Do Mergers and Acquisitions Improve Efficiency: Evidence from Power Plants*

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Abstract

Using rich data on hourly physical productivity and thousands of ownership changes from US power plants, we study the effects of mergers and acquisitions on efficiency and provide evidence on the mechanisms. We find that acquired plants experience an average of 5% efficiency increase five to eighteen months after acquisition. 80% percent of this efficiency gain is explained by increased productive efficiency; the rest comes from dynamic efficiency by reducing ramps. Investigating the mechanism, the evidence suggests that acquired plants achieve higher efficiency through low-cost operational improvements rather than high-cost capital investments. Finally, acquired plants improve their performance beyond efficiency by increasing output and reducing outages and emission intensity.

JEL: L22, L25, G34, L40

Keywords: mergers and acquisitions, efficiencies, productivity, power generation

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1 Introduction

A fundamental issue in antitrust policy is the trade-off between the efficiency and market power effects of mergers. The increase in market power raises prices for consumers; however, potential efficiency gains can counteract this effect, making the net effect of mergers on welfare ambiguous (Williamson, 1968). While there is an extensive literature on the price effects of mergers, we have limited evidence on how mergers affect efficiency. With little guidance from empirical evidence, researchers analyzing the competitive effects of prospective mergers often rely on hypothetical efficiency gains (Farrell and Shapiro, 2010; Nocke and Whinston, 2022).[1]

A major challenge in analyzing the efficiency effects of mergers is distinguishing true efficiency gains from other factors, such as changes in market power, buyer power, and product quality. Due to the limitations of common production datasets, most research has studied revenue-based productivity (TFPR), which is estimated from revenues and input expenditures, rather than quantity-based measures (Foster et al., 2008; Atalay, 2014). Using TFPR is particularly problematic in merger retrospectives because an increase in market power, buyer power, or a decline in product quality could raise TFPR even in the absence of any efficiency gains. This makes it difficult to identify true efficiency gains of mergers.

In this paper, we provide a detailed and large-scale analysis on the efficiency effects of mergers while tackling these challenges. We focus on mergers in the US electricity generation industry between 2000 and 2023. Four distinct features of this industry and available rich data allow us to overcome the challenges of estimating the efficiency effects of mergers. First, we observe, at the hourly frequency, the physical quantities of both output and the largest single input, the consumption of fuel (which makes 80% of variable cost) (Fabrizio et al., 2007). We construct an efficiency measure (heat rate) using this high-frequency data, and analyze how it changes around the time of acquisition. Second, electricity is a homogeneous product, ruling out potential quality changes that could confound our analysis. Third, the efficiency measure relies mainly on sensor measurements rather than survey responses. Finally, and most importantly, the power generation industry experienced a significant number of acquisitions during the sample period. Our sample includes 505 transactions with 3515 ownership changes, corresponding to an average of 4.5% of

[1] As an example, consider these quotes from Nocke and Whinston (2022): "there is a clear need for much better evidence on the efficiency effects"; "we observe that the literature on efficiency effects of horizontal mergers is extremely limited"; "while casual observation and the agencies' skepticism about efficiency claims suggest that 5% is rather optimistic for most mergers, there is remarkably little solid empirical evidence on this point."

industry capacity annually. These ownership changes exhibit significant heterogeneity by transaction, firm, and plant characteristics, which we use to study the mechanisms of efficiency gains.

Our analysis begins by using a difference-in-differences estimator to compare the efficiency of acquired plants with those not involved in an acquisition. We find that, on average, the efficiency of acquired plants increases by 2% two years after acquisitions. We then explore the impact of different types of ownership changes on efficiency. Our data reveals two types of ownership changes: at the parent owner level and at the subsidiary owner level. We find that a parent company ownership change does not lead to any significant increase in efficiency, whereas a subsidiary owner change leads to a 5% increase. This finding underscores the limited role of the parent owner in operational changes occurring at a power plant. When we look at the timing of efficiency increase, we find that it begins to manifest five months after the acquisition and stabilize after eighteen months. This suggests that new owners need time to implement changes that lead to efficiency improvements.

We then move to other important outcomes that are indicator of generator performance such as output, capacity utilization, outages and emissions. We find that acquired generators show an average increase in generation by 6.3% and an increase in capacity utilization by 1.4 percentage points following the acquisition. Moreover, they experience a 25% reduction in outages and derates (forced reduction in available capacity). These results indicate that acquirers improve other dimensions of performance beyond efficiency, so efficiency increase does not come at the expense of lower production and increased outages. Finally, we find that acquired generators reduce their CO_2 emission intensity by 4.4%, which reflects lower fuel usage.

Although the evidence of efficiency gains after mergers is itself important, to inform merger policy and generalize the evidence from this industry to other industries, it is crucial to understand the underlying mechanisms. With this motivation, we investigate what observable acquisition characteristics are correlated with efficiency gains and what potential mechanisms generate them.

We start by analyzing the characteristics of acquired plants, acquiring firms, and transactions that might be indicative of overall efficiency gains. We consider two generator characteristics: capacity and age. We find that the efficiency increase is 3% larger if the generator capacity is higher than the median of acquired generator capacity. This may reflect the fact that the acquirer has a greater incentive to improve efficiency in larger-capacity units, as any improvement in efficiency would yield higher returns. Regarding firm characteristics, efficiency improvement is 4.2% higher when the acquirer firm is larger than the median acquirer and 5.9% higher when the acquirer is a serial acquirer. These results are consistent with the interpretation that a firm's experience in plant operation and acquisition is an important predictor of post-acquisition efficiency gains. Finally, we study whether the efficiency impact differs for cross-market acquisition and find cross-market acquisition leads to efficiency gains that are 3.8% lower than within-market acquisitions.[2]

We then move to a more formal and structural analysis of mechanisms of efficiency gains. We propose that a firm can improve the overall efficiency of electricity generation via three distinct mechanisms: (i) increasing the productive efficiency at individual power plants, (ii) reducing ramping by better dynamic allocation production within a plant (dynamic efficiency), and (iii) better allocating production across plants (portfolio efficiency). We develop predictions for each of these mechanisms and test them empirically. The test for productive efficiency involves comparing generator-specific cost curves for pre- and post-acquisition periods. The test for dynamic efficiency looks at the volatility of an acquired plant's production profile, with less volatility over time indicating greater dynamic efficiency. Finally, testing for portfolio efficiency involves measuring the efficiency improvements of the acquirer's existing plants in the acquisition market.

We find that productive efficiency explains the majority, 75–80%, of the total efficiency gain. The average cost curve of acquired generators shift down after acquisition at every production level, suggesting that acquirers improve the efficiency of individual generators. We also find evidence for an increase in dynamic efficiency. Following acquisition, generators' coefficient of variation of production decrease and they cycle less often. We find no evidence supporting portfolio efficiency theory.

After establishing the role of productive efficiency, we next ask how acquirers improve productive efficiency. There are two potential channels: (i) low-cost process improvements, which involve, for example, installing control software, effective maintenance, personnel training, adopting best practices, and (ii) high-cost capital investments, which involve equipment upgrades. Process improvements indicate information transfers after acquisition (Atalay et al., 2014); capital upgrades indicate credit constraints of the former owner. To distinguish between these two hypotheses, we augment the efficiency data with two different datasets: (i) data on plant managers and (ii) annual non-fuel costs, capital expenditures, and number of employees for a subset of plants. Starting with the manager data, we find that 55% of acquired power plants change managers within three months of acquisition. These managers are 5 percentage points more likely to have a master's degree and 4 percentage points more likely to have a bachelor's degree than managers not

[2]This result might suggest the potential role of synergies in efficiency gains, which we investigate in Section 5.

associated with with acquired plants. In contrast, we find no evidence of an increase in capital expenditures after acquisition. These findings suggest that the new owner of the power plant improves efficiency through operational improvements rather than high-cost capital investment.

As in all retrospective merger analyses, an important concern in our paper is the endogeneity of mergers. We include several additional analyses to address this concern. First, we include a rich set of controls along with flexible time trends (fuel, technology, vintage, state) that would account for factors that could lead to selection into acquisitions. Second, we carefully analyze the timing of the effect, showing parallel trends between the treated and control groups three years before acquisitions and an increase starting a few months after acquisition. This suggests that efficiency gains are unlikely to be driven by industry trends. Third, we run a battery of robustness tests and show that our results are robust to empirical specification, acquisition definition, and data frequency. Fourth, we look at whether other important changes in the plant in the absence of mergers generate similar efficiency effects. For example, we look at how management changes in the absence of mergers affect efficiency and find that management change leads only to a 0.8% efficiency gain, in contrast to 5% caused by mergers. Finally, we run placebo tests by looking at the efficiency effects of minority acquisitions and company restructuring, finding no efficiency effects in either.

We conclude the introduction by highlighting that our results do not fully characterize the impact of mergers on consumers, as we identified only one component of the welfare analysis. Moreover, the efficiency effects identified in this paper may not be generalizable to merger analyses in other industries, especially in industries where production techniques differ significantly from electricity generation. While we focus on a single industry to take advantage of the available data and numerous acquisitions, we provide detailed evidence for mechanisms to draw broader lessons from this study. Our view is that more research is needed to understand the net effects of mergers from different industries, and we provide a detailed analysis of the efficiency effects from a large and important industry with environmental externalities.

Contribution to the Literature This article contributes to several bodies of literature. The first is the literature studying the effects of mergers and acquisitions on productivity. Since many merger retrospectives focus on price effects, there is a very limited number of papers that study the productivity effects of mergers (Braguinsky et al., 2015; Blonigen and Pierce, 2016; Kulick, 2017). Blonigen and Pierce (2016) use the methods of De Loecker and Warzynski (2012) to separately identify market power and productivity for manufacturing plants in the US and study how mergers affect them. Their findings suggest significant effects of mergers on market power, but provide no evidence of a productivity effect. Kulick (2017) studies mergers in the ready-mix concrete industry. He finds evidence for a price increase due to a rise in market power post-merger despite a 6% productivity increase in acquired plants. Braguinsky et al. (2015), which relates most closely to our paper, studies the Japanese cotton spinning industry at the turn of the 20th century, which experienced a wave of acquisitions over 30 years. They find that acquirers were not more productive conditional on operation, but they were more profitable due to better inventory management and higher capacity utilization. After acquisition, the acquirer improves capacity utilization in the acquired plant, raising both productivity and profitability.[3]

This article also contributes to the literature studying efficiency in the power generation industry. This literature has primarily focused on how deregulation that started in the 1990s affected efficiency (Knittel, 2002; Bushnell and Wolfram, 2005; Fabrizio et al., 2007; Davis and Wolfram, 2012). These papers compare the performance of plants in states that pursued restructuring against plants in states that did not. Overall, the results point to a positive influence of restructuring on the operations of plants.[4] Our paper differs from this literature as we analyze the effects of mergers on productivity. We focus on the post-deregulation period and exclude a small number of forced divestitures occurring during our sample period from our analysis.

Finally, this paper is related to a recent wave of papers that use retrospective merger analyses to understand how mergers affect firm behavior. The insights from this growing literature advance the understanding of cross-market mergers (Lewis and Pflum, 2017; Dafny et al., 2019), monopsony power (Prager and Schmitt, 2021), buyer power (Craig et al., 2021), quality (Eliason et al., 2020), product availability (Atalay et al., 2020), firm entry (Fan and Yang, 2020), and the price effects of mergers (Luco and Marshall, 2020; Bhattacharya et al., 2022). We complement this literature by studying how mergers affect firm efficiency and providing evidence on the mechanisms.

[3] Evidence of cost savings from other industries includes meat products (Nguyen and Ollinger, 2006), railroads (Bitzan and Wilson, 2007), electricity distribution (Clark and Samano, 2022; Chen, 2021), radio (Jeziorski, 2014), banking (Focarelli and Panetta, 2003), and healthcare (Dranove and Lindrooth, 2003; Harrison, 2011; Schmitt, 2017). Another literature provides evidence on efficiency effects by analyzing a single merger. Some examples are the Molson and Coors merger (Grieco et al., 2018), Miller and Coors merger (Ashenfelter et al., 2015), and Boeing-McDonnell Douglas merger (An and Zhao, 2019)

[4] Bushnell and Wolfram (2005) studies the effect of ownership changes on efficiency. However, their study focuses on utility divestitures that took place in the context of industry deregulation. By contrast, we study ownership changes that took place after deregulation. Moreover, the ownership changes we look at are not utility divestitures.

2 Institutional Background and Plant Productivity

This section begins by describing the institutional background of the power generation sector, followed by an overview of mergers and acquisitions in the industry. We then explain power plant operation and our methodology for measuring its efficiency.

2.1 The Power Generation Sector in the US

The US electric power sector accounts for roughly 2% of the US GDP (Bradley & Associates, LLC, 2017). Prior to 1990s, US electricity generation was overwhelmingly supplied by regulated and vertically integrated utilities. Typically, these entities served a specific territory and controlled all components of the sector: generation, transmission, distribution, and retailing. The returns of these utilities were regulated through rate-of-return on capital investments and cost-of-service regulation. This highly regulated market structure offered minimal incentives for efficiency improvements, leading to significant inefficiencies (Fabrizio et al., 2007; Cicala, 2015).

In the 1990s, the industry underwent significant deregulation. Electricity generation was decoupled from transmission and distribution, with most generators transitioning to market-based compensation. This shift coincided with the establishment of independent system operators (ISOs), which manage the electricity grid and organize the wholesale market where electricity is bought and sold. By 2020, about 70% of US electricity demand was serviced through seven ISOs (EIA, 2003).[5]

2.2 Mergers and Acquisitions in the Power Sector

Large power companies are often structured into multiple subsidiaries under a single parent company, each serving distinct locations and segments of the power sector. These parent companies often own assets in generation, transmission, and distribution within the same region, although some operate subsidiaries across various parts of the country. Following the deregulation wave in the 1990s, there was a notable increase in mergers and acquisitions among these entities (Davis and Wolfram, 2012). Additionally, financial firms, especially private equity firms and bank funds, started to invest heavily in the power generation sector (Andonov and Rauh, 2023).

Acquisitions in the power sector can be divided into three categories: (i) asset acquisitions, (ii) subsidiary acquisitions, and (iii) mergers. Asset acquisitions involve a firm selling parts of its power plant portfolio while retaining its corporate structure, with the acquired assets then falling under a subsidiary of the acquiring company. Subsidiary acquisitions

[5] We use ISO as an umbrella term for both ISOs and regional transmission organizations.

occur when a parent company acquires another company's subsidiary, including all its assets. In this scenario, the plant's subsidiary owner remains the same, but the parent owner changes. The third category, mergers, occur when two companies merge to form a new entity. For a visual explanation of these acquisition types, see Appendix Figure OA-2

All proposed power plant acquisitions within the US electricity sector are subject to review by the Federal Energy Regulatory Commission (FERC), the Department of Justice (DOJ), and state Public Utility Commissions (PUCs) (Niefer, 2012). FERC conducts its review under Section 203 of the Federal Power Act, assessing whether mergers align with the public interest. The DOJ's review focuses on the potential anticompetitive effects of mergers.[6] If either the DOJ, FERC, or the relevant state PUC concludes that an acquisition harms consumers, they may challenge it or require remedies.[7] Despite reviews by three government agencies, the majority of mergers that were proposed in the US electricity industry over the past two decades gained approval.[8]

Firms cite various motives for acquisitions, including improving efficiency of power plants. Merging firms often argue that mergers will generate synergies, citing both financial benefits and complementarities between different asset types.[9] Since fuel represents an important part of operational costs, fuel efficiency improvements are often cited as an important source of cost savings post-merger.[10]

2.3 Electricity Production and Construction of the Efficiency Measure

A major challenge in analyzing efficiency effects of mergers is the scarcity of suitable data, as reliable measures of cost and physical productivity are often lacking in most industries. The power generation industry is unusual in this respect due to the public availability of detailed and high-frequency fuel efficiency data. This section describes the efficiency

[6] The FERC relies on the 1996 revision of the Horizontal Merger Guidelines (HMG) and puts more emphasis on market concentration levels (Niefer, 2012), whereas the DOJ's review relies on the 2023 HMG.

[7] To give some examples, in 2005, the Exelon-PSEG merger was not completed after failing to get approval from state PUCs. In 2012, following the DOJ's request, Exelon Corporation and Constellation divested three generating plants in Maryland. The FERC concluded that the merger would not harm competition in both cases.

[8] We reviewed a list of large mergers occurring between 2000 and 2022 provided by the FERC, in addition to merger press releases, and found that only a few of them were publicly challenged.

[9] For most mergers in our sample, we have access to investor presentations and conference calls, which allow us to identify the stated motives. Some examples are: (i) improvements in management (AES-DPL merger); (ii) measurable and actionable cost synergies of $175 million per year (NRG-GenOn merger); (iii) annual cost savings of $150 million (Mirant-RRI Energy merger); (iv) geographic, fuel, market, and earnings diversification benefits (Vistra-Dynegy merger). Other cited reasons include increasing the consumer base, diversifying the portfolio across technologies and regions, and accelerating efforts to meet potential future environmental regulations.

[10] As an example, Figure OA-1 shows a slide from the investor presentation of the 2018 Dynegy and Vistra Energy merger, in which merging parties argue that heat rate improvements will lead to 125 million dollars in cost savings.

measures used in this study and explains the production process at power plants.

A power plant is an industrial facility that generates electricity. As of 2020, there were 11,070 utility-scale electric power plants in the US (EIA, 2020). Typically, a power plant includes multiple generators, transforming different forms of energy (primarily heat, wind, or solar) into electricity using various production technologies. Our research focuses on fossil fuel power plants (coal, natural gas, and oil), because their efficiency is easier to measure and observable with available data. Fossil fuel power plants generate electricity by using the heat energy released from burning fuel.[11] In this process, the total input is measured as the heat content of the fuel used in electricity generation. This leads to a natural efficiency measure, called *heat rate*, which measures how efficiently a generator converts fuel into electricity. Heat rate is calculated as the ratio of the fuel's heat content, in million British thermal units (MMBtu), to the generator's electricity output in megawatt-hours (MWh). Our primary measure of efficiency is the inverse of this measure:

$$\text{Fuel Efficiency (Inv. Heat Rate)} = \frac{\text{Energy Output (MWh)}}{\text{Energy Input (MMBtu)}}. \tag{1}$$

Heat rate is the critical determinant of generator efficiency since fuel is the major input, representing roughly 80% of operating costs (Fabrizio et al., 2007). For this reason, it is a standard efficiency metric in the industry, commonly used by regulatory agencies and firms (EPRICA, 2014; EIA, 2015).

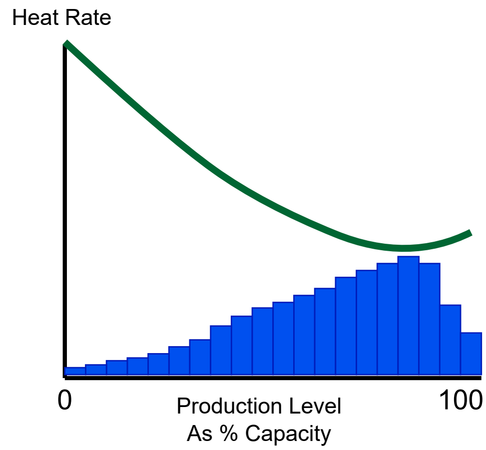
Most importantly for this paper, fuel efficiency provides key advantages in analyzing the efficiency impacts of acquisitions. First, fuel efficiency is a quantity-based efficiency measure derived from input and output quantities, rather than from revenues and input expenditures. Consequently, it is not directly affected by changes in buyer and market power, allowing us to distinguish efficiencies from other changes induced by mergers. Second, electricity is a homogeneous product, precluding any potential quality impacts of acquisitions.[12] Finally, the efficiency measure relies primarily on sensor measurements rather than survey responses as in many other industries.[13]

[11] In a typical thermal power plant, water is heated in a boiler to generate steam, which is then moved through a turbine that is attached to a shaft. As the steam moves, it causes the shaft to spin. This spinning shaft is connected to a generator, which produces electricity.

[12] Some changes post-acquisition, such as reliability and environmental performance, might be considered aspects of the 'quality' of electricity generation. We will revisit these aspects of electricity generation later in the paper.

[13] It is worth noting that our efficiency measure is fuel efficiency rather than TFP, and does not take into account non-fuel inputs. Although we believe that, in electricity generation, the role of other inputs is not as significant as in other manufacturing industries and substitution from fuel to other inputs is limited, we study them in Section 6.

Figure 1: Representative Heat Rate Curve



Note: The green line represents the typical heat rate curve in electricity generation, showing how heat rate changes with the production level. The blue bars represent a hypothetical distribution of production as a function of capacity.

Several factors can influence the heat rate in a power plant. Figure 1 displays a hypothetical example of a heat rate curve, where the green line represents the heat rate and the blue bars represent a typical production distribution as a percentage of capacity. As indicated by the heat rate curve, a power plant's efficiency depends on its production level, typically reaching its peak close to its capacity. Moreover, fluctuations in production levels can significantly impact efficiency. Since electricity cannot be stored at scale and demand is volatile, power plants frequently adjust their production in response to market conditions. This adjustment cost, known as the ramp cost, can reduce overall efficiency in electricity generation. These factors of power plant efficiency depend on the skills and expertise of power plant personnel who monitor and control production (Bushnell and Wolfram, 2009).

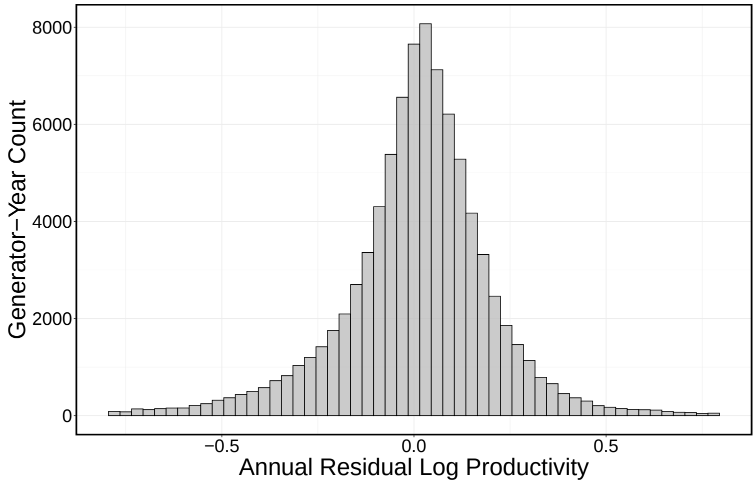
Although the electricity generation process may appear relatively mechanical, power plant productivity in the US exhibits significant variation. Figure 2 shows the distribution of yearly residual log efficiency of generators after controlling for a rich set of observables that include production volatility, generator age, fuel type, technology, capacity, generator manufacturer, and generator model.[14] The difference between the 10th and 90th percentiles of log productivity is 0.32, indicating that generators in the top decile of the distribution are more than twice as productive as those in the bottom decile of the distribution.[15,16]

[14]We provide the details of this estimation procedure in Section B.1.

[15]This dispersion is slightly smaller than the dispersion documented in other industries (Syverson, 2011).

[16]This heterogeneity in productivity has also been observed by others (Sargent & Lundy, LLC, 2009; Staudt and Macedonia, 2014). Sargent & Lundy, LLC (2009) report commissioned by the EPA found that the heat rates of coal-fire power plants range from 5 MMBtu/MWh to 32.7 MMBtu/MWh. Staudt and Macedonia (2014) examine factors that contributed to heat rate, including facility size, capacity factor, emission controls,

Figure 2: Distribution of Residual Log Productivity



Note: This figure shows the distribution of residual yearly log productivity of fossil fuel generators in the US between 2000 and 2023, after controlling for ramp (standard deviation of heat rate), generator age, fuel type, technology, capacity, generator manufacturer, and generator model.

The large dispersion in productivity conditional on a large set of observables highlights the role of unobserved heterogeneity in efficiency and suggests the potential for efficiency improvements in many power plants.

Improving the heat rate performance of a power plant is a complex process that can be achieved in two main ways: (i) low-cost operational improvements and (ii) high-cost capital upgrades. Low-cost improvements include a range of practices such as installing control software, monitoring unit and equipment performance on a continuous basis, personnel training, immediate repairs of equipment that directly affect heat rate, and effective maintenance.[17] Every year, power plant managers gather at the Heat Rate Improvement Conference to discuss these practices (EPRI, 2022).[18] A second way to improve plant efficiency is by upgrading critical equipment, such as boilers, fuel feeders, and cooling systems, as old equipment degrades and new technology becomes available.

A critical factor influencing operational practices is managerial and engineering input. As documented in detail in Bushnell and Wolfram (2009), the individual skills of key personnel can have a profound impact on the performance of power generating plants. These personnel are responsible for continuous monitoring of unit and equipment performance,

steam cycle, and coal type. They determine that each factor is essential to the generator's heat rate, but there is considerable unexplained variability in the data.

[17] There are several control software products available to monitor and improve power plant performance, such PI data historian, EtaPRO/Virtual Plant, and Emerson Enterprise Data Server. Moreover, heat rates can be improved with turbine enhancements such as blade and seal repairs, cycle control optimization, and deposit removal. Boiler improvements involve heat transfer surface maintenance, burner system inspection, and intelligent sootblower utilization.

[18] Appendix Figure OA-3 highlights a few case studies of low-cost improvements from this conference.

conducting periodic tests to assess equipment condition, and planning production and maintenance schedules. Bushnell and Wolfram (2009) underscores the operator's impact with the following quote: "the act of balancing all of these input parameters was described by one manager as playing the piano and one star operator was considered a virtuoso on the instrument."[19]

Improving the efficiency of a power plant is also important for environmental considerations. The higher a plant's efficiency, the less fuel it needs, leading directly to reduced emissions of local pollutants and greenhouse gases. As a result, improving fuel efficiency can be an effective method to reduce pollution, which is recognized by policymakers in the 2016 Clean Power Plan Act (EPA, 2018b).

3 Data and Summary Statistics

Our main objective is to construct a measure of generator efficiency and the universe of ownership changes to study how acquisitions affect power plant productivity. We first describe our datasets and then provide key summary statistics.

3.1 Data

We combine several datasets from FERC, the Environmental Protection Agency (EPA), the Energy Information Administration (EIA), the North American Electric Reliability Corporation (NERC), S&P Capital IQ, S&P Capital IQ Pro, and Velocity Suite at the firm, plant, and generator levels for fossil fuel-fired power plants in the continental US between January 2000 and March 2023. This section briefly describes the datasets, while Appendix A provides more detailed information on the data sources, construction of variables, and descriptive statistics.

Generator and Plant Level Data We use data from EIA Forms 860 and 923, EPA, FERC Form 1, Velocity Suite, and S&P Capital IQ Pro to construct generator- and plant-level datasets. For generators, the information includes the install year, fuel type, technology type, capacity, boiler model, and boiler manufacturer. For plants, we construct data on regulation status, location, ISO, and FERC region. In addition, for approximately half of the power plants in the sample, we have information on the number of employees, non-fuel costs, and capital expenditures between 2008 and 2023.[20]

[19] As another example of the importance of personnel, PacifiCorp Energy state in their 2016 Heat Rate Improvement Plan Document that "Continuous improvement and management of unit heat rates is the responsibility of all plant personnel" and "Good management of heat rate requires that plant management make optimizing heat rate a priority each day." (PacifiCorp Energy, 2016)

[20] The data source for this information is FERC Form 1, which is available only for investor-owned utilities.

Production Data We use the EPA's Continuous Emissions Monitoring Systems (CEMS) to obtain hourly generation and input data. This dataset provides hourly power output, heat input, and CO_2 emission for nearly all fossil fuel generation units in the US.[21] Additionally, CEMS provides panel information on the environmental programs each generator is subject to, and the scrubbers used for various pollutants. We merge this dataset with our generator- and plant-level data as detailed in Appendix A.1.

Ownership and Acquisition Data We construct a detailed dataset on ownership of fossil fuel generators. This dataset combines ownership and transaction data from S&P Capital IQ Pro, as well as company press releases and newspaper articles. The ownership data includes every shareholder of all US generators at the subsidiary and parent company levels. The transaction data provides information on the transferred assets, transaction size, the buyer and seller, announcement and close dates, conference call transcripts, and deal descriptions. Since regulatory authorities review all transactions in the power industry, this data is available for the universe of transactions during the sample period. Ownership datasets can be prone to inaccurately identifying ownership changes as firm name-changes and restructurings may be misinterpreted as acquisitions. We identify these cases by cross-matching the transaction and ownership data, reading transaction descriptions, and reviewing corresponding press releases and news articles.

Maintenance and Outage Data We obtain event-level data on outages, derates (reductions in available capacity), and maintenance from the Generating Availability Data System Database (GADS) through a data-sharing agreement with NERC. This dataset covers all generators with nameplate capacities over 20 MW, which are required to report events affecting their electricity generation capabilities to NERC. This data is available starting from 2013 through 2021 and includes each event's start time, end time, type, and cause. The generator names are deidentified in this dataset, but their capacity, state, fuel type, and monthly production hours are available. Using this information, we matched this data to CEMS units using an algorithm described in Section A.7. We were able to successfully match 92.8% of total CEMS units capacity.

Personnel Data We compile monthly panel data on plant personnel from the EPA, which maintains a database of plant representatives, including names, tenure start and end dates, and contact information. We successfully matched about 70% of the personnel names to their LinkedIn profiles, thereby obtaining their titles, education, and employment histories. Using LinkedIn data, we verify that 78% of the listed personnel are plant managers, while

[21] Every generator in the US with a capacity greater than 25 MW using fossil fuel must comply with the EPA CEMS program. This sample represents approximately 95% of the US fossil fuel generating capacity.

the rest are primarily environmental compliance personnel and engineers. Therefore, for the purposes of this study, we consider plant representatives as plant managers.

Other Datasets We collect hourly data on ambient temperature, humidity, and weather conditions from Velocity Suite for all power plants in our sample as weather can affect generation performance. We also obtain information about power plant owners, including asset size, market cap, and industry from S&P Capital IQ.

3.2 Generator and Acquisition Sample Construction

Our initial sample include all generators that operated in the continental United States between January 2000 and March 2023 and are subject to CEMS regulations (5,876 generators). From this set, we first exclude cogenerators that produce both steam and electricity due to the complexity of calculating their heat rate, which result in a total of 5,265 generators.

For acquisitions, we start with 6,336 generator acquisitions involved in a transaction between January 2000 and March 2023. We eliminate acquisitions that occur before a unit becomes operational and after its retirement (760), as well as minority acquisitions where less than 50 percent of the shares change ownership (1103). We also exclude instances of company restructuring where only the subsidiary owner changes, but the ultimate parent owner remains the same (532). Additionally, we filter out ownership changes that correspond to divestitures due to deregulation to eliminate the potential confounding effects of deregulation (615). To identify these events, we use the EIA Electricity Monthly Reports, Cicala (2015), Abito et al. (2023) and other data sources detailed in Appendix A.4. This sample restriction gives us 3,769 generator acquisition events.

For our baseline specification, we limit our main sample to the first acquisition of each generator if a generator is acquired multiple times. However, we conduct robustness checks using the full acquisition sample. These criteria result in a total of 2,046 first acquisitions used in our main analysis.

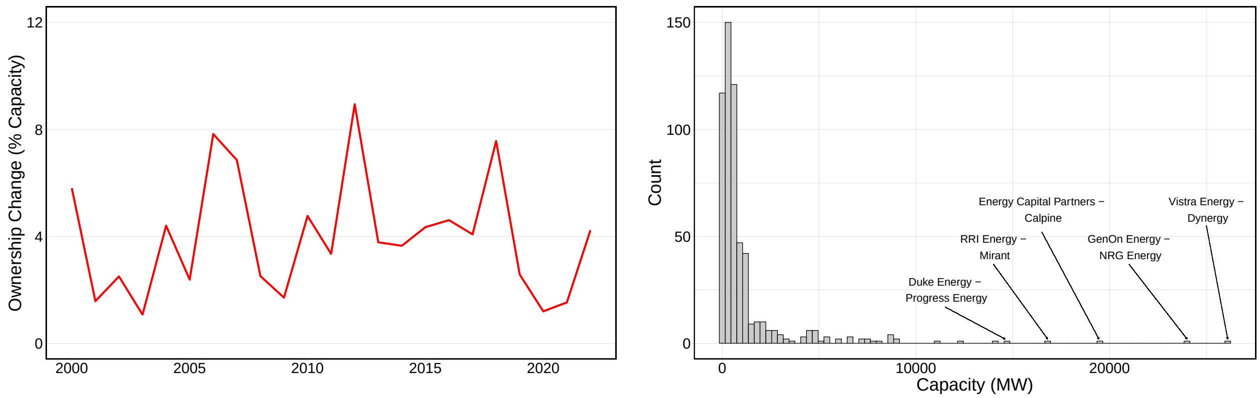
3.3 Descriptive Statistics on US Power Plant Acquisitions

This section provides descriptive statistics on fossil fuel power plant acquisitions in the US. We show that the industry has seen a considerable number of acquisitions, exhibiting significant heterogeneity in transaction size, type of acquirer firms, and plant characteristics, which allow us to study several aspects of how acquisitions affect efficiency.

Figure 3(a) shows the percentage of fossil fuel electricity generation capacity that changed ownership between 2000 and 2023.[22] On average, 4.5% of industry capacity

[22] We define acquisition as an ownership change if a different firm owns the majority of the generator's shares

Figure 3: Transaction Characteristics



(a) Share of Capacity with Ownership Change **(b)** Distribution of Transaction Size

Note: Panel (a) shows the percent of capacity of fossil fuel plants that change ownership annually in the US between 2000 and 2023. Panel B shows the distribution of transaction size by fossil fuel generation capacity in the US between 2000 and 2023. In Panel (b), the unit of observation is a transaction. The largest five transactions are labeled.

changes ownership annually, with some fluctuations year-to-year. Cumulatively, this corresponds to 103.0% of industry capacity during the sample period, including the generators acquired multiple times. As seen in Figure 3(b), these transactions show large heterogeneity in terms of total capacity transacted. While most transactions include a few plants, there are some moderately-sized transactions involving 5,000–10,000 MW capacity, as well as mega-mergers involving over 10,000 MW capacity.[23] Observing this heterogeneity is useful because it indicates that our results do not come from a small number of large mergers, and we can test the heterogeneity of the effect by different transaction characteristics.

Table 1 presents summary statistics on plants, firms, and deal characteristics from acquisitions. Our acquisition sample, as shown in Column (2), includes 505 transactions involving 3,515 generation units and 1,223 plants. We observe that 2,048 generators have been acquired at least once. These generators are predominantly gas-fired generators (82%) and operate in organized markets (77%). About half of these acquisitions are cross-market transactions, where the acquirer does not have existing capacity in the acquisition market. Finally, we note that there are 244 unique acquirer firms and 224 unique target firms in the data, with acquirers owning a slightly higher number of units than the target firms.[24]

after the acquisition. For a small number of generators, no firm owns more than 50% of shares. For those generators, an acquisition is defined as change in the largest shareholder.

[23] Appendix Table OA-1 lists the largest 25 transactions during the sample period.

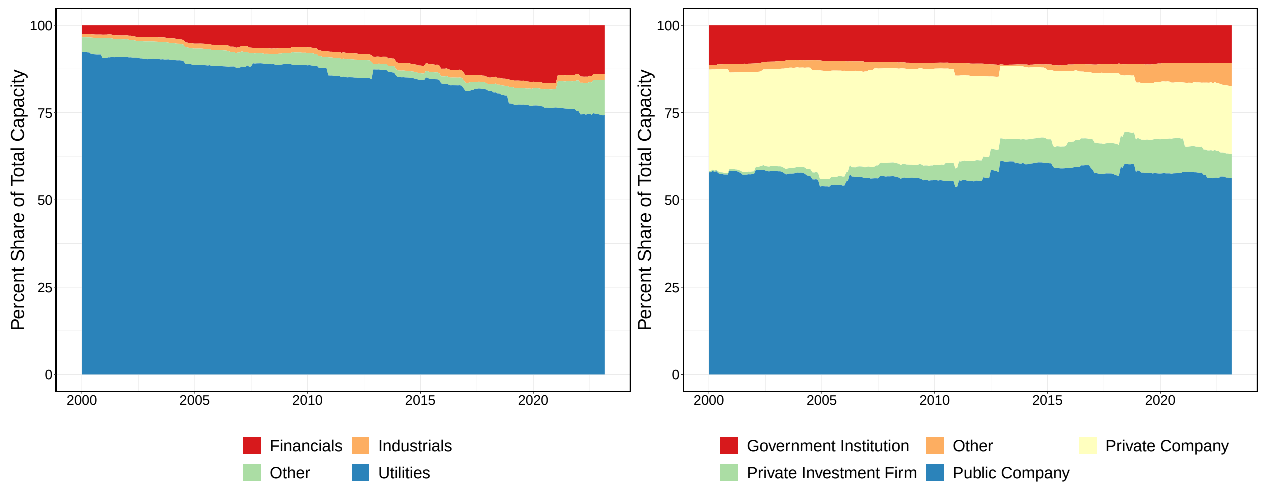
[24] Despite many acquisitions in the study period, there has been no significant change in market concentration in the US. Appendix Figure OA-4 reports the national market shares of the largest 5, 10, 20, and 30 firms in terms of capacity owned. The concentration fluctuates over time; however, it is broadly stable in the

Table 1: Acquisitions Summary Statistics

	All Units (1)	All Acquisitions (2)	First Acquisitions (3)	Subsidiary/Parent Change (4)	Only Parent Change (5)
			Panel A. Unit Characteristics		
# of Units	5264	3515	2048	1089	1142
# of Plants	1581	1223	744	380	405
# of Unique Units	5264	2048	2048	1089	1142
# of Unique Plants	1581	726	726	373	400
% Gas	0.71	0.82	0.77	0.89	0.68
% Coal	0.18	0.09	0.12	0.04	0.17
% Other	0.10	0.09	0.11	0.07	0.15
% Cross-Market	-	0.57	0.58	0.51	0.57
% in ISO	0.69	0.77	0.74	0.81	0.70
Avg. Unit Capacity	173.04	164.43	171.28	155.77	171.16
	(184.75)	(159.01)	(173.39)	(145.02)	(179.41)
Avg. Installation Year	1986.37	1990.59	1989.29	1994.60	1984.43
	(20.08)	(16.24)	(17.27)	(14.25)	(17.86)
			Panel B. Firm Characteristics (Pre-merger)		
# of Acquirer Firms	-	244	182	126	61
# of Target Firms	-	224	159	111	70
Avg. # of Units Acquirer Owns	-	45.81	45.94	50.72	39.35
	-	(53.40)	(49.20)	(54.88)	(39.54)
Avg. # of Units Target Owns		32.13	33.91	37.51	38.07
	-	(47.23)	(49.57)	(50.64)	(53.30)
Avg. Acquirer Firm Capacity	-	5244	5595	6369	6391
	-	(8698)	(9112)	(9605)	(9507)
Avg. Target Firm Capacity	-	7314	7466	8312	6200
	-	(9862)	(9335)	(9948)	(7532)
			Panel C. Transaction Characteristics		
# of Deals	-	505	318	213	72
Avg. Deal Size in # of Units	-	7.0	6.4	5.1	15.9
	-	(12.9)	(11.2)	(7.8)	(19.9)
Avg. Deal Size in Capacity	-	1191	1164	812	2909
	-	(2378)	(2039)	(1491)	(3510)

Note: This table includes summary statistics on acquisitions that include fossil fuel-generating units in the US between 2000 and 2023. A description of the sample's construction can be found in Section 3.2. Each column reports the data's counts and characteristics at varying sample restriction levels. Column (1) reports statistics for the full sample of units, regardless of acquisition status. Column (2) reports data from all majority acquisitions. Column (3) restricts the acquisition sample to the first acquisition of each generator. Column (4) reports statistics of generators with both subsidiary and parent owner changes, whereas Column (5) reports statistics for only parent owner changes. The numbers in parentheses represent the standard deviation. The market definition for cross-market is the power control area. All capacity information is reported in MWh.

Figure 4: Market Share by Firm Type



(a) Industry Type

(b) Owner Type

Note: Panel (a) shows the percent share of fossil fuel generation capacity in the US between 2000 and 2023 by the primary industry type of the parent company. Panel (b) shows the same statistics by categorizing parent owners into Public Company, Private Investment Firm, Private Company, and Government Institutions. These classifications are obtained from S&P Capital IQ Pro.

In Column (3), we present the same statistics, but this time for the first acquisition of each generator, which forms our baseline empirical sample. Observable unit characteristics are similar between this subsample and all acquisitions, suggesting that focusing on first acquisitions does not lead to a significant selection bias. When we compare acquired generators with all units in our sample (Column 1), we see that they are broadly similar in terms of average capacity, average installation year and operating in an organized market (ISO). One important difference is the fuel type, where acquired generators are more likely to be gas-fired than an average unit. This primarily comes from the large number of coal-fired power plant retirements in the 2010s. We control for these differences by allowing for fuel type, technology and install year specific trends in our empirical specification.

Finally, Columns (4) and (5) categorize the acquisition sample into two types of ownership changes we identified: subsidiary and parent owner changes and parent-only owner changes. Typically, a subsidiary of a parent company is the legal entity that owns the power plant, with the parent company owning that subsidiary. Some transactions involve changes in both subsidiary and parent ownership (asset acquisition, see Figure OA-2(b)), while others involve only parent owner changes (subsidiary acquisition, see Figure OA-2(c)). A comparison of Columns (4) and (5) reveals that these transaction types primarily differ in transaction size, with parent-only ownership changes being significantly larger.

sample period. This is because there is a considerable firm turnover in the industry, as suggested by the large number of acquirers and targets in Table 1. Some examples can be seen in Appendix Figures OA-5 and OA-6, where we report firms with the largest capacity increase and decrease between 2010 and 2023.

This observation is consistent with the nature of parent-only ownership changes, which often include taking over a significant part of the target's subsidiary portfolio.

To illustrate the composition of firms in the industry over time, Figure 4(a) displays the evolution of ownership by the primary activity of the parent company (utilities, industrials, and financials), and Figure 4(b) shows the evolution of ownership by company type. Figure 4(a) indicates an increasing presence of financial firms in the industry between 2000 and 2023.[25] The share of total capacity owned by financial firms increased from 3% in 2000 to 20% in 2023, suggesting substantial asset reallocation from utilities to financial firms. Figure 4(b) highlights that public firms own half of the industry capacity, and their share has remained stable over time. Finally, government institutions own 12% of industry capacity. With the exception of the federally run Tennessee Valley Authority, these are predominantly local governments in rural areas operating power plants.

The return on power generation for plants in some states is closely governed by regulatory policies. One might be concerned about the role of regulations, as they change the incentives to improve productivity after an acquisition. Table 1 shows that the majority of acquisitions (77%) happen in organized markets where generators earn profit through market mechanisms. This is also reflected in the geographic variation of acquisitions as most large increases occur in deregulated states (Appendix Figure OA-7).

4 Empirical Results

Our empirical strategy aims to identify the causal effect of acquisitions on power plant efficiency and other important outcomes. To do this, we compare productivity trends of acquired generators to those that were never and not-yet acquired. We refer to the latter type as "control generators." In most estimations, each observation is a combination of generator and week, with variables containing heat rate, ownership, and several other generator characteristics and performance measures. The main advantage of our empirical setting is the availability of a high-frequency measure of generator efficiency, which allows us to track productivity immediately before and after acquisition in a short time frame.

We find that acquisitions increase the productivity of power plants by 5%, but only when there are ownership changes at both the subsidiary and parent owner levels. In contrast, ownership changes only at the parent company level do not lead to a significant increase in productivity. The productivity increase starts five months after the acquisition and stabilizes after eighteen months. We conclude the section by studying the heterogeneity of the effects.

[25] These financial firms primarily include private equity firms, pension funds, and bank funds. The classification is taken from S&P Capital IQ Pro.

4.1 Effects of Ownership Change on Efficiency

This section presents the difference-in-differences results from estimating the effects of mergers on efficiency. We estimate this effect using a regression of the following form:

$$\log(y_{it}) = \delta_1 \mathbb{1}_{\{\text{Pre-year1}\}} + \delta_2 \mathbb{1}_{\{\text{Post-year1}\}} + \delta_3 \mathbb{1}_{\{\text{Post-year2}\}} + \delta_4 \mathbb{1}_{\{\text{Post-year3}\}} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \qquad (2)$$

where y_{it} is the efficiency of generator i at week t (measured as inverse heat rate given in Equation (1)), α_i and μ_t are generator and week fixed effects, respectively. The controls, X_{it}, include ambient temperature and humidity (which can influence heat rate), a dummy variable for each environmental regulation indicating whether the generator is subject to that regulation, and pollution control device (scrubber) indicators for NO_x, SO_2 and PM.[26] Controlling for factors related to environmental regulation is particularly important due to the changes in US environmental policies in the last two decades. These policy changes could influence firms' acquisition decisions or directly influence efficiency due to scrubber installations.

In addition to these variables, X_{it} includes monthly time trends that vary by state, generation installation year, fuel type, and technology type (combined cycle or not). By incorporating state-specific time trends, we account for changes in the supply of non-fossil fuel electricity generation (primarily entry of renewables) and demand factors at the state level. Furthermore, the time trends for generator characteristics allow for different efficiency trajectories based on generator type. For example, power plants might experience decline in efficiency over their lifespans, which can be nonlinear and vary by their vintage. We capture this variation by including installation year by month fixed effects.

The regression in Equation (2) includes four coefficients of interest: (i) δ_1, an indicator variable for 1 to 12 months pre-acquisition; (ii) δ_2, an indicator variable for 0 to 12 months post-acquisition; (iii) δ_3, an indicator variable for 13 to 24 months post-acquisition; and (iv) δ_4, an indicator variable for 25 to 36 months post-acquisition. By including year-specific post-treatment indicators, we aim to capture the dynamic effects of acquisitions. We include δ_1 to examine whether there are any productivity effects of acquisitions before the acquisition occurs. This could happen due to anticipation effects or disruptions in the production process during the transition. The regression coefficients are normalized

[26] These programs are Clean Air Interstate Rule NOx Program, Nitrogen Oxides Budget Trading Program, Cross-State NOx Program, Ozone Transport Commission Program, State Implementation Plan NOx Program, Regional Greenhouse Gas Initiative, Clean Air Interstate Rule Ozone Season Program, Cross-State Ozone Season Group 2 Program, Cross-State NOx Ozone Season Program, New Hampshire NOx Program, Mercury and Air Toxics Standards, Clean Air Interstate Rule SO2 Program, Cross-State SO2 Group 2 Program, Cross-State Ozone Season Group 3 Program, Cross-State Ozone Season Group 1 Program, Cross-State SO2 Group 1 Program, New Source Performance Standards for Toxics, Texas SO2 Program.

relative to 12-18 months before the acquisition. We cluster standard errors at the plant level and exclude all treated generators from the sample three years after their acquisition, ensuring their post-treatment periods are not used as controls for other units.

It is important to highlight that the unit of analysis is a generator rather than a plant. Although a single firm usually owns all the generators within a plant, these generators often have different production profiles, maintenance schedules and retirement years (Gowrisankaran et al., 2022). Aggregating input and production at the plant level could bias efficiency estimates. Therefore, we think the generator is the proper level of analysis, and it is maintained throughout the paper.

Table 2 presents results from estimating Equation (2) with log productivity as the outcome variable. These results cover the first acquisition of all acquired units with different control variables (Columns 1-4) and different acquisition types based on subsidiary and parent owner changes (Columns 5-6). The results from Columns 1-4 demonstrate that efficiency increases following ownership changes. The efficiency of acquired generators increases by 0.6% one year after acquisition and reaches 2% after two years. The efficiency increase is robust to including a rich set of controls and flexible time trends, and there is no efficiency change in the year leading up to the acquisition (δ_1). Overall, we conclude that the efficiency of acquired generators improves following acquisitions, although it takes time for this to fully manifest.

Columns (5) and (6) of Table 2 test whether the efficiency effect differs by the type of ownership change.[27] Column (5) shows estimates from Equation (2) when including ownership changes at both the parent and subsidiary levels. By contrast, Column (6) includes ownership changes at only the parent owner level. One might expect the efficiency effects to differ in these two cases because the subsidiary owner typically has direct control over the operation and personnel of the power plant, whereas the parent owner exercises indirect control. Furthermore, ownership changes at the parent level tend to be financial acquisitions, which could be motivated by diversification. The results suggest significant heterogeneity in the efficiency impact based on acquisition type. When only the parent owner changes, the effect is small and not statistically significant, whereas both subsidiary and parent ownership change leads to an efficiency increase of 5%. This finding underscores that the direct owner plays a more important role than the parent in operational changes occurring at a power plant after acquisitions.

After demonstrating the significant impact of acquisitions on generator efficiency, we

[27]When estimating the effects of acquisition on one subsample of acquired units, we completely exclude the other subsample from the regression, as opposed to grouping them with the controls. In other words, the control group is always the group of never-acquired generators, regardless of the subsample being studied.

Table 2: Regression Results

	All Acquisitions (1)	All Acquisitions (2)	All Acquisitions (3)	All Acquisitions (4)	Subsidiary and Parent Changes (5)	Only Parent Changes (6)
	Dependent Variable: Log of Efficiency					
Pre-acquisition (1 Year)	0.002	0	-0.003	-0.003	-0.002	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
Post-acquisition (1 Year)	0.018	0.016	0.006	0.006	0.015	-0.01
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
Post-acquisition (2 Years)	0.035	0.035	0.02	0.02	0.039	-0.002
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Post-acquisition (3 Years)	0.039	0.038	0.02	0.02	0.05	-0.007
	(0.009)	(0.009)	(0.008)	(0.008)	(0.012)	(0.008)
Temp. & Humidity Controls	X	X	X	X	X	X
Unit & Week FE	X	X	X	X	X	X
State by Month		X	X	X	X	X
Unit Characteristic by Month FE			X	X	X	X
Scrubber & Enviro. Prog. FE				X	X	X
R^2	0.707	0.725	0.752	0.753	0.763	0.764
# of Observations	1.838M	1.838M	1.838M	1.838M	1.494M	1.575M
# of Control Units	2311	2311	2311	2311	2311	2311
# of Treated Units	2046	2046	2046	2046	1089	1142

Note: This table presents the coefficient estimates of δ_1, δ_2, δ_3, and δ_4 from estimating Equation (2). Columns (4-6) present our baseline specification, where we allow for time trends to vary flexibly by unit characteristic and include weather, scrubber, and environmental program controls. Unit characteristic fixed effects include installation year, fuel type, technology type, and unit capacity. The dependent variable is the logarithm of inverse heat rate. Standard errors are clustered at the plant level.

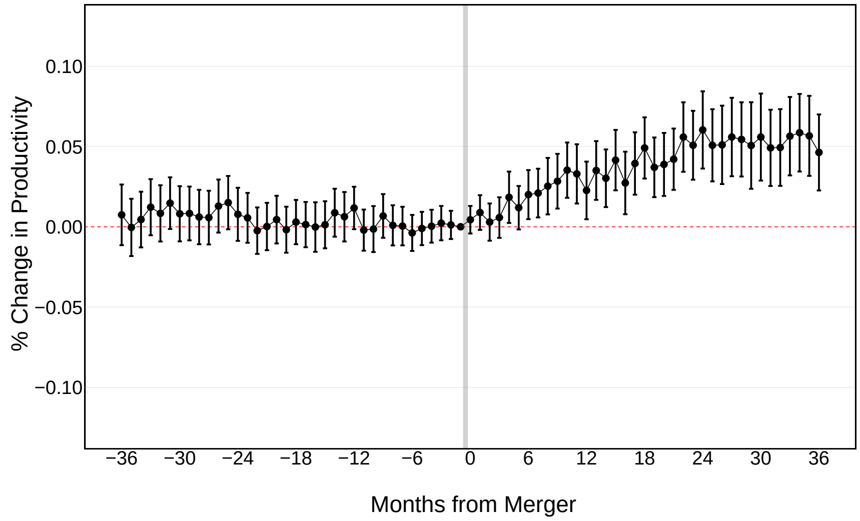
shift our focus to the dynamic effects. Our goal is to determine the timing of efficiency changes and to assess if there are any different pre-treatment trends between the treated and control groups. To this end, we estimate the change in efficiency around the time of acquisition using the following regression specification:

$$\log(y_{it}) = \sum_{s \in (-36,36)} \hat{\delta}_s D_{i(t'-s)} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \tag{3}$$

where $D_{i(t'-s)}$ is a monthly indicator variable equal to 1 for generator i if it is acquired in month t', and zero otherwise. X_{it} includes the full set of control variables as in Equation (2). Since we find efficiency effects for acquisitions where both the subsidiary and parent company change, we focus exclusively on those acquisitions hereafter.

The dynamic effect regression results are presented in Figure 5. The coefficients on $s \in (-36, 0)$ are small and not statistically significant, indicating that acquired generators exhibit a similar efficiency trend prior to acquisition as those not acquired. The difference

Figure 5: Impact of Merger on Productivity



Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors. The dependent variable is the logarithm of the inverse weekly heat rate. The unit of observation is the generator-week. Standard errors are clustered at the plant level.

between treated and control groups remains small until five months post-acquisition. Afterward, the efficiency of acquired plants begins to diverge from control units, increasing on average by 5% eighteen months post-acquisition and then stabilizes. Observing efficiency gains five months after the acquisition suggest that the new owner requires some time to implement efficiency improvements.[28]

To interpret the results from the specification in Equation (2) as causal, we rely on the assumption that an acquisition creates a discontinuous change in power plant behavior and any efficiency trends that might lead to selection would be gradual enough to be distinguished from the more discrete direct effect. This assumption is likely to hold in our setting because we observe production at short intervals and incorporate a rich set of controls along with flexible time trends that would account for factors likely to cause selection into acquisitions. Moreover, the parallel trends observed between the treated and control groups three years before acquisitions, along with the productivity increase starting a few months after acquisition, offer additional evidence that efficiency gains are not likely driven by industry trends.

Still, ownership changes in power plants are of course not random, and unobservable factors could change efficiency in the absence of mergers. If those factors are observed by the acquirers, they can lead to selection, violating the assumptions for causality. For

[28] This finding is suggestive of how the efficiency gain occurs. Our interviews with power plant managers indicated that five months is insufficient to make costly capital investments and upgrades. This suggests that efficiency improvements occur primarily due to operational changes and adopting best practices rather than costly capital investments. We will return to this question later for a more formal analysis.

example, the acquirer might observe that the target plant's manager will retire soon and decide to buy the plant, anticipating that the new manager will improve efficiency. To address such a concern, we estimate the effects of manager changes on efficiency in the absence of mergers and find that the efficiency increase is only 0.6% (Appendix Figure OA-8). Finally, we do a battery of robustness checks including matching estimators, the Callaway and SantAnna (2021) estimator, estimation with daily data, estimation with net generation, and weighted estimation, and placebo tests with minority acquisitions and corporate restructuring. We find that the results are robust to several specification choices.[29] See Section 7 for a summary of robustness checks and placebo tests and Appendix E for the corresponding results.

The results so far suggest that the efficiency of power plants improves with ownership changes. Yet, it is important to recognize that this efficiency gain can occur in various ways, not all of which are beneficial to overall welfare. For example, generators might decrease production and reduce ramping, which would improve their average efficiency, but could lead other plants to ramp more and become less efficient. Alternatively, new owners might operate generators more intensively, increasing their short-term efficiency but possibly causing increased outages and declining long-term performance. In the rest of this section, we provide additional analysis to gain insights into efficiency gains, while reserving a more formal mechanism investigation for the next section.

We investigate the impact of ownership changes on key generator outcomes beyond efficiency, including generation, capacity utilization, operating hours, outages, and the carbon intensity of production. Capacity utilization is defined as the average hourly production as a proportion of capacity over a week, conditional on operation. Operating hours are calculated as the total hours a unit is operational in a given week. For outages, which is available only after 2013, we calculate the proportion of hours in a given week a unit is in forced outage or derate (energy output curtailment). Finally, the CO_2 intensity is calculated by dividing total weekly CO_2 emissions by the total weekly MWh of electricity generation. Using these outcome measures, we estimate the same specification as in Equation (2).

Table 3 presents the regression coefficients. In Column (1), we find that acquired generators show an average increase in generation of 6.3% following the acquisition. This result indicates that the efficiency improvements do not come at the expense of a decline in

[29] We also want to emphasize that our estimates report the average effects on treated (ATT) generators, specifically the efficiency effects of the proposed and approved acquisitions. The ATT, not the ATE, is the main (policy-relevant) object of interest in our setting because we are not interested in the effects of randomly occurring mergers.

Table 3: Impact of Merger on Generator Performance

Dep. Var.	Log Total Generation (1)	Capacity Utilization (2)	Operating Hours (3)	Forced Outages/Derates (4)	Log CO_2 Intensity (5)
Pre-acquisition (1 Year)	0	0.002	-0.696	-0.009	0.007
	(0.024)	(0.004)	(0.81)	(0.014)	(0.006)
Post-acquisition (1 Year)	0.052	0.005	0.77	-0.033	-0.008
	(0.033)	(0.005)	(1.192)	(0.017)	(0.008)
Post-acquisition (2 Years)	0.089	0.012	1.409	-0.04	-0.035
	(0.036)	(0.006)	(1.35)	(0.021)	(0.01)
Post-acquisition (3 Years)	0.063	0.014	1.68	-0.069	-0.044
	(0.037)	(0.006)	(1.442)	(0.02)	(0.012)
Temp. & Humidity Controls	X	X	X	X	X
Unit & Week FE	X	X	X	X	X
Unit Characteristic by Month FE	X	X	X	X	X
Scrubber & Enviro. Prog. FE	X	X	X	X	X
Pre-acquisition Mean	-	0.654	39.703	0.158	-
R^2	0.808	0.595	0.695	0.243	0.859
# of Observations	1.493M	1.494M	2.612M	0.705M	1.418M
# of Control Units	2311	2311	2311	1383	2026
# of Treated Units	1089	1089	1089	409	977

Note: This table presents the coefficient estimates of $\delta_1, \delta_2, \delta_3$, and δ_4 from estimating Equation (2). Unit characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity. Unit of observation is generator-week. Standard errors are clustered at the plant level. The number of observations in Column (4) is significantly lower than the rest because the outage & maintenance data begins in 2013.

production. Columns (2) and (3) provide additional insight into the increase in production. We observe that acquired power plants increase capacity utilization by 1.4 percentage points and operating hours by 1.68 hours, although the latter is not statistically significant at the 5% level. Moving to Column (4), the results point to a reduction in forced outages and derates of 3-7 percentage points after the acquisition, implying that the acquirers improve other dimensions of performance beyond efficiency. Finally, we note a 5% decrease in CO_2 intensity, mirroring the results on efficiency gains since CO_2 emissions are inversely proportional to heat input.

4.2 Discussion

Our findings in this section indicate that acquisitions lead to a 5% increase in efficiency, but only when both subsidiary and parent owners change. Additionally, acquired generators increase production and utilization, reduce outages, and improve CO_2 emission rates. How significant is the average 5% efficiency gain post-acquisition, and what are the corresponding cost savings? To answer these questions, it is helpful to compare our estimates to average within-generator productivity growth. In the power generation industry, within-generator productivity growth is modest, at only 0.3% annually.[30] Given this small within-plant productivity growth, the efficiency gains due to ownership changes is particularly noteworthy.

We also estimate the reduction in CO_2 emissions attributable to efficiency gains in electricity generation due to acquisitions, using the pre-merger CO_2 intensity as a baseline. As we detailed in Appendix B.3, three key assumptions underpin our calculation: First, we assume that the efficiency improvements start following the first acquisition of the unit. Second, we assume that the units maintain their production profiles post-acquisitions. Third, we exclude the within-generator intensity reduction that would happen in the absense of acquisitions. Under these assumptions, we calculate a total cumulative decrease in CO_2 emissions due to acquisitions from January 2000 to March 2023 to be approximately 360 million tons. This reduction is comparable to the emissions savings resulting from substituting 800 TWh of electricity generation from gas-fired power plants with renewable energy sources.

4.3 What Predicts Efficiency Gains: Heterogeneity Analysis

Our next set of analyses will focus on heterogeneity of efficiency effects. With this exercise, we aim to derive broader lessons from this industry and inform merger policy by uncovering which merger attributes may predict merger outcomes.

We examine the relationship between efficiency gains and key generator, firm, and transaction characteristics. For this purpose, we modify Equation (2) by interacting treatment indicators with observables to detect heterogeneity:

$$\log(y_{it}) = \delta_1 \mathbb{1}_{\{\text{Pre-year1}\}} + \delta_2 \mathbb{1}_{\{\text{Post-year1}\}} + \delta_3 \mathbb{1}_{\{\text{Post-year2}\}} + \delta_4 \mathbb{1}_{\{\text{Post-year3}\}} + \bar{\delta}_1 \mathbb{1}_{\{\text{Pre-year1}\}} \times Z_{it} + \tag{4}$$

$$\bar{\delta}_2 \mathbb{1}_{\{\text{Post-year1}\}} \times Z_{it} + \bar{\delta}_3 \mathbb{1}_{\{\text{Post-year2}\}} \times Z_{it} + \bar{\delta}_4 \mathbb{1}_{\{\text{Post-year3}\}} \times Z_{it} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \tag{5}$$

We separately estimate this equation for different generator, firm or transaction characteristics that might be indicative of overall efficiency gains. In particular, we consider plant capacity, plant age, whether the acquirer is a serial acquirer, acquirer size and whether the acquisition is a cross-market acquisition. The details of the construction of these variables are provided in Appendix B.

[30] See Appendix Figure OA-9, which plots the average year-to-year within-generator productivity growth for generators not involved in acquisitions. The productivity growth fluctuates around zero, averaging a 0.3% annual increase over the sample period. Most aggregate productivity growth in the industry comes from entry and retirements.

Table 4: Heterogeneity of the Merger Effects on Productivity

Interaction Var. (Z)	Capacity >Median (1)	Age >Median (2)	Serial Acquirers (3)	Firm Size >Median (4)	Cross-Market Mergers (5)
	Dependent Variable: Log of Efficiency				
Pre-acquisition (1 Year)	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Post-acquisition (1 Year)	0.001	0.016	0.009	0.01	0.014
	(0.01)	(0.011)	(0.008)	(0.008)	(0.01)
Post-acquisition (2 Years)	0.017	0.037	0.014	0.019	0.048
	(0.011)	(0.013)	(0.01)	(0.01)	(0.013)
Post-acquisition (3 Years)	0.029	0.054	0.025	0.033	0.068
	(0.014)	(0.017)	(0.013)	(0.013)	(0.017)
Post-acquisition (1 Year) × Z	0.023	-0.002	0.014	0.012	0.001
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Post-acquisition (2 Years) × Z	0.035	0.004	0.059	0.05	-0.021
	(0.015)	(0.016)	(0.016)	(0.017)	(0.015)
Post-acquisition (3 Years) × Z	0.033	-0.011	0.059	0.042	-0.038
	(0.018)	(0.02)	(0.02)	(0.02)	(0.019)
Temp. & Humidity Controls	X	X	X	X	X
Unit & Week FE	X	X	X	X	X
Unit Characteristic by Month FE	X	X	X	X	X
Scrubber & Enviro. Prog. FE	X	X	X	X	X
R^2	0.763	0.763	0.763	0.763	0.763
# of Observations	1.494M	1.494M	1.494M	1.494M	1.494M
# of Units	2311	2311	2311	2311	2311
# of Acquisitions	1089	1089	1089	1089	1089

Note: This table presents the coefficient estimates of $\bar{\delta}_1, \bar{\delta}_2, \bar{\delta}_3$, and $\bar{\delta}_4$ from estimating Equation (4). Each column reports results from a different regression by varying the interaction variable, Z. Unit characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity. Unit of observation is generator-week and the dependent variable is the logarithm of the inverse weekly heat rate. Standard errors are clustered at the plant level. Details about the heterogeneity variables are provided in Appendix B.4.

Table 4 reports the results. We consider two generator characteristics: capacity and age. We find that the efficiency increase is 3.3% larger if the generator capacity is higher than the median of acquired generator capacity. This may reflect the fact that an acquirer has a higher incentive to enhance efficiency in larger capacity generators plants, as any improvements in efficiency would yield higher returns. We do not find any significant effect with respect to generator age, as shown in Column (2). Next, we turn to firm characteristics. We focus on whether the acquirer is a serial acquirer and the size of the acquirer (total owned pre-acquisition fossil fuel capacity). The results reported in Columns (3-4) indicate that the efficiency improvement is 5% higher when the acquirer firm is large and is 6.2% higher when the acquirer is a serial acquirer. These results are consistent with the interpretation that a firm's experience in plant operation and acquisition is an important predictor of post-acquisition efficiency gains.

Finally, in Column (5), we report whether the efficiency effects differ for cross-market mergers. We define a generator acquisition as a cross-market acquisition if the acquirer does not own any existing fossil fuel generation capacity in the acquisition market (defined as a power control area). One might expect different efficiency effects in cross-market acquisitions due to the absence of market power effects. On one hand, the efficiency effects of within-market mergers might be smaller because they can still be profitable in the absence of efficiencies due to increased market power. On the other hand, within-market merger efficiencies could be higher because the merging parties need to show efficiencies to get merger approval. Alternatively, there could be within-market synergies or firm specialization in the acquisition market. We find that cross-market acquisition leads to efficiency gains that are 3.8% lower than within-market acquisitions. Although this result does not precisely identify the mechanism behind lower efficiencies in cross-market mergers, the next section will offer more insights by analyzing within-market portfolio-level synergies.

The analysis in this section indicates the extent to which efficiency gains correlate with certain generator, firm, and transaction characteristics. While these findings do not establish any causal effect, they are still important for antitrust policy. Predicting the efficiency impacts of mergers ex-ante is especially challenging, as most merger simulations primarily focus on forecasting price effects. Therefore, relating efficiency gains to a merger's specific attributes offers key information for understanding its potential efficiency effects.

5 Mechanisms

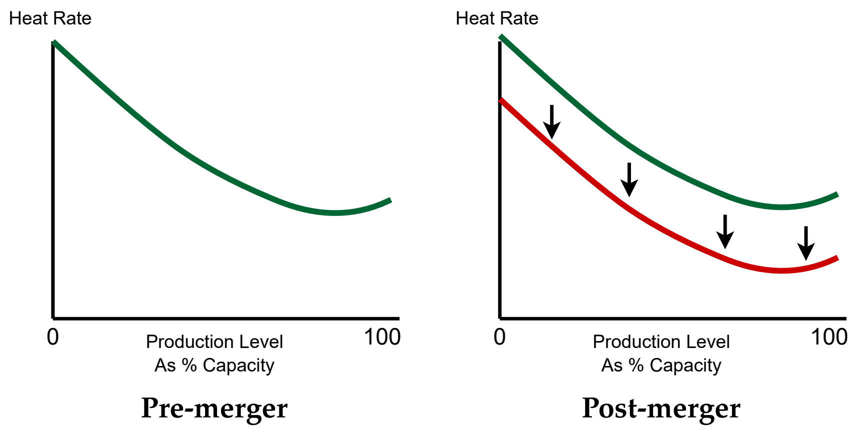
This section investigates the underlying mechanisms of efficiency gains and highlights two major findings: (i) the majority of efficiency gains stem from increasing productive efficiency within a generator, and (ii) acquirer firms achieve these efficiency gains through operational improvements rather than capital investments.

5.1 Mechanisms of Efficiency Improvements

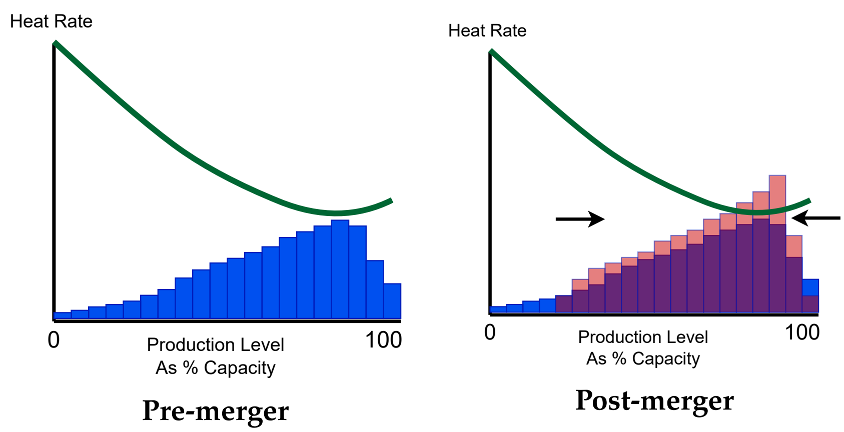
We propose three mechanisms that could explain the estimated efficiency gains: (i) productive efficiency, (ii) dynamic efficiency, and (iii) portfolio efficiency. We first explain these mechanisms and then develop a testable prediction for each of them.

Productive Efficiency. The first mechanism is productive efficiency. Productive efficiency

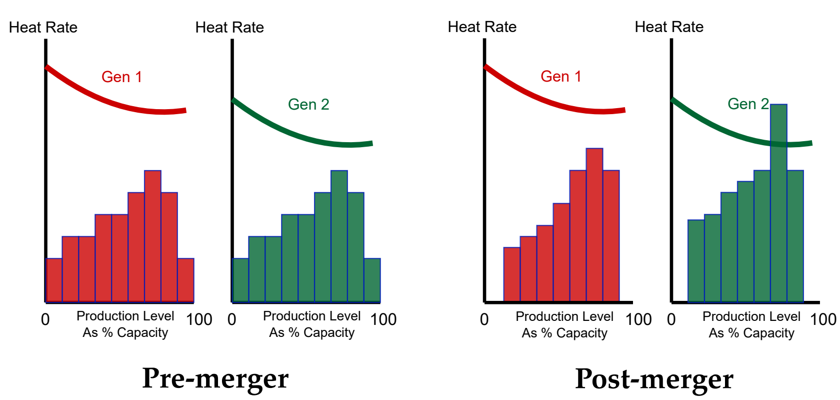
Figure 6: Illustration of Efficient Mechanisms



(a) Productive Efficiency



(b) Dynamic Efficiency



(c) Portfolio Efficiency

Note: Each panel shows the illustration of mechanisms of efficiency increase described in Section 5.1.

arises when the plant's new owner implements operational processes that reduce production costs or invests in new equipment. This mechanism is independent of synergies with other plants in the same market or changes in ramp frequency; it occurs solely through increasing the generator's efficiency. An implication of productive efficiency is a lower heat rate curve, as illustrated in Figure 6(a). Thus, a prediction of this mechanism is:

Prediction 1: If acquirers improve productive efficiency, the generator's cost curve shifts down.

Dynamic Efficiency. The second mechanism relates to dynamic efficiency, which arises from changes in production allocation over time. As discussed in Section 2.3, a key aspect of power generation is that efficiency is influenced by both the level of production and change in production. Generators experiencing significant production shifts face ramp-up and ramp-down costs, which lower overall efficiency. The stochastic nature of electricity demand necessitates managing ramp-up and ramp-down costs and requiring coordination between trading desk personnel, who are responsible for submitting supply bids, and plant operators, who monitor fuel costs and oversee production. Jha and Leslie (2019) notes that uncertainty in residual demand or mismanagement in production can significantly increase costs. Figure 6(b) illustrates the dynamic efficiency effect, showing more concentrated production, and hence lower ramp-up and ramp-down costs, post-acquisition. A prediction of this mechanism is:

Prediction 2: If acquirers improve dynamic efficiency, the volatility of generation goes down.

Portfolio Efficiency. The third mechanism to improve efficiency is portfolio effects. Electricity markets are complex, with stochastic demand, time-varying transmission constraints, and the need to meet demand in real-time. The role of market operators (ISOs) is to maintain coordination, allocate production to lower-cost generators through real-time auctions, and aggregate information from generators. However, some inefficiencies could still be present due to frictions and asymmetric information between market operators and firms, which might come from firms not having the right tools or incentives to convey its information to the system operator. Therefore, owning multiple power plants with different production costs could lead to portfolio level efficiencies with ramp-up and ramp-down synchronizations and efficient production allocation (Reguant, 2014). This effect is illustrated in Figure 6(c). As this mechanism only occurs when firms have multiple plants in the same market, a prediction for portfolio efficiency is:

Prediction 3: The efficiency of the acquirer firm's existing plants in the acquisition market improves, while in other markets, it remains the same.

5.2 Quantifying Productive Efficiency Using Production Function

We start by testing for productive efficiency using an empirical strategy guided by Prediction 1. In particular, we estimate a production function for generators where we model efficiency (heat rate) as follows:

$$y_{it} = f_{i\tau}(Q_{it}, X_{it}) + \epsilon_{it}, \tag{6}$$

where $y_{it} = \log(\text{Fuel}_{it}/Q_{it})$ is log heat rate, and Q_{it} is production of generator i at time t. The control variables include the ramp defined as the percentage change in production at time t relative to $t-1$, ambient temperature and ambient humidity. Subscript i denotes generator, t denotes hour, and τ indicates post- or pre-acquisition periods.

As described in Bushnell and Wolfram (2005) this form of production function can be micro-founded from a Leontieff electricity production function. To see this, assume that electricity is produced according to the following production function:

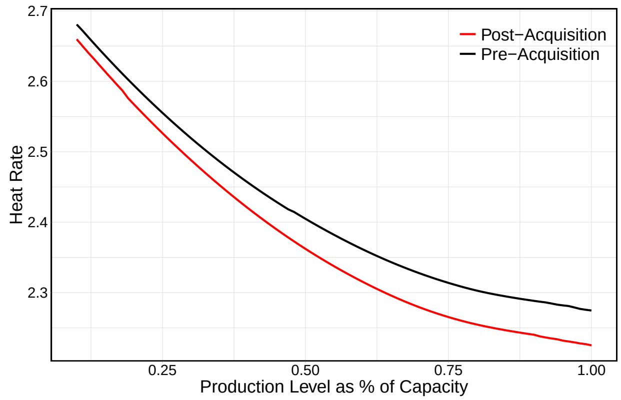
$$Q_{it} = \min(g(F_{it}, X_{it})\epsilon_{it}, h(K_{it}, L_{it}))\omega_{it}, \tag{7}$$

where F_{it}, K_{it}, L_{it} are fuel, capital and labor inputs, ϵ_{it} is fuel efficiency, X_{it} are factors that affect fuel efficiency, and ω_{it} is total factor productivity. This Leontief production function, under a cost minimization assumption, implies that $Q_{it} = g(F_{it})\epsilon_{it}$. Assuming that $g(\cdot)$ is monotonic in F_{it}, one can invert it and write F_{it} as $F_{it} = g^{-1}(Q_{it})\epsilon_{it}$. By dividing both sides by Q_{it}, and taking the logarithm, we obtain the form given in Equation (6).

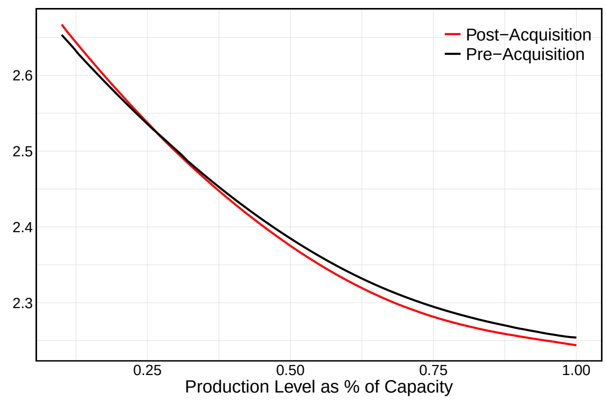
Importantly, our production function in Equation (6) is indexed by i and τ, where τ equals 1 in the post-acquisition periods and 0 in the pre-acquisition periods. This means that we estimate a generator-specific production function separately for the pre- and post-acqusition periods, so f_{i0} corresponds to production technology before the acquisition, and f_{i1} corresponds to production technology after the acquisition.

It is worth highlighting the advantages of estimating generator-specific production functions. The production function in Equation (6) captures heterogeneity in production technology and productivity level across generators with generator-specific and time-varying production function $f_{i\tau}$. Since productivity differences across generators and over time are captured by $f_{i\tau}$, ϵ_{it} corresponds to an ex-post shock (or measurement error) to output that is orthogonal to inputs. Therefore, our specification is robust to the standard endogeneity concern in production function estimation that more productive firms use

Figure 7: Estimated Average Cost Curves



(a) Treated Group



(b) Control Group

Note: This figure shows estimates of average heat rate curves three years before acquisition and three years after acquisition. Panel (a) shows this for the acquired generators group, and Panel (b) shows this for the control group constructed by a matching procedure detailed in Section D.4. The treated group sample is the same as Column (5) of Table 2. We find the difference to be statistically significant at every production level. Further details of the estimation procedure is provided in Section B.2.

different input levels, creating correlation between unobserved productivity and inputs, which is commonly called transmission bias (Marschak and Andrews, 1944). Second, we allow for a time-varying production function by estimating a separate production technology in the pre- and post-acquisition periods. This allows for not only the change in productivity level due to acquisitions, but also in the production technology.

We can estimate this production function flexibly due to the availability of hourly data, which provides thousands of observations for each generator even in a short window around acquisitions. This estimation underscores the benefits of a data-rich environment, contrasting with the traditional production function literature that often has to impose a functional form at the industry level due to data constraints.

We use a nonparametric local polynomial regression to estimate the functions f_{i0} and f_{i1} for each acquired generator. To estimate f_{i1}, we use three years of post-acquisition data, while f_{i0} is estimated using data three years prior to the acquisition. We also construct a control group by matching acquired generators to those never acquired based on capacity, age, fuel type, and technology type[31]. We repeat the same estimation procedure for the control generators to quantify productivity changes in the absence of acquisitions.

After estimating the heat rate curves both pre- and post-acquisition, we measure the gains in productive efficiency by calculating the difference between the post-acquisition and pre-acquisition cost curves for each generator, and then averaging these differences

[31]The details of how the control units are constructed are given in Appendix B.2

across all generators. Specifically, we calculate:

$$\Delta C(Q) = c_{post}(Q) - c_{pre}(Q) = \frac{1}{N_{acq}} \sum_{i=1}^{N_{acq}} \left(f_{i1}(Q, \bar{X}_i) - f_{i0}(Q, \bar{X}_i) \right),$$

where N_{acq} represents the number of acquired generators and $Q \in [10, 100]$ is production level as a function of capacity. The terms $c_{pre}(Q)$ and $c_{post}(Q)$ denote the average heat rate at production level Q before and after acquisition, respectively.[32] The control variables are set to $\bar{X}_i$, which is 0 for ramp and pre-acquisition medians for temperature and humidity, to isolate the effects of potential changes in these variables post-acquisition. Thus, $\Delta C(Q)$, which is called the average structural function (Blundell and Powell, 2001), gives us the change in the heat rate curve at each production level, after controlling for generator fixed effects and control variables.

Figure 7(a) illustrates $c_{post}(Q)$ and $c_{pre}(Q)$ for the acquired generators, while Figure 7(b) shows these functions for the control generators. A comparison of the pre- and post-acquisition heat rate curves reveals that the average curve for the treated generators shifts downward at each production level, whereas it remains largely unchanged for the control generators.[33] The difference between the curves for the treated group is slightly larger at production levels close to the capacity. We also bootstrapped standard errors for the average difference between cost curves, which shows the difference is statistically significant at every production level. These results provide direct evidence that the acquirers improve the productive efficiency of the acquired plants and that efficiency gains are not due to only simply changing ramp and production allocation.

Having estimated cost curves, we focus our attention on the total efficiency gain resulting from the downward shift in these curves. To quantify this, we integrate the difference between the post- and pre-acquisition curves as follows:

$$\Delta = \frac{1}{N_{acq}} \sum_{i}^{N_{acq}} \int \left(f_{i1}(Q, \bar{X}_i) - f_{i0}(Q, \bar{X}_i) \right) dF_i(Q),$$

where $dF_i(Q)$ denotes the distribution of production of generator i before acquisition. This calculation yields an efficiency gain of 4.2%, corresponding to roughly 80% of the total efficiency gain identified in the event study analysis. This indicates that the majority of

[32]The utilization values start at 10 because very low values of production are rarely observed and give noisy estimates.

[33]The small shift in the heat rate curve of control generators is consistent with the within-generator aggregate efficiency growth documented in Figure OA-9.

Table 5: Change in Variation of Heat Rate

Dep. Var.	CoV of Heat Rate (1)	CoV of Utilization (2)	Number of Ramps (3)
Pre-acquisition (1 Year)	-0.005	0	0.072
	(0.006)	(0.004)	(0.101)
Post-acquisition (1 Year)	-0.019	-0.015	-0.136
	(0.008)	(0.006)	(0.143)
Post-acquisition (2 Years)	-0.03	-0.025	-0.234
	(0.009)	(0.007)	(0.155)
Post-acquisition (3 Years)	-0.033	-0.029	-0.298
	(0.01)	(0.007)	(0.161)
Temp. & Humidity Controls	X	X	X
Unit & Week FE	X	X	X
Unit Characteristic by Month FE	X	X	X
Scrubber & Enviro. Prog. FE	X	X	X
Pre-acquisition Mean	0.25	0.375	3.915
R^2	0.195	0.528	0.449
# of Observations	1.476M	1.476M	1.493M
# of Control Units	2309	2311	2311
# of Treated Units	1089	1089	1089

Note: This table presents coefficient estimates of $\bar{\delta}_1$, $\bar{\delta}_2$, $\bar{\delta}_3$, and $\bar{\delta}_4$ from a regression of the standard deviation of heat rate on treatment dummies using Equation (2). Generator characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity.

the efficiency gain is due to increased productive efficiency, resulting from changes made by the new owners to improve the internal operations of the power plant.

5.3 Quantifying Dynamic and Portfolio Efficiency

We next quantify the role of dynamic efficiency. According to Prediction 2, an increase in dynamic efficiency would lead to less variability in production and fewer ramps post-acquisition. To test this hypothesis, we consider three distinct measures of production variability and estimate Equation (2) for these measures. In particular, we consider the weekly coefficient of variation (CoV) of heat rate, the CoV of utilization (the distributions shown in Figure 6(b)), and number of ramps.[34] These measures provide a comprehensive view of how acquisition impacts the production profile of generators.

Table 5 presents the results of our estimation. We observe a significant decrease in all

[34] We define a ramp as an event where production either increases from below 20% to above 80% of capacity, or decreases from above 80% to below 20% of capacity, within a span of less than three days.

measures of production variability following acquisitions. The CoV of heat rate shows an average decline of 0.033, a large shift given its pre-acquisition mean of 0.25. Similarly, the CoV of utilization decreases by an average of 0.029. Additionally, there is a notable decline in the number of ramps, amounting to an approximate 8% reduction relative to pre-acquisition levels; however, this result is significant only at the 10% level. These findings lead us to conclude that while improving productive efficiency is the primary method of achieving efficiency gains, acquirers also manage to lower ramp costs.

It is important to note that less frequent cycling in production can arise from several sources. One possibility is that it results from increased productive efficiency; a marginal generator becoming more efficient post-acquisition will be infra-marginal more often and, therefore, experience less ramping. Another explanation could be a decrease in outages and forced maintenance. Furthermore, the new owner might change the power plant's operation or improve coordination between the bidding desk and power plant. While our analysis cannot disentangle the role of these sources, it does provide evidence that the reduction in ramp cost contributes to an overall efficiency increase post-acquisition.

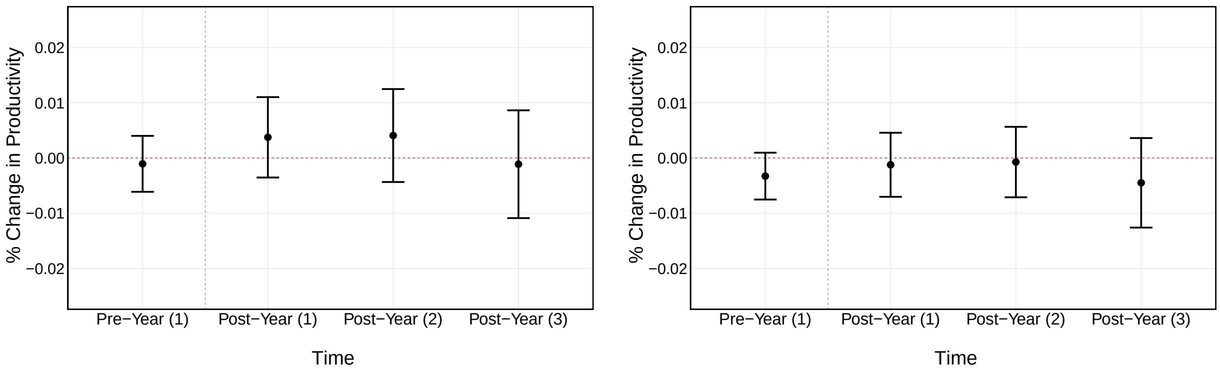
Finally, we test the portfolio efficiency mechanism. Prediction 3 suggests that portfolio efficiency occurs when the acquirer already owns capacity in the acquisition market, with generators in the same market increasing in efficiency while those in other markets remain unaffected. To examine this, we estimate Equation (2) twice: first for the acquirer's generators in the acquisition market (Figure 8(a)), and second for those outside the acquisition (Figure 8(b)) market. The results indicate that acquirers' generators do not exhibit efficiency improvements, regardless of their market location, suggesting a limited scope for portfolio efficiency improvements.

6 How Do Acquirers Improve Productive Efficiency?

Thus far, our analysis has shown an improvement in efficiency following ownership changes, mainly due to increased productive efficiency. The next natural question is how acquirers achieve this efficiency gain. In this section, we investigate this question.

In Section 2.3, we posited two potential ways to improve the productive efficiency of a power plant. The first is that acquiring firms implement low-cost operational improvements in the plants, such as better personnel training and performance monitoring, more efficient production management and improvements in repairs and maintenance. These improvements would indicate knowledge transfer from the acquirer to the acquired generator. The second mechanism involves large-cost capital investments by acquirers to upgrade existing equipment. If efficiency improvements occur this way, it would sug-

Figure 8: Impact of Merger on Other Plants



(a) Same Market **(b)** Different Market

Note: Panel (a) shows coefficient estimates from a regression of log efficiency on $\bar{\delta}_1, \bar{\delta}_2, \bar{\delta}_3,$ and $\bar{\delta}_4$ where existing units of the acquirer in the acquisition market are treated. Panel (b) shows the results from the same regression, except that existing units of the acquirer outside the acquisition market are treated. Error bars show 95% confidence intervals. Standard errors are clustered at the plant level.

gest that the previous owner had credit constraints or did not have incentives to make efficiency-improving capital investments.

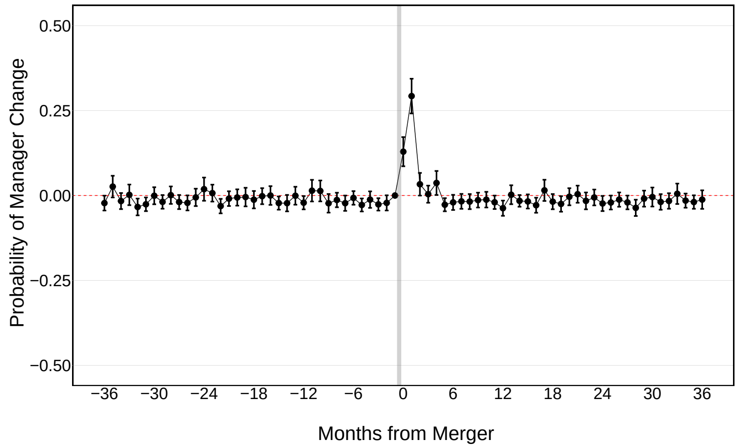
Disentangling these two sources is important not only for understanding the nature of efficiency gains, but also for antitrust policy. Efficiency gains must be merger-specific to be considered cognizable.[35] Efficiencies due to relaxing capital constraints may not be merger-specific, as they could be achieved without a merger, such as by raising new capital or through minority ownership. However, knowledge transfer can be considered merger-specific, since it involves the transfer of organizational knowledge between merging entities, a process unlikely to occur outside of a merger.

We aim to disentangle the sources of productive efficiency improvements using additional data on manager changes, capital investments, non-fuel inputs and maintenance schedules. Specifically, we examine whether power plants experience personnel changes or increase in capital expenditures following acquisition. Personnel changes would suggest significant operational changes, whereas changes in capital expenditures would provide direct evidence for the role of capital investment. By looking at non-fuel inputs and maintenance, we also analyze the role of other inputs in efficiency improvements and explore the possibility of input substitutions.

We start with manager changes and estimate the dynamic difference-in-differences in Equation (3) to investigate whether acquired plants are more likely to change managers after acquisitions compared to control plants. The outcome is an indicator variable set to

[35] The 2010 HMG define cognizable efficiencies as follows: "Cognizable efficiencies are merger-specific efficiencies that have been verified and do not arise from anticompetitive reductions in output or service."

Figure 9: Probability of Manager Change



Note: This figure shows coefficient estimates of a manager change dummy on $\hat{\delta}_s$ where $s \in (-36, 36)$. Error bars show 95% confidence intervals. The unit of observation is the generator-week. Standard errors are clustered at the plant level.

1 if the power plant manager is replaced in a given month and 0 otherwise. We include the same control variables as before.

Results in Figure 9 reveal that the likelihood of manager change jumps after acquisition, with acquired power plants on average 15% more likely to change managers within 1 month and 30% more likely within two months relative to the control group. The cumulative change reaches 55% within a year of acquisition.[36] We also investigate whether the characteristics of new managers after mergers differ from those of new managers without mergers. For a subset of managers, we observe the manager's education degree. We find that these managers are 5 percentage points more likely to have a master's degree and 4 percentage points more likely to have a bachelor's degree compared to manager changes without mergers.[37,38]

These results suggest that acquired firms often implement operational changes through new management. The potential role of management changes in explaining productivity differences echo important findings in the literature. Macchiavello and Morjaria (2022) find that foreign acquirers improve the performance of coffee mills in Rwanda by implementing management changes, and Bloom and Van Reenen (2010) show that productivity measures correlate with various management practices.

[36]The unconditional probability of management change in a given year is only 10%.

[37]Another important question is whether mergers with manager changes explain the efficiency gain entirely. For this, we look at whether mergers with manager changes lead to larger efficiency gains than mergers without any change in management. The results suggest that the effect is 2 percentage points larger, but it is not statistically significant.

[38]Another interesting analysis would be to estimate manager fixed effects using the managers that move between power plants to quantify their productivity. In our manager data, we do not observe many managers moving between power plants, so we do not have power for such an analysis.

Table 6: Effects of Mergers on Non-fuel Costs

Dep. Var.	Log Capital Expenditures (1)	Log Nonfuel Cost (2)	Log Total Number of Employees (3)	Maintenance Duration (4)
Pre-acquisition (1 Year)	-0.217	-0.336	-0.22	-0.727
	(0.16)	(0.402)	(0.111)	(0.96)
Post-acquisition (1 Year)	-0.051	-0.109	-0.322	-2.109
	(0.162)	(0.207)	(0.125)	(0.941)
Post-acquisition (2 Years)	-0.238	0.096	-0.057	-3.21
	(0.169)	(0.264)	(0.136)	(1.095)
Post-acquisition (3 Years)	-0.239	-0.304	0.001	-3.18
	(0.175)	(0.294)	(0.156)	(1.147)
Temp. & Humidity Controls	X	X	X	X
Unit & Week FE	X	X	X	X
Unit Characteristic by Month FE	X	X	X	X
Scrubber & Enviro. Prog. FE	X	X	X	X
Pre-acquisition Mean	-	-	-	5.109
R^2	0.896	0.704	0.946	0.123
# of Observations	0.018M	0.018M	0.017M	0.705M
# of Control Units	1472	1643	1553	1383
# of Treated Units	176	203	148	409

Note: This table presents the coefficient estimates from estimating the effects of mergers on non-fuel cost, number of employees and capital expenditures with annual data. Standard errors are clustered at the plant level. Note that the capital expenditure information, sourced from FERC Form 1, is available exclusively for investor-owned utilities from 2008 to 2023.

Next, we examine the changes in capital expenditures and non-fuel inputs after acquisitions, noting that this analysis uses a different and limited dataset. Specifically, we observe data on capital expenditures, employee numbers, and non-fuel costs for a subset of plants reporting to FERC only after 2010. This dataset is at the annual frequency, in contrast to the hourly frequency of previous data. Consequently, while these results offer valuable insights, they should be interpreted with caution due to these limitations.

The coefficient estimates reported in Table 6 suggest that acquired plants do not increase capital expenditures. The coefficient estimate on capital expenditure is -24%, but it is not statistically significant due to the small sample size. However, we can still reject the hypothesis that capital expenditure increases by more than 5% at the 10% significance level.[39] Results on non-fuel inputs are also noisy, but they show evidence against large increases. These findings, alongside the data on personnel changes, suggest that opera-

[39]Additional evidence contradicting the capital expenditure hypothesis is the timing of efficiency gains and operating hours. Significant capital investments often take longer than five months, and they usually necessitate considerable downtime, which we do not observe.

tional improvements are the key drivers of productive efficiency and efficiency increases do not come at the expense of an increase in other input expenditures. This is in line with Atalay et al. (2014)'s finding that vertical mergers help transfer intangible capital between merging firms.

In our final analysis, we look at how maintenance duration changes after acquisitions. We define maintenance duration as the number of hours a generator is under maintenance in a given week. Maintenance is also important to analyze because if the new owners manage the equipment better, we could see less maintenance, due either to less wear on equipment or due to a single maintenance session being more effective at addressing issues. This would also raise production as the generator goes offline less often for maintenance purposes. The results in Column 4 suggests that maintenance duration goes down after acquisitions suggesting that excessive maintenance is not the main way of improving efficiency.

A natural question arising from the findings in this section is why previous owners do not implement the operational improvements. Given that our study is an industry-level analysis rather than a firm-level case study, we cannot provide a definitive answer to this question. Nonetheless, it is important to note that our results align with the substantial evidence of persistent productivity differences across firms in various industries (Syverson, 2011; Gibbons and Henderson, 2012). We interpret our evidence to suggest that some firms develop intangible capital over time for more efficient power plant operation, and this within-organization knowledge is transferable primarily through ownership changes. Therefore, acquisitions provide a channel for the intangible capital to spread across plants, which is unlikely to happen through other means.

7 Robustness Checks

In this section, we investigate the robustness of our results to alternative specifications. The details of these robustness checks are described in Appendix D, and we report the corresponding results in Appendix E.

Acquisition Sample. In our analysis, we focus only on each generator's first acquisition. We take this approach because it is unclear how to correctly estimate the event study with generators acquired more than once. In a robustness check, we include all acquisitions of generators within our sample period. The findings, reported in Column (3) of Appendix Table OA-2, Appendix Table OA-3, and Appendix Figure OA-13, are largely consistent with our main results.

Estimation Frequency. Our main analysis uses weekly data to estimate the effects of acquisitions, as the aggregation reduces noise in the hourly data and is computationally convenient. To assess the robustness of our findings to this approach, we conduct the same estimation using daily and hourly data. The results remain consistent across different frequencies, although there is a slight increase in standard errors.

Staggered Difference-in-Differences. Recent developments in econometrics suggest that the two-way fixed effects difference-in-differences approach might produce a weighted average of all potential combinations of pairwise difference-in-differences estimators, where the control unit in the pair could be a unit that is treated at a different time (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and SantAnna, 2021; Goodman-Bacon, 2021). To tackle this issue, we estimate cohort-specific treatment effects using the Callaway and SantAnna (2021) method to find similar results, which we report in Appendix Figure OA-14.

Weighted Estimator In our primary analysis, we estimate the average treatment effects without accounting for the varying capacity sizes of acquired generators. In a robustness check, we weight observations by their capacity, which would be a more accurate measure of total cost savings. The results from this specification suggest slightly higher efficiency effects, suggesting that the evidence does not primarily come from small units. See Column 4 of Appendix Table OA-2, Appendix Table OA-4, and Appendix Figure OA-16.

Matching Estimator We match each acquired generator with similar ones from our pool of never-acquired control generators. For each generator, we first construct a pool of potential control units with the same fuel type and technology that operate in a different market to avoid spillover effects. Then we match these generators based on capacity and age at the time of the acquisition using a least-squares distance metric between generation units, with weights inversely proportional to the standard deviation of each variable. We allow control units to be matched to multiple acquired generators. See the results in Column (5) of Appendix Table OA-2 and Appendix Figure OA-15.

Net Generation In our primary analysis, we used gross generation when quantifying generator efficiency because of its availability in high frequency. We also think gross generation is the relevant variable for understanding the overall efficiency of power plants since we study how fuel is transformed into electricity, not revenue obtained from net generation. However, we repeat the analysis using monthly net generation data from EIA as a robustness check. The effect is broadly similar but slightly lower.

Estimation after 2010 One potential concern in our analysis is the effect of deregulation which overlaps with our sample period for a few years in the early 2000s. Even though we exclude ownership changes that correspond to divestitures, as a robustness check, we repeat our analysis by restricting to acquisitions after 2010. The results, reported in

Column (1) of Table OA-2, is similar to our baseline result.

Placebo Tests We use two types of events as placebo tests: minority acquisitions and corporate restructuring. We use these events as placebo tests to test for unobservable characteristics that could drive both acquisitions and efficiency changes; should these unobservables exist, they would likely drive minority acquisitions and corporate restructuring. The results, reported in Columns (6) and (7) of Appendix Table OA-2 confirm our expectation that there is no significant change in power plant efficiency after these events.

8 Conclusion

By reallocating resources between firms, mergers and acquisitions affect a significant portion of the economy. Despite this importance, there is limited systematic evidence of their effects on productivity. This study provides detailed empirical analyses of the efficiency effects of mergers by examining a large sample of power plant mergers and acquisitions between 2000 and 2023. Our empirical results can be summarized into three principal findings. First, we find that acquired plants experience on average a 5% efficiency increase in five to eighteen months after acquisition. Second, these generators produce more, increase their capacity utilization, decrease their outage frequency and decrease cycling. Finally, we find that the new owners improve productivity by changing operational processes rather than by making costly capital investments.

Our findings take advantage of a large number of acquisitions in the power generation industry and high-frequency data on productivity and inputs obtained via physical monitoring systems. Using physical measurements in this homogeneous product setting allows us to disentangle the productivity effects from other potential merger effects, such as market power, buyer power, or changes in quality. With high-frequency data, we can treat mergers as discrete events and compare generator productivity immediately before and after acquisitions. Finally, by aggregating evidence from a large number of mergers and acquisitions, we have statistical power to uncover many interesting mechanisms that could generate efficiency gains.

Our findings have important policy implications, as they can be a direct input to evaluating the trade-off between market power and efficiency due to mergers. However, we want to emphasize that our results do not give a conclusive answer to the overall impact of mergers on consumer harm, as we identified only one factor going into the welfare analysis. Moreover, our efficiency results are not generalizable to industries where the production process differs significantly from electricity generation, such as service industries.

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Do Mergers and Acquisitions Improve Efficiency: Evidence from Power Plants

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Appendix - For Online Publication

Contents

A Data Appendix

This section provides the details of the data sources used in the paper.

A.1 Unit-Level Data

We use EIA Forms 860 and 923, EPA's Continuous Emissions Monitoring Systems (CEMS), S&P Global, and Velocity Suite to construct a dataset for generator characteristics and production. The EIA forms and CEMS data sources are public, whereas S&P Global and Velocity Suite are private data providers for energy markets. The EIA Forms cover the universe of generators in the US, whereas the CEMS data includes generators with a capacity above 25 MWh that are subject to a set of environmental regulations. The data providers S&P Global and Velocity Suite compile unit- and plant-level information from various resources, including EIA, EPA, FERC, and proprietary. We merge these datasets based on generator names and plant ids (orispl code). The merged data is a monthly panel data that include information on plants and generators. These include regulation status, technology type, installation year, fuel type, coal type, boiler type, boiler model, boiler manufacturer, capacity, fuel cost, prime mover category, dispatch type, whether a unit is connected to the grid, internal generator, whether the unit is marginal or infra-marginal, and whether the unit is able to switch fuel. We provide more details about some of the variables below.

Generation Most fossil fuel power plants are required, under EPA regulations, to make continual compliance determinations for environmental regulations. For this purpose, EPA collects boiler-level hourly production and emissions data (heat input, gross electricity generation, emissions) from power plants and makes this data publicly available. The coverage of this data corresponds to roughly 96% of US fossil-powered generation in 2018 (EPA, 2018a). While this data is available starting in 1995, the data quality is poor before 2000. For this reason, we restrict the study period from 2000 to March 2023. With these restrictions, the final data includes all US fossil fuel generators that comply with the CEMS program, except those in Alaska and Hawaii. This procedure results in an hourly unit-level dataset on generation, fuel input, and heat rate between 2000 and March 2023. We aggregate this data to weekly levels in some of the analyses employed in the paper.

The heat rate quantity is calculated by dividing the total heat input by the total electricity output at the frequency of the analysis (hourly, daily, or weekly). If there are significant changes in the production within the hour, the heat rate could be very high or very low. This sometimes generates noise in hourly heat rates, especially at small production levels. To account for this, we winsorize heat rates above 16 or below 6 MMBtu per MWh. This winsorization affects less than 3% of all observations.

We match unit-level generation data from CEMS to unit-level data from the other data sources mentioned above. While most units are easily matched using the unit name, some do not match as EPA uses boilers as a unit, whereas EIA uses generator names. For those cases, we rely on the EPA's Power Sector Data Crosswalk available on the EPA's website.[40] This crosswalk does not include units that retired before 2020. We manually match those retired and other unmatched units based on capacity, installation year, and retirement year information.

Enviromental Programs CEMS provide information on which enviromental programs units are subject to. These programs include Acid Rain Program (ARP); Cross-State Air Pollution NOX Annual Program (CSNOX); Cross-State Air Pollution NOX Ozone Season Group 1 Program (CSOSG1): Cross-State Air Pollution NOX Ozone Season Group 2 Program (CSOSG2) Cross-State Air Pollution NOX Ozone Season Group 3 Program (CSOSG3) Cross-State Air Pollution SO2 Annual Group 1 Program (CSSO2G1), Cross-State Air Pollution SO2 Annual Group 2 Program (CSSO2G2), Mercury and Air Toxics Standard (MATS), New Hampshire NOX Program (NHNOX), NSPS Greenhouse Gas Rule (subpart TTTT, NSPS4T), Regional Greenhouse Gas Initiative (RGGI), SIP Call NOX Budget Trading Program (SIPNOX/NBP), Texas SO2 Trading Program (TXSO2).

Enviromental Control Equipments CEMS provides data on environmental control equipment used in boilers for SO_2, NO_x and particulate matter (PM) reduction. This includes the installation date and type of each equipment. A generator may use multiple pieces of equipment for a particular pollutant. From this dataset, we create control variables that indicate whether a unit has at least one scrubber for each particle type.

Capacity Estimation EPA data does not provide capacity data. We infer yearly capacity from generation using the following algorithm. For each year, we keep generators that operate cumulatively for more than two weeks each year. Then, we obtain the annual hourly generation distribution and use the 99.5th percentile of the generation as the capacity for the unit every year. This algorithm yields generator capacity that is stable over time for most units. If a unit generates less than two weeks over the course of a year, this algorithm does not yield any capacity estimates. For those units, we backfill capacity information from previous years. To check the accuracy of this algorithm, we run it for the units that have a perfect match in the EPA and EIA, for which we have the true capacity information. We find that capacity generated from the EPA data aligns with those provided by the EIA.

[40] https://www.epa.gov/airmarkets/power-sector-data-crosswalk.

A.2 Plant-Level Data

We use EIA Forms 860 and 923 and Velocity Suite to construct data for plant-level characteristics. From these data sources, we obtain information on location, ISO, FERC region, regulation status, and other important plant-level information. We also obtain data on non-fuel input from Velocity Suite, such as capital expenditures, number of personnel, and non-fuel costs. Velocity Suite compiles this data from the annual FERC Form 1, a comprehensive financial and operating report submitted for Electric Rate regulation and financial audits. This form is only mandatory for investor-owned utilities, so the coverage for these variables is lower than the coverage of other variables.

A.3 Personnel Data

Each power plant subject to at least one EPA program must submit a representative contact to the EPA. This representative information is essential for the EPA, as potential problems like leakage need to be addressed quickly, and responsible parties should be accountable. This data includes the representative's name, start and end date, and contact information and is available through EPA's Envirofacts Data Service API.[41] We use this data on plant representatives from the EPA between 2000 and 2020 to construct personnel data. However, this database does not include some key information, such as job titles. To obtain this information, we matched representative names to their LinkedIn profiles and found about 70% of representatives on LinkedIn. The match rate improves over time, reaching 80–90% in later years. We obtain a history of job titles, employment, and education from LinkedIn profiles. The job title suggests that about 70–80% of submitted representatives are plant managers and the rest are engineers or regulatory compliance managers. Considering that most of these representatives are plant managers, we treat the representative personnel as the plant manager in this study.

This procedure results in monthly plant-level panel data on plant managers. In this data, we know the manager's start and end date of employment and education history if it is successfully matched to LinkedIn profiles.

A.4 Divestiture Data

After the 1990s, significant deregulation reshaped the power generation industry. To differentiate between mergers and deregulation-driven divestitures, we compiled a dataset focusing on divestiture-related acquisitions after the year 2000. This dataset was formed by amalgamating various resources, with a primary focus on post-deregulation divestiture

[41] https://www.epa.gov/enviro/envirofacts-data-service-api

activities.

Our initial step involved utilizing the divested plants from Cicala (2022) and Abito et al. (2023), which provided a detailed account of deregulation from 2000 to 2012, integrating data from the EIA and other resources. For data prior to September 2002, similar to Cicala (2022) and Abito et al. (2023) we primarily relied on the EIA Electric Power Monthly reports, which featured a specific section highlighting divestiture cases, titled "Electric Utility Plants Sold/Transferred and Reclassified as Non-utility Plants." This section was crucial in identifying the divestiture events and the corresponding acquisition dates. Post-2002, we merged several datasets. This included tracking changes in the EIA's regulation status, S&P Global's regulation status, and Velocity Suite's data regarding the regulatory status of the plant owners.

The next step in our methodology was to identify the exact month of divestiture post-2002 accurately. For this, we analyzed changes in ownership data, specifically looking at 'Owner' and 'Ultimate Owner' as per S&P Global, and 'Owner' and 'Holding Company' according to Velocity Suite data. Our time frame for this analysis was set at a 12-month window – six months before and after the first observed change post-2002. In instances of conflicting data between these sources, we gave precedence to S&P Global, owing to its better alignment with EIA's pre-2002 data. This results in a total of 615 acquisition events between 2000 and 2023 that we remove from the acquisition sample.

A.5 Ownership and Acquisition Data

Every acquisition that involves a power plant should be notified to the corresponding state or federal agency for approval. For this reason, the power generation industry has comprehensive data on the universe of power plant mergers and acquisitions. To construct this dataset, we use two separate datasets from S&P Global: ownership and transaction datasets. We augment this dataset using company press releases and newspapers articles about these acquititions.

We access data on ownership shares of electricity generators from the S&P Global Capital IQ database (previously called SNL Financial). This dataset has been previously used by many researchers to study electricity markets (Davis and Hausman, 2016; Jha, 2020; Borenstein and Bushnell, 2018). We exclude generators categorized as in development, terminated, announced, or under construction as of August 2023 and focus only fossil fuel generators. The name of the owning company, their percent share of equity in the generating unit, and the owner's ultimate parent company characterize the ownership information for each generator-share. If a generator's ownership changes over time due to a merger or acquisition, a share has an event date, event id (transaction id) and an end date. The status of each share is recorded as either “Current" or “Sold". “Current" shares do not have an end date as it indicates the current ownership while “‘Sold" shares do have an end date indicating the end of a past ownership. There are also “Pending" ownership shares, but these represent transactions which have yet to complete as of August, 2023, so these observations are disregarded.

From the raw generator-share data, we construct a panel that records information about the companies that own each generating unit for the duration our study period. We rely on the dates listed with each ownership share to determine when a generating unit should enter the panel and when ownership changes occur. These data record the set of companies that own each generating unit, the percent shares attributable to each owner, and each owner's respective ultimate parent company. If an ownership group is active for less than a full month, meaning the event occurs after the first of the month and expires before the end of that same month, then we exclude the ownership group involved in this intra-month change from the panel. Intra-month ownership changes account for less than one percent of the generator-share data. S&P Global backfills any company name change, so firm name changes are not reflected as ownership change. Moreover, S&P Global maintains a consistent company identifier for owner throughout the panel, so we do not need to rely on company names. To summarize, this procedure results in a month-generator panel data with the following information: the largest three shareholders of the generator, the parent company of each shareholder, and the percentage of the power plant owned by each shareholder.

The second dataset is mergers and acquisition data. This dataset provides detailed information for every transaction, such as buyers, sellers, transaction type (divestitures, cash deal, LBO), and deal value. This dataset includes a transaction ID and transaction description. Around 80–85% of transactions include transaction descriptions where one can see acquired assets, acquisition motives, and other important information. The rest of the transactions do not have a description. For these transactions, we manually search for companies involved and classify whether these are true ownership changes. This search revealed that the majority of transactions with no description are false acquisitions due to corporate restructuring or name changes. For this reason, we decided to exclude acquisitions with no description and corresponding ownership changes from our sample. For other transactions, we read the description and found corresponding newspaper articles and press releases (often listed in S&P Global Capital IQ) to make sure that they are true ownership changes.

Next, we merged the two datasets using transaction IDs that are available in both datasets. The merged data gives us a complete picture of ownership changes, including new and previous owners and important transaction characteristics.

A.6 Firm Data

Even though the ownership and transaction data provide buyer and seller names and identifiers, they do not provide information on firms, such as their industry and asset size. To obtain this information we used another data portal owned by S&P Global called S&P Capital IQ Pro.[42] S&P Capital IQ Pro and S&P Global Capital IQ use the same company identifier if the firm is classified as a utility. For other firms, we manually searched for company names in the platforms to create a crosswalk between company identifiers. We could match all company names except for a few companies that went bankrupt or were company funds. Using these company identifiers, we merged S&P Capital IQ Pro database to our ownership panel and obtained key information about firms such as industry, year founded, asset size, and various balance sheet information.

A.7 Maintenance and Outage Data

The Generating Availability Data System (GADS), managed by the NERC, is a database and reporting system that collects and analyzes data on the performance and reliability of power plants. The data collected helps utilities and other stakeholders in analyzing performance trends, developing benchmarks for equipment reliability and availability, and in making informed decisions about plant operations and maintenance. The GADS database is divided into events, performance, and units datasets containing information on unit maintenance and disruptions at the hourly level, monthly unit generation, and time-invariant unit characteristics, respectively. The intersection of these datasets yields a panel ranging from 2013 to 2021 for 6,914 units that experience any type of event.

A.7.1 GADS Data Description

The primary focus of the GADS database are the events data, which are aggregated at the event level and describe the duration of disruptions and other issues experienced by generators. These events can be broadly categorized as outages, which indicate a complete disruption of production; derates, which are associated with periods of production lower than expected capacity; non-curtailing, which do not affect the productive capabilities of units; and inactive, during which units are not producing for some reason other than those associated with outages. Outages and derates are further categorized as forced, planned, or maintenance events, depending on the urgency. Forced events must be addressed immediately or near-immediately, whereas planned and maintenance events are disruptions

[42] https://www.capitaliq.com/

that have been anticipated over a longer period of time; planned events typically coincide with planned inspections and are thus scheduled months in advance, whereas maintenance events are less-emergent than forced events, but require attention prior to the next planned event.

In addition to the events data, the GADS data also includes data describing unit generation. These data, referred to as the performance data, are aggregated at the monthly level and report generation in terms of hours, along with descriptive information such as fuel and unit type. NERC also provides time-invariant unit characteristics in the units dataset; of particular interest in these data are the unit's geographic location and name-plate capacity.

A.7.2 Processing GADS Data

The raw GADS data are combined to construct an events panel unique at the unit-hour level. The foundation of this panel is the events data, though the performance and units data supplement the events data with unit characteristics and production information. The units data provide capacity and geographic information of a unit, and the performance data provide fuel type information, which is taken as the most recently reported fuel type for a given unit, as well as monthly production hours. The processing of these data is minimal; the performance data contain some duplicate observations which are dropped, but cleaning efforts are otherwise focused on the events data.

Similar to the Performance data, the Events data include some apparent duplicate observations that contradict the documentation. The data documentation suggest that the data should be unique at the unit-event level, where an event is described by a combination of descriptors and date range. These event descriptors include event type, contribution code, cause code, and amplification code, where contribution code indicates whether an event was the primary cause of disruption, and cause and amplification codes each provide more detail describing the event (such as a particular part malfunction). Contrary to this intuition, the raw data include a unique event identifier that seems to distinguish between events that are otherwise identical on all other variables. For this reason, we assign our own event identifier based on the combination of descriptors detailed above, and drop duplicate events based on this definition. This cleaning step drops 1,380 observations, which accounts for 0.03% of the raw sample.

The raw events data are split into yearly files, and so individual events that span multiple years must be concatenated manually. The raw data include a flag indicating whether an observation corresponds to an event that continues into the next year or is a continuation of an event from a previous year. We concatenate events across years, using this flag to distinguish between events that actually span calendar years as opposed to those events that start (end) on the first (last) date of a given year. It follows that an event continuing into the next year should match to a corresponding event such that the end and start dates are the same. For a given pair of adjacent years, we concatenate events when appropriate, matching them based on the event descriptors described above (i.e., unit owner, unit, event type, contribution code, cause code, and amplification code) as well as coinciding start and end dates. We repeat this exercise once more to account for events that may span multiple years, matching 75% of events flagged as spanning multiple years.

The Events data also include partially or completely overlapping events that are otherwise identical; in other words, there are events which are identical across descriptors that start at the same time but end at different times, and vice versa. These events are always derating or non-curtailing events, and likely correspond to different periods of work or, alternatively, different periods of capacity restriction. Given our focus on the timing and nature of events, and not the extent of work or capacity restrictions, we drop any event that is completely subsumed by another event that is identical in terms of descriptors. One important distinction is partially overlapping events, which we keep in the data as distinct disruptions. This excludes 1424 superfluous events.

In sum, this process drops 0.7% of the raw sample and yields a dataset defined at the event level, in which a unit can experience multiple concurrent events. Observations are identified by Unit-Owner-Event Type-Cause-Contribution-Amplification-Start Date combinations. From this dataset, we generate a restricted Events dataset that excludes units that are not located in the contiguous United States or produce for less than 100 hours over the sample period. Additionally, hydro or nuclear units are excluded from this restricted set, which accounts for 71.2% of units and 69.3% of reported events in the full Events dataset.

Taking the cleaned Events data as input, we construct a balanced hourly events panel for all units that includes event ID and descriptors for up to five concurrent events. Units may experience up to 47 events simultaneously in the raw data, but maintaining information on each of these events is not tractable given computational constraints. Units seldom experience more than five events simultaneously, account for 0.05% of all unit-hours or 0.09% of unit-hours conditional on at least one observed event, so this restraint has minimal impact qualitatively. The raw events data report event duration by the minute, though this level of precision is unnecessary and intractable. To limit the granularity, start dates are rounded up and end dates are rounded down to the nearest hour, such that events generally begin in the first full hour and end in the last full hour of occurrence.

A.7.3 Matching GADS Units to CEMS Data

The hourly events panel facilitates and granular comparison between GADS event incidence and CEMS production. Additionally, the GADS performance data allows a direct comparison between GADS production and CEMS production data, albeit at the monthly level due to the limitations of GADS granularity. As a first step, we attempt to match units across datasets by correlating monthly production hours; this approached is supplemented with an hourly comparison, in which we calculate the probability of production conditional on events. This process, described in further detail below, matches 3,988 GADS units to CEMS units.

Monthly Algorithm The monthly algorithm attempts to match units across datasets by correlating monthly production hours. The GADS performance data reports monthly production in terms of generation hours; to ease comparison,the hourly CEMS production data are aggregated to the monthly level by calculating the number of hours in a given month during which a unit produces any output. Units are grouped into "buckets" based on state and a broad categorization of fuel type, distinguishing between coal, gas, and other fuels, in order to limit the scope of comparison. Within each bucket, production is correlated for all unit-pairs across datasets over the months that both units are available for production. Correlations are calculated with a variety of measures to account for outlier sensitivity; the key measures include Spearman, Kendall, and Pearson coefficients, though we run additional correlations for robustness that winsorize the production hour distributions, and, separately, focus on months where both units are actively producing. We calculate the average correlation coefficient across measures and produce a scatter plot for each potential match, which were manually reviewed to determine true matches. Each potential match was given a score of 1 through 6, based on the following definitions: definite unit match, definite plant match, probable match, multiple potential matches, no match, and no need to match on account of low production. To supplement the correlation calculation and distinguish between multiple strong candidates, we also compared unit characteristics, such as retirement status or capacity. In sum, this algorithm matched 3,671 (3,469) GADS units to CEMS (Velocity) units.

This process is repeated again on the subset of unmatched GADS units with buckets defined by state, allowing for some flexibility with fuel type when comparing units across datasets. For this additional iteration, we restrict attention to unmatched CEMS units as well as CEMS units that are not matched with utmost confidence; in other words, we exclude CEMS units matched to GADS units for which we are reasonably certain that the unit match is precise. This step generated an additional 304 GADS unit matches.

Hourly Algorithm The hourly algorithm matches units across datasets by calculating the probability of production, conditional on an observed event. We evaluate matches based on the rate at which unit production accords with event occurence. To underpin this logic, we take the monthly matches as given and plot the distribution of production probabilities conditional on various event types. Focusing in particular on units that are matched with confidence, these distributions show that units experiencing an outage event overwhelmingly do not produce; likewise, a unit experiencing an isolated derate event (i.e., a derating without any concurrent events) is very likely to produce. These findings square with the GADS documentation describing each of these events. Intuitively, a unit that experiences an outage is not able to produce, whereas a unit experiencing a derating event without any other extenuating circumstances (i.e., simultaneous outage or reserve shutdown) should operate at reduced capacity. Approximately 66.4% of units experience an isolated derating event, though 99% of units experience an outage event at some point; the overwhelming majority of units that experience an isolated derating event also experience an outage at some point during the sample period.

Given these patterns, we devise scores to rate the extent to which a unit's production coincides with expectations, given an outage or isolated derating event. We calculate four different scores: (i) a derate score, which is the probability of production, conditional on an isolated derating event, (ii) an outage score, which is the probability of no production, conditional on any outage, (iii) an average score, which is a simple average of the derate and outage scores[43], (iv) and a composite score: the probability of production conditional on an isolated derating or the probability of no production conditional on any outage.

These scores are calculated over the intersecting periods of GADS event times and CEMS production times. As such, we do not calculate conditional probabilities during times prior to a unit's entry following a unit's retirement. This is meant to reduce the amount of false positives that may arise from an inactive unit perfectly overlapping with an outage event. However, this approach introduces an additional source of false positives, in that production and event times may overlap minimally and thus achieve an erroneously high score. To account for this possibility, we also calculate the share of event time during which a unit is available for production, and scale the average and composite scores by this share. Doing so minimizes the potential for false positives by scaling down the scores of matches that barely overlap.

As in the initial monthly algorithm, GADS units are compared to CEMS units based on the state and broad fuel grouping. To provide additional focus, comparisons are restricted to those units that operate over similar time periods; this operational overlap is calculated

[43] If a unit does not experience an outage (derate), then the average score is equal to the derate (outage) score

as the share of months during which both units produce any amount of output. We only attempt to match those units whose production shares are within 2.5 percentage points. Additionally, we exclude CEMS units that never produce electricity.

We calculate the scores discussed above for all unit combinations within these constraints. To identify additional matches, we rely on the monthly matches as a benchmark because these have been manually reviewed and verified. For each score, we calculate the share of GADS units for which the hourly algorithm and monthly algorithm generate the same match; the score that yields the highest rate of concurrence across algorithms is considered the optimal score.

Rates of concurrence tend to vary considerably across fuel types, so we select optimal scores for each fuel grouping: the optimal score for coal, gas, and other units is composite, average scaled by overlap, and composite scaled by overlap, respectively. For each unit, we calculate the difference in optimal scores between the top matches, based on the assumption that the score of a true match will far exceed the next best option. We plot the distribution of these differences, breaking them out by fuel grouping, as well as whether the match concurs with the monthly algorithm match. Focusing on the GADS units which are matched to different CEMS units (i.e., the hourly algorithm does not correctly identify the unit match given the monthly results), we use this distribution to identify a threshold above which false positives are very unlikely based on the right tail of the distribution. We apply this threshold to GADS units that were not matched to any unit in the monthly algorithm in order to identify additional matches that are unlikely to be false positives. Taking these additional matches, we manually review correlation matrices similar to those generated in the monthly algorithm to weed out erroneous matches, applying match scores based on the scheme outlined in the monthly algorithm. This procedure yields an additional 13 matches to CEMS units.

Match Results This iterative matching process yields 3994 matched GADS units in total; matches to CEMS (Velocity) units account for 81.1% (70.6%) of GADS units, and matches make up 92.8% of CEMS capacity. The entire process matches approximately 90% of GADS coal units and 87.5% of GADS gas units to CEMS units, while less than 50% of other units are matched. Though we were not able to match every GADS unit, these matches account do account for the vast majority of GADS units As well as the vast majority of CEMS and Velocity capacity. The bulk of unmatched units fall into the "other" fuel category; likewise, the capacity of these units tends to be towards the lower extremes or negligible, suggesting that the most relevant and significant units have been matched.

B Estimation Details

In this section, we provide the details of various estimation procedures employed in the main text.

B.1 Estimation of Residual Productivity

This section explains how we estimate the annual residual log-productivity. Our goal is to account for the observable factors that can affect plant productivity and document that there is large heterogeneity in residual plant productivity over time and across firms.

We estimate regressions with a rich set of observables and fixed effects to obtain residual productivity. In particular, in the first step, we use weekly heat rate data aggregated from hourly data and regress the logarithm of the inverse heat rate on time-varying observed plant characteristics and unit-year indicators. These time-varying variables include week fixed effects, state-month fixed effects, regulation status, total load, the number of idle hours, the standard deviation of heat rate, and the number of times the production increases by more than 2% and 5% in that week. By controlling for these factors, we account for the potential effects of production profiles on efficiency. In the second step, we take the estimated unit-year fixed effects and regress them on time-invariant unit characteristics that include capacity, fuel type, boiler manufacturer, and generator model.[44] The second regression accounts for productivity differences that are explained by observable generator characteristics. We use the estimated residuals from this second regression and plot them in Figure 2. The time-varying observables in the first-step regression explain 45% of the variation in weekly heat rate, and the time-invariant observables explain 42% of the remaining variation in the second step.

B.2 Cost Curve Estimation

We estimate the generator-specific cost curves using hourly data before and after the merger by controlling for productivity level (percent of capacity) and ramp-up and ramp-down. We define ramp as the absolute change in production compared to the previous hour.

We estimate the cost curves for treated and control groups separately. We use the sample of acquired generators used to estimate in Equation (3) for the treated group. Then, we take the production profile of these generators one year preceding the merger and one year following the merger. We remove generators from the sample if a generator is inactive more than 80% of the time, either during the pre-period or post-period. The results

[44] Generator model and characteristics are missing for about 20% of generators. For those, we include a missing dummy variable.

are robust to this restriction, but they are unstable because, for rarely active generators, the cost curve is noisy. With this sample, we non-parametrically estimate the cost curve using a local polynomial regression fitting in R. In particular, we use the `loess()` function in R's `stats` package with the default tuning parameters.

To construct the control group, we match each treated generator to a never-treated generator. For the matching procedure, we follow what is described in Section D.4 except that we match each generator to only one rather than three. After constructing the control sample, we estimate pre- and post-acquisition cost curves as if these control generators are acquired at the same time as the matched acquired generators.

We estimate the confidence band for the difference between pre- and post-acquisition cost curves for the treated generators using a bootstrap procedure. We re-sample the treated generators with replacement and estimate the cost curve for the sample. We repeat this 200 times and report the 2.5 and 97.5 percentiles of the bootstrap distribution.

B.3 Calculation of Fuel and CO_2 Emission Savings

To quantify the efficiency gains from mergers in terms of changes in fuel usage and CO_2 emissions for each unit, our analysis is limited to our main sample, which involves Subsidiary/Parent Company changes from the first merger. We assume that, after the merger, generators produce the same amount of electricity as they would have if not acquired. Additionally, we assume a uniform industry-wide efficiency increase of 0.3% per year, applied consistently across months and plants.

Using the CEMS dataset, we analyze monthly CO_2 emissions at the unit level. We identify the month of the first merger for each unit and calculate CO_2 emission intensity for every month. Post-merger, we adjust this intensity to account for non-merger related gains due to the industry-wide efficiency increase. Then, we aggregate the total generation and CO_2 emissions before the merger and compare them to the total generation and implied CO_2 emissions after the merger, to determine CO_2 intensity changes. Assuming no change in production post-merger, we calculate the hypothetical total emissions if the unit had maintained its pre-merger CO_2 emission intensity. The total CO_2 emission savings are then determined by the difference between this hypothetical scenario and the actual post-merger emissions.

With this set of assumptions, the total cumulative decline in CO_2 emissions between 2000 and 2023 is roughly 360 million tons. This corresponds to the emissions reduction from replacing 800 TWh generation from natural-gas fired plants with renewables, assuming CO_2 emissions are roughly 0.4 tons per MWh for gas-fired power plants. . With the assumption of a 30% utilization rate of wind power plants, this is roughly equal to 13 GW capacity investment in wind power plants from 2000 to 2023.

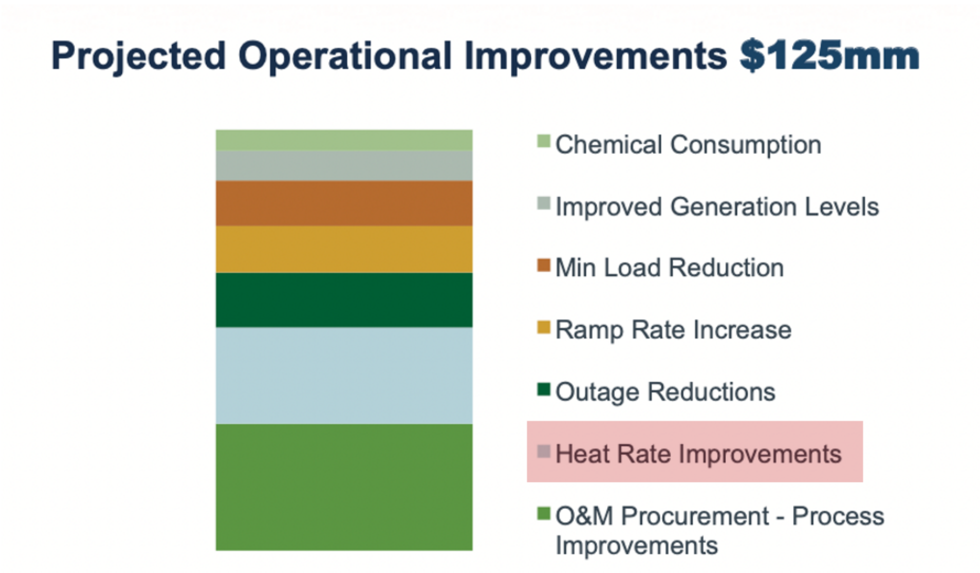
B.4 Heterogeneity Analysis

In this subsection, we describe the constructions of variables used in the heterogeneity analysis.

- **Gas Plant:** An indicator variable that equals 1 if the acquired generator is powered by natural gas and 0 otherwise. Since most of the acquired generators are natural gas-fired, this variable equals 1 for 90% of transactions.
- **Plant Age** > **Median** An indicator variable that equals 1 if the age of the acquired generator is larger than the median. We consider all the generators in our main specification to calculate the median age and find the median value.
- **Unit Capacity** > **Median:** An indicator variable that equals 1 if the age of the acquired generator is larger than the median. To calculate the median capacity, we consider all the generators in our main specification and find the median capacity.
- **Acquirer Size** > **Median:** An indicator variable that equals 1 if the total capacity of the acquirer pre-transaction is larger than the median capacity of firms that have been involved in a transaction between 2000 and 2023.
- **Serial Acquirer:** An indicator variable that equals 1 if the total capacity acquired by the acquirer between 2000 and 2023 is larger than the median of the total capacity acquired by firms between 2000 and 2023.

C Additional Tables and Figures

Figure OA-1: A Slide from Investor Presentation About Efficiency Claims



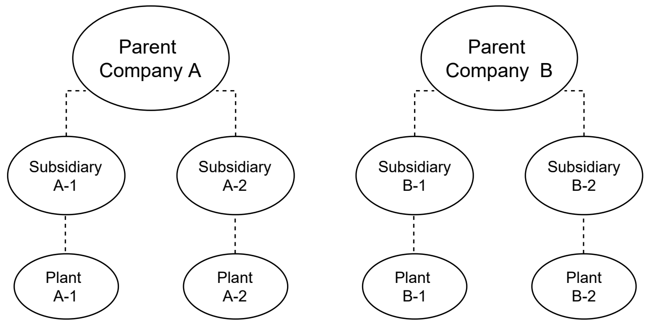
Note: This figure is from a slide deck presented in the conference call of the acquisition of Dynegy by Vistra Energy in 2018.

Table OA-1: Largest 25 Acquisitions by Fossil Fuel Power Plant Capacity

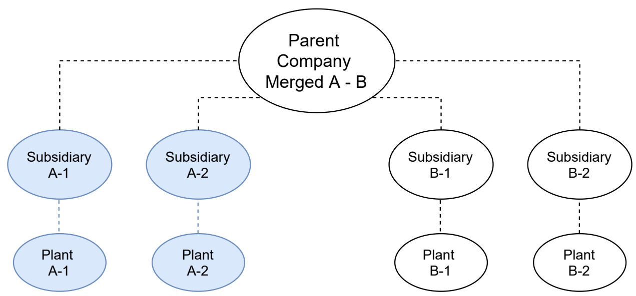
Acquirer	Target	Year	Cap. (MWh)	# of units
Vistra Energy Corp.	Dynegy Inc.	2018	27198	99
NRG Energy, Inc.	GenOn Energy, Inc.	2012	26174	139
Volt Parent, Lp	Calpine Corporation	2018	22991	127
RRI Energy, Inc.	Mirant Corporation	2000	22748	140
Duke Energy Corporation	Progress Energy, Inc.	2012	19048	134
Duke Energy Corporation	Cinergy Corp.	2006	14923	70
GC Power Acquisition LLC	CenterPoint Energy, Inc.	2004	13204	43
NRG Energy, Inc.	Texas Genco Inc.	2006	13017	42
Westar Energy, Inc.	Great Plains Energy	2018	12237	66
Vistra Corp.	TXU Corp.	2007	11116	45
Exelon Corporation	Constellation Energy Group	2012	10790	66
PPL Corporation	E.ON AG	2010	10035	44
NRG Energy, Inc.	Edison Mission Energy	2014	9052	30
FirstEnergy Corp.	Allegheny Energy, Inc.	2011	8631	36
NextEra Energy, Inc.	Engie SA	2017	8604	39
Dynegy Inc.	Duke Energy Corporation	2015	8387	26
Reliant Resources, Inc.	Orion Power Holdings, Inc.	2002	8247	85
AES Corporation	DPL Inc.	2006	7879	33
Carolina Power & Light Company	Florida Progress Corporation	2000	7721	63
Powergen PLC	LG&E Energy Corp.	2000	7445	31
ArcLight Capital Partners, LLC	Tenaska Energy Inc.	2015	7398	79
Dynegy Inc.	Energy Capital Partners LLC	2015	7334	28
MidAmerican Energy Holdings	NV Energy, Inc.	2013	7149	52
Astoria Generating Co.	EBG Holdings LLC	2007	7143	66
Riverstone Holdings LLC	Talen Energy Corporation	2016	6941	12

Note: Largest 25 acquisitions in the fossil fuel power generation industry between 2000 and 2020. The columns indicate the year the transaction occurred, total production capacity involved in the transaction, and the total number of units that changed ownership.

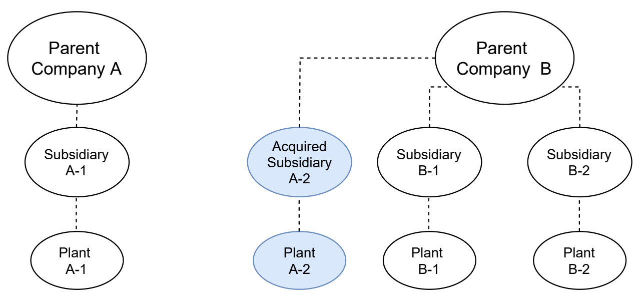
Figure OA-2: Ownership Change Types



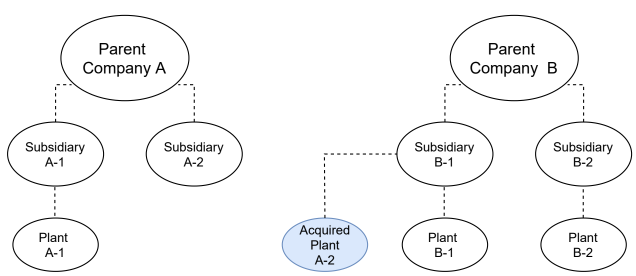
(a) Before



(b) Asset Acquisitions



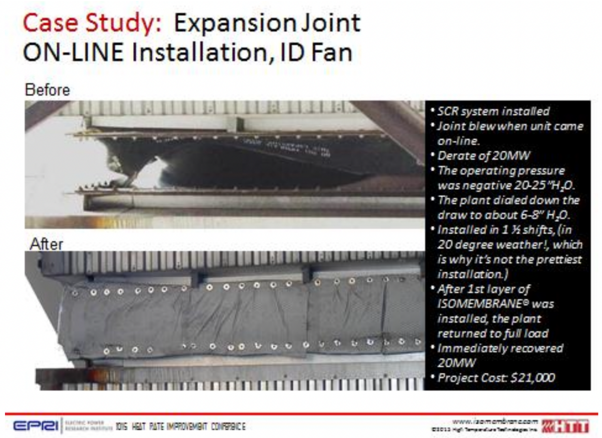
(c) Subsidiary Acquisitions



(d) Mergers

Note: This figure demonstrates different types of acquisitions. Panel (a) is the corporate structure of companies before the acquisition. Panels (b), (c), and (d) show the corporate structure after the acquisition for partial asset sales, subsidiary acquisitions, and mergers separately.

Figure OA-3: Case Studies of Heat Rate Improvement

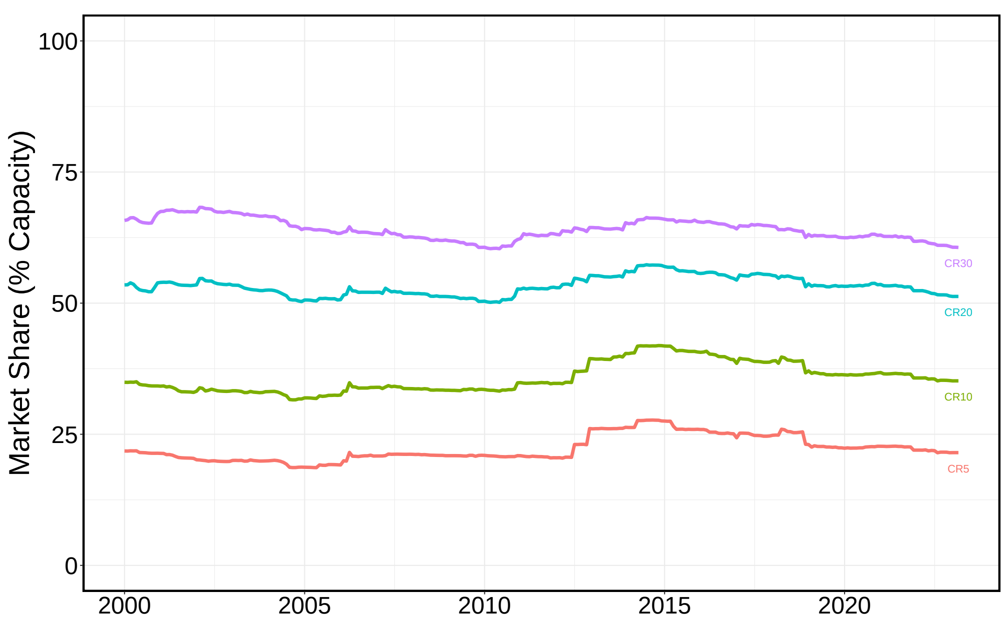


(a) Case Study 1

(b) Case Study 2

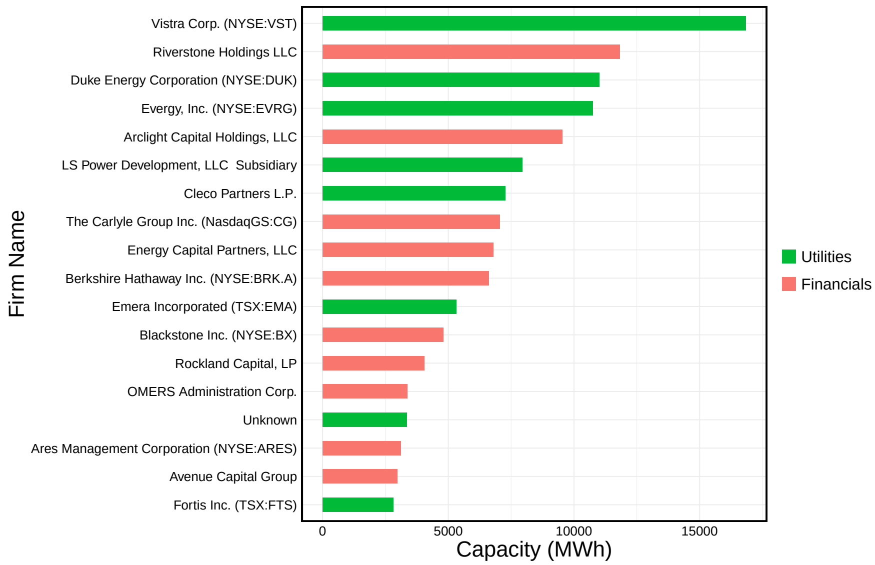
Note: These pictures demonstrate some methods that were implemented in power plants to improve heat rate. Source: Fitzgerald and Gelorme (2015).

Figure OA-4: Change in Market Concentration



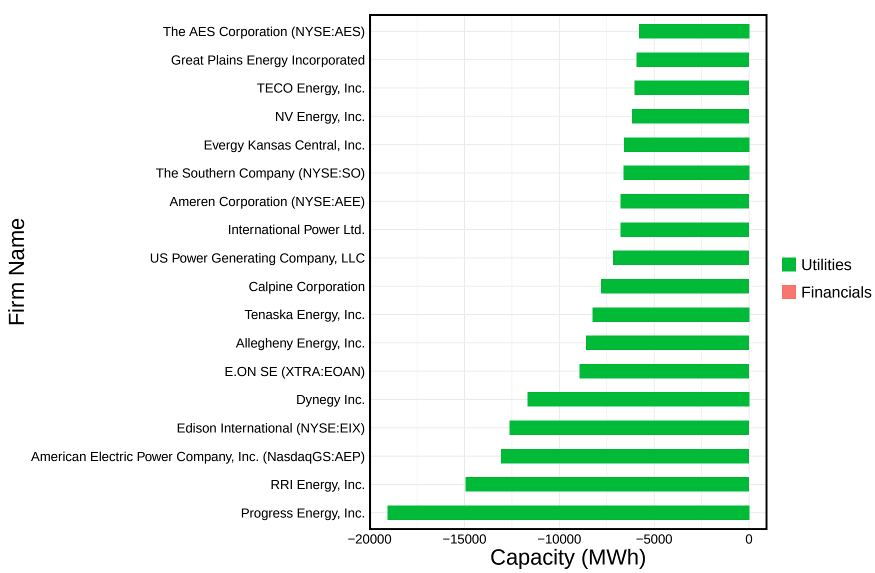
Note: This figure shows the change of national concentration ratios in the overall US fossil fuel power plant market between 2000 and 2023. For every concentration ratio, we calculate the total fossil fuel capacity of the largest corresponding number of firms in the US and divide that by the total fossil fuel capacity in the US.

Figure OA-5: Firms with Largest Capacity Increase, 2010–2023



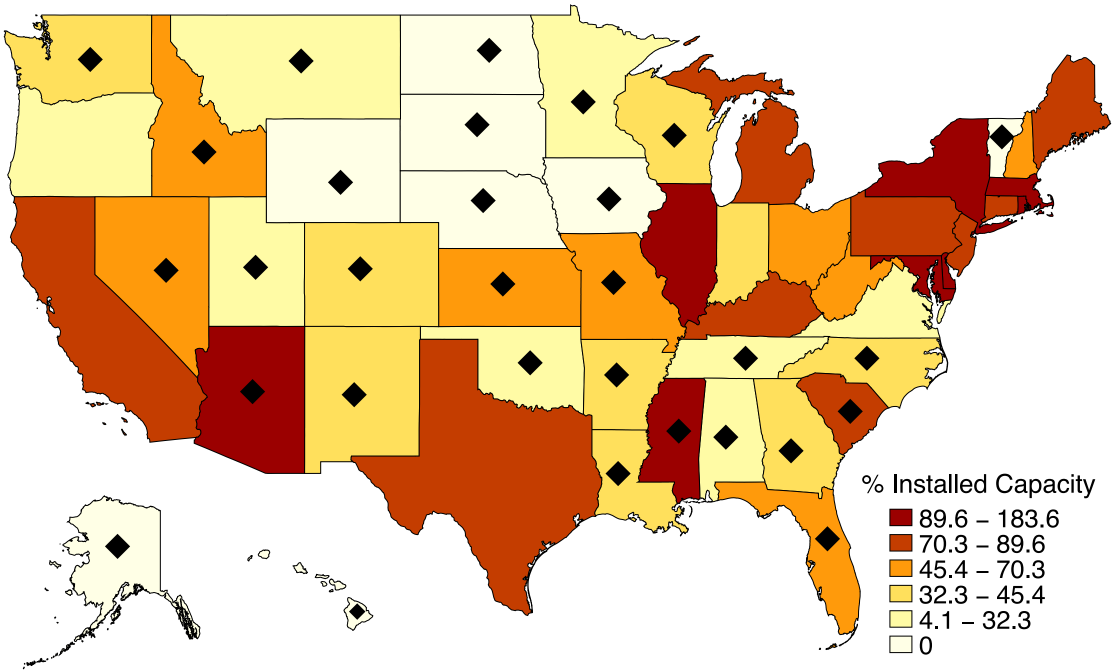
Note: This figure shows firms with the largest capacity increase in fossil fuel generation capacity in the US between 2010 and 2020.

Figure OA-6: Firms with Largest Capacity Decrease, 2010–2023



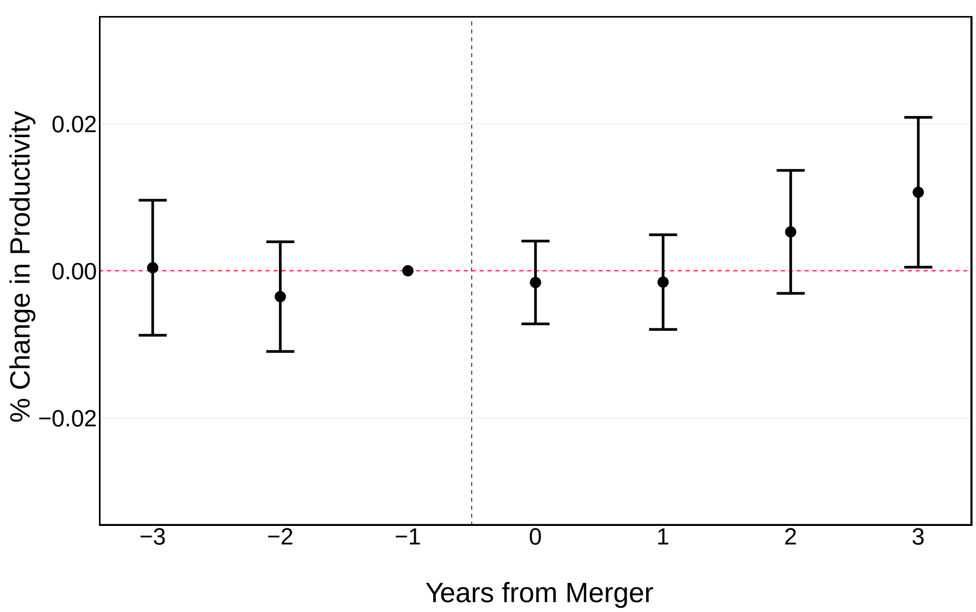
Note: This figure shows firms with the largest capacity decrease in fossil fuel generation capacity in the US between 2010 and 2020.

Figure OA-7: Change of Percentage of Fossil Fuel Generation Capacity



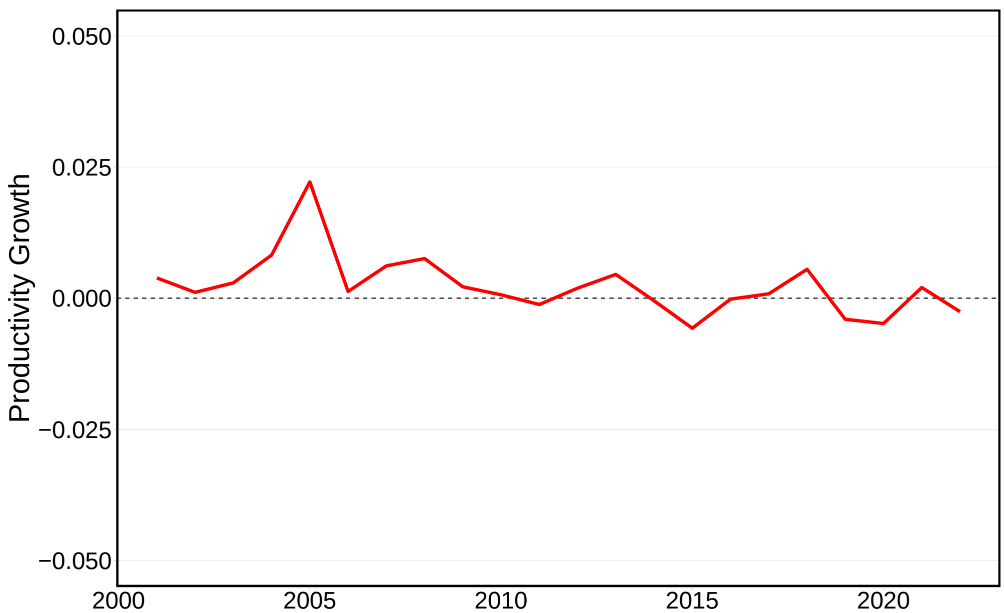
Note: Geographical distribution of power plant acquisitions by capacity. The diamond indicates the regulated states.

Figure OA-8: The Effect of Manager Change without Mergers on Efficiency



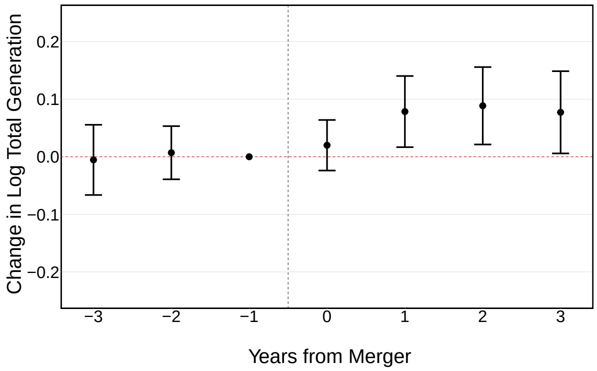
Note: This figure shows the effects of manager change on efficiency estimated using the specification given in Equation (3). In particular, we treat a unit if the manager of that unit changes and there is no acquisition in the three months preceding and following the manager change.

Figure OA-9: Average Within-Plant Annual Productivity Change

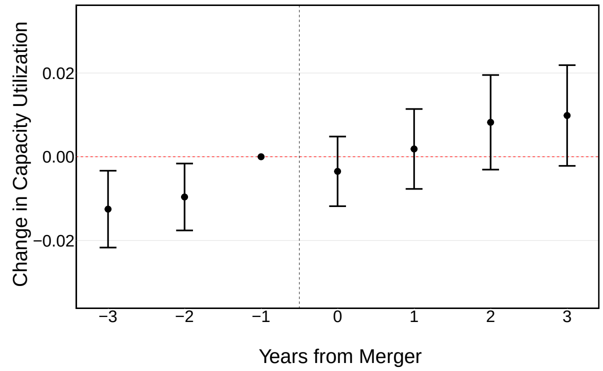


Note: This figure shows average year-to-year within-plant productivity growth for the plants that were not involved in an acquisition.

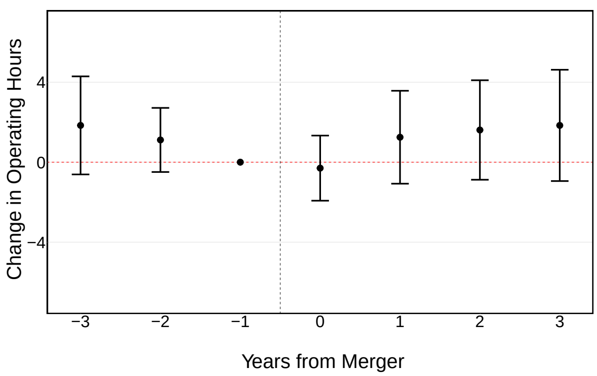
Figure OA-10: Impact of Merger on Generator Performance



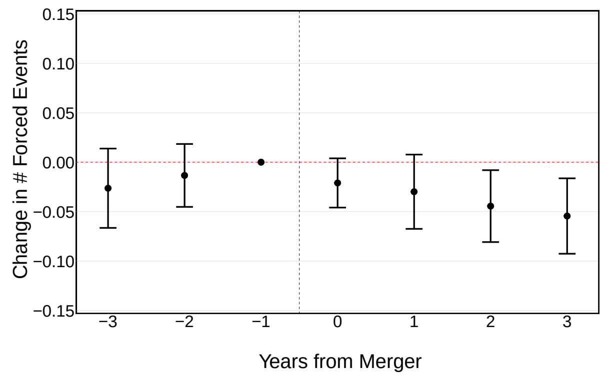
(a) Log Total Generation



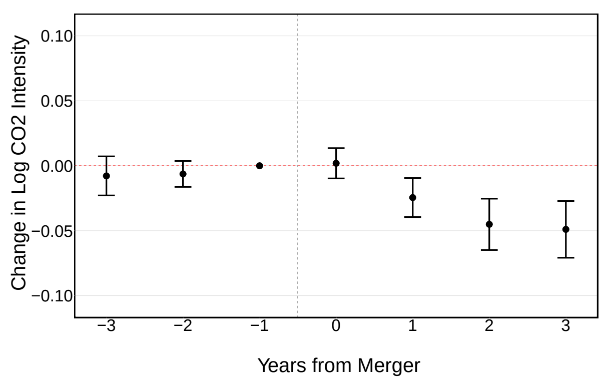
(b) Capacity Utilization



(c) Operating Hours



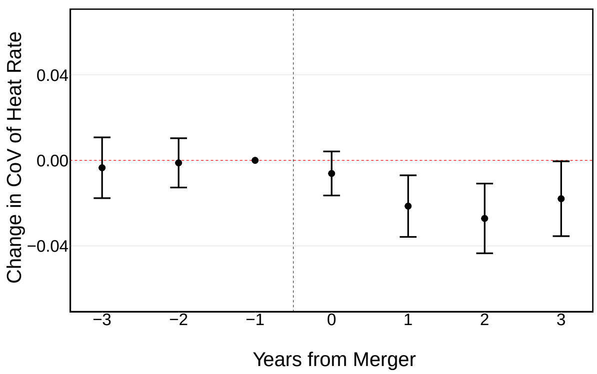
(d) Forced Outages/Derates



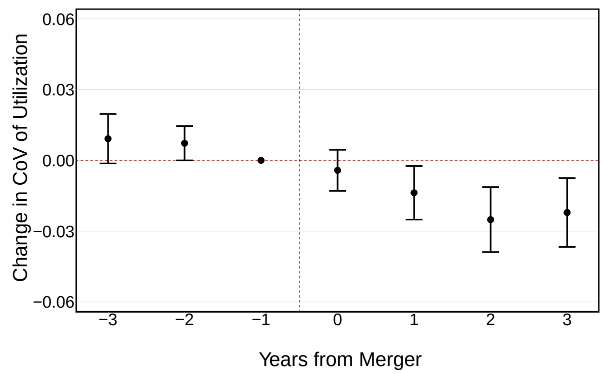
(e) Log CO_2 Intensity

Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-3, 3)$ from estimating Equation (2) with yearly treatment indicators to improve precision. Unit characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity. Unit of observation is generator-week. Standard errors are clustered at the plant level

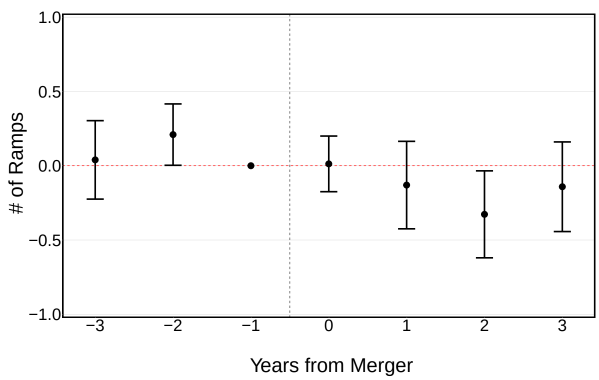
Figure OA-11: Change in Variation of Heat Rate (Annually)



(a) CoV of Heat Rate



(b) CoV of Utilization



(c) Number of Ramps

Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-3, 3)$ from a regression of the standard deviation of heat rate on treatment dummies using Equation (2), using yearly treatment indicators to improve precision. Unit characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity.

D Robustness Checks

In this section, we provide the details of the robustness checks we employ in this paper.

D.1 Acquisition Sample

Since our sample covers 20 years of plant production, many generators are acquired multiple times. Of the 2,365 units that have been ever acquired, around half of them experienced multiple ownership changes during the study period. In our main specification, we considered only the first acquisition of each generator because, with multiple acquisitions, the post period of the first acquisition overlaps with future acquisitions. For those generators, it is unclear how to estimate a proper event study. In this section, we investigate the robustness of our results to this sample restriction by estimating event studies that include all acquisitions and units acquired only once.

The first robustness check includes all acquisitions except those within 32 months of each other. We drop these acquisitions because the post- and pre-acquisition periods overlap. Using this sample, we estimate Equation (2) with the following differences. First, for each event, we include post-treatment indicator variables 36 months following the acquisition, and we include pre-treatment indicator variables 36 months before the acquisition. The treatment variables are set to 0 for 36 months after acquisition and 36 months before the next acquisition. Therefore, we assume that treated plants follow the same trend as the control group between the two acquisitions. The results from this estimation procedure are reported in Appendix Table OA-2, Table OA-3, and Figure OA-13. The estimates are similar to the results from our main specification.

D.2 Data Frequency

We estimated our main specification with weekly data, where efficiency is defined as total electricity output divided by total heat input that week. We made this choice because estimation with weekly frequency reduces the computational burden and reduces noise due to the aggregation of hourly data. In this section, we analyze whether our results are robust to data frequency by considering hourly and daily data.

Estimation with daily data follows the same steps as the estimation in weekly data. We aggregate fuel input and electricity output to a daily level and define daily efficiency as total daily electricity input divided by total daily fuel input. The treatment variables are monthly indicator variables for each month 36 months before and 36 months after acquisition. We estimate the same specification as in Equation (2), but include the day of the week as an additional control variable. Since the day of the week is a strong determinant of electricity demand, estimation with daily data controls for demand fluctuations more accurately. The effect of ownership changes on efficiency is similar to what we found with the weekly data.

In the estimation with hourly data, we use the raw data obtained from CEMS, hourly electricity output, and fuel input without any processing. We consider the same specification as weekly and daily data, but the hour of the day as an additional control. Since the hour of the day is a strong determinant of electricity demand, the hourly specification controls for electricity demand much more precisely than daily and hourly data. The effect of mergers on efficiency is similar to the results with weekly data. However, estimates are less precise since hourly data is noisier than weekly and daily data.

Overall, these robustness checks suggest that our results are robust to aggregation of input and output at the weekly levels.

D.3 Staggered Difference-in-Differences

Before estimating the Callaway and SantAnna (2021) method, we do some modification. Our main specification includes weekly heat rate data, but the treatment coefficients are included at the monthly level to increase the precision. Since the staggered treatment effect estimation requires data frequency to be the same as treatment frequency, we aggregate our data to the monthly level by taking the average of weekly heat rates in a give month. So the staggered difference-in-differences is estimated at the monthly level. We use the never-treated group as the control group and control for generator age and capacity in the cohort specific treatment effect estimation.

To implement the procedure, we use the R package DiDforBigData (Setzler, 2022), which provides a big-data-friendly and memory-efficient difference-in-differences estimator for staggered treatment contexts. The results, which are similar to our main set of estimates, are reported in Appendix Figure OA-14.

D.4 Matching Difference-in-Differences

Our main specification uses standard difference-in-differences estimation estimated with two-way fixed effects. In this section, we also consider a difference-in-differences matching estimator as a robustness check.

We match each of our acquired units to the three nearest neighbors from the pool of control units that have never been acquired during our sample period. For each treated unit, we first find the never-treated active units during the acquisition time with the same fuel type but in a different ISO (to prevent spillovers). This never-treated sample constitutes the pool of candidate control units for that unit. Then, we find the nearest neighbor units with respect to capacity and age using a least-squares metric to calculate the distances between generation units. The weights in the metric are inversely proportional to the standard deviation of the corresponding variable. We allow control units to be matched to multiple acquired plants. Using these nearest neighbors, we calculate the unit-specific treatment effect as follows:

$$\hat{\Delta} Y_{it} = Y_{it}(1) - \hat{Y}_{it}(1), \tag{8}$$

where $\hat{Y}_{it}(1)$ is the average heat rate of the control units that are matched to i and scaled such that the average outcome of the control at the time of acquisition is the same as the outcome of the treated unit. By indexing the levels to a baseline period, we obtain a unit-specific "difference-in-differences" estimate for any outcome of interest. We take the average of the unit-specific treatment effects to obtain the final estimates.

To construct the confidence intervals, we employ a bootstrap procedure, where we resample without replacement the treated generators and follow the same matching procedure described above. We repeat this procedure 100 times and obtain a distribution of efficiency gains from the bootstrap samples. To construct the confidence bands, we take the 2.5 and 97.5 percentiles of the bootstrap distribution to construct the confidence intervals.

The results from this estimation are reported in Appendix Table OA-2 and Figure OA-15. We find that results are qualitatively similar to our main specification.

D.5 Observation Weights

In our regressions, we weighted units equally. A natural alternative to this is to weigh them by generator capacity, which would be robust to a potential concern that all efficiency gains come from small units. Moreover, it would be more informative about the total production affected by efficiency gains. To investigate this, we estimate Equations (2) and (3) by weighting units by their capacity in that year. The results from this estimation are reported in Appendix Table OA-2, Table OA-4, and Figure OA-16. We find that the efficiency effect is slightly larger when we weigh units by capacity, which is consistent with the findings reported in Table 4 that the efficiency effect is larger for larger units. This finding also indicates that acquisitions of small units do not drive our main results.

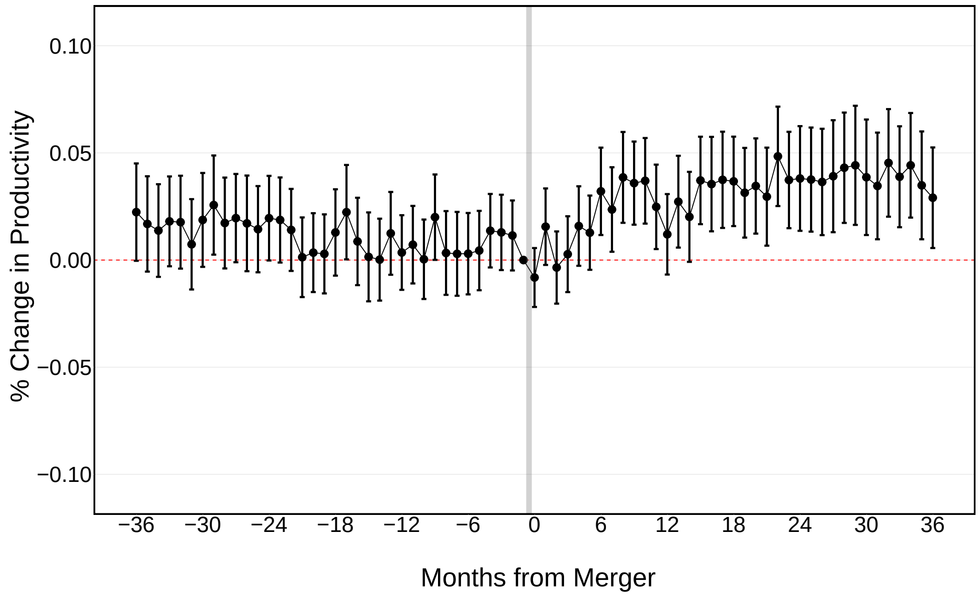
E Robustness Checks Results

Table OA-2: Regression Robustness Results

	After 2010 (1)	Net Generation (2)	All Acquisitions (3)	Weighted Regressions (4)	Matching (5)	Minority (Placebo) (6)	Restructuring (Placebo) (7)
			Dependent Variable: Log of Efficiency				
Pre-acquisition (1 Year)	-0.008	-0.003	-0.001	0	-0.002	-0.003	0.016
	(0.005)	(0.006)	(0.004)	(0.005)	(0.002)	(0.005)	(0.01)
Post-acquisition (1 Year)	-0.003	0.009	0.014	0.021	0.021	-0.001	0
	(0.006)	(0.007)	(0.006)	(0.009)	(0.004)	(0.008)	(0.014)
Post-acquisition (2 Years)	0.016	0.025	0.028	0.05	0.035	-0.009	0.009
	(0.01)	(0.009)	(0.008)	(0.014)	(0.006)	(0.01)	(0.016)
Post-acquisition (3 Years)	0.031	0.029	0.034	0.053	0.047	-0.009	0.023
	(0.014)	(0.01)	(0.009)	(0.017)	(0.007)	(0.01)	(0.017)
Temp. & Humidity Controls	X	X	X	X	X	X	X
Unit & Week FE	X	X	X	X	X	X	X
Unit Characteristic by Month FE	X	X	X	X	X	X	X
Scrubber & Enviro. Prog. FE	X	X	X	X	X	X	X
R^2	0.769	0.655	0.77	0.86	-	0.615	0.62
# of Observations	1.387M	1.491M	1.769M	1.493M	0.001M	1.568M	1.217M
# of Control Units	2311	2308	2311	2311	-	2311	2311
# of Treated Units	529	1089	1089	1089	-	663	304

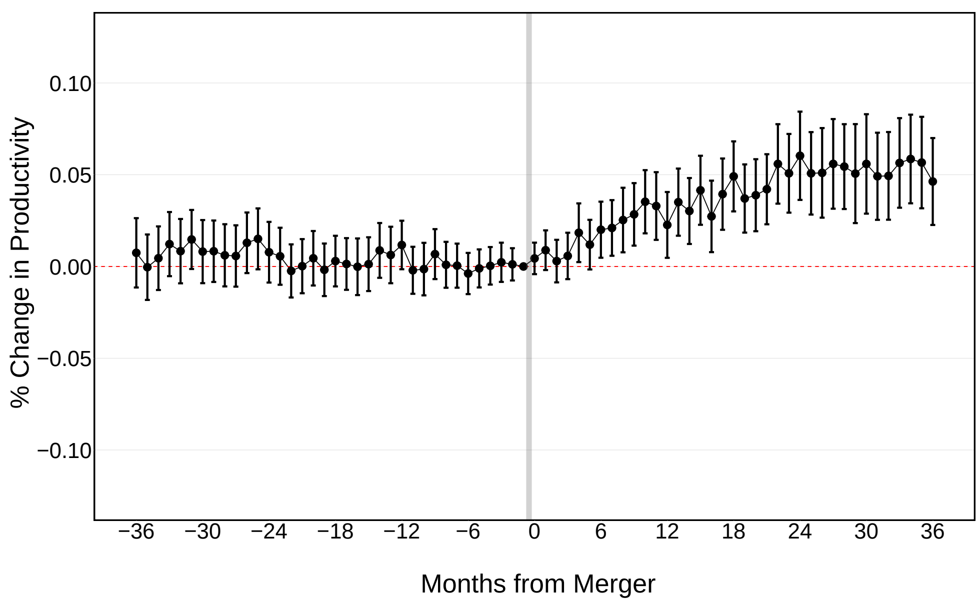
Note: This table presents the coefficient estimates of $\bar{\delta}_1, \bar{\delta}_2, \bar{\delta}_3,$ and $\bar{\delta}_4$ from estimating Equation (2) with various robustness checks, discussed generally in Section D. Unit characteristic fixed effects include state, installation year, fuel type, technology type, and unit capacity. Standard errors are clustered at the plant level.

Figure OA-12: Impact of Merger on Productivity (Net Generation)



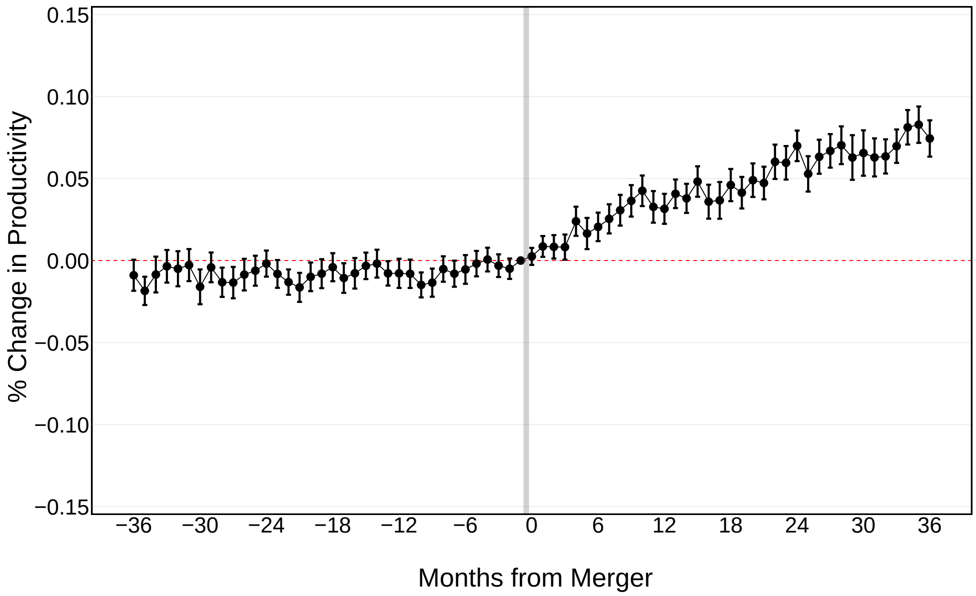
Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors. The dependent variable is the logarithm of the inverse weekly heat rate, calculated using net generation as opposed to gross generation as discussed in Section 7. Standard errors are clustered at the plant level.

Figure OA-13: Impact of Merger on Productivity (All Acquisitions)



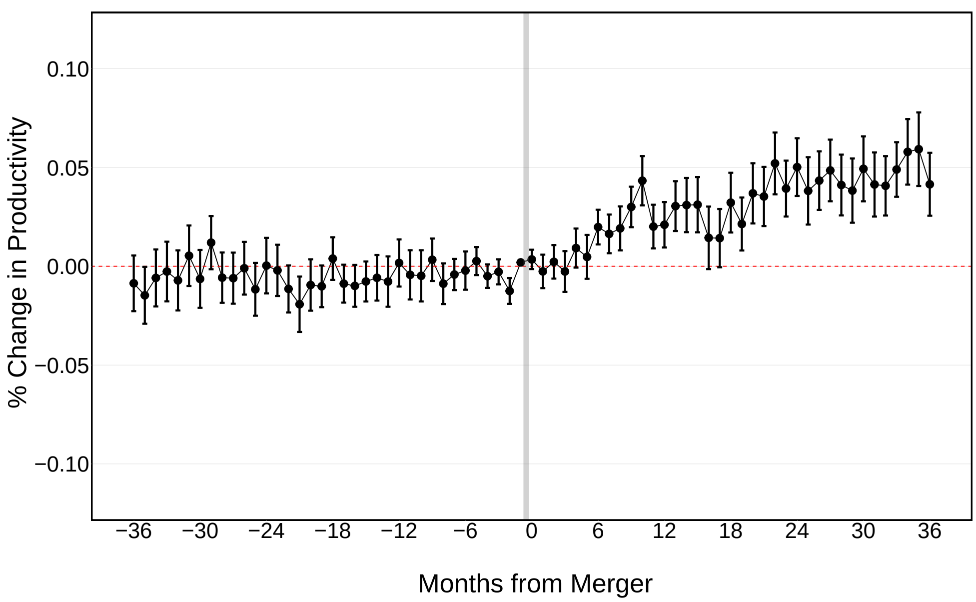
Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors, using all acquisitions. The acquisition sample is described in Section D.1. The dependent variable is the logarithm of the inverse weekly heat rate. Standard errors are clustered at the plant level.

Figure OA-14: Impact of Merger on Productivity (Staggered Difference-in-Differences)



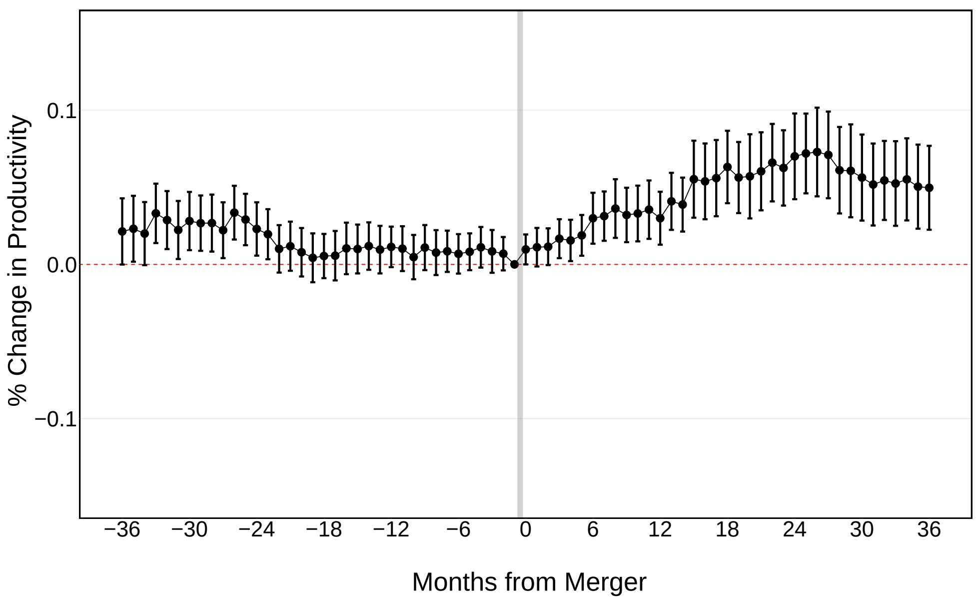
Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors, using the method of Callaway and SantAnna (2021) method. The details are provided in Section D.3. The dependent variable is the logarithm of the inverse weekly heat rate. Standard errors are clustered at the plant level. This specification does not include unit characteristics time trends due to computational complexity.

Figure OA-15: Impact of Merger on Productivity (Matching Estimator)



Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors, using the matching method described in Section D.4. The dependent variable is the logarithm of the inverse weekly heat rate.

Figure OA-16: Impact of Merger on Productivity (Weighted By Capacity)



Note: This figure presents the coefficient estimates of $\hat{\delta}_s$ where $s \in (-36, 36)$ from Equation (3) along with standard errors, weighting observations by capacity as described in Section D.5. The dependent variable is the logarithm of the inverse weekly heat rate. Standard errors are clustered at the plant level.

Table OA-3: Impact of Merger on Productivity All Acquisitions

	All M&A (1)	All M&A (2)	All M&A (3)	All M&A (4)	Subsidiary or Parent Changes (5)	Only Parent Changes (6)
	Dependent Variable: Log of Efficiency					
Pre-acquisition (1 Year)	0.001	0	-0.003	-0.003	-0.002	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
Post-acquisition (1 Year)	0.011	0.016	0.006	0.006	0.015	-0.01
	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
Post-acquisition (2 Years)	0.019	0.035	0.02	0.02	0.039	-0.002
	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Post-acquisition (3 Years)	0.022	0.038	0.02	0.02	0.05	-0.007
	(0.006)	(0.009)	(0.008)	(0.008)	(0.012)	(0.008)
Temp. & Humidity Controls	X	X	X	X	X	X
Unit & Week FE	X	X	X	X	X	X
State by Month		X	X	X	X	X
Unit Characteristic by Month FE			X	X	X	X
Scrubber & Enviro. Prog. FE				X	X	X
R^2	0.713	0.725	0.752	0.753	0.763	0.764
# of Observations	2.335M	1.838M	1.838M	1.838M	1.494M	1.575M
# of Control Units	2311	2311	2311	2311	2311	2311
# of Treated Units	2048	2046	2046	2046	1089	1142

Note: This table presents the coefficient estimates of $\bar{\delta}_1$, $\bar{\delta}_2$, $\bar{\delta}_3$, and $\bar{\delta}_4$ from estimating Equation (2) using all acquisitions. Unit characteristic fixed effects include installation year, fuel type, technology type, and unit capacity. The acquisition sample is described in Section D.1. Standard errors are clustered at the plant level.

Table OA-4: Impact of Merger on Productivity (Weighted Regressions)

	All M&A (1)	All M&A (2)	All M&A (3)	All M&A (4)	Subsidiary or Parent Changes (5)	Only Parent Changes (6)
Dependent Variable: Log of Efficiency						
Pre-acquisition (1 Year)	0.003	0.002	0	0	0	-0.004
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Post-acquisition (1 Year)	0.021	0.018	0.011	0.012	0.018	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)
Post-acquisition (2 Years)	0.036	0.036	0.023	0.023	0.051	0.007
	(0.007)	(0.008)	(0.007)	(0.007)	(0.013)	(0.007)
Post-acquisition (3 Years)	0.042	0.04	0.02	0.02	0.053	0.005
	(0.009)	(0.01)	(0.009)	(0.009)	(0.015)	(0.008)
Temp. & Humidity Controls	X	X	X	X	X	X
Unit & Week FE	X	X	X	X	X	X
State by Month		X	X	X	X	X
Unit Characteristic by Month FE			X	X	X	X
Scrubber & Enviro. Prog. FE				X	X	X
R^2	0.776	0.806	0.836	0.837	0.859	0.847
# of Observations	1.838M	1.838M	1.838M	1.838M	1.494M	1.575M
# of Control Units	2311	2311	2311	2311	2311	2311
# of Treated Units	2046	2046	2046	2046	1089	1142

Note: This table presents the coefficient estimates of $\bar{\delta}_1, \bar{\delta}_2, \bar{\delta}_3,$ and $\bar{\delta}_4$ from estimating Equation (2) by weighting observations by capacity as described in Section D.5. Unit characteristic fixed effects include installation year, fuel type, technology type, and unit capacity. Standard errors are clustered at the plant level.