Private Equity and Gas Emissions: Evidence from Electric Power Plants

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First version: September 15, 2022
This version: July 31, 2023

How does private equity ownership affect firms' environmental performance? Using electricity generating unit level data from U.S. fossil fuel power plants, we find that private equity-backed buyouts reduce output-scaled CO_2 and NO_x emissions by 5.5% and 8.1%, respectively. The declines are mainly due to lower heat input per unit of output instead of lower input emission rates. The effects are concentrated in non-add-on deals, and are stronger for small plants and corporate divestiture deals. Our results suggest that private equity improves environmental performance by increasing production efficiency, but their effect on the non-efficiency component of environmental performance is generally insignificant.

JEL codes: G11, G20, G23

Keywords: Private equity, carbon emission, electricity sector, ESG, climate finance.

We are grateful for comments and suggestions from Aleksandar Andonov (discussant), Aymeric Bellon, Ioannis Branikas, Marco Ceccarelli, Caroline Flammer, Michael Goldstein, Bing Han, Jinyoung Kim (discussant), Charlotte Ostergaard (discussant), George Skiadopoulos, Zhi Wang, Michael Weisbach, Yang Zhao (discussant), and conference/seminar participants at the 7th-Shanghai-Edinburgh-London Green Finance Conference, 6th Private Markets Research Conference in Lausanne, 2nd Conference in Sustainable Finance at University of Luxembourg, China International Risk Forum in 2023, University of Oregon, University of Piraeus, and University of Macau. We also thank Craig Hillock and Sandeep Gill at the U.S. Environmental Protection Agency for answering our questions regarding the Power Sector Emissions Data.

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1 Introduction

Private equity firms are important players in today's economy. According to McKensey & Company (2022), the global asset under management of the private equity industry reached all-time high of \$6.3 trillion in the first half of 2021. As such, the impact of private equity ownership on firm operations has drawn increased attention. One question of particular relevance is private equity's influence on firms' environmental performance, especially in greenhouse gas emissions, which have been found to contribute to global warming. Widely viewed as a defining environmental challenge of our time, climate change has been the subject of many recent studies in finance (see the survey by Giglio et al. (2021) and the editorial overviews by Hong et al. (2020), Edmans and Kacperczyk (2022), and Calvet et al. (2022)). Despite the fast-growing literature on both private equity and climate/sustainable finance, studies on the environmental impact of private equity remain sparse.

We investigate the effect of private equity on environmentally harmful gas emissions using data from U.S. fossil fuel power plants. The electric power sector is a good venue for studying the environmental impact of private equity for several reasons. First, it is a major emitter. According to U.S. Environmental Protection Agency (EPA) (2022), it accounted for the second largest portion (24.8%) of total U.S. greenhouse gas emissions in 2020, surpassed only by the transportation sector (27.2%). About three quarters of U.S. gross greenhouse gas emissions consist of carbon dioxide (CO_2) from fossil fuel combustion. The electric power sector, which generated 61.5% of electricity from fossil fuels, contributed 30.5% of U.S. total CO_2 emissions from all sources in 2020. The sector is also an important emitter of two precursor greenhouse gasses sulfur dioxide (SO_2) and nitrogen oxides (NO_x, shorthand for NO and NO_2).[1] Not surprisingly, Utility (including Electric, Gas & Sanitary Services) tops the list of economic sectors ranked by exposure to climate risks according to both Sautner et al. (2022) and Li et al. (2022). Second, private equity firms have become major owners of U.S. power plants, a development that has raised significant concerns among the public. Andonov and Rauh (2022) report that private equity, institutional investors, and foreign corporations increased their ownership in U.S. electricity power plants from 8% in 2008 to 24% in 2020. Over their sample period, private equity owns on average 11.7% of all electricity generating

[1] While not being direct greenhouse gases themselves, precursor greenhouse gases such as SO_2 and NO_x can indirectly affect the earth's radiative balance and contribute to the formation of greenhouse gasses. SO_2 and NO_x can also harm human respiratory systems and contribute to acid rain that harms sensitive ecosystems.

capacity. Many advocacy groups voice strong concerns about the environmental impact of increasing private equity ownership in the power sector.[2] Third, comprehensive and accurate data about power plant emissions and operations are available from the regulators at highly granular level, and the homogeneity of input (measured by quantity of heat) and output in electricity production allows us to separate out the efficiency component of environmental performance.

We use the volume of emissions scaled by electricity produced, referred to as the output emission rate, as our main measure of emission intensity. We decompose it into two parts: the input emission rate and the heat rate. The former is measured by the volume of emissions scaled by the heat input, which reflects the effectiveness of a plant's emission control system. The latter is the heat input per unit of electricity output, which inversely measures a plant's production or thermal efficiency.[3] We argue that while private equity firms may have mixed incentives regarding socially beneficial but privately costly investments in reducing the input emission rates of environmentally harmful gases, they should have strong incentives to reduce the heat rate, because this not only boosts a plant's environmental performance, but also reduces fuel costs. Therefore, we hypothesize that private equity buyouts should lead to a reduction in the heat rate, which helps to reduce the output-scaled emissions, but their effect on the input emission rates is more ambiguous. To test this hypothesis, we obtain data on annual CO_2, SO_2 and NO_x emissions and operations of fossil fuel power plants from the Clean Air Markets Division (CAMD) of EPA. Our sample includes 1,340 power plants with 4,181 unique electricity generating units (EGUs) from 2003 to 2021, owned by 1007 firms. The gross electricity generation by the plants in our sample totaled 2.04 million gigawatt-hours (GWh) in 2021, which accounted for 80% of the U.S. electricity generation from fossil fuels in that year. By merging the plant owners with the targets of private equity buyout deals from Pitchbook, we identify 131 power plants bought out by private equity firms. Among them, we have data for 101 plants, with a total of 364 EGUs, both before and after the buyout deal.

We analyze the impact of private equity buyouts by running stacked difference-in-difference (DiD) regressions based on matched samples. To guide our design of the matching criteria, we analyze private equity firms' choice of buyout targets. We find that the buyout probability is

[2]For example, Americans for Financial Reform Education Fund (2022) argues that private equity firms "pose unique climate and safety risks" as they "deploy a highly predatory playbook to rapidly extract value from the firms and assets they purchase."

[3]Garvey et al. (2018) also emphasize the link between carbon emissions and production efficiency. But they do not isolate an efficiency component of environmental performance.

positively related to plant output and negatively related to plant age, but it is not significantly related to the emission rates or the heat rate. Based on these results, we match each of the 101 acquired plants to a control plant based on year, state and a Mahalanobis distance measure calculated using the log electricity output, log plant age, and the level and slope of the log heat rate. We consider the log heat rate because it not only captures the variation in production efficiency, but is also highly correlated with the output emission rates of all gases. Each pair of the treated (i.e., acquired) and control plants form a cohort. We stack all the cohorts and run DiD regressions controlling for both year-cohort and plant-cohort fixed effects. We use an 11-year window in our baseline analysis, from five years before to five years after the buyout.

We find strong evidence in support of our main hypothesis. Our regressions using the logarithmic rates as the dependent variables show that private equity buyouts on average reduce the CO_2 and NO_x output emission rates by 5.5% and 8.1%, respectively, at the EGU level. The SO_2 output emission rate also drops by 5.0%, although the decrease is not statistically significant. These declines result mainly from a 5.2% decrease in the heat rate. Regressions using the raw emission rates and heat rate as the dependent variables show that buyouts on average reduce CO_2 and NO_x emission rates by 32.4kg and 0.042kg, respectively, per megawatt-hour (MWh) electricity produced, and reduce the heat rate by 0.503 million British thermal unit (MBtu) per MWh. These numbers represent 15%, 4.5%, and 22% of the standard deviations of the corresponding variables in the full sample. In contrast, our baseline model does not show any significant buyout effect on the input emission rate of any gas, consistent with our hypothesis that while private equity firms have strong incentives to reduce the heat rate, they have less incentives to make costly investments to reduce the input emission rates. The coefficient plots support the identifying assumption of parallel trends.

The EGU-level data allow us to investigate whether the improvements in emission intensity and production efficiency arise from within-EGU variation or changes in the EGU composition. After we extend the benchmark model specification by controlling for EGU-cohort fixed effects, which subsume the less granular plant-cohort fixed effects, the magnitudes of the buyout effects on the CO_2 and NO_x output emission rates and the heat rate shrink by 7%, 18% and 8%, respectively, suggesting that the large majority of these effects are due to improvements on existing EGUs. We also examine whether the buyout effect we document is due to changes in production scale. We find that controlling for electricity output has little impact on the estimated effects on the CO_2 output emission rate and the heat rate, although it reduces the estimated effect on NO_x output emission rate by 38%. On the operation side, we find private equity buyouts have no significant effect on the scales of input, output, and operating time, but they increase the hourly electricity output without increasing the hourly heat input, consistent with the positive efficiency effect revealed by the heat rate. We also find that private equity firms operate EGUs at a lower capacity factor, and that EGUs are not less likely to be retired under private equity ownership.

To gain further insights into possible channels that lead to the post-buyout decreases in emission intensity and heat rate, we conduct triple DiD analysis on subsamples formed based on deal type and plant size. We find that the private equity buyout effect is larger for plants that are relatively small and for plants acquired through corporate divestiture deals. In fact, for the below-median acquired plants, we find not only significant declines in the output emission rates of all three gasses, but also significant declines in the input emission rates of CO_2 and SO_2. These cross-sample differences are consistent with the idea that sellers of small plants and sellers in corporate divestiture deals may be either unable or unwilling to make costly investments to improve plant efficiency and environmental performance. We further find that all the positive private equity buyout effects we describe above are concentrated in non-add-on buyout deals. For plants acquired through add-on deals, there are actually significant increases in the SO_2 output and input emission rates. This is consistent with the idea that private equity firms may have more limited influence on the operations of plants acquired indirectly via platform firms.

We conduct a series of additional tests to verify the robustness of our results. Specifically, we use a 7-year instead of 11-year event window; a 1-to-4 instead of 1-to-1 treated-to-control ratio; an additional matching condition based on the primary fuel type; and an alternative set of variables used for calculating the Mahalanobis distance measure. Our results remain largely the same in all these alternative tests. We also repeat our EGU-level tests using the plant level data. We find the plant-level results to be qualitatively similar, but with slightly smaller magnitudes, partly because the plant-level analysis does not differentiate between plants with more EGUs and those with fewer.

Our matching-based stacked DiD analysis mitigates potential biases due to staggered timing and treatment effect heterogeneity. However, the potential concern about the sensitivity to matching may not be fully addressed by using various matching methods. Therefore, our last set of tests consist of DiD panel regressions using the full sample. We control for a variety of fixed effects, including the owner fixed effects, plant fixed effects, year by fuel type fixed effects, and year by state fixed effects. The results are similar to those from the stacked DiD regressions.

Our paper is closely related to two recent studies on the effect of ownership structure on environmental performance: Bellon (2021) and Shive and Forster (2020). Bellon (2021) studies the effect of private equity buyouts on the oil and gas extraction practice. He finds that private equity ownership on average leads to a 70% reduction in the number of toxic chemicals used in the extraction process and a 50% reduction in "flaring", a practice that leads to more emissions of toxic chemicals and CO_2. However, in locations and periods where environmental liability risk is low, private equity-backed firms increase pollution. To the extent that electricity firms are highly regulated, our finding of a post-buyout decrease in emission intensity is consistent with his finding in the oil and gas industry. Shive and Forster (2020) find that public firms and private equity-backed private firms are more likely to pollute than independent private firms, while there are no differences between private equity-backed firms and public firms. Our study differs from these studies in several aspects. First, we focus on a homogeneous sample of electricity generating plants with accurately metered emission quantities relative to both input and output at the EGU level. Second, we decompose emission intensity into a production efficiency component and a non-efficiency component, and show striking differences in private equity's impact on these two components that are in line with private equity firms' profit motive. Third, we run stacked diff-in-diff regressions in our main analysis, controlling for both plant and time fixed effects within each cohort.[4] Recent studies (e.g., Baker et al. (2022)) have shown that this method can mitigate biases introduced by staggered treatment timing and treatment effect heterogeneity.

Our paper is also closely related to a recent study by Andonov and Rauh (2022) on the shifting finance of U.S. electricity generation. They show that market deregulation is the main driver of the changes in the ownership structure of the power sector. They find that new entrants increase their share largely through the adoption of innovative technologies and creation of new plants, and conclude that there is very little evidence that new entrants extend the lifespan of old fossil fuel plants by buying them from incumbents. They also document that private equity operates power plants at lower capacity factors, a result we find in our DiD analysis as well, and sells electricity

[4]Shive and Forster (2020) include firms from many different industries in their main analysis. They also do subsample analysis using electricity generating firms. There results using electricity-scaled emissions show no significant effect of private equity ownership after controlling for plant age. They do not control for firm or plant fixed effects.

for higher average price. While their paper uncovers many interesting facts about the industry organization of the electricity sector, it does not address the influence of ownership structure on environmental performance, which is the focus of our paper.

Our study contributes to the fast-growing literature on the real effect of private equity ownership. Our finding of a post-buyout increase in production efficiency resonates with previous studies documenting a positive efficiency effect of private equity ownership (e.g., Davis et al. (2014), Bloom et al. (2015)). Our finding of a post-buyout decrease in emission intensity adds to the literature on the effect of private equity on non-financial stakeholders. The evidence emerging from this strand of literature is more mixed.[5] Gupta et al. (2023) find that private equity ownership in healthcare reduces the quality of patient care, while Gao et al. (2022) find private equity-backed acquirers are not associated with worse patient satisfaction or mortality rates compared to other acquirers. Eaton et al. (2020) find that private equity buyouts in higher education lead to worse education outcomes and higher school profits. Sheen et al. (2022) show that private equity buyouts are followed by a rise in financial adviser misconduct. Bernstein and Sheen (2016) find that the number of health-related violations in restaurants trend downwards following private equity takeovers. Olsson and Tåg (2017) and Gornall et al. (2021) find that job security and perceived job quality decline after private equity buyouts, while Agrawal and Tambe (2016) find improvements in workers' skills and employability and Cohn et al. (2021) find reduced workplace injury rates after buyouts.

Our paper also contributes to the nascent stream of literature on the interaction between finance and firms' ESG (environmental, social and governance) performance. Previous studies have examined various channels through which finance can affect firms' environmental behavior, including cost of capital (Heinkel et al. (2001), Pástor et al. (2021)), financial constraints (Bartram et al. (2022), Xu and Kim (2022)), financial structure (De Haas and Popov (2022)), shareholder engagement (Dimson et al. (2015)), lender monitoring (Choy et al. (2021), Houston and Shan (2021)), organizational and ownership structure (Akey and Appel (2021), Shive and Forster (2020) and Bellon (2021)), and environmental activism (Akey and Appel (2019), Naaraayanan et al. (2020)). Many studies have shown that high carbon emissions and poor environmental performance increase cost of capital and reduce firm value (e.g., Fernando et al. (2017), El Ghoul et al. (2018), Bae et al.

[5]See Sorensen and Yasuda (2023) for a comprehensive review of this literature.

(2019), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022)).[6] This can be due to investors' concerns about climate risks (physical, regulatory, or technological), or due to investors' distaste of environmentally unfriendly firms. Concerns about climate risks are revealed in the trading behaviors of both retail and institutional investors and are priced in the option market (Choi et al. (2020), Krueger et al. (2020), Ilhan et al. (2021), and Cao et al. (2023)). Furthermore, socially oriented investors are found to be willing to forgo financial performance in order to invest in accordance with their social preferences (Riedl and Smetts (2017), Hartzmark and Sussman (2019), Barber et al. (2021)). These results imply that emission reduction can be rewarded not only socially but also financially, which may be an important reason for the decrease in emission intensity we observe after private equity buyouts.

2 Hypotheses

Since the volume of emissions naturally increases with production scale, to allow more meaningful comparisons between plants of different sizes, it is sensible to normalize it by output size. We use the volume of emissions scaled by electricity produced, which is called the output emission rate, as our main measure of emission intensity. Previous studies have used emissions scaled by sales or dollar values of output to measure emission intensity (e.g.,Bolton and Kacperczyk (2021), Shive and Forster (2020), Shapiro (2020)). Our quantity-based measure has the advantage of not being affected by output price, which can be driven by firms' market power.

How private equity affects emission intensity is an empirical question. On the one hand, a lower emission rate can reduce cost of capital and increase firm value, as shown by recent studies reviewed in Introduction. In addition, they can improve firms' reputation and social capital. Therefore private equity firms may have an incentive to reduce the emission rate for both financial and non-financial considerations. On the other hand, measures used for emission control and mitigation are costly, private equity firms may have an incentive to cut them back to improve short-term profitability, especially because they typically do not hold the plants for a long time. Which of these two forces outweighs the other is hard to tell ex ante.

However, sharper predictions can be made if we look further into the components of the emission

[6]Flammer (2015) finds that the adoption of close call corporate social responsibility proposals leads to positive announcement returns and superior accounting performance.

intensity we define. The output emission rate of a gas can be expressed as the product of its input emission rate and the heat rate, the former defined as emissions per unit of heat input and the latter defined as the heat input per unit of electricity produced:

$$\underbrace{\frac{Emission}{Electricity\ Output}}_{Output\ Emission\ Rate} = \underbrace{\frac{Emission}{Heat\ Input}}_{Input\ Emission\ Rate} * \underbrace{\frac{Heat\ Input}{Electricity\ Output}}_{HeatRate}, \tag{1}$$

where the heat input is equal to the quantity of fuel used in electricity production times the fuel's heat content. It follows that the log output emission rate can be fully decomposed into two parts:

$$ln(Output\ Emission\ Rate) = ln(Input\ Emission\ Rate) + ln(Heat\ Rate). \tag{2}$$

The heat rate inversely measures the thermal efficiency of electricity production process, which can be viewed as the efficiency component of emission intensity. The input emission rate inversely measures the effectiveness of emission control, which can be viewed as the non-efficiency component of emission intensity. To reduce the output emission rate, a firm can either invest in measures and technologies that improve production efficiency or invest in tools and methods that reduce emissions per unit of heat input.

From the private equity firm's perspective, the two alternative approaches have very different profit implications. The reduction of the heat rate means a decrease in fuel consumption rate, which saves production costs. Therefore, it not only boosts a plant's environmental performance, but also contributes directly to the gross margin of the plant. In other words, the societal benefits of cleaner production in this dimension are aligned well with private equity firms' profit motive. Therefore, we expect them to have strong incentives to reduce the heat rate. Given that private equity firms are known for their ability to improve operational efficiency (e.g., Davis et al. (2014)), we can also expect them to be able to make it happen. In contrast, investments in measures to reduce the input emission rate, while socially beneficial, are expenditures that reduce the short-term profits. Therefore, private equity firms may not be as willing to pursue. Based on these considerations, we hypothesize that private equity buyouts should lead to a reduction in the heat rate, which helps to reduce the output-scaled emissions, but their effect on the input emission rate is more ambiguous.

Obviously, technologies and measures that improve production efficiency are not free, otherwise they would have been implemented before private equity takes over. Therefore, we expect improvements to be more significant in situations where the previous plant owners are unwilling or unable to make costly investments. One example is the plants acquired through corporate divestiture deals. A divestiture is the disposal of assets or business units by a company, which often occurs when an asset or business unit is no longer viewed as the company's core competency or when the company is in financial distress. In either case, the company divesting a plant is unlikely to invest in the plant to improve production efficiency. Therefore, we expect the post-buyout improvements in efficiency and environmental performance to be stronger for plants acquired through corporate divestiture deals. Another example is small plants, which likely face financial constraints that prevent them from adopting the most up-to-date production technologies and emission control systems. Therefore, we also expect the buyout effect to be stronger for small target plants.

The strength of the buyout effect should also depend on the private equity firm's involvements in plant operations, which are likely to differ between an add-on deal and non-add-on deal (the latter is sometimes referred to a new-platform deal). In an add-on deal, instead of being directly bought out by private equity, the target is bought by a platform company that the private equity firm controls. Targets in those deals are often evaluated based on its value-added to the private equity firm's portfolio in a certain market sector instead of its standalone value. The platform company is also likely to have more influence than the private equity firm does over the target's post-buyout operations. As a result, we expect the private equity effect to be weaker for plants bought in add-on deals.

3 Data and Summary Statistics

3.1 Sample construction

3.1.1 Power plant emissions and operating data

We obtain the annual emissions and operating data of U.S. fossil fuel power plants from the Clean Air Markets Division (CAMD) of the Environmental Protection Agency (EPA). The regulations in Title 40 Code of Federal Regulations Part 75 establish requirements for large electricity generating units (i.e., those with nameplate capacity greater than 25 MW) burning fossil fuel(s) for sale to continuously measure emissions and report those measurements, along with operating data, to

EPA. EPA and state agencies use these data to assess compliance with emission trading programs and other air quality programs. EPA makes these data, collectively referred to as CAMD's Power Sector Emissions Data, publicly available on its website.

The CAMD data are at the electricity generating unit (EGU) level. An EGU means a combination of physically connected generator(s) and the associated apparatus whose electrical output can be separately identified and metered. An average power plant (or facility) in our sample has three EGUs. The key data items include the raw quantities of carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) emissions;[7] heat input; electricity generated, referred to as Gross Load in the database; owner and primary fuel type(s) of each unit. We exclude unit-years with missing emissions or electricity output data (including those with a recorded quantity of zero).[8] While we do most of our analysis at the EGU level, we also conduct some analysis at the plant level, and our matching of the treated and control plants are based on the plant-level data. We aggregate the data from the EGU to the plant level using the facility ID associated with each EGU. We record plant ownership at the year end and exclude units/plants with multiple owners at a given time (about 6% of the observations). While the emission data are available from 1995 to 2021, the ownership information is only available since 2003, so our sample period is from 2003 to 2021. Our final sample includes 4,181 unique EGUs in 1,340 plants owned by 1,007 owners, with a total of 56,575 annual observations.[9] In 2021, the gross electricity generation by the plants in our sample is 2.04 million GWh. According to U.S. Energy Information Administration (2022), the net electricity generation (i.e., generation excluding electricity used for power plant operations) from fossil fuels was about 2.51 million GWh in 2021. Assuming a commonly-used net-to-gross electricity generation ratio of 0.98, our final sample covers 80% of the U.S. electricity generation from fossil fuels in the last sample year.

[7]Coal-fired EGUs are also required to report mercury emissions. We do not include mercury emissions in our analysis because this item is only widely available for years after 2017.

[8]Most observations with missing electricity data are about units generating steam instead of electricity. A very small number of units generate both steam and electricity in a given year. We exclude those units as well to maintain the homogeneity of output.

[9]Since the name of the same plant owner may be recorded slightly differently in different years, we manually create an owner ID that is consistent across years.

3.1.2 Private equity buyout data

We construct our sample of power plants bought out by private equity using the December 2021 version of the Pitchbook database. We focus on the completed Buyout/LBO deals in the Private Equity deal class in which the target firm is headquartered in the U.S. We first match the target companies to plant owners by name in our emission data set using a fuzzy matching algorithm. We manually check the algorithm-generated matches to identify the correct matches, using deal- and plant-related information gathered from both databases and the internet. We then identify the plant(s) sold in each deal by reading the Pitchbook deal synopses and gathering more details from the internet. This is important because in some cases a deal may include only some plants of an owner, while in other cases a deal may include multiple plant owners (i.e., when a parent company of multiple owners is acquired). A plant can be bought by a private equity firm and sold to another multiple times. To examine the private equity treatment effect, we consider only a plant's first buyout deal, as the effect of subsequent ones are likely diminished.

Among the 1,340 power plants in our emission sample, we identify 131 that are bought out by private equity at least once, through 74 deals involving 84 plant owners. While all these plants are included in our DiD panel regressions, in our stacked DiD analysis, we require the treated plant to have data for at least two years before the buyout and one year after the buyout. There are 101 target plants with a total of 364 EGUs that meet this requirement. Figure 1 shows the breakdown of the number of private equity deals by year. The first deal occurred in 2003, which happens to coincide with the start year of our emission data.[10]

3.2 Variables and summary statistics

The raw emission quantities are measured in short tons, the heat input in million British thermal units (MBtu), and the electricity output in megawatt hours (MWh). We convert them into metric tons, billion British thermal units (BBtu), and gigawatt hours (GWh), respectively.[11] We scale the emissions by electricity produced to obtain our output emission rates CO_2/E, SO_2/E, and NO_x/E,

[10]There were a few power plant owners bought out by private equity before 2003 according to Pitchbook, but none of those acquired owners owned a plant in our final sample of emission data.

[11]One megawatthour is equal to 1,000 kilowatthours (kWh). According to the U.S. Energy Information Administration (EIA), the average annual electricity consumption for a U.S. residential utility customer was 10,632 kWh in 2021. One British thermal unit is defined as the amount of heat required to raise the temperature of one pound of water by one degree Fahrenheit.

measured in kilograms (kg) per MWh. We scale the emissions by heat input to obtain our input emission rates CO_2/H, SO_2/H, and NO_x/H, measured in kilograms per MBtu. We also scale the heat input by the electricity produced to obtain the heat rate H/E, expressed in MBtu per MWh (or equivalently, Btu/Wh). Because the emission rates and heat rate variables are highly skewed, we take the natural log of them in most of our analysis. One additional advantage of using the log rates is that it allows an additive decomposition of the output emission rate, as shown in Equation (2). We also use the non-logarithmized emission and heat rates for some of our analysis, in which case the rates are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers.

We sum the input, output and emissions across the EGUs to get the quantities at the plant level and calculate the corresponding ratios accordingly. We measure the plant age by the number of years since the start of commercial operation (based on the earliest start date across all EGUs in the plant). We drop the first operation year of each plant, as it is generally not a full year. We measure the growth of each plant by the log difference of electricity produced in two consecutive years. We also construct the output weight of each fuel type based on the weight of electricity generated by EGU(s) primarily fired by that type of fuel.

Panels A and B of Table 1 show the summary statistics at the EGU and plant levels, respectively. The definitions of the variables are summarized in Table A.1 in the Appendix. The average plant in our sample produces 1,988 GWh electricity annually, with the largest producing 25,400 GWh. The average plant age is 27, while the oldest one reaches age 86. 73% of EGUs in our sample use gas as the primary fuel, 21% use coal, and only 6% use oil, mixed, or other fuels. Both input and output emission rates show wide dispersions. For example, the CO_2 output emission rate at the EGU level ranges between 342kg and 1,339kg per MWh, with a mean of 676kg per MWh and a standard deviation of 220kg per MWh. The relative dispersions are even higher for the SO_2 and NO_x output emission rates: Their coefficients of variation (i.e., the ratios of the standard deviations to the means) are 2.5 and 1.4, respectively, compared to 0.33 for the CO_2 output emission rate.

4 Empirical Methodology

Following Gormley and Matsa (2011), Fracassi et al. (2022), and Sheen et al. (2022), we run stacked DiD regressions using matched samples to analyze the private equity buyout effect on emissions. Recent studies (e.g., Baker et al. (2022)) show that this method can estimate the treatment effect efficiently while circumventing the problems introduced by staggered treatment timing and treatment effect heterogeneity.

We match each private equity-acquired plant to a control plant based on year, state, and a Mahalanobis distance measure. The pool of potential controls includes all plants that have never been acquired by private equity. We require the control and treated plants to be located in the same state because emissions may be affected by state-specific emission and energy policies. To determine the variables that enter the calculation of the distance measure, we use linear probability models to examine the determinants of private equity's choice of buyout targets. Based on the estimated results, we calculate the Mahalanobis distance measure using the log electricity output, log plant age, and the level and slope of the log heat rate prior to the buyout.

Each pair of matched treated and control plants form a cohort, and all cohorts are stacked together for the DiD regressions. The baseline specification for our EGU-level regressions is:

$$y_{i,j,c,t} = \beta Treated_{j,c} \times Post_{t,c} + \gamma Controls_{i,j,c,t} + \lambda_{j,c} + \sigma_{t,c} + \epsilon_{i,j,c,t}, \tag{3}$$

where $y_{i,j,c,t}$ is the outcome variable for EGU i of plant j belonging to cohort c in year t; $Treated_{c,j}$ and $Post_{c,t}$ are dummy variables indicating the treated plants and post-buyout years, respectively; $\lambda_{j,c}$ and $\sigma_{t,c}$ are terms capturing plant and year fixed effects within each cohort, respectively. The plant-cohort fixed effects term $\lambda_{j,c}$ captures the difference in the outcome variables between the treated and control plants due to time-invariant plant characteristics within a cohort, while the year-cohort fixed effects term $\sigma_{t,c}$ captures the common variation within each year of a cohort. The main outcome variables of interest include the output and input emission rates and the heat rate. We cluster the standard errors by plant owner. If private equity buyout leads to a decline in an outcome variable, the coefficient on the interaction term Treated$\times$Post, β, should be significantly negative. Note that the dummy variables Treated and Post themselves are subsumed because we control for both plant-cohort and year-cohort fixed effects.

Considering the typical holding period of the private equity firms, we adopt an 11-year buyout event window for our baseline analysis, including the event year (0), five years before and five years after the event year. We require both the treated and control firms to have data at least in the two years before the buyout and in the first year after the buyout. We conduct various robustness checks using a different event window, a different treated-to-control ratio, and two different matching criteria.

We run similar regressions at the plant level. The EGU-level regressions give more weight to plants with more EGUs, because each EGU-year is an observation. This is not the case for the plant-level regressions, as data for all EGUs in the same plant are aggregated to the plant level. Furthermore, while EGUs with different production scales are treated in the same way in the EGU-level regressions, the plant-level variables are driven more by the large EGUs in the plant.

In addition to the stacked DiD regressions, we also run DiD panel regressions with high-dimensional fixed effects using the full sample. The baseline model specification is as follows:

$$y_{i,j,k,t} = \beta Post_{j,t} + \gamma Controls_{i,j,k,t} + \lambda_j + \sigma_k + \delta_{s,t} + \theta_{f,t} + \epsilon_{i,j,k,t}, \tag{4}$$

where $y_{i,j,k,t}$ is the year-t outcome variable for EGU i in plant j of owner k; $Post_{i,j,t}$ is a dummy variable that equals one for the post-buyout years of EGU i in treated plant j and zero for all other observations; λ_j, σ_k, $\delta_{s,t}$ and $\theta_{f,t}$ are plant fixed effects, owner fixed effects, year-by-state fixed effects, and year-by-fuel type fixed effects, respectively. Note that unlike in Equation (3), the dummy variable Post in Equation (4) can only be non-zero for treated EGUs. Therefore, it is identical to $Treated_j \times Post_{j,t}$. We double cluster the standard errors by plant owner and year. To focus on the years around the buyout event, we drop observations more than five years away (before or after) from the buyout year. Our DiD panel regression model (4) is in the style of the classical two-way fixed effects regression (TWFE) model, except that we control for more fixed effects. Compared to the stacked DiD regression approach, an advantage of this approach is that it does not rely on any specific matching method. The disadvantage is that like the standard TWFE models, it may give biased results due to staggered timing and treatment effect heterogeneity (e.g., Sun and Abraham (2021)).

5 Private Equity Buyout Effect: Stacked DiD Regressions

In this section, we present the results on the effect of private equity buyouts on power plant emission rates and production efficiency estimated from the stacked DiD regressions.

5.1 Characteristics of private equity-targeted plants

We first investigate what drives a plant's probability of being bought out by private equity. The answer to this question can not only give us insight into motives of private equity buyouts, but also inform us on the design of the matching criteria for our stacked DiD analysis.

We estimate several linear probability models using annual plant-level data. The dependent variable is equal to 100 if a plant is bought out by private equity in a given year and zero otherwise. The explanatory variables, which are all lagged by one year, include the log output emission rates of CO_2, SO_2 and NO_x, log heat rate, log plant age and log electricity output, annual growth of electricity output, and the output weights of EGU types classified by primary fuel. We leave out the output weight P(Other) to avoid perfect collinearity. Since we are interested in the first buyout deal of each target plant, we drop the observations after a plant is bought out by a private equity firm for the first time (i.e., we do not model the probability that an acquired plant is subsequently bought out by another private equity firm). Seven plants drop out of the sample due to the lack of pre-buyout data. As a result, the sample includes 1,333 unique plants, among which 117 plants are bought out by private equity. We control for year fixed effect and cluster the standard errors by plant owner.

Table 2 show the estimation results for six model specifications. The models show consistently that the buyout probability is negatively related to log plant age and positively related to log electricity output, suggesting that private equity is more interested in new and large plants. This does not support the idea that private equity extends the lifespan of old fossil plants by buying them from incumbents. None of the output emission rates are significantly related to the buyout probability, irrespective of whether they enter the model jointly (columns (1) and (2)) or separately (columns (3) to (5)). Nor is the heat rate or the output growth rate.[12] These results suggest that private equity does not filter targets by emission intensities of environmentally harmful gases, nor does it target plants struggling with low production efficiency or output growth. Columns (2) to (5) also show that plants primarily fired by gas and oil are more likely to become buyout targets than those fired by other fuels.

The results from these models suggest that the treatment and control groups in our DiD analysis

[12] We also run the regressions using input instead of output emission rates as the explanatory variables, the results are similar.

should be matched by log plant age and log electricity output. To enhance the comparability of the two groups, we also consider the logarithm of the average heat rate and the average change in the log heat rate in the years (up to three) prior to the buyout in our distance measure. The heat rate not only measures a plant's thermal efficiency, but also indirectly captures a plant's emission intensity, as it is positively related to the output emission rates of all gas types (due to Equation (2)). To account for correlations between the matching variables, we use the Mahalanobis distance measure.

For each of the 101 private equity-acquired plants, we select one control plant with an exact year and state match and the shortest Mahalanobis distance. Table 3 shows the comparison of the treatment and control groups in the year before the buyout. It shows that the two groups are comparable in all potentially relevant dimensions that are observable. None of the variables show a statistically significant difference betwen the two samples. This provides the foundation for our match-based DiD analysis.

5.2 Baseline stacked DiD regression results

Table 4 shows the results of the baseline stacked DiD regressions at the EGU level. In Panel A, we use the logarithms of output emission rates (columns (1) to (3), heat rate (column (4)) and input emission rates (column (4) to (7)) as the dependent variables. In Panel B, we use the winsorized raw rates as the dependent variables. We include the log EGU age, which is unlikely affected by the buyout, as a control variable.

The first three columns of Panel A show that the log output emission rates of both CO_2 and NO_x decrease significantly after the private equity buyout. The DiD coefficient on the interaction term Post$\times$Treated is -0.057 (with a t-statistic of -5.38) in column (1), suggesting that buyouts on average lead to a decline of the CO_2 output emission rate by 5.5% ($= 1 - e^{-0.057}$). Similarly, the estimate of the same coefficient is -0.084 (with a t-statistic or -2.26) in column (3), suggesting private equity buyouts on average lead to an 8.1% decline in the NO_x output emission rate. These effects are economically large. The estimate of the DiD coefficient for the log output emission rate of SO_2 is of a similar magnitude, but it is not statistically significant, potentially due to the large variability of this variable, as shown in Table 1.

Another way to assess the economic magnitudes of these effects is to express them in terms of the standard deviation. The standard deviations of $\ln(CO_2/E)$ and $\ln(NO_x/E)$ are 0.357 and 1.426, respectively, in the full sample. The coefficient estimates above suggest that private equity buyouts reduce $\ln(CO_2/E)$ by 0.16 standard deviations and reduce $\ln(NO_x/E)$ by 0.06 standard deviations. This explains why the *t*-statistic for the DiD coefficient estimates is smaller in column (3) than in column (1).

Equation (2) implies that the decline in the log output emission rate is the sum of the declines in the log heat rate and log input emission rate. Columns (4) to (7) show that the post-buyout reductions in the log output emission rates of CO_2 and NO_x are mainly due to the decline of the log heat rate ($\ln(H/E)$). Private equity buyouts on average lead to a decline of the heat rate by 5.2% (column (4)), but they have no significant effect on the input emission rate of any of the three types of gases. Thus, the post-buyout improvements in output-scaled CO_2 and NO_x emissions are mostly due to an increase in production efficiency, which reduces the heat input required for each unit of electricity output. They are not due to more effective emission control measures that reduce emissions per unit of heat input. This supports the hypothesis we propose in Section 2, and is consistent with the profit motive of private equity firms. An increase in production efficiency reduces both fuel costs and environmentally harmful emissions. Therefore, private equity firms have a strong incentive to pursue it. In contrast, while measures used to reduce the input emission rates are beneficial to the environment, they are a deduction from the bottom line of income statement. Therefore, private equity firms have less incentive to undertake them.

Panel B of Table 4 show similar results in terms of the raw emission rates and heat rate. The point estimates in column (1) and (3) suggest that buyouts on average reduce CO_2 and NOX_x emissions by 32.418kg and 0.042kg, respectively, for each MWh of electricity produced. Column (4) shows that buyouts reduce the heat input by 0.503 MBtu for each MWh of electricity produced. These numbers are equivalent to 15%, 4.5%, and 22% of the standard deviations of the corresponding variables in the full sample, which further suggest that the buyout effect is economically large. As in Panel A, there is no statistically significant buyout effect on the raw SO_2 output emission rate and any of the raw input emission rates.

The key identifying assumption for our DiD analysis is that the outcome variables for both the treated and control plants follow parallel trends in the absence of the buyout. To test whether this assumption holds for the pre-buyout years and examine the dynamics of the buyout effect, we modify Equation (3) to allow the coefficient on the interaction term to vary across the event-time years. Specifically, we create a dummy variable for each event-time year in the 11-year window and replace the interaction term in (3) by the interactions of the Treated dummy with all the event-time year dummies. That is, we estimate the following generalized DiD model:

$$y_{i,j,c,t} = \Sigma_{\tau=-5}^{\tau=5} \beta_\tau Treated_{j,c} \times T(\tau)_{t,c} + \lambda ln(Age)_{i,j,c,t} + \delta_{t,c} + \theta_{i,c} + \varepsilon_{i,c,t}, \tag{5}$$

where $T(\tau)_{t,c}$ is a dummy variable that equals 1 for EGUs in the bought-out plants in year τ relative to the buyout year and zero for all other observations. We use the year $\tau = -1$ is as the base year, and plot the coefficients on the interaction terms in Figure 2 for the models of the output emission rates and heat rate. All the four panels in the figure show that the coefficients for the pre-buyout years are largely flat, in support of the parallel trend assumption and our empirical design. Panel (A) and (D) show, respectively, a significant decline in ln(CO_2/E) and ln(H/E) starting from the first year after the buyout. Panel B shows a temporary drop in ln(SO_2/E) in the first two post-buyout years, which was reversed subsequently. Panel (C) shows a steady decline in ln(NO_x/E) starting from buyout year. These patterns are consistent with the results reported in Table 4.

5.3 Exploring the mechanisms

5.3.1 Within-EGU improvements vs. EGU composition effect

The post-buyout reductions in the CO_2 and NO_x emission rates and heat rate can be due to either improvements of existing EGUs or the change in the EGU composition (by the retirement of old EGUs and the installation of new EGUs). To examine which force is more important, we extend the baseline model specification (3) by controlling for EGU-cohort fixed effects, which subsume the less granular plant-cohort fixed effects. This allows us to identify the within-EGU effects of private equity buyouts. If private equity mainly improves the performance of existing EGUs through, for example, software or equipment upgrades, or more efficient planning and operating procedures, then the results should be largely the same irrespective of whether we control for plant-cohort or EGU-cohort fixed effects. In contrast, if private equity improves the output emission rates and production efficiency by retiring old and inefficient EGUs and installing new and efficient ones, the buyout effect should diminish after controlling for the EGU-cohort fixed effects.

Table 5 shows the results from the extended model for the log rates. The results are very close to those in Table 4. The DiD coefficient estimates in the models for $\ln(CO_2/E)$, $\ln(NO_x)$ and $\ln(H/E)$ shrink by 7%, 18% and 8%, respectively, in magnitude, and all of them remain statistically significant. This suggests that a large majority of the private equity buyout effect we uncover in the baseline model comes from improvements of existing EGUs instead of the change in the EGU composition. As we show below, EGU retirements and installations are rare for both the treated and the control plants, and there is not significant private equity buyout effect on the probabilities of these events.

5.3.2 Production scale and other aspects of plant operations

The post-buyout decrease in output emission rate and heat rate may also be due to an increase in production scale. To examine this possibility, we extend the baseline model by controlling for log electricity output. The results reported in Panel B of Table 5 show that output scale is indeed negatively related to the CO_2 and NO_x output emission rates and heat rate. But its ability to explain the buyout effect on CO_2 output emission rate and heat rate is rather minor. Compared to the baseline results in the Panel A of Table 4, the DiD coefficient estimates shrink only by 9% and 19%, respectively, for $\ln(CO_2/E)$ and $\ln(H/E)$, and they remain statistically significant at the 1% level. Output scale has more explanatory power for the effect on $\ln(NO_x/E)$, which shrinks by 38% and becomes statistically insignificant.

In Panel C of Table 5, we examine the effect of private equity buyouts on various aspects of plant operations, including total output, input, operating time (OPT), hourly output and input (E/OPT and H/OPT), capacity factor (CapFactor), and EGU retirement. The first three columns show that private equity buyouts do not significantly affect the total output, input and operating hours at the EGU level. However, they increase the hourly electricity output by 3.9% (column (4)) while decreasing the hourly input by 1.2% (column (5)), although the latter effect is statistically insignificant. This is further evidence for the positive buyout effect on production efficiency. Column (6) shows that EGUs operate at a lower capacity factor after the buyout, which is consistent with the finding of Andonov and Rauh (2022), suggesting that private equity does not operate EGUs more intensively. The last column shows whether private equity buyouts affect the EGU retirement. Since the retirement includes plant closure, which can only happen at the end of a plant's lifespan, we do not control for plant-cohort fixed effect. As a result, the dummy variable Treated is no subsumed.[13] The result shows that private equity ownership has no effect on the retirement decision. Therefore, private equity firms are not more likely to extend EGU lifespans than are other owners. This is also largely consistent with the finding of Andonov and Rauh (2022).

5.3.3 Subsample analysis

To gain further insight into the mechanisms behind the private equity buyout effect on emission intensity and production efficiency, we examine how the effect varies across various subsamples using triple DiD regressions.

Corporate divestiture vs. other deals. We hypothesize in Section 2 that the post-buyout efficiency and environmental performance improvements should be more pronounced in plants acquired through corporate divestiture deals because the divesting companies are likely unwilling or unable to invest in those plants. To test this hypothesis, we extend the baseline specification by adding a three-way interaction term, Post$\times$Treated$\times$Divestiture, where Divestiture is a dummy variable that equals one for cohorts in which the treated plants are acquired in a divestiture deal and zero for other cohorts.[14] 46 out of the 101 acquired plants used in our stacked DiD analysis are bought out via corporate divestiture deals, involving 172 EGUs (out of 364 in total).

The results from the triple DiD regressions are presented in Panel A of Table 6. The coefficient estimates on the three-way interaction term are negative in all seven columns, and they are statistically significant in column (1) and (4) (with t-statistics of -2.75 and -2.55, respectively). The point estimates in column (3) reveal that while the heat rate for EGUs acquired in other deals declines by 2.4% after the buyout, it declines by 7.0% ($= 1 - e^{-0.024-0.049}$) for EGUs acquired in corporate divestiture deals. Accordingly, column (1) shows that the post-buyout CO_2 output emission rate declines by 2.4% (7.8%) for non-divestiture (divestiture) deals. This demonstrates that the buyout effect is indeed more significant for plants acquired in corporate divestiture deals. It supports the idea that the post-buyout improvements in plant performance arises because the acquiring private equity firms have stronger incentives and more financial resources to invest in the plants than the

[13] Specifically, we identify whether an EGU is retired by checking whether it is included in the August 2022 version of the Power Sector Emission Data. If not, then we record the last year of an EGU's appearance as its retirement year. There are a total of 25 EGU retirements in our matched samples. 11 of them coincide with plant closure (note that we only require plants to have data for at least one post-buyout year.)

[14] Like the variables Post and Treated, the variables Divestiture, Divestiture$\times$Post, Divestiture$\times$Treated are subsumed in the triple DiD regressions.

divesting companies do.

Small vs. large target plants. We also hypothesize that the private equity buyout effect should be more significant for small plants because those plants may not have the financial resources needed to adopt the up-to-date technologies and measures. To test this hypothesis, we classify the 101 acquired plants used in our stacked DiD analysis into two groups based on their pre-buyout electricity output. We create a dummy variable, Large, that equals one for the cohorts in which the treated plant's pre-buyout output is above the median. We run the same type of triple DiD regressions as above.

The results reported in Panel C of Table 6 support our hypothesis. The coefficient estimates on interaction term Post$\times$Treated are negative in all seven columns, and they are statistically significant except in the last column. This suggests that private equity buyouts reduce the output emission rates of small plants not only by increasing production efficiency, but also by reducing the input emission rates. However, the negative coefficient Post$\times$Treated is fully reversed for large plants in column (2), (5), and (6), suggesting that private equity buyouts of large plants do not reduce the SO_2 output emission rate or the input emission rate of any gas. The larger buyout benefits observed in small plants indicate that private equity may improve plant performance by easing the financial constraints of the acquired plants.

Add-on deals vs. non-add-on deals. Lastly, we hypothesize in Section 2 that the private equity buyout effect should be weaker for plants bought in add-on deals because the operations of those plants may be more influenced by the platform company used by the private equity firm to acquire them than by the private equity firm itself. To test this hypothesis, we extend the baseline specification by adding a three-way interaction term, Post$\times$Treated$\times$Add-On, where Add-On is a dummy variable that equals one for cohorts in which the treated plants are acquired in an add-on deal and zero for other cohorts. 28 out of the 101 acquired plants used in our stacked DiD analysis are bought out via add-on deals, involving 73 EGUs.

The results from the triple DiD regressions are presented in Panel C of Table 6. Strikingly, the coefficient estimates on Post$\times$Treated are negative in all columns, and they are statistically significant except in columns (5) and (7), suggesting that non-add-on buyout deals reduce the output emission rates of all gases, as well as the heat rate and SO_2 input emission rate. However, the coefficient estimates on Post$\times$Treated$\times$Add-On are positive in all columns, which largely offsets or fully reverses the negative coefficients on Post×Treated. Indeed, if we only consider add-on deals in our DiD regressions, we do not find significant reductions in any emission rate or heat rate after the buyout. Instead, there are significant increases by 20% and 22%, respectively, in the SO_2 output and input emission rates. Therefore, the beneficial private equity buyout effects are purely driven by non-add-on deals, suggesting that direct and active involvements of private equity firms in plant operations are important for post-buyout improvements in plant performance.

5.4 Robustness checks

We perform a set of robustness checks on our main results using an alternative event window, an alternative treated-control ratio, an additional matching condition, and a different distance measure. The results from these additional tests, which are reported in Table 7, further show that private equity buyouts make power plants more efficient and cleaner, confirming the robustness of our baseline results.

5.4.1 An alternative event window

In our baseline analysis, we use an 11-year event window, which implicitly assumes that private equity firms hold the acquired plants for five years. Some private equity firms may exit earlier. Therefore, our first robustness check is to use a shorter event window of seven years, from $t-3$ to $t+3$. The results, reported in Panel A of Table 7, are even stronger than those in Table 4. Not only do the CO_2 and NO_x output emission rates and heat rate drop significantly after the buyout, but so do the SO_2 output and input emission rates, consistent with what is shown in Figure 2.

5.4.2 An alternative treated-control ratio

In our baseline analysis, we match each private equity-acquired plant to one control plant. This maximizes the comparability of the treated and control plants. As another robustness check, we match each treated plant to up-to four control plants, using the same matching criteria. This increases the statistical power of our tests, at the expense of losing some comparability. Panel B of Table 7 shows the results. They are largely the same as those in Table 4, with the exception that now the input emission rate of NO_x also shows a significant drop after the buyout (column (7)).

5.4.3 An additional matching condition

In our baseline analysis, we require the treated and control plants to be matched by year and state, in addition to having the shortest Mahalanobis distance. Additionally, one may also require matching of the primary fuel type. To implement this condition, we classify plants into different fuel types based on the type with the highest output weight, where the weight of each fuel is calculated using the output of EGUs fired by that fuel. For example, if the EGUs listing multiple fuels as primary fuels contribute most to a plant's output, the plant is designated as a mixed-fuel plant.[15] We then select the shortest-distance control for each treated plant only among those that are exactly matched by year, state, and fuel type. Four treated plants drop out of the estimation as no match can be found for them. The results based on this alternative matching approach are presented in Panel C of Table 7. They are qualitatively and quantitatively similar to the baseline results reported in Table 4.

5.4.4 An alternative distance measure

The Mahalanobis distance we calculate in our baseline analysis is based on the log electricity output, log plant age, and the level and slope of the log heat rate prior to the buyout. As an alternative, we use the logarithms of the average $CO2_2/E$, average $SO2_2/E$, and average NO_x/E in up-to-three pre-buyout years, as well as the average changes of $\ln(CO2_2/E)$, $\ln(SO2_2/E)$, and $\ln(NO_x/E)$ in those years to calculate the Mahalanobis distance measure. The results based on this alternative distance measure are reported in Panel D of Table 7. They are similar to those in Table 4 except that the buyout effect on the output and input emission rates of NO_x are stronger.

5.5 Stacked DiD regressions at the plant level

While we focus primarily on the EGU-level data in our analysis, which provide more power due to more observations, we perform a similar analysis using the plant level data. The results from the plant-level stacked DiD regressions are presented in Table 8. Panel A shows the estimates from the baseline model specification. Consistent with the EGU-level baseline results, there are statistically significant drops in both the CO_2 output emission rate and heat rate after the buyout. The magnitudes of these drops are very close to each other (both about 3.9%), suggesting that

[15]If none of the single fuel type contributes more than 80% of a plant's output, we also designate the plant as a mixed-fuel plant.

the drop in the CO_2 output emission is almost completely due to the improvement in production efficiency. These magnitudes are slightly smaller than those estimated from the EGU-level data. Another notable difference is that buyouts do not seem to have a significant effect on the NO_x output emission rate at the plant level.

The difference between the EGU-level and plant-level results can arise from multiple sources. First, the EGU-level regressions give more weights to plants with more EGUs. If the private equity buyout effect is stronger in plants with more EGUs, then the EGU-level results will be stronger than the plant-level results. Consistent with this interpretation, if we weight the observations by the number of EGUs a plant has in the plant-level regressions, the results are closer to those obtained from the EGU-level regressions. Specifically, the coefficient estimates on Post×Treated are -0.048, -0.045 and -0.048 in columns (1), (3) and (4), respectively. Another possible reason for the difference is that the EGU-level regressions treat each EGU within a plant equally, while the plant-level variables are driven by EGUs with larger sizes. If the buyout effect is stronger for smaller EGUs, the plant-level results will be weaker than the EGU-level results. However, this does not seem to be the case, because the plant-level results do not get stronger if we calculate the plant-level variables using simple averages across EGUs.

In Panel B, we control for log electricity output. As in the EGU-level regressions, this only has very minor effects on the estimates of the DiD coefficient. In Panel C, we examine whether private equity buyouts have a significant scale effect measured by aggregate electricity output, heat input, the number of EGUs in the plant, and emission volumes at the plant level. None of these variables changes significantly after the buyout, although the point estimates suggest a larger increase in output relative to heat input and emissions. This further suggests that the private equity buyout effect on production efficiency and emission intensity is not due to an expansion of production scale.

To summarize, our stacked DiD regressions using EGU-level data show that private equity buyouts lead to significant declines in the CO_2 and NO_x output emission rates. The declines are mainly caused by the increase in production efficiency, which reduces the heat input per unit of electricity output, instead of more effective emission control. They occur primarily via improvements of existing EGUs instead of changes in the EGU composition. The beneficial effects of private equity buyouts on environmental performance are stronger for small plants and plants acquired through corporate divestiture deals, and they are concentrated in non-add-on deals. These results suggest that private equity improves power plants' environmental performance by investing in production technologies that facilitate both cost saving and emission reduction. They also suggest the private equity firms are less willing to make environmentally beneficial investments that are less aligned with the profit motive.

6 Results From DiD Panel Regressions

Our match-based DiD analysis in Section 5 is suited for identifying the private equity buyout effect as it mitigates potential biases due to staggered timing and treatment effect heterogeneity. However, its reliance on matching leads to the concern that it may not be robust to other plausible matching criteria, even though we have conducted multiple robustness checks. In this section, we complement our previous analysis by running DiD panel regressions using all EGU-level observations (except the observations of the treated plants outside the 11-year buyout event window). Instead of relying on matching, we control for a host of fixed effects. Specifically, we estimate Equation (4) and its variations.

Table 9 presents the results. Panel A corresponds to the baseline model specified in Equation (4). The results are very similar to those from the stacked DiD regressions reported in Table 4. The point estimates imply that private equity buyouts reduce the CO_2 and NO_x output emission rates by 4.4% and 8.7%, respectively, and they reduce the heat rate by 4.2%. Furthermore, they have no significant effect on the input emission rate of any gas.

To assess the dynamic effect of the private equity buyout and the pre-event trends, we estimate the following generalized model for the log output emission rates and log heat rate:

$$y_{i,j,k,t} = \Sigma_{\tau=-5}^{t=5} \beta_\tau T(\tau)_{j,t} + \gamma ln(Age)_{i,j,k,t} + \lambda_j + \sigma_k + \delta_{s,t} + \theta_{f,t} + \epsilon_{i,j,k,t}, \tag{6}$$

where $T(\tau)_{j,t}$ is a dummy variable equal to one for EGUs in the bought-out plants in year τ relative to the buyout year (year 0) and zero for all other observations. The other terms in the equation are the same as those in (4). We use the year $\tau = -1$ as the base year, and plot the coefficients β_τ in Figure 3. Panels (A), (C) and (D) show significant declines in the log output emission rates of CO_2 and NO_x and log heat rate after the buyout. While the pre-event trends are not as flat as in Figure 2, they are largely consistent with the parallel trend assumption.

In Panel B, we explore within-EGU variation by controlling for the EGU instead of the plant fixed effects, and the coefficient estimates show little change. Consistent with our findings in Table 5, the private equity buyout effect comes almost exclusively from within-EGU variation. In Panel C, we add ln(Electricity) to the benchmark model as an additional control. The DiD coefficient estimates on *Post* drop in magnitude by 15%, 25%, and 14%, respectively, in the models of ln(CO_2/E), ln(NO_x/E), and ln(H/E). Consistent with our results from the stacked DiD regressions, changes in outputs scale only explain a small fraction of the private equity buyout effect.

7 Conclusion

We study the effect of private equity ownership on firms' environmental performance using emission data from U.S. fossil fuel power plants. We isolate an efficiency component of emission intensity and examine the private equity effect separately for the efficiency and non-efficiency components. Our difference-in-difference analysis at the EGU level shows that private equity buyouts lead to significant declines in output-scaled CO_2 and NO_x emissions. The declines in the output emission rates are mainly due to an increase in production efficiency, which reduces the heat input for each unit of electricity output. They occur primarily via improvements of existing EGUs instead of changes in the EGU composition. Private equity buyouts have little effect on input emission rates except when the acquired plants are relatively small, nor do they significantly change the power plants' production scales or retirement decisions. Furthermore, we find the private equity buyout effect to be stronger in plants acquired through corporate divestiture deals, in which the prior plant owners may be unwilling or unable to make costly investments for plant improvements. We also find that the beneficial effect of private equity buyouts is concentrated in non-add-on buyout deals, which is consistent with the idea that private equity firms may have more limited influence on the operations of plants acquired indirectly via platform firms.

Overall our results suggest that private equity firms improve power plants' environmental performance by investing in production technologies that facilitate both cost saving and emission reduction, but they are less willing to invest in emission reduction measures that are socially beneficial but privately costly. As an emitter contributing 30% of the U.S. CO_2 emissions, the power sector is at the center of many environmental policy debates. Many U.S. states have committed to the goal of switching to 100% carbon-free electricity by 2050 or earlier. Some advocacy groups are highly critical about the increasing presence of private equity in the power sector. Our findings suggest that private equity firms on average bring positive effect to the plants they take over, although more research in needed to fully understand their role in the transition to carbon-free electricity. Since firms in the power sector are monitored closely by regulators, the extent to which our results can be extended to other industries is an interesting question for future research.

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Appendix

Table A.1: Variable definitions

This table summarizes the variable definitions. The non-logarithmized heat rate (H/E), output emission rates (CO_2/E, SO_2/E, NO_x/E), input emission rates (CO_2/H, SO_2/H, NO_x/H), and the capacity factor (CapFactor) are winsorized at the 1st and 99th percentiles.

Variable	Description
Acquired	A dummy variable that equals 100 if a plant is bought out by PE in a given year and 0 otherwise.
Treated	A time-invariant dummy variable that equals 1 for plants bought out by PE and 0 for other plants.
Post	A dummy variable that equals 1 for the post-buyout years and 0 for other years.
Electricity (GWh)	Gross electricity generated in a year, in gigawatt hour (GWh).
Age_P (year)	Plant age, measured as the number of years since a plant's first commercial operation date.
Heat Input (BBtu)	Quantity of heat input, calculated by multiplying the quantity of fuel by the fuel's heat content, in billion British thermal unit (BBtu).
CO_2 (metric ton)	Emitted carbon dioxide mass in metric tons.
SO_2 (metric ton)	Emitted sulfur dioxide mass in metric tons.
NO_x (metric ton)	Emitted nitrogen oxides mass in metric tons.
H/E (MBtu/MWh)	Heat input in million British thermal unit (MBtu) per megawatt hour (MWh) electricity generated, an inverse measure of thermal efficiency.
CO_2/E (kg/MWh)	CO_2 emissions (in kilogram) per MWh electricity generated.
SO_2/E (kg/MWh)	SO_2 emissions (in kilogram) per MWh electricity generated.
NO_x/E (kg/MWh)	NO_x emissions (kilogram) per MWh electricity generated.
CO_2/H (kg/MBtu)	CO_2 emissions (in kilogram) per MBtu heat input.
SO_2/H (kg/MBtu)	SO_2 emissions (in kilogram) per MBtu heat input.
NO_x/H (kg/MBtu)	NO_x emissions (in kilogram) per MBtu heat input.
Growth	The log difference between the electricity generated in two consecutive years.
P(Gas)	Weight of electricity generated by units using natural or process gas as the primary fuel. Other fuel weight variables *P(Coal)*, *P(Oil)*, *P(Mixed)*, and *P(Other)* are defined similarly.
N_Unit	The number of electricity generating units (EGUs) a plant has.
Age_U	EGU age, measured by the number of years since an EGU starts its commercial operation.
D(Gas)	A dummy variable that equals one if an EGU uses gas as the primary fuel. Other fuel type dummy variables *D(Coal)*, *D(Oil)*, *D(Mixed)*, and *D(Other)* are defined similarly.
OPT (hour)	The total number of hours an EGU is operating in a year.
E/OPT (GWh/hour)	The average amount of electricity generated (in GWh) by an EGU per operating hour.
H/OPT (BBtu/hour)	The average heat input used (in BBTu) by an EGU per operating hour.
CapFactor)	Capacity factor, defined as the hourly heat input divided by the design heat input capacity for an EGU or the highest hourly heat input rate observed in the past five years, whichever is greater.
Retirement	A dummy that equals 1 if an EGU ceases to operate and 0 otherwise.
ln(X)	The natural logarithm of any variable X.

Table 1: **Summary statistics: Full sample**

Panel A shows the summary statistics of our sample at the electricity generating unit (EGU) level, including the mean, standard deviation (sd), minimum (min), median (p50), maximum (max), and the number of observations of each variable. Panel B shows the summary statistics for selected variables at the plant level. The sample is constructed using the annual CAMD Power Sector Emissions Database from 2003-2021. Only plants with a single owner at the year end are included. The full sample consists of 4181 EGUs at 1340 electric power plants owned by 1007 owners. Variable definitions are provided in Table A.1.

Panel A. Summary statistics at the EGU level

	mean	sd	min	p50	max	count
Electricity	681.210	1,094.616	0.000	148.808	11,347.775	56,575
Heat Input	6,228.952	10,116.858	0.019	1,602.435	105,802.336	56,575
Age_U	23.186	18.025	0.000	17.000	75.000	56,575
CO_2/E	676.158	219.794	342.406	626.163	1,339.026	56,575
SO_2/E	0.885	2.254	0.002	0.003	12.590	56,575
NO_x/E	0.673	0.923	0.018	0.317	5.058	56,575
H/E	10.647	2.304	6.378	10.613	18.477	56,575
CO_2/H	63.472	16.316	53.092	53.916	96.656	56,575
SO_2/H	0.084	0.218	0.000	0.000	1.224	56,575
NO_x/H	0.058	0.073	0.002	0.030	0.354	56,575
OPT	3,287.292	3,072.908	0.250	1,971.940	8,784.000	56,575
E/OPT	0.136	0.139	0.000	0.090	1.359	56,575
H/OPT	1,307.598	1,263.113	11.199	977.872	13,088.797	56,575
ln(CO_2/E)	6.466	0.357	0.940	6.440	19.283	56,575
ln(SO_2/E)	-3.994	2.905	-9.712	-5.703	13.054	56,575
ln(NO_x/E)	-1.250	1.426	-5.359	-1.150	13.006	56,575
ln(H/E)	2.344	0.258	-0.890	2.362	14.750	56,575
ln(CO_2/H)	4.121	0.241	-1.633	3.987	6.340	56,575
ln(SO_2/H)	-6.338	2.872	-11.611	-8.201	1.033	56,575
ln(NO_x/H)	-3.595	1.308	-7.762	-3.503	-0.239	56,575
ln(OPT)	7.197	1.712	-1.386	7.587	9.081	56,575
ln(E/OPT)	-2.431	0.967	-13.077	-2.403	0.307	56,575
ln(H/OPT)	6.821	0.855	2.416	6.885	9.480	56,575
CapFactor	0.661	0.167	0.205	0.689	1.005	56,524
Retirement	0.008	0.090	0.000	0.000	1.000	56,575
D(Gas)	0.728	0.445	0.000	1.000	1.000	56,575
D(Coal)	0.211	0.408	0.000	0.000	1.000	56,575
D(Oil)	0.057	0.232	0.000	0.000	1.000	56,575
D(Other)	0.002	0.046	0.000	0.000	1.000	56,575
D(Mixed)	0.002	0.043	0.000	0.000	1.000	56,575

Panel B. Summary statistics at the plant level

	mean	sd	min	p50	max	count
Electricity	1,987.596	3,056.506	1.001	658.661	25,400.309	19,390
Heat Input	18,174.470	27,847.674	7.801	6,577.462	226,548.004	19,390
Age_P	27.427	19.754	1.000	20.000	86.000	19,390
CO_2	1,411,444.009	2,503,767.536	40.551	404,172.008	21,086,791.500	19,390
SO_2	3,064.356	10,326.598	0.003	3.794	187,283.797	19,390
NO_x	1,250.350	3,134.036	0.064	100.427	41,207.633	19,390
CO_2/E	674.851	227.877	345.822	618.151	1,334.756	19,390
SO_2/E	0.961	2.302	0.002	0.003	12.733	19,390
NO_x/E	0.612	0.750	0.018	0.323	3.879	19,390
H/E	10.319	2.118	6.436	10.366	17.221	19,390
CO_2/H	65.143	17.370	53.238	53.916	98.767	19,390
SO_2/H	0.093	0.226	0.000	0.000	1.275	19,390
NO_x/H	0.056	0.066	0.002	0.031	0.318	19,390
$\ln(CO_2/E)$	6.458	0.353	0.940	6.427	8.754	19,390
$\ln(SO_2/E)$	-3.785	3.008	-8.214	-5.699	3.889	19,390
$\ln(NO_x/E)$	-1.293	1.410	-5.000	-1.129	2.893	19,390
ln(H/E)	2.314	0.225	-0.775	2.338	4.324	19,390
$\ln(CO_2/H)$	4.144	0.256	-1.633	3.987	6.340	19,390
$\ln(SO_2/H)$	-6.099	2.975	-10.893	-8.198	0.988	19,390
$\ln(NO_x/H)$	-3.607	1.301	-7.292	-3.484	-0.239	19,390
Growth	-0.012	0.575	-1.984	-0.008	1.818	17,815
P(Gas)	0.703	0.452	0.000	1.000	1.000	19,390
P(Coal)	0.255	0.432	0.000	0.000	1.000	19,390
P(Oil)	0.035	0.178	0.000	0.000	1.000	19,390
P(Other)	0.004	0.064	0.000	0.000	1.000	19,390
P(Mixed)	0.002	0.041	0.000	0.000	1.000	19,390
N_Unit	2.918	2.313	1.000	2.000	24.000	19,390

Table 2: **Determinants of the private equity buyout probability**

We estimate linear probability models to examine what drives a power plant's probability of being acquired by private equity firms. The dependent variable is equal to 100 if a plant is bought out by private equity in a given year and zero otherwise. All explanatory variables are lagged by one year. Observations for post-buyout years are dropped from the sample (i.e., only the first buyout deal of each target firm is considered). The sample includes 1333 unique plants, among which 117 plants are bought out by private equity. All variables are defined in Table A.1. Standard errors are clustered by plant owner. We report t-statistics in parenthesis, with statistical significance levels of 10%, 5%, and 1% indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Acquired	Acquired	Acquired	Acquired	Acquired	Acquired
$\ln(CO_2/E)$	-0.783	0.264	0.582			
	(-1.47)	(0.73)	(1.64)			
$\ln(SO_2/E)$	-0.019	0.016		0.050		
	(-0.36)	(0.24)		(0.85)		
$\ln(NO_x/E)$	0.100	0.125			0.163	
	(1.03)	(1.26)			(1.64)	
ln(H/E)	1.189	0.138				0.649
	(1.63)	(0.24)				(1.44)
ln(Age_P)	-0.380***	-0.397***	-0.320***	-0.310***	-0.391***	-0.323***
	(-3.88)	(-4.03)	(-3.29)	(-2.94)	(-4.09)	(-3.36)
ln(Electricity)	0.099*	0.127**	0.102**	0.068*	0.110**	0.105**
	(1.96)	(2.30)	(2.23)	(1.67)	(2.17)	(2.18)
Growth	-0.004	-0.015	-0.004	0.012	-0.010	-0.006
	(-0.04)	(-0.12)	(-0.03)	(0.10)	(-0.09)	(-0.05)
P(Gas)		1.388***	1.369***	0.981***	1.093***	1.074***
		(3.49)	(3.20)	(3.41)	(3.66)	(3.69)
P(Coal)		0.420	0.511**	0.215	0.338*	0.530**
		(1.57)	(2.26)	(0.95)	(1.66)	(2.21)
P(Oil)		1.464***	1.527***	1.103**	1.294***	1.353***
		(2.71)	(2.97)	(2.51)	(2.80)	(2.93)
P(Mixed)		0.690**	0.782***	0.385	0.560**	0.680***
		(2.35)	(2.77)	(1.60)	(2.44)	(2.65)
Constant	3.525	-1.894	-3.943	0.542	0.436	-1.493
	(1.46)	(-0.93)	(-1.44)	(1.18)	(1.02)	(-1.03)
Observations	16690	16690	16690	16690	16690	16690
R^2	0.007	0.007	0.007	0.007	0.007	0.007
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: **Comparison between the treated and control plants**

The first column shows the mean values for the private equity-acquired plants in the year prior to the buyout. The second column shows the mean values for the matched control plants. The third column shows the mean difference between the two groups. The last column shows the t-statistics for the t-tests of equal group means. For each acquired plant, we find a control plant matched by the state, year, and a Mahalanobis distance measure calculated using log plant age and log electricity output in the pre-buyout year, the logarithm of the average heat rate and the average change in the log heat rate in up-to-three pre-buyout years. All variables are defined in Table A.1.

	mean(Treated)	mean(Control)	Difference	t-stat
Electricity	1381.534	1208.814	172.720	0.75
Age_P	18.822	18.436	0.386	0.16
CO_2/E	595.804	604.224	-8.420	-0.30
SO_2/E	0.213	0.231	-0.018	-0.17
NO_x/E	0.389	0.297	0.092	1.28
H/E	10.119	10.069	0.050	0.17
CO_2/H	57.876	59.391	-1.514	-0.89
SO_2/H	0.020	0.022	-0.002	-0.15
NO_x/H	0.035	0.028	0.008	1.26
Growth	0.025	0.114	-0.088	-1.04
P(Gas)	0.886	0.866	0.021	0.45
P(Coal)	0.069	0.124	-0.055	-1.34
P(Oil)	0.045	0.011	0.034	1.55
P(Other)	0.000	0.000	0.000	.
P(Mixed)	0.000	0.000	0.000	.
N_Unit	3.040	2.921	0.119	0.40
Observations	101	101		

Table 4: **Private equity buyout effect: Baseline stacked DiD regressions**

This table shows the EGU-level stacked DiD regression results using matched samples of treated and control plants. The dependent variables are the natural logarithms of output emission rates (CO_2/E, SO_2/E, NO_x/E), heat rate (H/E), and input emission rates (CO_2/H, SO_2/H, NO_x/H) in Panel A, and the winsorized raw emission rates and heat rate in Panel B. Each acquired plant is matched to a control plant based on year, state, and a Mahalanobis distance measure. The event window is 11 years, from t-5 to t+5, with t=0 being the buyout year. Post is a dummy variable equal to one for the post-buyout years and zero for other years. Treated is a dummy variable equal to one for acquired plants and zero for control plants. All models include plant-cohort and year-cohort fixed effects. Regression constants are not reported. Standard errors are clustered by plant owner, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Log emission rates and heat rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.057***	-0.052	-0.084**	-0.053***	-0.004	0.001	-0.031
	(-5.38)	(-1.10)	(-2.26)	(-5.33)	(-1.13)	(0.02)	(-0.92)
ln(Age_U)	0.044	0.016	0.780***	0.015	0.029	0.001	0.765***
	(0.82)	(0.04)	(7.51)	(0.51)	(0.47)	(0.00)	(8.46)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.873	0.917	0.929	0.820	0.855	0.912	0.929
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Winsorized raw emission rates and heat rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CO_2/E	SO_2/E	NO_x/E	H/E	CO_2/H	SO_2/H	NO_x/H
Post × Treated	-32.418***	0.047	-0.042**	-0.503***	-0.156	0.007	-0.002
	(-5.33)	(1.11)	(-2.34)	(-5.64)	(-0.62)	(1.54)	(-1.53)
ln(Age_U)	24.347	0.103	0.262***	0.115	2.159	0.012	0.025***
	(0.63)	(0.70)	(6.23)	(0.36)	(0.48)	(0.76)	(4.68)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.899	0.719	0.805	0.853	0.849	0.734	0.828
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Sources of the private equity buyout effect**

In Panel A, we explore within-EGU variation by controlling for EGU-cohort fixed effects, which subsume the plant-fixed effects in the baseline model. In Panel B, we extend the baseline stacked DiD regression to control for production scale measured by log electricity output. In Panel C, we examine the effect of private equity buyouts on various aspects of plant operations, including total output, input, operating time (OPT), hourly output and input (E/OPT and H/OPT), capacity factor (CapFactor), and EGU retirement. Each acquired plant is matched to a control plant based on year, state, and a Mahalanobis distance measure. The event window is 11 years, from t-5 to t+5, with t=0 being the buyout year. Post is a dummy variable equal to one for the post-buyout years and zero for other years. Treated is a dummy variable equal to one for acquired plants and zero for control plants. All models include plant-cohort and year-cohort fixed effects. Regression constants are not reported. Standard errors are clustered by plant owner, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Controlling for EGU-cohort fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.053***	-0.050	-0.069*	-0.049***	-0.003	-0.000	-0.019
	(-4.94)	(-0.95)	(-1.96)	(-5.02)	(-1.22)	(-0.01)	(-0.62)
ln(Age_U)	0.015	-0.267**	-0.045	0.020	-0.005	-0.287**	-0.065
	(0.81)	(-2.31)	(-0.73)	(1.07)	(-1.42)	(-2.56)	(-1.08)
Observations	5786	5786	5786	5786	5786	5786	5786
R^2	0.921	0.955	0.976	0.891	0.982	0.955	0.978
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed
EGU-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Controlling for output scale

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.052***	-0.058	-0.052	-0.043***	-0.008	-0.015	-0.009
	(-5.00)	(-1.24)	(-1.43)	(-4.60)	(-1.63)	(-0.33)	(-0.27)
ln(Age_U)	0.049	0.009	0.814***	0.025	0.025	-0.016	0.789***
	(0.90)	(0.03)	(8.45)	(1.51)	(0.44)	(-0.04)	(8.49)
ln(Electricity)	-0.038**	0.045	-0.222***	-0.066***	0.028***	0.111**	-0.156***
	(-2.27)	(0.97)	(-4.52)	(-5.25)	(2.68)	(2.31)	(-3.13)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.881	0.918	0.946	0.856	0.874	0.913	0.940
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Effect on plant operations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Electricity)	ln(HeatInput)	ln(OPT)	ln(E/OPT)	ln(H/OPT)	CapFactor	Retirement
Post × Treated	0.142	0.090	0.102	0.040***	-0.012	-0.019**	-0.002
	(1.56)	(1.02)	(1.14)	(2.73)	(-0.87)	(-2.44)	(-0.37)
Treated							-0.004
							(-1.55)
ln(Age_U)	0.151	0.166	0.380	-0.229**	-0.214***	-0.117***	0.006
	(0.46)	(0.55)	(1.42)	(-2.47)	(-2.83)	(-4.99)	(1.57)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.908	0.908	0.904	0.897	0.896	0.805	0.504
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	No

Table 6: **Private equity buyout effect: Cross-sectional differences**

The table shows the difference in the private equity effect on emission rates and production efficiency for different subsamples. Divestiture is a dummy variable equal to one for cohorts involving a corporate divestiture deal and zero for other cohorts; Large is a dummy variable indicating cohorts in which the treated plant has an above-median electricity output in the year prior to the buyout; Add-On is a dummy variable for cohorts involving an add-on deal and zero for other cohorts. Each acquired plant is matched to a control plant based on year, state, and a Mahalanobis distance measure. The event window is 11 years, from t-5 to t+5, with t=0 being the buyout year. Post is a dummy variable equal to one for the post-buyout years and zero for other years. Treated is a dummy variable equal to one for acquired plants and zero for control plants. All models include plant-cohort and year-cohort fixed effects. Regression constants are not reported. Standard errors are clustered by plant owner, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Corporate divestiture vs. other deals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.024*	0.027	-0.028	-0.024*	0.000	0.051	-0.003
	(-1.77)	(0.38)	(-0.53)	(-1.80)	(0.03)	(0.70)	(-0.06)
Post × Treated × Divestiture	-0.057***	-0.136	-0.097	-0.049**	-0.008	-0.087	-0.048
	(-2.75)	(-1.26)	(-1.33)	(-2.55)	(-0.81)	(-0.81)	(-0.72)
ln(Age_U)	0.042	0.013	0.778***	0.014	0.029	-0.001	0.764***
	(0.79)	(0.04)	(7.46)	(0.48)	(0.47)	(-0.00)	(8.42)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.873	0.917	0.929	0.820	0.855	0.912	0.929
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Large vs. small target plants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.059***	-0.166**	-0.119**	-0.048***	-0.012**	-0.119*	-0.071
	(-4.16)	(-2.54)	(-2.30)	(-3.77)	(-2.45)	(-1.93)	(-1.52)
Post × Treated × Large	0.005	0.255***	0.077	-0.011	0.017***	0.266***	0.089
	(0.26)	(2.86)	(1.06)	(-0.56)	(2.95)	(3.12)	(1.33)
ln(Age_U)	0.044	0.014	0.780***	0.015	0.029	-0.000	0.765***
	(0.82)	(0.04)	(7.50)	(0.52)	(0.47)	(-0.00)	(8.45)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.873	0.918	0.929	0.820	0.855	0.912	0.929
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Add-on deals vs. other deals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.072***	-0.143***	-0.117***	-0.067***	-0.006	-0.076*	-0.051
	(-5.87)	(-2.93)	(-2.92)	(-5.87)	(-1.62)	(-1.68)	(-1.39)
Post × Treated × Add-On	0.059***	0.348***	0.127	0.053**	0.006	0.295***	0.074
	(2.90)	(3.44)	(1.50)	(2.55)	(0.74)	(2.83)	(0.93)
ln(Age_U)	0.043	0.010	0.778***	0.014	0.029	-0.004	0.764***
	(0.79)	(0.03)	(7.48)	(0.48)	(0.47)	(-0.01)	(8.43)
Observations	5791	5791	5791	5791	5791	5791	5791
R^2	0.873	0.918	0.929	0.820	0.855	0.912	0.929
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Private equity buyout effect: robustness checks**

This table shows the robustness of our baseline results. In Panel A, we use an event window 7 years (from t-3 to t+3 instead t-5 to t+5). In Panel B, we match each treated plant to up to four control plants (instead of one). In Panel C, we modify the baseline matching criteria by further requiring the matching of primary fuel type. In Panel D, we compute the Mahalanobis distance measure using an alternative set of variables: the logarithms of the average CO_2/E, average SO_2/E, average NO_x/E in up-to-three pre-buyout years, and the average changes of ln($CO2_2$/E), ln($SO2_2$/E), and ln(NO_x/E) in those years. The model specifications are the same as those in Table 4. Standard errors are clustered by plant owner, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. A 7-year event window

	(1) ln(CO_2/E)	(2) ln(SO_2/E)	(3) ln(NO_x/E)	(4) ln(H/E)	(5) ln(CO_2/H)	(6) ln(SO_2/H)	(7) ln(NO_x/H)
Post × Treated	-0.060***	-0.094**	-0.069**	-0.053***	-0.006*	-0.040	-0.016
	(-5.26)	(-2.01)	(-2.05)	(-5.11)	(-1.68)	(-0.93)	(-0.52)
ln(Age_U)	0.048	0.009	0.819***	0.017	0.031	-0.008	0.802***
	(0.89)	(0.03)	(5.63)	(0.48)	(0.50)	(-0.02)	(6.12)
Observations	4041	4041	4041	4041	4041	4041	4041
R^2	0.862	0.920	0.931	0.805	0.863	0.915	0.933
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. A 1-to-4 treated-control ratio

	(1) ln(CO_2/E)	(2) ln(SO_2/E)	(3) ln(NO_x/E)	(4) ln(H/E)	(5) ln(CO_2/H)	(6) ln(SO_2/H)	(7) ln(NO_x/H)
Post × Treated	-0.055***	-0.028	-0.106***	-0.047***	-0.007	0.019	-0.058*
	(-4.63)	(-0.52)	(-2.73)	(-4.28)	(-1.64)	(0.36)	(-1.73)
ln(Age_U)	0.096***	0.442**	0.844***	0.040*	0.056*	0.402**	0.804***
	(2.75)	(2.17)	(6.69)	(1.68)	(1.79)	(1.99)	(7.18)
Observations	14384	14384	14384	14384	14384	14384	14384
R^2	0.862	0.916	0.881	0.790	0.881	0.915	0.879
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Matching also on primary fuel type

	(1) ln(CO_2/E)	(2) ln(SO_2/E)	(3) ln(NO_x/E)	(4) ln(H/E)	(5) ln(CO_2/H)	(6) ln(SO_2/H)	(7) ln(NO_x/H)
Post × Treated	-0.051***	-0.023	-0.065*	-0.051***	0.000	0.028	-0.014
	(-4.81)	(-0.50)	(-1.74)	(-4.99)	(0.01)	(0.64)	(-0.42)
ln(Age_U)	0.038	0.062	0.743***	0.014	0.024	0.048	0.730***
	(1.20)	(0.45)	(5.27)	(0.48)	(0.83)	(0.33)	(5.85)
Observations	5581	5581	5581	5581	5581	5581	5581
R^2	0.878	0.934	0.912	0.818	0.880	0.929	0.911
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel D. Alternative distance measure

	(1) ln(CO_2/E)	(2) ln(SO_2/E)	(3) ln(NO_x/E)	(4) ln(H/E)	(5) ln(CO_2/H)	(6) ln(SO_2/H)	(7) ln(NO_x/H)
Post × Treated	-0.054***	-0.048	-0.137***	-0.046***	-0.008	-0.001	-0.090**
	(-4.15)	(-0.76)	(-2.99)	(-3.87)	(-1.50)	(-0.02)	(-2.16)
ln(Age_U)	0.018	0.058	0.654***	-0.008	0.026	0.066	0.662***
	(0.40)	(0.19)	(4.74)	(-0.36)	(0.60)	(0.21)	(5.12)
Observations	5866	5866	5866	5866	5866	5866	5866
R^2	0.877	0.915	0.912	0.821	0.871	0.909	0.911
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Stacked DiD regressions at the plant level**

This table shows the private equity buyout effect on the emission rate, heat rate and production scale at the plant level. Panel A shows the results from the baseline plant-level stacked DiD regressions. Panel B shows the results after controlling for production scale. Panel C shows the effect of private equity buyout on the aggregate output, input, emissions, and the number of EGUs (N_Unit) at the plant level. Each acquired plant is matched to a control plant based on year, state, and a Mahalanobis distance measure. The event window is 11 years, from t-5 to t+5, with t=0 being the buyout year. Post is a dummy variable equal to one for the post-buyout years and zero for other years. Treated is a dummy variable equal to one for acquired plants and zero for control plants. All models include plant-cohort and year-cohort fixed effects. Regression constants are not reported. Standard errors are clustered by plant owner, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.040***	-0.053	-0.015	-0.039***	-0.001	-0.015	0.023
	(-2.78)	(-0.66)	(-0.24)	(-2.88)	(-0.23)	(-0.20)	(0.39)
ln(Age_P)	-0.052	-0.402	-0.124	-0.048	-0.003	-0.354	-0.075
	(-1.06)	(-1.56)	(-0.86)	(-1.03)	(-0.28)	(-1.50)	(-0.63)
Observations	1882	1882	1882	1882	1882	1882	1882
R^2	0.968	0.979	0.974	0.950	0.989	0.980	0.973
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Controlling for output scale

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(CO_2/E)	ln(SO_2/E)	ln(NO_x/E)	ln(H/E)	ln(CO_2/H)	ln(SO_2/H)	ln(NO_x/H)
Post × Treated	-0.036***	-0.046	-0.000	-0.035***	-0.001	-0.010	0.035
	(-2.72)	(-0.57)	(-0.00)	(-2.86)	(-0.26)	(-0.14)	(0.60)
ln(Age_P)	-0.033	-0.357	-0.036	-0.029	-0.004	-0.328	-0.007
	(-0.72)	(-1.42)	(-0.28)	(-0.67)	(-0.33)	(-1.41)	(-0.06)
ln(Electricity)	-0.036***	-0.088***	-0.170***	-0.037***	0.001	-0.051*	-0.133**
	(-4.71)	(-2.98)	(-2.61)	(-4.81)	(0.41)	(-1.67)	(-2.04)
Observations	1882	1882	1882	1882	1882	1882	1882
R^2	0.970	0.979	0.976	0.954	0.989	0.980	0.974
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Aggregate production scale and emissions

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Electricity)	ln(HeatInput)	N_Unit	ln(CO_2)	ln(SO_2)	ln(NO_x)
Post × Treated	0.089	0.050	0.044	0.049	0.035	0.073
	(1.04)	(0.62)	(0.99)	(0.60)	(0.33)	(0.92)
ln(Age_P)	0.515	0.467	0.320	0.464	0.113	0.392
	(1.63)	(1.56)	(1.56)	(1.53)	(0.30)	(1.40)
Observations	1882	1882	1882	1882	1882	1882
R^2	0.967	0.965	0.990	0.966	0.978	0.964
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Private equity buyout effect: Results from DiD panel regressions**

This table shows the private equity effect on the EGU-level emission rates and heat rate estimated from the DiD panel regressions using the full sample. Panel A presents the results from the baseline specification, controlling for plant, firm, and year-by-state, and year-by-fuel type fixed effects. In Panel B, we further control for EGU fixed effects, which subsume plant-fixed effects. In Panel C, we extend the baseline specification by controlling for output scale. Regression constants are not reported. Standard errors are clustered by plant owner and year, t-statistics are in parentheses, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(CO_2/E)$	$\ln(SO_2/E)$	$\ln(NO_x/E)$	$\ln(H/E)$	$\ln(CO_2/H)$	$\ln(SO_2/H)$	$\ln(NO_x/H)$
Post	-0.046***	0.012	-0.091*	-0.043***	-0.002	0.055	-0.048
	(-3.46)	(0.24)	(-2.10)	(-3.32)	(-1.19)	(1.15)	(-1.30)
ln(Age_U)	0.064***	0.386***	0.507***	0.054***	0.010**	0.332***	0.453***
	(5.10)	(4.25)	(7.85)	(4.57)	(2.57)	(3.77)	(7.70)
Observations	53013	53013	53013	53013	53013	53013	53013
R^2	0.779	0.924	0.875	0.637	0.931	0.926	0.880
Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fuel Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Controlling for EGU fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(CO_2/E)$	$\ln(SO_2/E)$	$\ln(NO_x/E)$	$\ln(H/E)$	$\ln(CO_2/H)$	$\ln(SO_2/H)$	$\ln(NO_x/H)$
Post	-0.044***	0.050	-0.085*	-0.047***	0.003	0.096	-0.038
	(-3.02)	(0.83)	(-1.94)	(-3.15)	(1.29)	(1.61)	(-1.05)
ln(Age_U)	-0.024**	0.139***	-0.065**	-0.032***	0.008**	0.171***	-0.033
	(-2.83)	(3.02)	(-2.78)	(-3.56)	(2.88)	(3.47)	(-1.50)
Observations	52887	52887	52887	52887	52887	52887	52887
R^2	0.866	0.953	0.953	0.767	0.962	0.953	0.955
Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fuel Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed
EGU FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Controlling for output scale

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(CO_2/E)$	$\ln(SO_2/E)$	$\ln(NO_x/E)$	$\ln(H/E)$	$\ln(CO_2/H)$	$\ln(SO_2/H)$	$\ln(NO_x/H)$
Post	-0.039***	0.026	-0.069*	-0.037***	-0.002	0.063	-0.032
	(-3.10)	(0.54)	(-1.76)	(-2.96)	(-1.08)	(1.34)	(-0.95)
ln(Age_U)	0.047***	0.351***	0.451***	0.038***	0.009**	0.313***	0.413***
	(4.94)	(4.18)	(8.28)	(4.28)	(2.44)	(3.76)	(7.81)
ln(Electricity)	-0.068***	-0.144***	-0.230***	-0.065***	-0.003**	-0.079**	-0.165***
	(-10.22)	(-4.10)	(-12.52)	(-9.73)	(-2.16)	(-2.25)	(-8.95)
Observations	53013	53013	53013	53013	53013	53013	53013
R^2	0.814	0.926	0.900	0.698	0.931	0.927	0.895
Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fuel Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

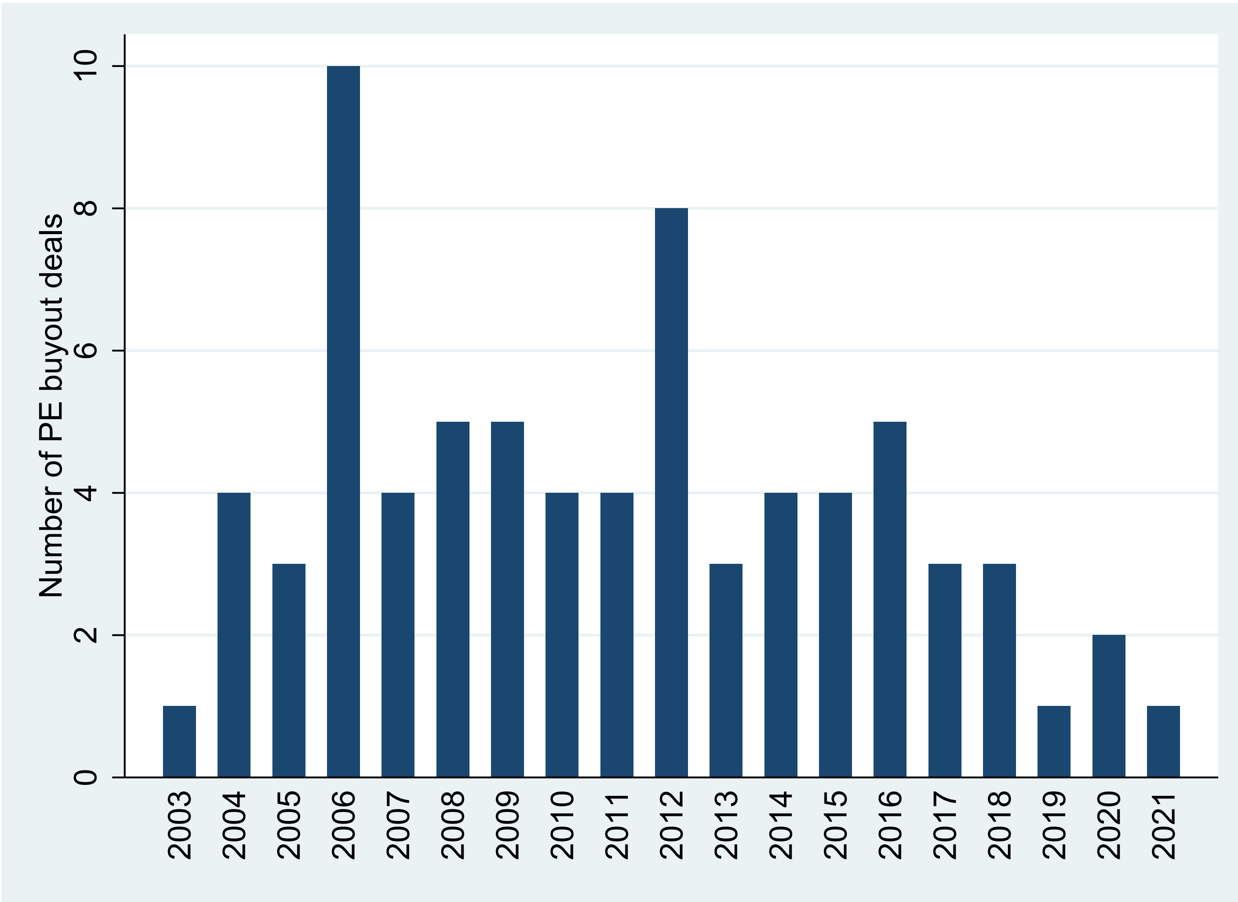
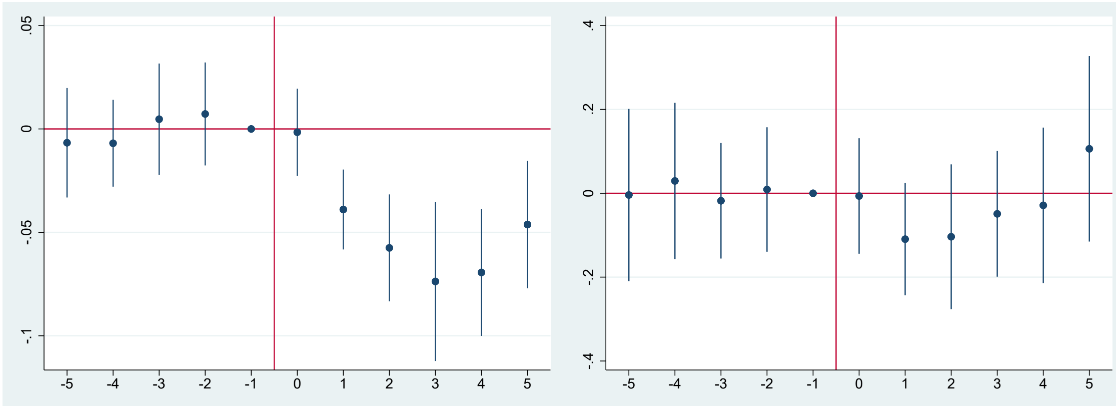
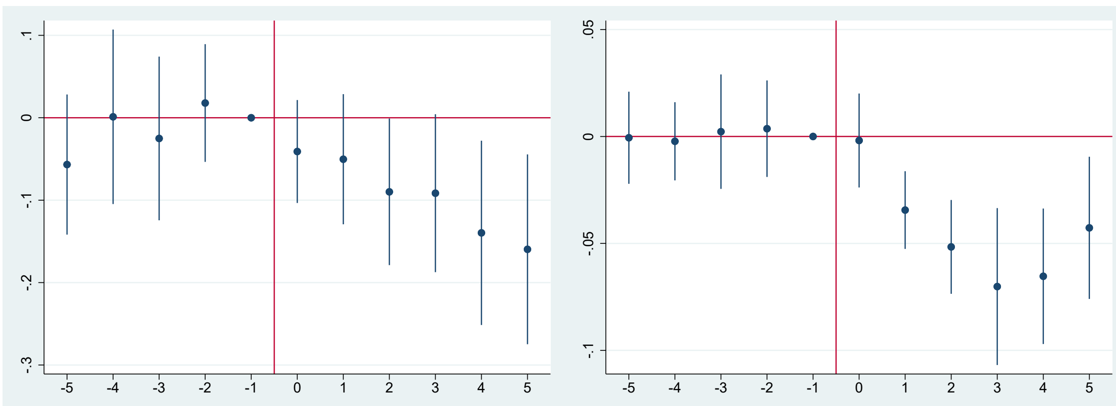


Figure 1: **The number of private equity buyout deals in the power sector**. This figure shows, year by year, the number of completed private equity buyout deals in which the target firm is an owner of an electric power plant in our emissions data set. If a firm is acquired by private equity in multiple deals, we only count the first deal.



(A) Dependent variable: $\ln(CO_2/E)$

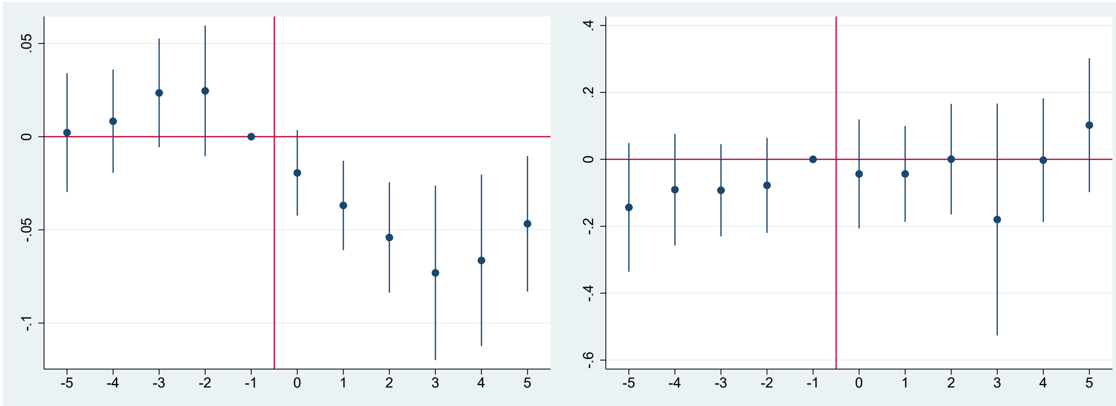
(B) Dependent variable: ln(SO2/E)



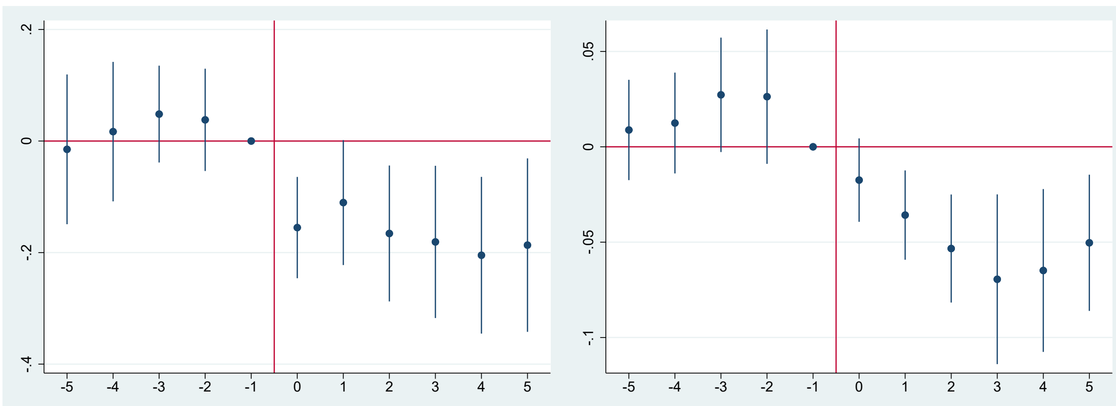
(C) Dependent variable: $\ln(NOX_2/E)$

(D) Dependent variable: ln(H/E)

Figure 2: **Coefficient plot for stacked DiD regressions**. This figure shows the point estimates and 95% confidence intervals of the coefficients β_τ in Equation (5), where τ is the year relative to the buyout year (year 0). The dependent variables are the logarithms of the CO_2, SO_2, NO_2 output emission rates and heat rate, respectively, in panels A to D.



(A) Dependent variable: $\ln(CO_2/E)$ (B) Dependent variable: ln(SO2/E)



(C) Dependent variable: $\ln(NOX_2/E)$ (D) Dependent variable: ln(H/E)

Figure 3: **Coefficient plot for DiD panel regressions**. This figure shows the point estimates and 95% confidence intervals of the coefficients β_τ in Equation (6), where τ is the year relative to the buyout year (year 0). The dependent variables are the logarithms of the CO_2, SO_2, NO_2 output emission rates and heat rate, respectively, in panels A to D.