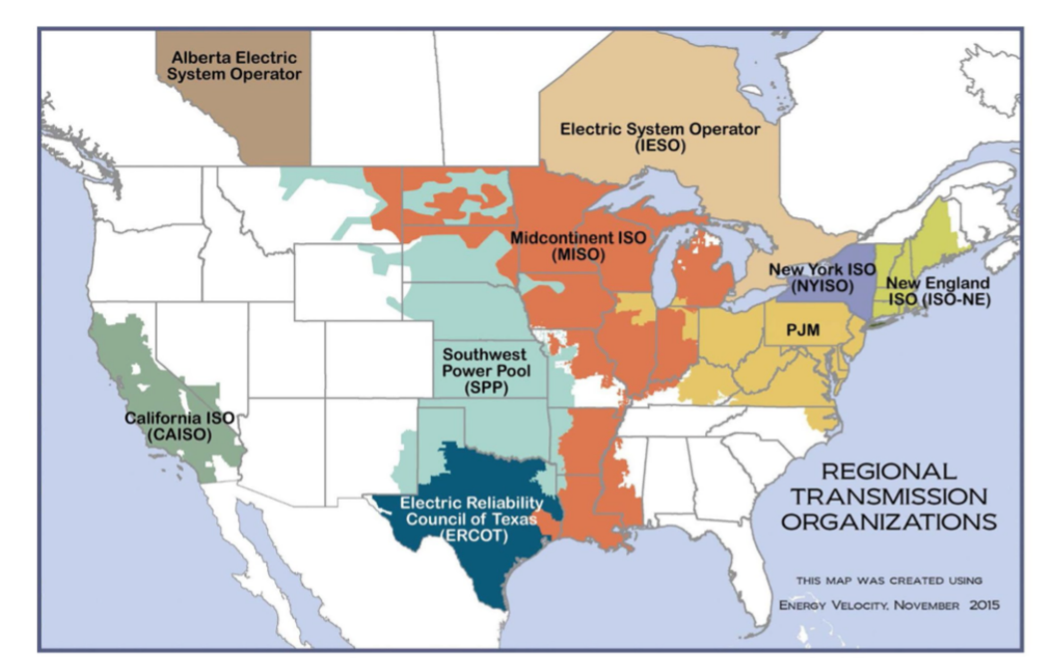


(e) Other Owners 2004



(f) Other Owners 2020

Figure 6: Evolution of Market Share of Different Owner Types



(a) Deregulated Wholesale Electricity Markets (2015)

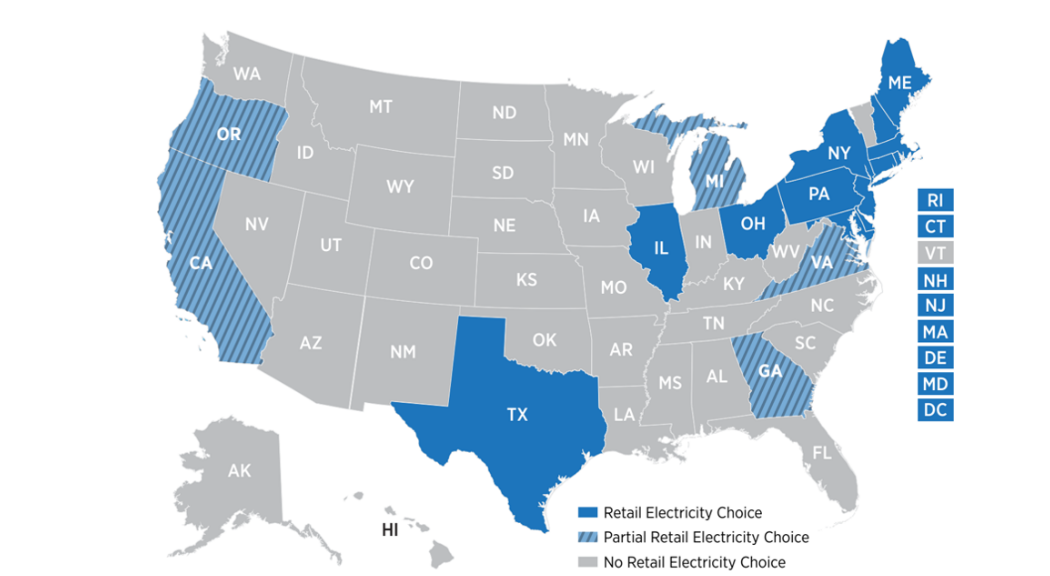
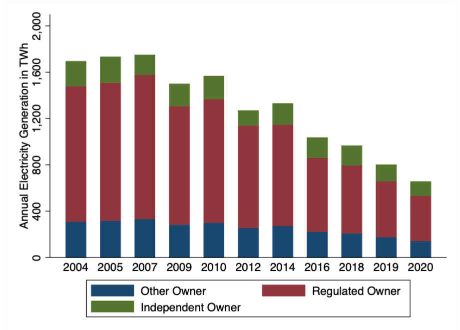


Figure 1. States with retail electricity choice

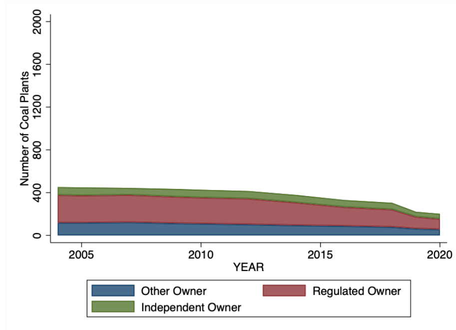
Source: State public utility commissions (2017)*

(b) Deregulated Retail Electricity Markets (2017)

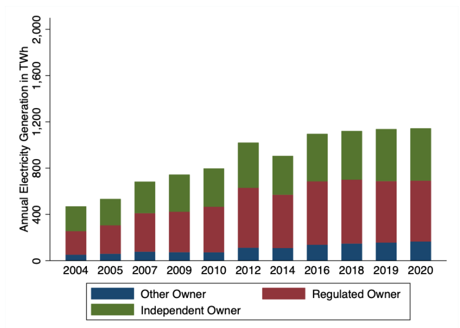
Figure 7: Geographic Variation of Electric Utility Deregulation



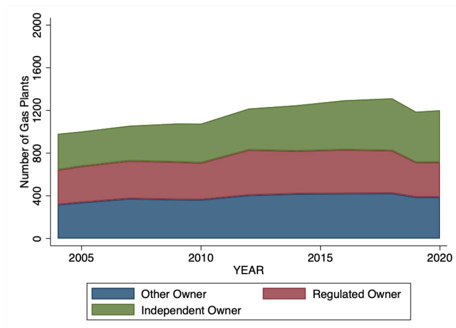
(a) Annual Generation from Coal Plants



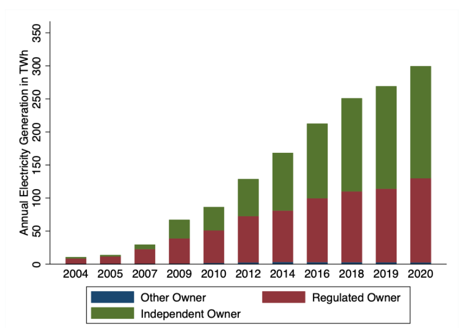
(b) Number of Coal Plants



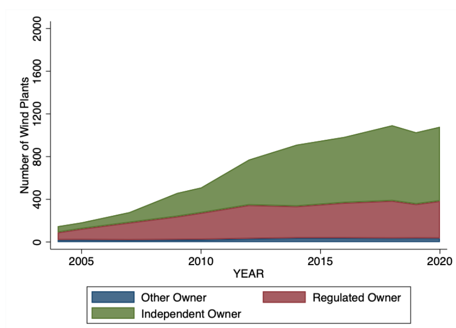
(c) Annual Generation from Gas Plants



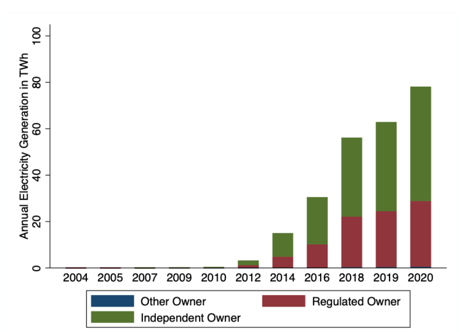
(d) Number of Gas Plants



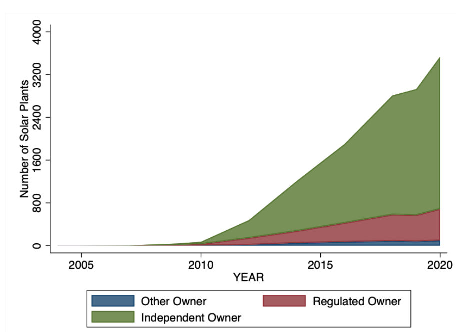
(e) Annual Generation from Wind Plants



(f) Number of Wind Plants

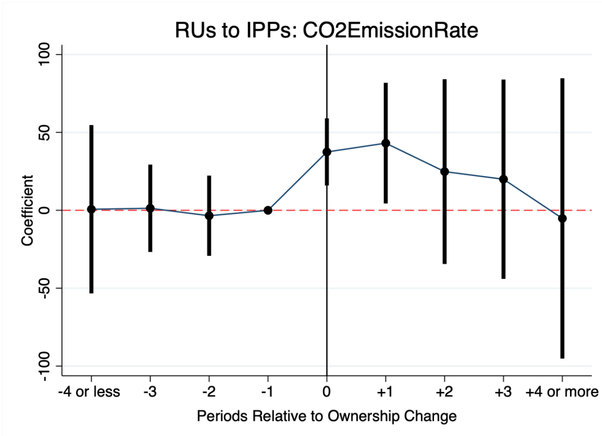


(g) Annual Generation from Solar Plants

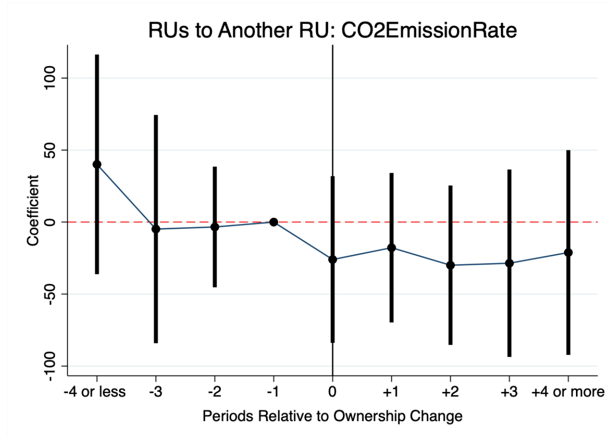


(h) Number of Solar Plants

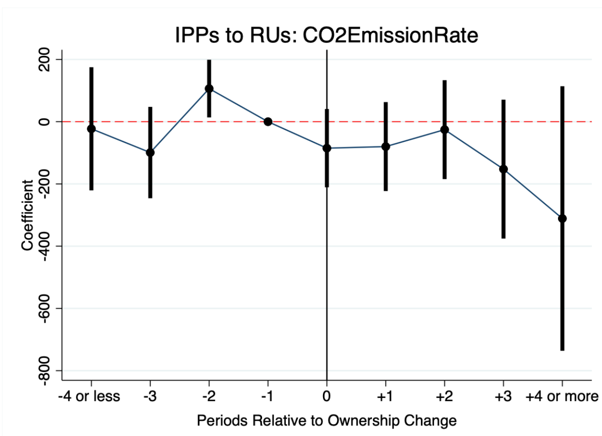
Figure 8: Annual Generation and Number of Plants by Primary Fuel Type: Renewable Fuel



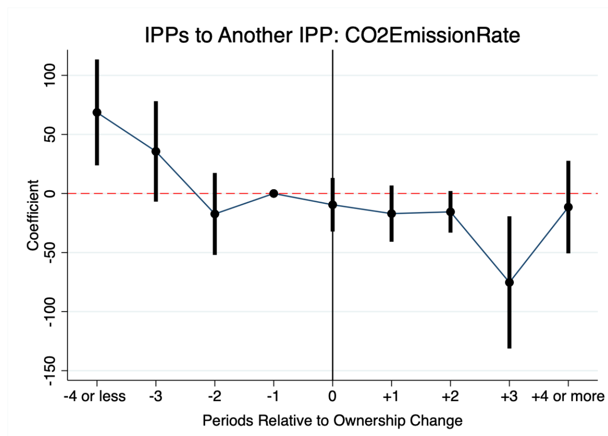
(a) Incumbent To IPPs



(b) Incumbent To Another Incumbent

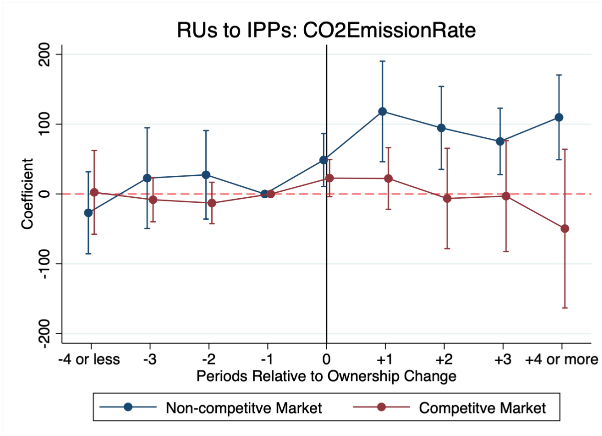


(c) IPP to Incumbent

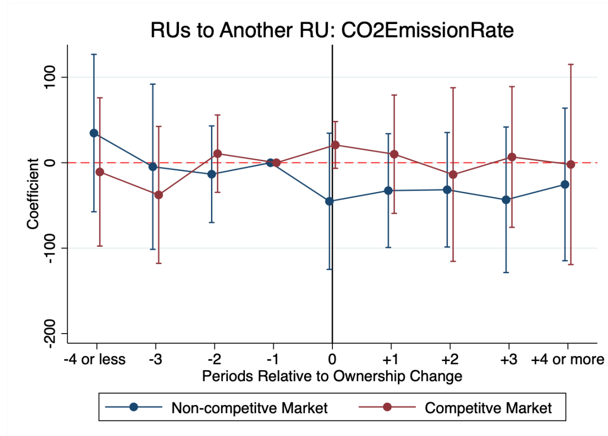


(d) IPP to Another IPP

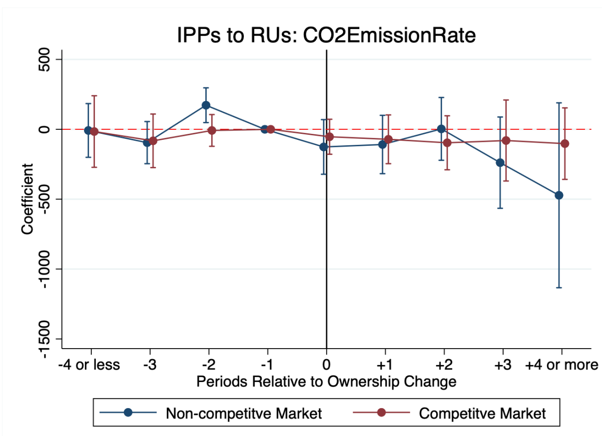
Figure 9: **CO_2 Emission Rate Trends Around Ownership Change.** (a) and (b) plots CO_2 emission rate dynamics of plants transferred from RU to IPP or another RU as compared to untransferred RU plants; (c) and (d) are for plants transferred from IPP to RU or another IPP. The control groups are untransferred RU plants and untransferred IPP plants, respectively. The plot depicts coefficient estimates of θ_t their 95% confidence intervals from the following difference-in-differences (DiD) regression: $EmissionRates_{i,t} = \sum_{t \neq -1} \theta_t Periods_t * Transferred_i + \alpha_i + \alpha_t + \epsilon_{i,t}$. The dependent variable is the CO_2 emission rate (lb/MWh) for plant i at period t, winsorized at 99.5% and 0.05% levels. *Transferred* indicates whether a plant changes parent owner during the sample period. *Period* is an indicator that equals one if the observation corresponds to event period t. α_i and α_t represent plant and period fixed effects.



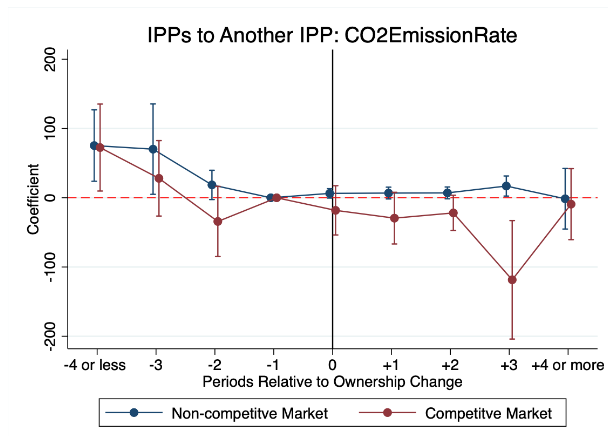
(a) Incumbent To IPPs



(b) Incumbent To Another Incumbent

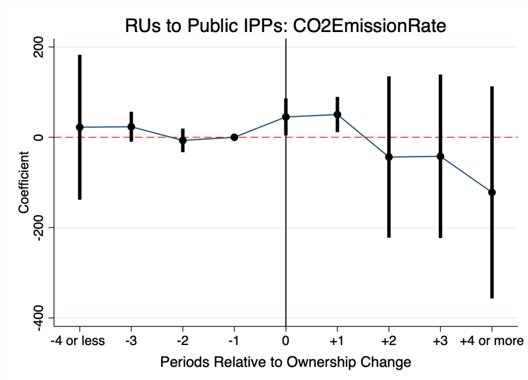


(c) IPP to Incumbent

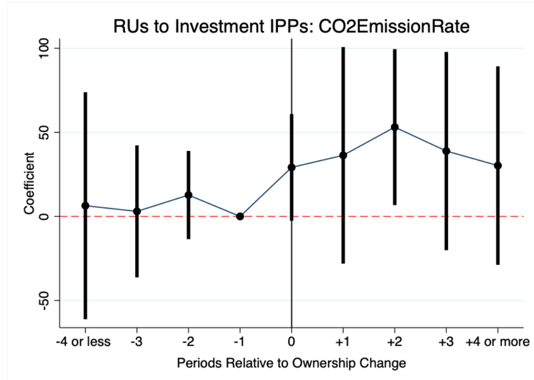


(d) IPP to Another IPP

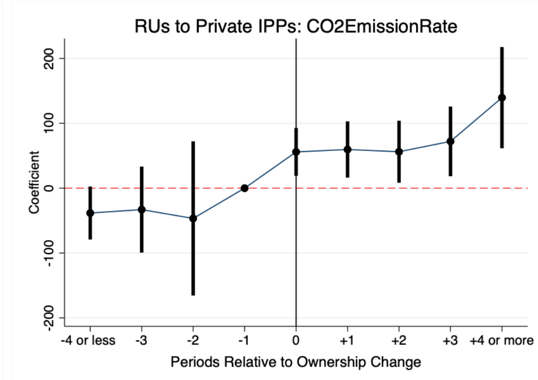
Figure 10: **CO_2 Emission Rate Trends Around Ownership Change Across Markets.** (a) and (b) plots CO_2 emission rate dynamics of plants transferred from RU to IPP or another RU as compared to untransferred RU plants in two markets; (c) and (d) are for plants transferred from IPP to RU or another IPP. The control groups are untransferred RU plants and untransferred IPP plants, respectively. The plot depicts coefficient estimates of θ_t their 95% confidence intervals from the following difference-in-differences (DiD) regression: $EmissionRates_{i,t} = \sum_{t \neq -1} \theta_t Periods_t * Transferred_i + \alpha_i + \alpha_t + \epsilon_{i,t}$. The dependent variable is the CO_2 emission rate (lb/MWh) for plant i at period t, winsorized at 99.5% and 0.05% levels. *Transferred* indicates whether a plant changes parent owner during the sample period. *Period* is an indicator that equals one if the observation corresponds to event period t. α_i and α_t represent plant and period fixed effects.



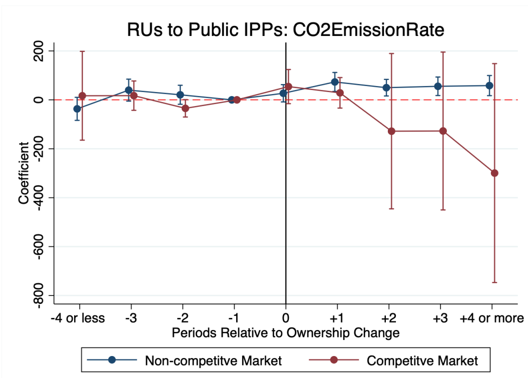
(a) To Publicly Traded IPPs



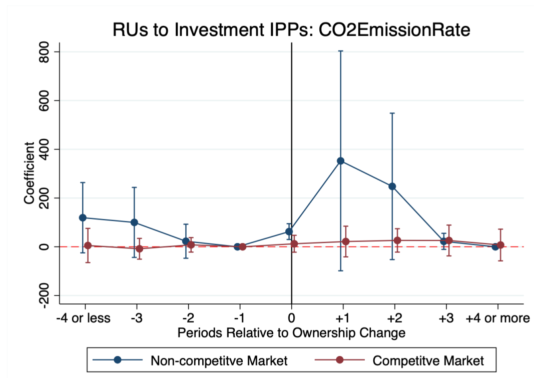
(b) To IPPs that are investment firms (Infrastructure Funds and PE Firms)



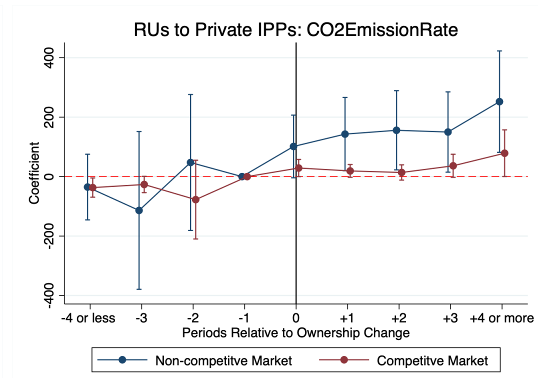
(c) To Private Non-investment IPPs



(d) To Public IPPs, Two Markets

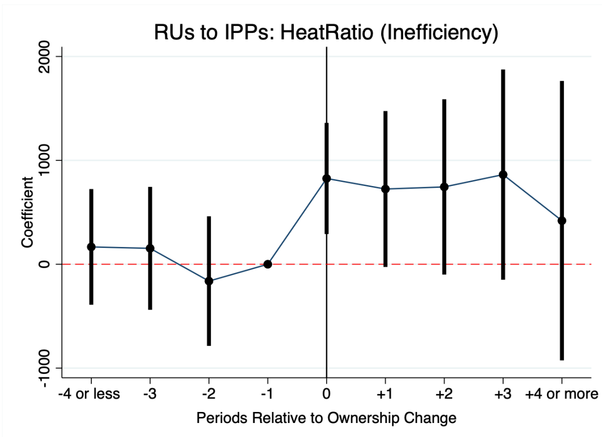


(e) To Invest IPPs, Two Markets

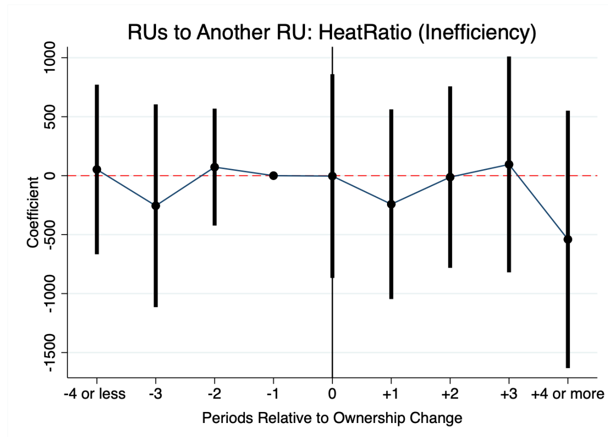


(f) To Private IPPs, Two Markets

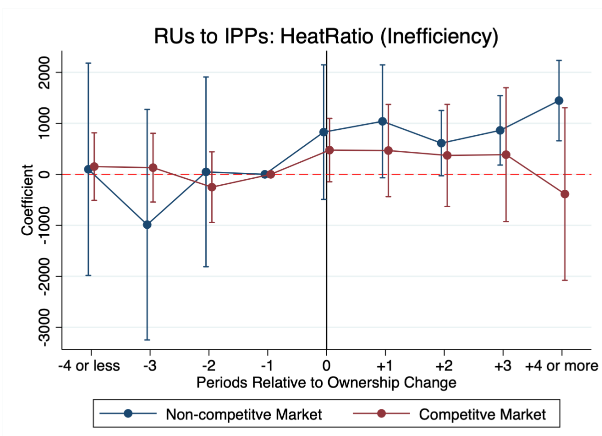
Figure 11: **Trends in CO_2 Emission Rate Around Ownership Change: Examine Different Types of Acquirers.** All figures are plotted using the same methodology as in Figure **??**, using different sub-samples. (a), (b), and (c) show the evolution of CO_2 emission rates of plants transferred to three mutually exclusive types of IPPs that likely have very distinct ownership structures. Acquirers are divided into IPPs that are publicly traded firms (public IPP), IPPs that are infrastructure funds or PE firms (invest IPP), and IPPs that are private firms (private IPP). (d), (e), and (f) are plotted in the same way as Figure 10(a), showing dynamics across different markets and different acquirer types.



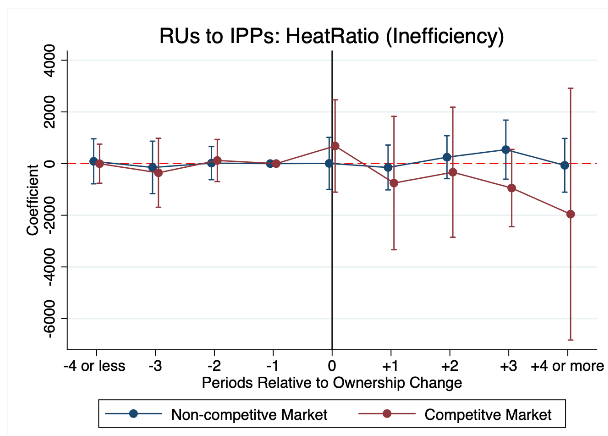
(a) To IPPs



(b) To Another RU



(c) To IPPs, Two Markets



(d) To Another RU, Two Markets

Figure 12: **Trends in Plant Inefficiency Around Ownership Change.** The above figures show the evolution of plant heat rate, of plants transferred from RUs to IPPs, and from RUs to another RU, as compared to the untransferred plants owned by RUs.

Tables

	Regulated Owner		Independent Owner		Difference	
	mean	sd	mean	sd	mean diff	t value
CO2EmissionRate	706.96	959.22	336.61	687.76	370.35***	(44.27)
NetGeneration	615340.28	1075455.89	213167.28	603875.43	402173.00***	(45.72)
Number of Generators	3.02	2.96	2.18	2.51	0.84***	(28.89)
Nameplate Capacity	326.78	595.46	105.35	295.86	221.43***	(47.19)
Capacity Factor	0.30	0.26	0.30	0.24	0.00*	(1.96)
OwnerPercent	98.39	6.89	98.30	7.93	0.10	(0.86)
Plant Opening Year	1975.12	33.21	1999.14	23.88	-24.01***	(-85.53)
coal	0.12	0.32	0.02	0.15	0.10***	(37.26)
gas	0.20	0.40	0.15	0.36	0.06***	(15.25)
oil	0.10	0.29	0.03	0.18	0.06***	(25.52)
biomass	0.02	0.13	0.11	0.32	-0.10***	(-45.53)
geothermal	0.00	0.02	0.02	0.12	-0.01***	(-19.81)
hydro	0.26	0.44	0.14	0.35	0.12***	(31.10)
nuclear	0.02	0.16	0.00	0.02	0.02***	(21.21)
solar	0.12	0.33	0.36	0.48	-0.23***	(-62.22)
wind	0.15	0.35	0.15	0.36	-0.00	(-1.13)
Publicly Traded Owner	0.99	0.11	0.26	0.44	0.73***	(268.45)
Observations	15189		24648		39837	
TotalABCapex	11592.06	42500.99	5603.90	30802.65	5988.17***	(4.88)
OMExpenses	5477.53	11763.32	4946.36	49645.81	531.17	(0.34)
NetCost	16192.49	49487.80	8733.33	59591.54	7459.16***	(3.63)
Observations	3046		1039		4085	

Table 1: Summary Statistics of Power Plants Information and Emission Rates

Panel A: Transaction Cases by Time and Owner Type

	Unique # of Plants		Owner Change Cases				
	All	RU Owned	Total	RU to IPP	RU to RU	IPP to RU	IPP to IPP
Whole Sample	7314	2941	1426	268	333	76	749
By Time Periods:							
2004	2024	1267					
2005	2084	1276	36	4	2	3	27
2007	2198	1300	98	7	73	6	12
2009	2422	1364	131	9	58	4	60
2010	2485	1372	22	7	2	8	5
2012	2950	1537	134	22	79	4	29
2014	3739	1725	164	40	43	2	79
2016	4613	1977	184	57	34	10	83
2018	5624	2187	291	34	33	10	214
2019	5867	2013	155	59	9	15	72
2020	6512	2156	211	29	0	14	168

Panel B: Transaction Cases by Market and Fuel Type

	Plant Type by Primary Fuel								
	Coal & Petroleum	Gas	Biomass	Geothermal	Hydro	Nuclear	Solar	Wind	Other
Competitive Market	73	115	104	2	151	9	254	89	0
Non-Competitive Market	77	84	32	3	88	3	239	94	2

Table 2: Details of Ownership Change Cases

Panel A: Carbon Emission Intensity

	CO2EmissionRate					
	Full Sample		Coal or Petroleum Plant		Other Plant	
	(1)	(2)	(3)	(4)	(5)	
RU_Owned=1	12.52**	5.57	25.51	-231.18*	10.00**	18.74***
	[2.16]	[0.60]	[0.52]	[-1.73]	[2.34]	[3.14]
RU_Owned=1 × Competitive		10.48		318.28**		-13.49
		[0.88]		[2.45]		[-1.52]
Capacity	-0.08***	-0.08***	-0.07***	-0.06***	-0.09***	-0.09***
	[-10.47]	[-10.45]	[-4.44]	[-3.80]	[-9.93]	[-9.91]
Utilization	-316.68***	-316.55***	-360.81***	-367.47***	-317.72***	-317.95***
	[-7.30]	[-7.30]	[-5.18]	[-5.14]	[-6.75]	[-6.75]
LogPlantAge	65.85***	65.89***	21.57	26.87	68.53***	68.48***
	[12.67]	[12.65]	[0.79]	[0.95]	[13.07]	[13.05]
RegulatoryStatus	36.83***	38.57***	-59.32	24.49	47.71***	45.64***
	[3.71]	[4.19]	[-0.91]	[0.47]	[6.87]	[6.69]
FERCSmallPower	24.96***	25.00***	138.06*	123.05	26.30***	26.24***
	[4.88]	[4.89]	[1.67]	[1.45]	[5.37]	[5.36]
FERCExemptWholesale	10.04	9.99	-91.48**	-66.26*	18.59**	18.77***
	[1.35]	[1.34]	[-2.33]	[-1.94]	[2.56]	[2.58]
State × Year × Fuel FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.85	0.85	0.32	0.33	0.79	0.79
N	38410	38410	4051	4051	34359	34359

Panel B: Log(Total Carbon Emission)

	LogCO2Emission					
	Full Sample		Coal or Petroleum Plant		Other Plant	
	(1)	(2)	(3)	(4)	(5)	
RU_Owned=1	0.07*	0.09*	0.60***	1.63***	0.00	-0.02
	[1.76]	[1.84]	[3.39]	[4.60]	[0.03]	[-0.40]
RU_Owned=1 × Competitive		-0.04		-1.29***		0.03
		[-0.63]		[-3.78]		[0.48]
Capacity	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	[21.20]	[21.17]	[9.64]	[9.45]	[16.01]	[16.03]
Utilization	1.88***	1.88***	4.03***	4.04***	1.72***	1.72***
	[7.41]	[7.41]	[8.84]	[8.98]	[6.70]	[6.70]
LogPlantAge	0.20***	0.20***	0.29***	0.26***	0.21***	0.21***
	[5.41]	[5.41]	[2.98]	[2.92]	[5.40]	[5.40]
RegulatoryStatus	-0.13***	-0.14***	-0.12	-0.46**	-0.12**	-0.12**
	[-2.58]	[-2.81]	[-0.62]	[-2.11]	[-2.41]	[-2.46]
FERCSmallPower	-0.01	-0.01	-0.26	-0.21	-0.01	-0.01
	[-0.28]	[-0.29]	[-1.12]	[-0.90]	[-0.38]	[-0.38]
FERCExemptWholesale	0.20***	0.20***	0.89***	0.79***	0.12***	0.12***
	[5.86]	[5.87]	[6.09]	[5.41]	[3.49]	[3.47]
State × Year × Fuel FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.90	0.90	0.81	0.81	0.89	0.89
N	39254	39254	4113	4113	35141	35141

t statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: **Plant Carbon Emission and Plant Owner Type.** This table shows the relationship between plant ownership and its carbon intensity, using the full sample and sub-samples of plants depending on their primary fuel. The primary fuel of a plant is determined solely by the fuel that has the maximum heat input, or the fuel with the highest nameplate capacity for plants that do not consume any combustible fuel. Coal and petroleum plants are the most polluting ones in terms of carbon emission generation. *RU_Owned* equals one for a plant whose parent owner is an incumbent utility firm with rate-based regulation exposure. The omitted case is when the parent owner is an independent power producer. Plant-level control variables include plant generation capacity, plant capacity factor (proportion of capacity that has been taken up), plant age, and three regulatory-based measures. RegulatoryStatus=1 if a plant is subject to rate-based regulation, FERCSmallPowerProducer=1 if a plant is a FERC-granted small producer, and FERCExemptWholesale=1 means that a plant can engage in the wholesale sale of electricity without having to comply with certain regulations that would typically apply to larger utilities and power producers. Robust standard errors clustered at fuel-state-year level.

Panel A: Divested Plants Compared to Originator Plant Prior to Transaction

	Plant Utilization		Log(Capacity)		LogCO2Emission		CO2EmissionRate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested	0.01	0.02	0.34***	0.40**	0.28	0.18	47.96***	35.40*
	[1.30]	[1.13]	[3.08]	[2.46]	[1.56]	[0.80]	[2.74]	[1.95]
Divested × Competitive		-0.01		-0.09		0.14		17.14
		[-0.47]		[-0.46]		[0.51]		[0.78]
Plant Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Fuel × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.76	0.76	0.90	0.90	0.97	0.97	0.99	0.99
N	9883	9883	9927	9927	9872	9872	9867	9867

Panel B: Acquired Plants Compared to Acquirers' Plant Prior to Transaction

	Plant Utilization		Log(Capacity)		LogCO2Emission		CO2EmissionRate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Acquired	0.01	0.02	-0.55***	-0.63***	-0.56**	-1.17***	-85.66**	-149.27***
	[1.25]	[1.63]	[-3.31]	[-2.67]	[-2.39]	[-3.45]	[-2.49]	[-3.07]
Acquired × Competitive		-0.01		0.12		0.97***		101.64**
		[-0.59]		[0.42]		[2.77]		[2.30]
Plant Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Fuel × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.84	0.84	0.90	0.90	0.98	0.98	0.98	0.98
N	10956	10956	11012	11012	10940	10940	10939	10939

t statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **Transferred Plants Compared to Acquirer and Originator Plants Before Transaction.** This table compares the features of transferred plants with the average originator and acquirer plants before the transaction. In panel A, sample is restricted to 1) plants whose parent firm had divested at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. In panel B, sample is restricted to 1) plants whose parent firm had acquired at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. *Originator FE* is a firm fixed effect applied for firms that divested the plants, and *Acquirer FE* is a firm fixed effect applied for firms that acquired the plants. Three regulatory-related measures are included as controls. Robust standard errors clustered at the plant level.

Panel A: Divested Plants Compared to Originator Plant Post Transaction

	Plant Utilization		Log(Capacity)		LogCO2Emission		CO2EmissionRate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × Post	-0.01***	0.00	-0.03***	-0.04***	-0.10	-0.03	27.78**	27.70*
	[-2.61]	[0.28]	[-2.81]	[-3.79]	[-0.92]	[-0.19]	[2.20]	[1.71]
Divested × Post × Competitive		-0.03***		0.02**		-0.13		0.14
		[-2.89]		[2.06]		[-0.63]		[0.01]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.84	0.84	0.99	0.99	0.97	0.97	0.96	0.96
N	11031	11031	11158	11158	11028	11028	11009	11009

Panel B: Acquired Plants Compared to Acquirer's Plant Post Transaction

	Plant Utilization		Log(Capacity)		LogCO2Emission		CO2EmissionRate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × Post	-0.02***	-0.02**	-0.04***	-0.03***	-0.13	0.28**	-0.65	41.79*
	[-4.08]	[-2.15]	[-4.08]	[-2.79]	[-1.23]	[2.12]	[-0.03]	[1.79]
Divested × Post × Competitive		-0.00		-0.01		-0.57***		-58.19*
		[-0.36]		[-0.52]		[-3.22]		[-1.84]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.83	0.83	0.99	0.99	0.96	0.96	0.95	0.95
N	13172	13172	13365	13365	13182	13182	13145	13145

t statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Transferred Plants Compared to Acquirer and Originator Plants Post Transaction.** This table compares the features of the transferred plant with the average originator and acquirer plants after the transaction. In panel A, sample is restricted to 1) plants whose parent firm had divested at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. In panel B, sample is restricted to 1) plants whose parent firm had acquired at least one plant over the sample period; and 2) plants whose parent firm owns more than two plants each year. Robust standard errors clustered at the plant level.

Panel A: Plant Transferred from RU to IPP/Another RU

	CO2EmissionRate					
	All Transactions		Non-Competitive Market		Competitive Market	
	(1)	(2)	(3)	(4)	(5)	(6)
Transferred × Post × ToIPP	57.15*	105.16**	116.06***	100.96**	0.14	8.33
	[1.68]	[2.33]	[2.85]	[2.05]	[0.00]	[0.16]
Transferred × Post	-28.58	-62.44	-38.82	-75.17	5.96	22.64
	[-1.21]	[-1.42]	[-1.18]	[-1.46]	[0.18]	[0.44]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score Reweighted	No	Yes	No	Yes	No	Yes
Adjusted R-Squared	0.89	0.88	0.87	0.91	0.91	0.96
N	15325	5668	8127	3020	6950	2482

Panel B: Plant Transferred from IPP to RU/Another IPP

	CO2EmissionRate					
	All Transactions		Non-Competitive Market		Competitive Market	
	(1)	(2)	(3)	(4)	(5)	(6)
Transferred × Post × ToRU	-112.05	-11.03	-210.91	19.79	-19.66	-29.72
	[-1.46]	[-0.33]	[-1.60]	[0.89]	[-0.26]	[-0.56]
Transferred × Post	-30.29***	11.51	-21.97	14.91	-34.56***	9.11
	[-2.84]	[0.72]	[-1.15]	[0.52]	[-2.59]	[0.48]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score Reweighted	No	Yes	No	Yes	No	Yes
Adjusted R-Squared	0.92	0.96	0.91	0.96	0.93	0.96
N	16157	5860	6563	2057	9594	3803

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **Plant Transferred Across Different Types of Owners: Comparison of Carbon Emission Intensity.** Panel A (B) presents the results of equation (6) ((7)), which compares post-transaction CO_2 emission rates as compared to the untransferred plants, using a plant-year panel. The test is repeated using subsamples of plants located in markets with different levels of competition. Emission rates (lb/MWh) are winsorized at 99.5% and 0.05% levels. The propensity score method is applied to select a matched sample based on lagged emission rates, lagged capacity, size of the prior owner, calendar year, and plant opening year. *FE* = fixed effects. *Transferred* indicates whether a plant changes parent owner during the sample period. *Post* indicates whether the plant-year observation is after the plant was transferred. *ToIPP* equals one if a plant is transferred to an independent owner. *ToRU* equals one if a plant is transferred to a regulated utility. Robust standard errors are clustered at the plant level.

Panel A: Plant Transferred from RU to Different Types of IPP

	CO2EmissionRate					
	Public IPPs		Investment IPPs		Private IPPs	
	(1)	(2)	(3)	(4)	(5)	(6)
Transferred × Post × ToPublic	-1.60	118.63**				
	[-0.02]	[2.39]				
Transferred × Post × ToInvest			63.30**	98.09**		
			[2.03]	[2.01]		
Transferred × Post × ToPrivate					132.86***	113.34***
					[3.32]	[2.60]
Transferred × Post	-30.39	-64.20	-30.17	-61.77	-30.87	-63.59
	[-1.18]	[-1.46]	[-1.18]	[-1.40]	[-1.20]	[-1.45]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score Reweighted	No	Yes	No	Yes	No	Yes
Adjusted R-Squared	0.89	0.93	0.89	0.93	0.89	0.92
N	14374	5246	14659	5371	14270	5206

Panel B: Plant Transferred from RU to Different Types of IPPs in Different Markets

	CO2EmissionRate					
	Non-Competitive Market			Competitive Market		
	Public IPPs	Investment IPPs	Private IPPs	Public IPPs	Investment IPPs	Private IPPs
	(1)	(2)	(3)	(4)	(5)	(6)
Transferred × Post × ToPublic	76.09**			-95.20		
	[2.40]			[-0.74]		
Transferred × Post × ToInvest		167.49**			11.76	
		[2.00]			[0.31]	
Transferred × Post × ToPrivate			204.95**			64.03
			[2.31]			[1.55]
Transferred × Post	-38.59	-38.45	-38.62	5.97	6.82	4.82
	[-1.17]	[-1.17]	[-1.17]	[0.18]	[0.21]	[0.15]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.87	0.87	0.87	0.91	0.91	0.91
N	8069	7970	8000	6305	6689	6270

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Plant Transferred from RU to Different Types of IPP and Plant Location: Comparison of Carbon Emission Intensity.** This table resembles Table 6 by studying plant transactions from RUs to different types of IPPs (public, investment, and private) in different markets (non-competitive vs. competitive). Emission rates (lb/MWh) are winsorized at 99.5% and 0.05% levels. *FE* = fixed effects. *Transferred* indicates whether a plant changes parent owner during the sample period, and *Post* indicates whether the plant-year observation is after the plant was transferred. Robust standard errors are clustered at the plant level.

Panel A: Plant Transferred from RUs to IPPs/Another RU

	LogCO2Emission		
	All Transactions	Non-Competitive Market	Competitive Market
	(1)	(2)	(3)
Divested × Post × ToIPP	0.21	0.36	0.12
	[1.26]	[1.35]	[0.49]
Divested × Post	-0.18	-0.25*	-0.06
	[-1.47]	[-1.70]	[-0.29]
Plant FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R-Squared	0.97	0.97	0.96
N	15665	8386	7279

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Plant Transferred from IPPs to RUs/Another IPP

	LogCO2Emission		
	All Transactions	Non-Competitive Market	Competitive Market
	(1)	(2)	(3)
Divested × Post × ToRU	0.10	-0.35	0.50**
	[0.59]	[-1.32]	[2.32]
Divested × Post	-0.13**	-0.02	-0.20**
	[-1.98]	[-0.20]	[-2.07]
Plant FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R-Squared	0.97	0.97	0.96
N	17429	7173	10256

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: **Plant Transferred from Regulated Utility (IPP): Comparison of LogCarbonEmission.** This table presents the results of equation (6) and (7), resembling Table 6 and substituting the outcome variable to the amount of CO_2 emission, using a plant-year panel. The test is repeated using subsamples of plants located in competitive and non-competitive markets. *Transferred* indicates whether a plant changes parent owner during the sample period. *Post* indicates whether the plant-year observation is after the plant was transferred.

	(1)	(2)	(3)
	log_TotalABCapex	log_OMExpenses	log_NetCost
Regulated	2.42***	0.65***	2.19***
	[0.000]	[0.005]	[0.000]
LogCapacity	2.52***	1.15***	1.30***
	[0.000]	[0.000]	[0.000]
LogPlantAge	0.82***	-0.54***	0.07
	[0.000]	[0.001]	[0.685]
Fuel FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Adjusted R-Squared	0.39	0.43	0.23
N	4016	4016	4016

p-values in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: **Plant Abatement Investment and Plant Ownership.** This table shows the relationship between plant ownership and three abatement-related variables. Abatement-related information is obtained from EIA-906, EIA-920, and EIA-923, and is only applicable to a subset of plants (around 10% of the master dataset used for baseline regressions) from 2008 to 2020. *TotalABCapex* is the capital expenditures (CAPEX) for new structures and equipment during the year, excluding land and interest expense. *OMExpenses* is the operation and maintenance (O&M) expenditures of abatement technology during the year. *NetCost* is the sum of CAPEX and O&M, netting out any by-product sales revenue during the year. Whenever the net cost is negative, I take the log of its absolute value and then revert the log value to negative. *Regulated* equals one for a plant whose parent firm is an incumbent regulated utility. The omitted case is when the parent owner is an independent power-generating company. Plant-level control variables include plant generation capacity and plant age. Robust standard errors are clustered at the state-year level in parentheses.

	CO2EmissionRate			
	All IPPs	Public IPPs	Investment IPPs	Private IPPs
	(1)	(2)	(3)	(4)
Transferred × Post × ToIPP	3.46	-137.49	140.75*	117.02**
	[0.03]	[-0.63]	[1.73]	[2.13]
Transferred × Post	-16.75	-14.32	-18.00	-19.59
	[-0.34]	[-0.29]	[-0.37]	[-0.40]
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.79	0.79	0.80	0.81
N	1921	1849	1827	1819

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: **A Case Study that re-examines baseline results using a subsample.** This table produces estimators from the baseline equations 6, using a subsample of plants from which I can obtain abatement investment and revenue information. Data is obtained from https://www.eia.gov/electricity/data/eia923/ and was linked to eGRID using a unique plant identifier.

Panel A: Change of Abatement Investment Measure 1

	$CAPEX_t/Production_{t-1}$			
	All IPPs	Public IPPs	Investment IPPs	Private IPPs
	(1)	(2)	(3)	(4)
Transferred × Post × ToIPP	-3.05	-2.92	-5.36	-0.50
	[-0.95]	[-1.36]	[-0.65]	[-0.23]
Transferred × Post	-0.87	-0.87	-0.89	-0.90
	[-0.24]	[-0.24]	[-0.24]	[-0.24]
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	-0.03	-0.03	-0.03	-0.03
N	495	475	466	464

Panel B: Change of Abatement Operating Cost Measure 1

	$OMExpense_t/Production_{t-1}$			
	All IPPs	Public IPPs	Investment IPPs	Private IPPs
	(1)	(2)	(3)	(4)
Transferred × Post × ToIPPs	-2.95*	-2.82**	-6.69**	1.51
	[-1.85]	[-2.43]	[-2.41]	[0.79]
Transferred × Post	1.15	1.12	1.11	1.12
	[1.15]	[1.12]	[1.11]	[1.12]
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.59	0.60	0.61	0.60
N	495	475	466	464

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: **Case Study on Plant Transferred from RU and Abatement Investment and Operating Cost.** This table presents the treatment effect estimator on plant abatement investment and related operating expenses. *CAPEX* is the capital expenditures for new structures and equipment invested for pollution control during the year, excluding land and interest expenses. *OMExpenses* is the operation and maintenance (O&M) expenditures of abatement technology during the year. *Production* (MWh) is the plant's annual net generation of electricity. *Revenue* is the plant annual revenue from resale. *FE* = fixed effects. Robust standard errors are clustered at the plant level.

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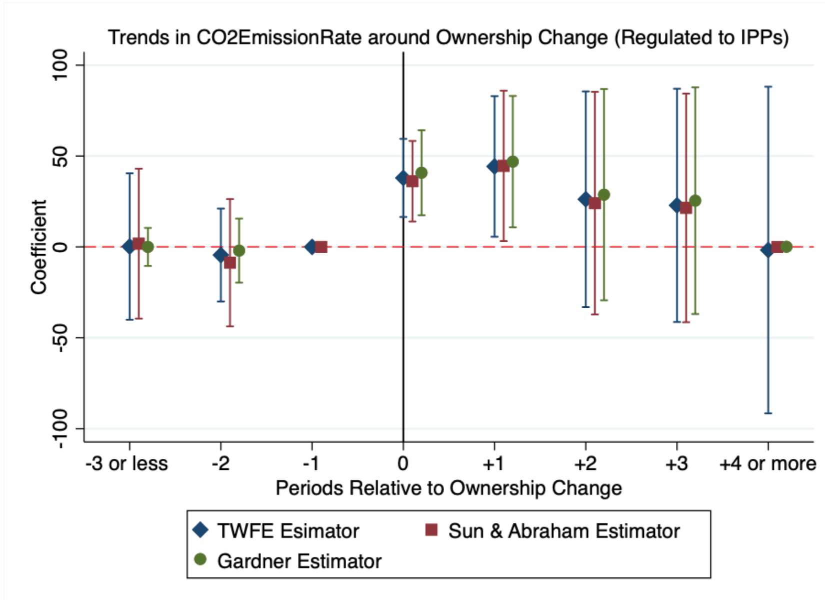
A Appendices

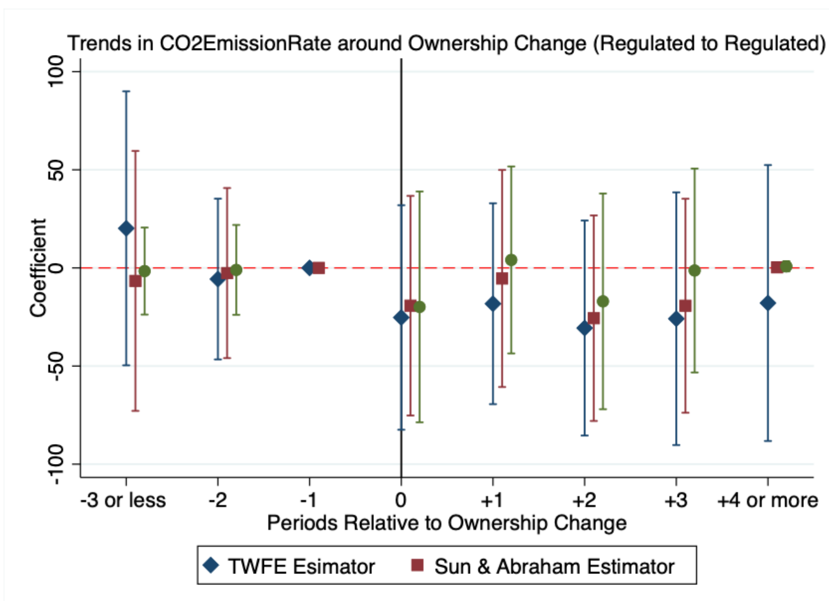
A.1 Robustness Check: Estimators adjusted for Heterogeneous Treatment Effects

In this section, I present a robustness check to the baseline result in Figure **??**, by employing estimators that are more robust to heterogeneous treatment effects across groups and periods. Specifically, I produce adjusted estimators following Sun and Abraham (2021), Gardner (2022), and De Chaisemartin and d'Haultfoeuille (2020), and compare them with the two-way fixed effect (TWFE) estimators I used in my baseline specifications (see Figure 13 and Figure 14). In general, the conclusion that plants transferred to IPPs increase CO_2 emission rates post-transaction relative to those transferred to another regulated utility pertains, and the trend is similar in the way that emission rates increase in periods 0, 1, and 2, and then reduce in further periods. As suggested by my cross-sectional results in Figure 11, such a trend is mainly driven by plants transferred to publicly traded IPPs. The magnitude of the treatment effect is also similar across different estimators. Figure 14 shows the treatment effect using the estimator proposed by De Chaisemartin & d'Haultfoeuille (2020).[49] The main conclusion pertains as well under this estimator and the magnitudes and trends of the treatment effect resemble those in Figures 13 and 14.

[49] They mainly address the problem that the TWFE method estimates weighted sums of the average treatment effects (ATE) in each group and period, with weights that may be negative.

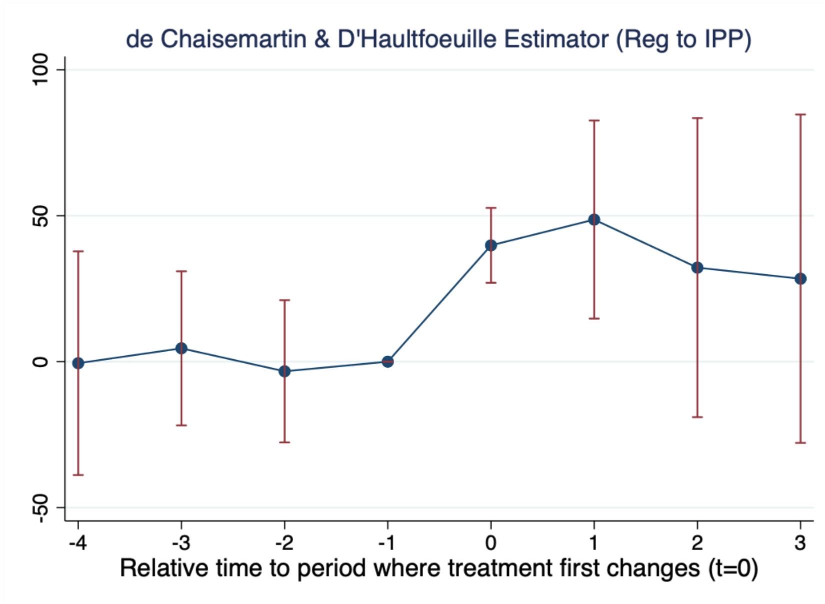


(a) Plants Transferred from Regulated to IPPs: Robustness Check1

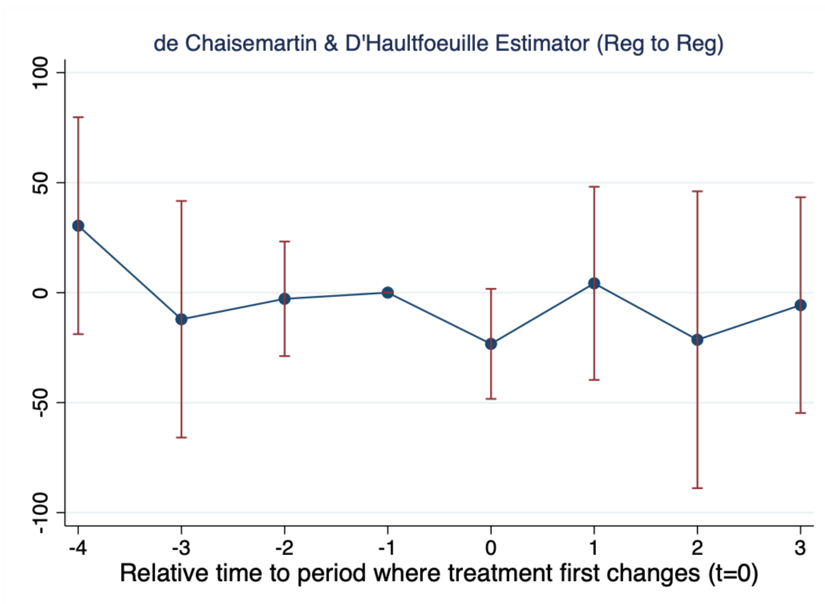


(b) Plants Transferred from Regulated to another Regulated: Robustness Check

Figure 13: **Treatment Effects under Different Estimators.** (a) plots CO_2 emission rate dynamics of plants transferred from a regulated utility to an IPP relative to those transferred to another regulated utility; (b) plots CO_2 emission rate dynamics of plants transferred from a regulated utility to another regulated utility relative to the untransferred plants. The plot depicts coefficient estimates of three different estimators: TWFE estimators from the baseline model, the Sun & Abraham estimators that capture the cohort average treatment effect, and the Gardner estimators that use a two-stage method to account for heterogeneous treatment effects across periods and groups (known as two-stage average treatment effect).



(a) Plants Transferred from Regulated to IPPs: Robustness Check2



(b) Plants Transferred from Regulated to another Regulated: Robustness Check

Figure 14: **Treatment Effects using De Chaisemartin & d'Haultfoeuille Estimators.** The plot depicts coefficient estimates of the De Chaisemartin & d'Haultfoeuille estimator, which adjusts for potential negative weights on average treatment effects. In the original cases, I bin observations 3 periods before and four periods after, which is not applicable under this estimation method, therefore I employ three lags and three leads.

A.2 Robustness Check: Using Wholesale Market Access as a Proxy for Regulation

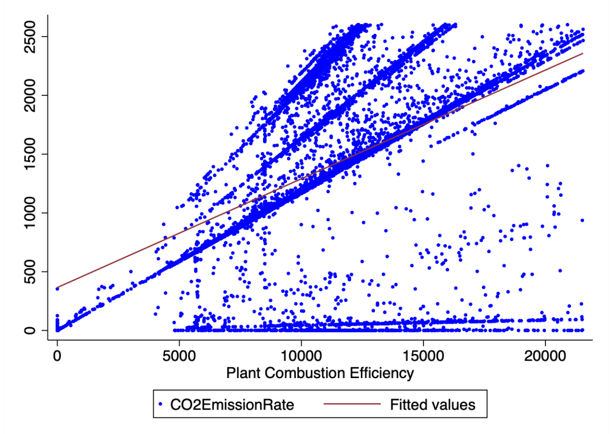
In my main analysis, I define regulated markets as grey states in Figure 7(b) and deregulated markets as the blue ones (both dark and shaded). In this section, I use wholesale market access as an alternative proxy for the level of regulation enforced on RUs' power generation businesses. Each plant is assigned an independent system operator (ISO) as a balancing authority acting in the regional-level wholesale market and providing nondiscriminatory grid access. The ISO data is only available starting in 2010 in my data set and was not very complete, so the number of observations dropped by over half. Areas not covered by ISOs are mainly states where vertically integrated RUs own a majority market share. Table 12 shows that my baseline result is robust to an alternative definition of regulation.

	CO2EmissionRate							
	Regulated Market				Deregulated Market			
	All IPPs	Public IPPs	Investment IPPs	Private IPPs	All IPPs	Public IPPs	Investment IPPs	Private IPPs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transferred × Post × ToIPPs	216.03***				35.06			
	[2.62]				[0.80]			
Transferred × Post × ToPublic		145.56***				-42.24		
		[3.04]				[-0.43]		
Transferred × Post × ToInvest							61.01	
							[1.55]	
Transferred × Post × ToOther				320.74**				56.40
				[2.15]				[1.56]
Transferred × Post	-97.32*	-97.15*	-96.71*	-97.76*	-32.78	-33.61	-33.23	-34.21
	[-1.95]	[-1.95]	[-1.94]	[-1.96]	[-0.84]	[-0.86]	[-0.85]	[-0.87]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.91	0.91	0.91	0.91	0.90	0.89	0.90	0.89
N	4275	4246	4197	4220	7357	6856	7110	6775

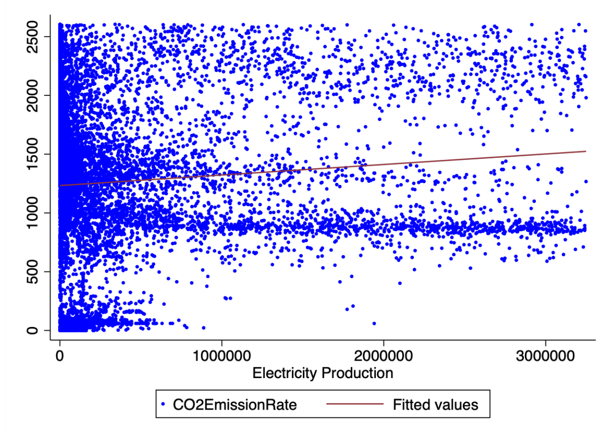
t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: **Robustness by Using Wholesale Market Access as a Proxy for Regulation**. This table resembles Table 7 in methodology while using wholesale market access as a proxy for regulation. Plants owned by RUs and with access to the wholesale market face less regulation than those located in regions without such access. Unfortunately, I do not observe any plant located in a wholesale market and being transferred to investment IPPs, so an estimator on column (4) is missing.



(a) Carbon Intensity and Combustion Inefficiency



(b) Carbon Intensity and Production

Figure 15: **Carbon Intensity and Power Plant Production**

A.3 Relationship between Carbon Intensity and Other Plant Measures

Figure 15(a) provides evidence that plant carbon intensity is positively correlated with plant combustion efficiency. In this section, I focus on a subsample of plants that use combustion fuel and add combustion efficiency to my baseline regression as a control variable, to control for the possibility that increased emission rate is driven by a mechanical relationship between carbon intensity and combustion efficiency. Table **??** presents the results. My main conclusion remains robust under this specification.

A.4 Within Divested Plants Variation

The results of using only transferred plants are robust in terms of both statistical significance and economic magnitude.

	CO2EmissionRate					
	Full Sample	Regulated	Deregulated	Public IPP	Investment IPP	Private IPP
	(1)	(2)	(3)	(4)	(5)	(6)
Transferred × Post × ToIPP	82.54*	180.83***	-29.21			
	[1.71]	[3.08]	[-0.69]			
Transferred × Post × ToPublic				24.64		
				[0.24]		
Transferred × Post × ToInvest					89.10*	
					[1.86]	
Transferred × Post × ToPrivate						159.16***
						[3.25]
Transferred × Post	-71.61	-134.90*	66.10	-83.96	-68.24	-88.22
	[-1.36]	[-1.96]	[1.49]	[-1.43]	[-1.22]	[-1.51]
Before(-1) × ToIPP	20.99	66.24	-18.92	39.32	4.51	43.97
	[0.51]	[1.20]	[-0.40]	[0.65]	[0.10]	[1.01]
Before(-2) × ToIPP	34.32	97.80**	-36.19	12.02	47.32	28.84
	[1.02]	[2.58]	[-1.02]	[0.22]	[1.22]	[0.49]
Before(-1)	-31.12	-61.59	47.22	-43.60	-30.66	-42.14
	[-0.68]	[-1.06]	[0.85]	[-0.87]	[-0.64]	[-0.85]
Before(-2)	-39.94	-71.59*	42.77	-43.08	-38.85	-43.12
	[-1.18]	[-1.75]	[1.12]	[-1.19]	[-1.11]	[-1.19]
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.93	0.91	0.95	0.91	0.93	0.92
N	3086	1692	1394	2383	2668	2279

t statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: **Plants transferred from RU: Transferred Plants Only**. This table compares post-transaction CO_2 emission rates of power plants that are transferred from an RU to an IPP to those transferred to another RU only (excluding all the untransferred plants). Emission rates (lb/MWh) are winsorized at 99.5% and 0.05% levels. *FE* = fixed effects. *Transferred* indicates whether a plant changes parent owner from RU to either an IPP or another RU, and *Post* indicates whether the plant-year observation is after the plant was transferred. *ToIPP* equals one if a plant is transferred to an independent owner. *Before (-t)* indicates that the plant-year is t years before transaction and takes zero otherwise. Robust standard errors are clustered at the plant level.

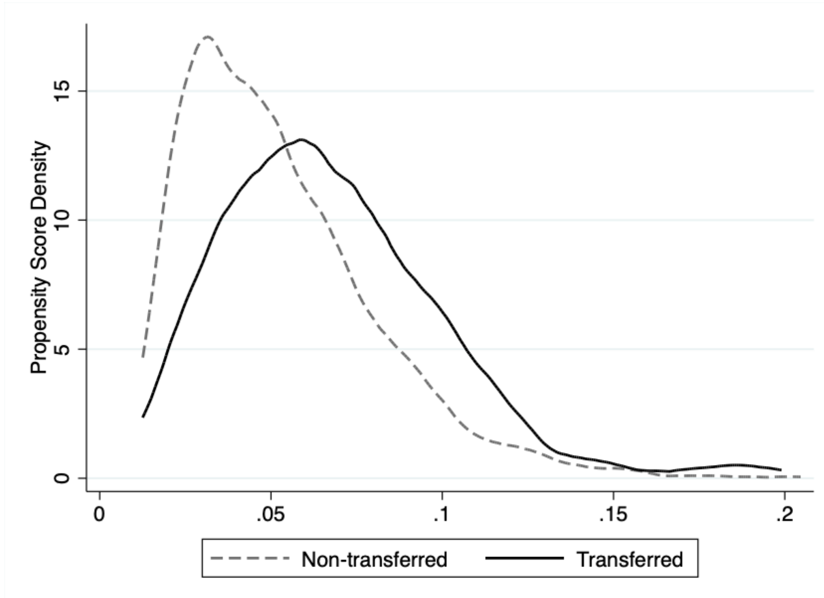
	CO2EmissionRate				
	Combustion Plants	Clean Plants	Coal	Gas	Oil
	(1)	(2)	(3)	(4)	(5)
Transferred × Post × ToIPP	149.48**	-0.09	189.83***	74.77	102.38
	[0.036]	[0.930]	[0.010]	[0.299]	[0.562]
Transferred × Post	-87.94	0.51	-76.49	-6.50	-119.67
	[0.104]	[0.668]	[0.210]	[0.908]	[0.467]
Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.63	0.93	0.57	0.49	0.52
N	6467	8836	1858	2810	1496

p-values in brackets

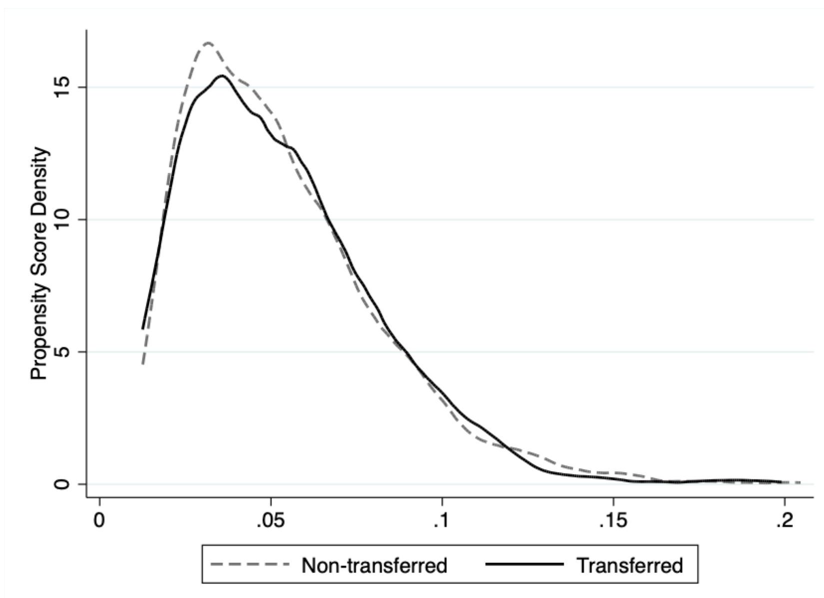
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: **Plants transferred by Regulated Owner: Plant Fuel Type**. This table presents the results of equation (6) using subsamples of plants using different primary fuels. Combustion plants are ones that use coal, gas, oil, biomass, and other fossil fuels as the primary fuel type, while clean plants are ones that use hydro, nuclear, wind, and solar as the primary fuel type. Emission rates (lb/MWh) are winsorized at 99.5% and 0.05% levels. *FE* = fixed effects. *Transferred* indicates whether a plant is acquired during the sample period, and *Post* indicates whether the plant-year observation is after the plant was transferred. *ToIPP* equals one if a plant is transferred to an independent owner. Robust standard errors are clustered at the plant level.

A.5 Kernel Density Distribution of Propensity Scores



(a) Unweighted



(b) Weighted

Figure 16: Propensity Score Distribution of Transferred and Untransferred Plants. This graph plots the kernel density distribution of propensity scores for the transferred and untransferred samples. Panel (a) uses the raw propensity score and Panel (b) uses the reweighted propensity score on each observation where I can obtain a score. A propensity score is constructed based on lagged emissions, lagged capacity, owner size, the exact event year, and the exact plant opening year. The propensity score reweighted control and treated groups matched with each other better than the raw samples and is used as a robustness check in Table 6.

A.6 Other Emission Types

One can argue that when firms are making abatement investments, they trade off the importance of different gases. For example, power plants also generate SO_2 and NO_x – two toxic gases that risk people's health and are closely monitored by regulators under the implementation of the Clean Air Act 1967.[50] Power plant owners might invest heavily in reducing other types of emissions while accidentally causing plant carbon intensity to increase. According to Figure 17, different types of emission are calculated based on quite different rules, and the type of fuel that generates the most carbon emission does not necessarily generate the most SO_2 or NO_x emissions.

In this section, I examine the performance of other types of emission rates around the transaction, including SO_2 and NO_x emission rates. Each type of fuel is associated with emission factors for each type of gas that converts the amount of heat input from combustion (in mmBtu, one million British thermal units) to the amount of gas emissions. For each fuel type, the emission factors differ between CO_2, SO_2, and NO_x. eGRID provides a detailed description of emission factors in the database technical support document, and I present some examples based on the document for eGRID 2016 in Figure 17. Emission factors can be updated every time a new database is released.

Following the method used to plot Figure **??**, I produce similar event graphs replacing the outcome variables to SO_2 emission rates and NO_x emission rates in Figures 18 and 19. On the one hand, it is clear that the parallel trend assumptions are violated, and more sulfur-intensive plants are sold to other RUs while less sulfur-intensive plants are sold to IPPs. However, in whichever case, SO_2 emission rates did not change as compared to the reference period, suggesting that the observed increase in carbon intensity is not due to investment in dealing with other types of pollution. Results on NO_x also show abnormal pre-trends and patterns around the event year, and even though NO_x emission rates are lower compared to the reference year, they are on average higher compared to the pre-trend period. Because event graphs show considerable targeting behavior, I cannot rely on them for causal inference.

[50] https://www.boem.gov/air-quality-act-1967-or-clean-air-act-caa

Table C-1. eGRID Emission Factors for CO_2, CH_4, and N_2O

Fuel Type	EIA Fuel Type Code	CO_2 EF (ton CO_2/mmBtu)	CH_4 EF (lb CH_4/mmBtu)	N_2O EF (lb N_2O/mmBtu)	Source
Agricultural Byproducts	AB	0.13026	0.07055	0.00926	(EPA, 2009)
Anthracite	ANT	0.11413	0.02425	0.00353	(EPA, 2009)
Blast Furnace Gas	BFG	0.30239	0.00005	0.00022	(EPA, 2009)
Bituminous	BIT	0.10296	0.02425	0.00353	(EPA, 2009)
Sulphite lyes (Black Liquor)	BLQ	0.11083	0.00698	0.00465	(IPCC, 2007)
Coke Oven Gas	COG	0.05164	0.00106	0.00022	(EPA, 2009)
Distillate Fuel Oil (avg)	DFO	0.08166	0.00661	0.00132	(EPA, 2009)
Hydrogen	H	0.00000	0.00000	0.00000	No EF
Kerosene-Type Jet Fuel	JF	0.07961	0.00661	0.00132	(EPA, 2009)
Kerosene	KER	0.08289	0.00661	0.00132	(EPA, 2009)
Landfill Gas	LFG	0.06350	0.00233	0.00023	(IPCC, 2007)
Lignite	LIG	0.10622	0.02425	0.00353	(EPA, 2009)
Municipal Solid Waste	MSW	0.09998	0.07055	0.00926	(EPA, 2009)
Megawatt hours	MWH	0.00000	0.00000	0.00000	No EF
Pipeline (Weighted U.S. Average)	NG	0.05844	0.00220	0.00022	(EPA, 2009)
Nuclear	NUC	0.00000	0.00000	0.00000	No EF

(a) CO_2 and its Equivalent CH_4 and N_2O

Table C-3. Sulfur dioxide (SO_2) emission factors

Prime Mover	Primary Fuel Type	Boiler Firing Type (if applicable)	Emission Factor	Emission Factor Numerator	Emission Factor Denominator
ST	AB	N/A	0.025	lb	MMBtu
ST	AB	STOKER	0.025	lb	MMBtu
ST	BFG	WALL	0.0006	lb	Mcf
ST	BFG	N/A	0.0006	lb	Mcf
ST	BFG	TANGENTIAL	0.0006	lb	Mcf
ST	BIT	WET VERTICAL	38*S	lb	short tons
ST	BIT	WET WALL	38*S	lb	short tons
ST	BIT	WET TANGENTIAL	38*S	lb	short tons
ST	BIT	WET OTHER	38*S	lb	short tons
ST	BIT	DRY VERTICAL	38*S	lb	short tons
ST	BIT	WET FLUIDIZED	38*S	lb	short tons
ST	BIT	OTHER	38*S	lb	short tons
ST	BIT	DRY WALL	38*S	lb	short tons

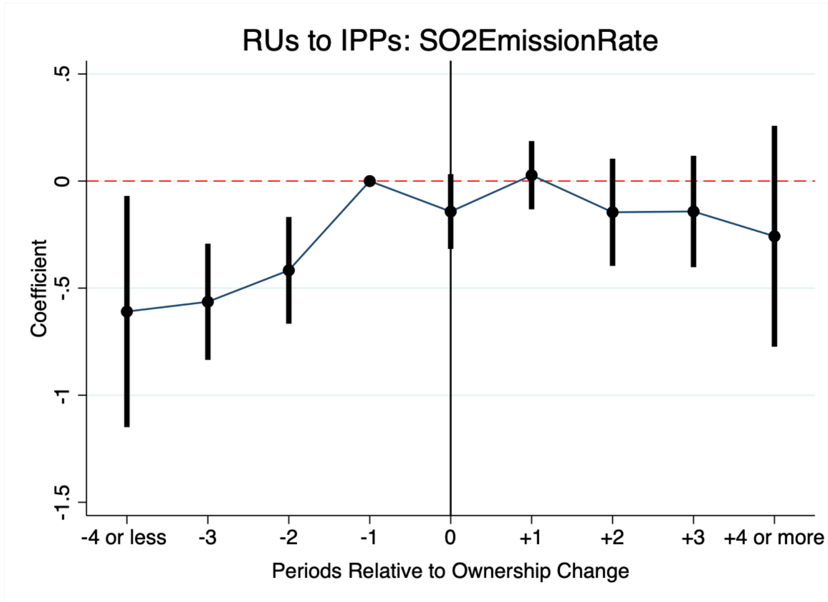
(b) SO_2

Table C-2. eGRID Emission Factors for Nitrogen Oxides (NO_x)

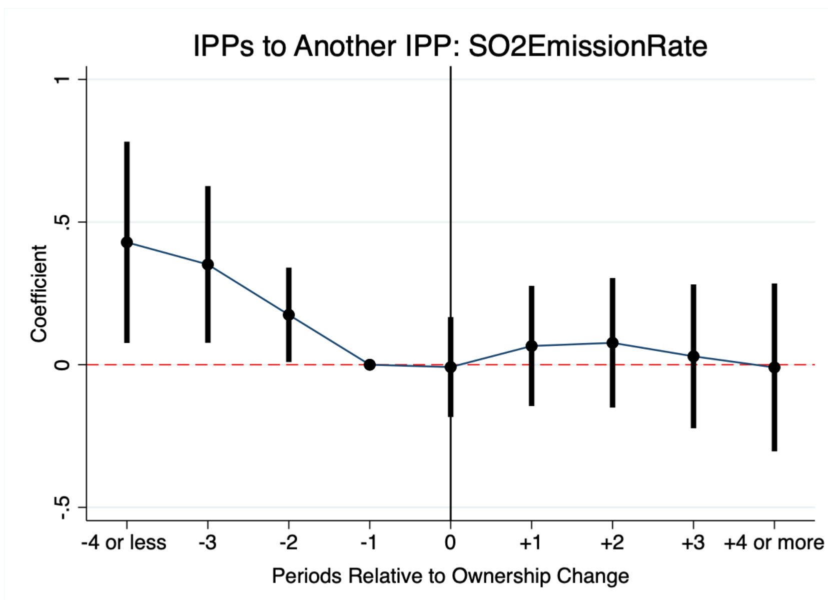
Prime Mover	Primary Fuel Type	Boiler Firing Type (if applicable)	Emission Factor	Emission Factor Numerator	Emission Factor Denominator
ST	AB	N/A	1.2	lb	ton
ST	AB	STOKER	1.2	lb	ton
ST	BFG	WALL	0.0154	lb	Mcf
ST	BFG	N/A	0.0154	lb	Mcf

(c) NO_x

Figure 17: Examples of Emission Factors for Different Gases

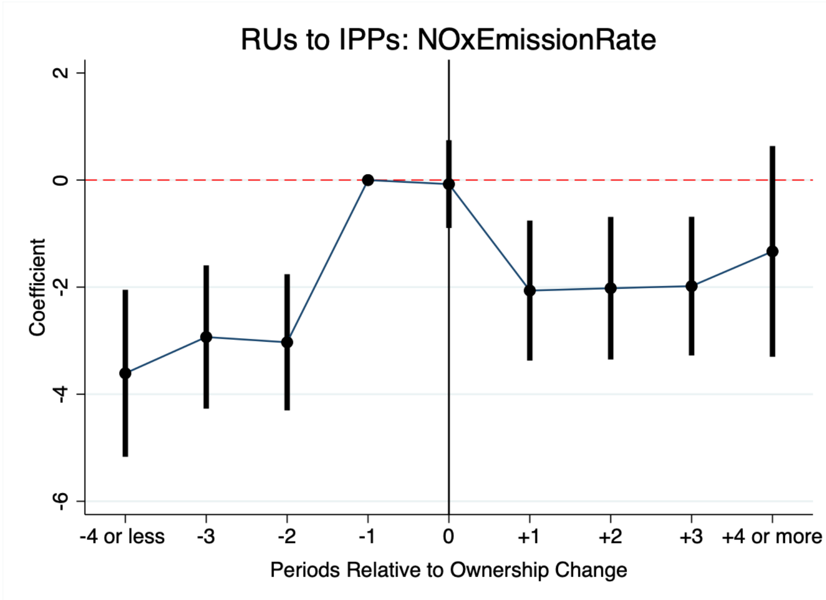


(a) Plants Transferred from Regulated to IPPs: SO_2 Emission Rate

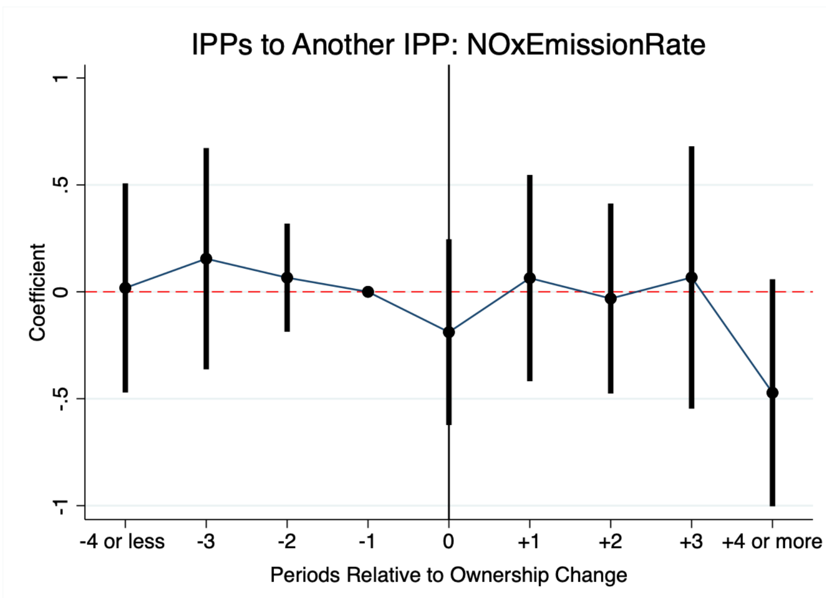


(b) Plants Transferred from Regulated to another Regulated: SO_2 Emission Rate

Figure 18: SO_2 Emission Rate Trends Around Ownership Change. (a) plots SO_2 emission rate dynamics of transferred plants from a regulated utility to an IPP relative to those transferred to another regulated utility; (b) plots SO_2 emission rate dynamics of transferred plants from a regulated utility to another regulated utility relative to the untransferred plants. The plot depicts coefficient estimates of β_t and θ_t their 95% confidence intervals from the following DiDs regression: $EmissionRates_{i,t} = \sum_{t\neq-1}(\beta_t Periods_t * Transferred_i * ToIPP_i + \theta_t Periods_t * Transferred_i) + \alpha_i + \alpha_t + \epsilon_{i,t}$. The dependent variable is the SO_2 emission rate (lb/MWh) for plant i at period t, winsorized at 99.5% and 0.05% levels. *Transferred* indicates whether a plant is acquired during the sample period. *ToIPP* equals one if a plant is transferred to an independent owner. *Period* is an indicator that equals one if the observation corresponds to event period t. α_i and α_t represent plant and period fixed effects.



(a) Plants Transferred from Regulated to IPPs: NO_x Emission Rate



(b) Plants Transferred from Regulated to another Regulated: NO_x Emission Rate

Figure 19: NO_x Emission Rate Trends Around Ownership Change. (a) plots NO_x emission rate dynamics of transferred plants from a regulated utility to an IPP relative to those transferred to another regulated utility; (b) plots NO_x emission rate dynamics of transferred plants from a regulated utility to another regulated utility relative to the untransferred plants. The plot depicts coefficient estimates of β_t and θ_t their 95% confidence intervals from the following DiDs regression: $EmissionRates_{i,t} = \sum_{t \neq -1}(\beta_t Periods_t * Transferred_i * ToIPP_i + \theta_t Periods_t * Transferred_i) + \alpha_i + \alpha_t + \epsilon_{i,t}$. The dependent variable is the NO_x emission rate (lb/MWh) for plant i at period t, winsorized at 99.5% and 0.05% levels. *Transferred* indicates whether a plant is acquired during the sample period. *ToIPP* equals one if a plant is transferred to an independent owner. *Period* is an indicator that equals one if the observation corresponds to event period t. α_i and α_t represent plant and period fixed effects.

A.7 Plant Green Outcomes, Plant Ownership, and Plant Primary Fuel Type.

In order to understand whether regulated owners have a comparative advantage in generating better environmental outcomes among certain types of fuels, I compare the emission rates of plants using different types of primary fuel between regulated utilities-owned plants and IPPs-owned ones, using the following specifications:

$$y_{ict} = \beta * Regulated_{ict} \times Fuel_{ict} + \gamma * Controls_{ict} + \xi_c + \xi_t + \epsilon_{ict} \tag{8}$$

i represents a unique plant, c represents the county a plant locates, and t represents the year. The outcome variables are different proxies for greenness at the plant level. *Regulated* is an indicator variable of the parent owner type. *Fuel* is a categorical variable of plant primary fuel. Controls include capacity, capacity factor, and age, and the standard error is clustered at the county-year level. Table 15 presents the result. The omitted fuel is coal. For display purposes, I exclude estimates of IPP plants of other fuels compared to IPP coal plants and retain only coefficients that estimate the difference in green outcomes between regulated utility plants and IPP plants across different fuel types. I implement the strictest geographic control, the county fixed effect, and include year fixed effect. Looking at CO2, regulated utilities are better at managing emissions at oil plants and plants whose primary fuel is renewable fuel, while IPPs are better at managing emissions at coal, gas, and nuclear plants. The result indicates that regulated firms may strategically allocate abatement resources to plants using certain fuels.

	(1)	(2)	(3)	(4)
	CO2EmissionRate	SO2EmissionRate	NOxEmissionRate	NR Gen Per
Regulated × Coal	82.25***	-0.19	-0.12	0.79*
	[0.002]	[0.114]	[0.595]	[0.052]
Regulated × Biomass	-72.08*	0.50***	-1.17***	1.50*
	[0.088]	[0.000]	[0.009]	[0.095]
Regulated × Gas	91.97***	0.26**	0.38	-0.66
	[0.002]	[0.028]	[0.119]	[0.161]
Regulated × Geothermal	-118.04***	0.33*	-1.61***	-0.35
	[0.007]	[0.076]	[0.001]	[0.415]
Regulated × Hydro	-110.99***	0.10	-0.10	-0.15
	[0.000]	[0.410]	[0.689]	[0.736]
Regulated × Nuclear	123.68**	0.28**	-0.90**	0.25
	[0.031]	[0.035]	[0.018]	[0.696]
Regulated × Other Fossil Fuel	-65.07	-0.13	-0.52	-38.20***
	[0.849]	[0.821]	[0.496]	[0.009]
Regulated × Petroleum	-300.93***	0.18	-3.42***	-1.60**
	[0.000]	[0.339]	[0.000]	[0.013]
Regulated × Other Source	91.21	0.18	-0.19	7.81**
	[0.294]	[0.324]	[0.728]	[0.015]
Regulated × Solar	-89.67***	0.18	0.18	-0.73*
	[0.001]	[0.142]	[0.421]	[0.083]
Regulated × Wind	-86.25***	0.17	0.19	-0.92**
	[0.001]	[0.160]	[0.391]	[0.025]
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.85	0.71	0.54	0.99
N	41963	41879	41900	42266

p-values in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: **Plant Green Outcomes, Plant Ownership, and Plant Primary Fuel Type.** This table shows the relationship between plant ownership and green outcomes among plants using different primary fuel. The primary fuel of a plant is determined solely by the fuel that has the maximum heat input, or the fuel with the highest nameplate capacity for plants that do not consume any combustible fuel. Green outcomes include emission rate (lb/MWh) of greenhouse gases and toxic gases: CO_2 equivalent, SO_2, and NO_x, all winsorized at 99.5% and 0.05% levels. Here CO_2 is an equivalent measure of emission from carbon dioxide (CO_2), methane (CH_4), and nitrogen dioxide (NO_2). $NRGenPer$ measures the percent of power generation from nonrenewable fuel. *Regulated* equals one for a plant whose direct owner is or is owned by a utility firm with rate-based regulation exposure. The omitted case is when the owner is $Independent$, which equals one for a plant whose direct owner is or is owned by an independent power generating company. Plant-level control variables include plant generation capacity, plant capacity factor, and plant age. Among the fuel type interactions, *coal* is the omitted fuel. Robust standard errors clustered at county-year level in parentheses.

A.8 Deregulated Plant Disposition: Quantity of Electricity Sold

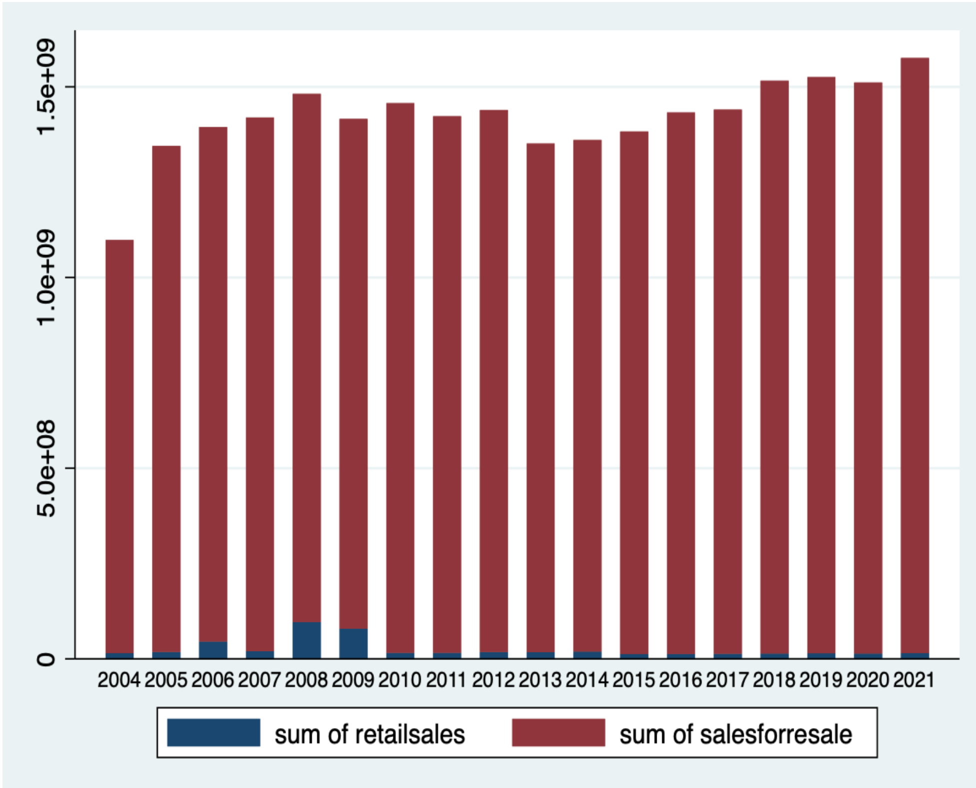


Figure 20: Amount of Electricity Sold