Do Mergers and Acquisitions Improve Efficiency: Evidence from Power Plants

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Abstract

Using rich data on hourly physical productivity and five thousand 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 four percent efficiency increase five to eight months after the acquisition. Three-quarters of this efficiency gain is explained by increased productive efficiency; the rest comes from improved capacity management at the plant level and allocative efficiency at the portfolio level. Our findings suggest that acquisitions reallocate assets to more productive uses: we find that *high* productive firms buy *under-performing* assets from *low* productive firms and make the acquired asset almost *as productive as* their existing assets after the acquisition. Finally, investigating the mechanism, the evidence suggests that acquired plants achieve higher efficiency through low-cost operational improvements rather than high-cost capital investments.

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1 Introduction

How do mergers and acquisitions (M&A) affect firm productivity? The answer to this question has important implications for antitrust policy as it is a fundamental input in evaluating the trade-off between market power and efficiency. 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 the empirical evidence, studies analyzing competitive effects of mergers often have to 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 most production datasets, the majority of research has been limited to studying revenue-based productivity (TFPR), which is estimated from revenues and input expenditures rather than quantity-based measures. Using TFPR is particularly problematic in merger retrospectives because other potential merger effects, such as an increase in market power, buyer power, or decline in quality, would raise TFPR even without any efficiency gains. This makes it very difficult to identify true efficiency gains of mergers.

In this paper, we provide a detailed analysis of the effects of mergers and acquisitions on efficiency while tackling these issues. In particular, we ask: (i) do mergers and acquisitions improve efficiency? (ii) if so, what are the mechanisms? (iii) how do mergers reallocate assets between firms?

To answer these questions, we focus on the US electricity generation industry between 2000-2020. Three distinct features of this industry and our data allow us to overcome the challenges of estimating the efficiency effects of mergers. First, we observe, at the hourly frequency, the physical quantity of output and the physical quantity of the largest single input, the consumption of fuel. With this unusually rich production data, we construct an efficiency measure at the hourly level and track plant efficiency at a high frequency around the acquisition. Second, electricity is a homogeneous product, preventing potential quality changes from confounding our estimates. Third, the fossil-fuel power generation industry has experienced a significant number of mergers and acquisitions during our sample period. We identify about 600 transactions in which 5000 generator units, corresponding to 95 percent of the cumulative industry capacity, change ownership. These ownership changes exhibit significant heterogeneity based on transaction type, transaction size, and firm type, which we use to test several mechanisms and analyze heterogeneous effects.

Our analysis starts by employing a differences-in-differences (DID) estimator to quantify the effects of acquisitions on efficiency. Our first finding is that acquiring firms improve the efficiency

[1] For 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", "our reading of the current (meager) evidence in the literature", "there is remarkably little solid empirical evidence on this point".

of the power plant by four percent on average. The efficiency increase starts five months after the acquisition and reaches the new steady-state level after eight months, suggesting that it takes time for the new owner to implement changes required for efficiency improvements. Our calculations suggest that these efficiency improvements correspond to an annual cost saving of 6 billion dollars, and the total cumulative decline in CO_2 emission between 2000 - 2020 is roughly 50 million tons.

This clear evidence of efficiency gains from mergers is important. However, to make broader lessons from this industry, it is crucial to understand the underlying mechanisms that generate efficiency gains in a power plant. Motivated by this, we investigate several mechanisms that generate efficiency gains in the rest of the paper.

Our first question is how mergers allocate assets between firms. There are two main theories on the allocative efficiency effects of asset allocations with mergers. The first theory suggests a "high-buys-low" pattern (Jovanovic and Rousseau (2002)) in which acquisitions transfer assets from low productivity firms to high productivity firms. The second theory assumes a "like-buy-like" (Rhodes-Kropf and Robinson (2008)) in which firms have no systemic productivity differences. However, there are complementaries between assets and firms, and assets are allocated to firms with a relatively higher ability to utilize those assets. Quantifying the role of these theories in efficiency gains is important to understand whether mergers put the asset to more productive use and contribute to aggregate productivity growth.

Our findings suggest that acquisitions reallocate assets to more productive uses: we find that *high* productive firms buy *under-performing* assets from *low* productive firms and make the acquired asset almost *as productive as* their existing assets after the acquisition. Acquirers are, on average, one percent more productive than the target firms, and the target firms are selling their underperforming assets relative to their other assets. After the acquisition, the productivity of the acquired asset goes up by four percent and becomes only one percent less productive than the existing assets in the acquirer firm's portfolio. This finding suggests that assets are allocated to firms with both relative and absolute advantages in utilizing those assets.

We then move to understand what mechanisms generate efficiency gains. A firm can improve the overall efficiency of a power plant with three distinct mechanisms: (i) increasing its productive efficiency, (ii) better allocating production dynamically, and (iii) allocative production more efficiency across plants. We develop predictions for each of these mechanisms and test them empirically. To understand the role of productive efficiency, we estimate firm-specific cost curves separately for pre-and post-acquisition periods and compare them. We find that after the acquisition the cost curve shifts down, explaining 75 percent of the total efficiency gain. We also find evidence consistent with other mechanisms, better production allocation and portfolio effect; however, their role is minor.

After establishing the role of productive efficiency, the next question is what firms do to improve productive efficiency. There are two alternatives (i) operational improvements and (ii) costly capital

investments. To distinguish between these two mechanisms, we augment our production data with data on plant managers, manager characteristics, non-fuel costs, and capital expenditures. We find that 55 percent of acquired power plants change their managers within three months of the acquisition, and those that change their manager have higher productivity gain. We find no evidence of an increase in non-fuel costs or capital expenditures after the acquisition, limiting the role of investment. These findings suggest that the new owner of the power plant improves efficiency through operational improvements rather than high-cost capital investment.

Like all retrospective merger analyses, an important concern in our paper is the endogeneity of mergers. We do additional analyses to address these concerns in three ways. First, we run placebo tests by looking at the efficiency effects of minority acquisitions and company name changes, finding no efficiency effects. Second, we run a battery of robustness tests and show that our results are robust to different specifications. Finally, 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. We find that management change leads to a one percent efficiency gain vs. four percent caused by mergers.

Although we believe our empirical setting is ideal for studying the efficiency effects of mergers, there are important caveats worth mentioning. First, the production process in electricity generation is different from other manufacturing industries in terms of variable cost structure and the role of labor. While we focus our analysis on a single industry to take advantage of the available data and many acquisitions, we provide detailed evidence for mechanisms to extrapolate findings from this study. Second, our efficiency measure is fuel efficiency rather than TFP, which is most commonly used in the literature. While it is possible to estimate TFP for power plants at the annual frequency and include other variable costs, we think due to the availability of high-frequency efficiency measures, it is a trade-off worth making.

We want to conclude the introduction by highlighting 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. Although more research is needed to understand the net effects of mergers, our paper provides a detailed analysis of the efficiency effects of mergers.

1.1 Literature

This article contributes to several bodies of literature. The first one is the literature studying the effects of mergers and acquisitions on productivity. Since much of merger retrospectives focus on price effects, there are only a few papers studying productivity effects of mergers (Blonigen and Pierce (2016), Kulick (2017), Braguinsky et al. (2015)). Blonigen and Pierce (2016) uses the methods of De Loecker and Warzynski (2012) to separately identify markup power and productivity for manufacturing plants in the U.S and study how mergers affect them. Their findings suggest significant effects of mergers on market power but no evidence for a productivity effect. Kulick (2017)

studies mergers in the ready-mix concrete industry. He finds evidence for price increase due to an increase in market power after the merger despite a 6 percent productivity increase in acquired plants.[2] Our paper is most closely related to Braguinsky et al. (2015) who study 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, but they were more profitable due to better inventory management and lower capacity utilization. After the acquisitions, the acquirer improves capacity utilization in the acquired plant, raising the productivity level by almost 13 percent.

This article contributes to the literature studying efficiency in the power generation industry. This literature has primarily focused on how restructuring that started in the 90s affected efficiency (Knittel (2002), Bushnell and Wolfram (2005), Davis and Wolfram (2012), Fabrizio et al. (2007)). These papers compared the performance of plants in states that pursued restructuring against plants in states that did not initiate a restructuring. Overall the results point to a positive influence of restructuring on the operations of plants.

We contribute to the literature studying the allocative efficiency effects of mergers (Jovanovic and Rousseau (2008), Jovanovic and Rousseau (2002), Rhodes-Kropf and Robinson (2008), McGuckin and Nguyen (1995), Schoar (2002)). These papers study mergers and acquisitions across a range of industries. They investigate the characteristics of buyers and sellers, how acquisitions transfer assets between firms, and the effects of this on reallocations of resources in the economy. We contribute to this literature by providing detailed evidence from a single industry on how mergers allocate resources in the economy.

Finally, our paper is related to a recent wave of papers that use retrospective merger analyses to analyze 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)), and the price effects of vertical mergers (Luco and Marshall (2020)). We complement this literature by studying how mergers affect firm efficiency and providing evidence on the mechanisms.

2 Institutional Background and Plant Productivity

In this section, we provide institutional background of the power generation sector, overview mergers and acquisitions in the industry and describe how we measure of efficiency.

[2]Some other evidence from other industries are meat product industries (Nguyen and Ollinger (2006)), railroads Bitzan and Wilson (2007), healthcare Schmitt (2017), Dranove and Lindrooth (2003), Harrison (2011).

2.1 Power Sector

Until the early 1990s, the US electricity generation was overwhelmingly supplied by regulated and vertically integrated investor-owned utilities (IOUs) or government-owned utilities (municipal- and state-owned). These entities usually served a territory exclusively and owned all parts of the power sector; transmission, distribution, and retailing. The primary return for the utility services was regulated through rate-of-return on capital investments and cost-of-service regulation. This highly regulated market structure left little room for efficiency improvements, which are shown to generate significant inefficiencies (Fabrizio et al. (2007), Cicala (2015)).

The industry went through significant deregulation, especially after the mid-1990s. The electricity generation is decoupled from transmission and distribution, and most generators began to earn profit paid through the market pricing system. This deregulation is accompanied by the creation of stand-alone independent system operators (or ISOs), which run the wholesale electricity markets by conducting cost minimization algorithms to meet demand based on generator-level willingness to produce through competitive bidding. In 2020, roughly 70 percent of the US electricity demand is provided through seven ISOs.[3] Although there are some market power concerns (Borenstein et al. (2002), Puller (2007), Mansur (2007), Ito and Reguant (2016)), the literature indicates that power plants in ISO operate more efficiently than their counterparts in regulated markets.

After the deregulation, the US electricity generation technology mix changed significantly with new power plant construction and the retirement of old power plants. In the early 1980s, coal was the primary fuel source for electricity generation. As the price of natural gas fell significantly with the expansion of fracking in the early-2010s, the gas-fired generation became competitive with the coal-fired plants, each providing roughly one-third of the market supply in 2015. In 2020 the gas-fired generation reached twice the size of the coal-fired generation.

2.2 Mergers and Acquisitions

Large utility companies are usually organized into several subsidiaries under a big parent company, serving in different locations and segments of the power sector. The structure of the subsidiaries tends to follow the boundaries of the legacy vertically integrated utilities before the deregulation. Parent companies typically own assets in the generation, transmission, and distribution in the same region, with some parent companies having subsidiaries serving different parts of the country. After the deregulation, significant mergers and acquisitions activity has occurred between these entities within and across regions. Moreover, financial firms, which predominantly involve private equities and bank funds, started to invest in power generation. In Section 4 we describe the trends in mergers and acquisitions in the power generation industry.

[3] The 7 ISOs are; California ISO (CAISO), New York ISO (NYISO), Electric Reliability Council of Texas (ERCOT), Mid-continent ISO (MISO), ISO New England (ISO-NE), Southwest Power Pool (SPP), Pennsylvania-New Jersey-Maryland Interconnection (PJM)

Mergers and acquisitions in the power sector can be divided into three main groups: (i) partial-firm asset sales, (ii) subsidiary acquisitions (divestitures), and (iii) mergers. The partial-firm asset sales happen when a firm acquires some of another firm's plants without any change in the ownership of both subsidiaries[4]. In this case, both the owner and the parent company of the plant change after the acquisition, and a new firm controls the power plant's operation. In subsidiary acquisitions, a parent company acquires an entire subsidiary with all its assets. In this case, the plant's owner (subsidiary) remains the same, but the parent company changes. The third type is a merger between two firms where two large companies merge and form a new company.

All plant transactions in the US electricity sector must go through a detailed regulatory review process from the Federal Energy Regulatory Commission (FERC), Department of Justice (DOJ), and State Public Utility Commissions (PUC). The FERC reviews mergers under Section 203 of the Federal Power Act, relying on the 1996 revision of the Horizon Merger Guidelines (HMG) and putting more emphasis on market concentration levels. DOJ's review is more extensive than FERC, relying on 2010 HMG and investigating potential anticompetitive effects of mergers. If either DOJ, FERC, or State PUC concludes that the merger harms competition, they either block the deal or require assets divestiture on the generation or distribution.[5] Despite these reviews, most proposed mergers have been approved in the US electricity sector, with only a few challenges in the last two decades.

There are several merger motives in the electricity industry and efficiency improvements in power plants is one of them.[6] Firms often argue that mergers will generate synergies between assets, citing enhancing financial flexibility, increasing cash flow benefits, and complementarities between different sectors such as distribution and generation.[7] As fuel represents roughly 80 percent of the operational cost; many merging firms include a section on operational efficiency synergies under prospective ownership and management to improve power plant efficiency and reduce cost.[8][9] As an example, Figure 25 in the appendix shows a slide from the investor presentation of

[4]In these acquisitions, one or several plants of a subsidiary are purchased by another firm and the remaining plants are still with the target firm.

[5]To give some examples, Exelon - PSEG merger did not go through in 2005 after failing to clear the deal with state PUCs. In 2012, following the DOJ's request, Exelon Corporation and Constellation divested three electricity generating plants in Maryland for the merger to go through. In both cases, the FERC concluded that the merger would not harm competition.

[6]For most mergers in our sample, we have access to investor presentations and conference calls; therefore, we can identify the motives precisely.

[7]Duke - Progress merger investor presentation states that the merger creates the largest US utility by diversifying earnings and cash flows and leveraging "best-in-class" operational and customer service practices.

[8]Some other examples (i) AES-DPL merger which argue their earlier merger IPL and successful management (ii) NRG-GenOn merger which cites measurable and actionable cost synergies of $175 million per year, (iii) Mirant-RRI Energy $150 million in annual cost savings, (iv) Vistra-Dynergy mentions geographic, fuel, market and earnings diversification benefits.

[9]Other cited reasons are increasing the consumer base and diversifying the portfolio across technologies and regions and accelerating the efforts to meet potential future environmental regulations.

Dynergy by Vista Energy merger in 2018. They argue that heat rate improvements will lead to a cost saving of 125 million dollars.

2.3 Measurement of Plant Productivity

Power plants transform one form of energy into electrical energy using different production technologies. This paper focuses on fossil fuel power plants (primarily gas or coal) because their inputs are easier to measure, allowing us to construct a physical efficiency measure. In a power plant, a generator is the unit of production, which takes fossil fuel as an input and converts that to electricity. Typically, a power plant contains multiple generators, where personnel, such as engineers and plant managers monitor and control the production. As the electricity demand varies, some power plants respond by adjusting their production. This adjustment requires technical expertise and can affect the power plant's overall efficiency.

Our main measure of plant performance is heat rate, defined as the ratio of energy output and input. The heat rate characterizes the productivity of fossil fuel power stations, representing how efficiently fuel is converted into electricity. It is often expressed as the ratio of the energy content of the fuel, British thermal unit (Btu), and the plant's electricity output, Megawatt-hour (MWh). In this paper, as an efficiency measure, we use

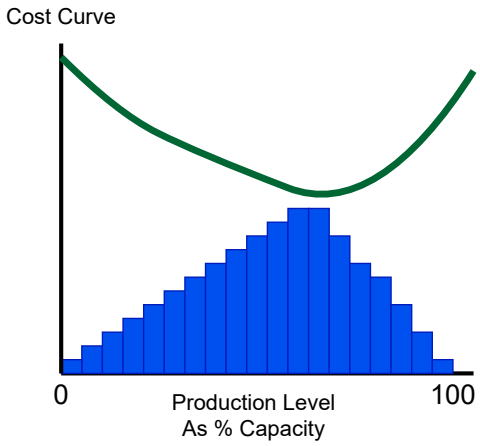
$$\text{Inverse heat rate: } \frac{\text{Energy Output (MWh)}}{\text{Energy Input (MMBtu)}}.$$

A lower heat rate means a more efficient production, as the plant generates the same MWh of electricity with less fuel. Thus, enhancing heat rates lowers fuel costs, which represent roughly 80 percent of operating costs Fabrizio et al. (2007).

Most importantly for our study, the fuel efficiency of a power plant provides an ideal setting to study the effects of mergers and acquisitions on productivity. First, our measure is a quantity-based efficiency measure obtained from quantity input and output. Therefore, other factors, such as buyer power or market changes, do not affect our efficiency measures post-merger. Second, electricity is a homogeneous product, ruling out the potential quality changes after the acquisition.

Several factors affect the heat rate in a power plant. Figure 1 shows an example of a heat rate curve. Blue bars show the production distribution as the percentage of capacity, and the green line shows the marginal cost curve (inverse heat rate). The overall efficiency of the generator is calculated by taking the weighted average of the cost curve based on the production profile. First, the efficiency of a power plant varies with its production level. Producing more at a low cost increases the plant's overall efficiency, whereas too low or too high generation leads to low efficiency. Second, power plants need to burn extra fuel to adjust their production level when responding to demand conditions, leading to higher heat rates. The associated cost with this adjustment is called ramp-up cost. Therefore, power plants whose production varies a lot tend to produce electricity

Figure 1: Heat Rate Curve



Note : Green line represents the marginal cost of producing electricity at a given capacity without potential ramping costs. Blue bars represents the distribution of actual production levels.

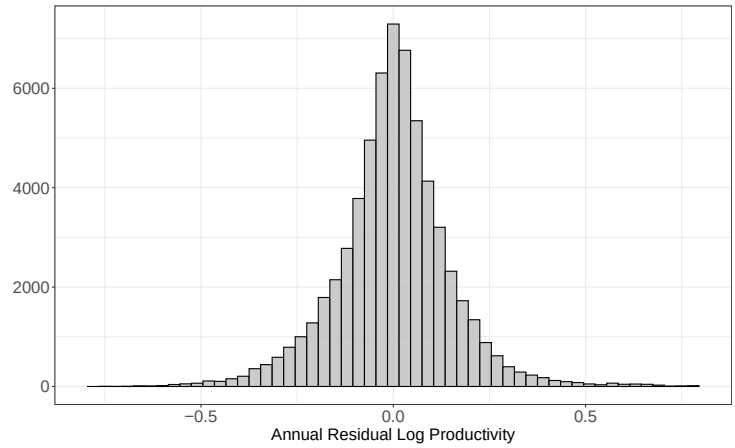
less efficiently. Lastly, the fuel type plays an important role. Coal-fired generators often have 10-12 MMBtu/MWh, whereas natural gas-fired generators have 7-9 MMBtu/MWh. However, note that heat rate should be neutral to change in the input type because it is measured based on the heat content of the input. footnoteDepending on the processing of the fuel, there could be small differences, especially for coal, due to factors like moisture content and pulverization procedures.

Even though the electricity generation process is relatively mechanical, there is considerable heterogeneity in power plant productivity in the US. Figure 2 shows the distribution of yearly residual log productivity of power plants in the US after controlling for plant age, fuel type, technology, capacity, and other characteristics. The difference between the 10th percentile and the 90th percentile is 0.38, indicating that plants in the top part of the productivity distribution are 38 percent more productive than plants in the bottom part of the productivity distribution.[10] This heterogeneity in productivity was observed by others in the literature (Sargent & Lundy (2009), Staudt and Macedonia (2014)).[11] The large dispersion in productivity conditional on a very rich set of observables highlights the role unobserved heterogeneity in efficiency, indicating potential room for improvement in many power plants.

[10] This dispersion is slightly smaller than the dispersion identified in other manufacturing industries (Syverson 2011)

[11] For example, Sargent and Lundy's report commissioned by EPA found that coal-fired power plants in the United States require on average 10400 British thermal units (Btu) to produce one kilowatt-hour (kWh) of electrical energy, but range from heat rates of 5 MMBtu/MWh to 32.7 MMBtu/MWh (Sargent & Lundy 2009). Staudt and Macedonia (2014) examines factors that contributed to heat rate using data from US EPA's National Electric Energy Database (NEEDS), including facility size, capacity factor, emission controls, steam cycle (supercritical versus subcritical), and coal type. They determined that each factor played an essential role in the generator's heat rate. However, they also determined that there was much-unexplained variability in the data.

Figure 2: **Distribution of Residual Log Productivity**



Note : This figure shows the distribution of residual yearly log productivity of fossil fuel plants in the US between 2000 - 2020 after controlling for plant age, fuel type, technology, capacity, and other characteristics.

Improving heat rate is a complex process and can be done in two main ways: (i) low-cost operational improvements and (ii) costly capital upgrades. Low-cost practices like process optimization, personnel training, and efficient maintenance can improve the heat rate at every production level. Managing the load and maintaining the utilization at high-efficiency levels of electricity production lead to avoiding ramp-up costs and lower heat rates. The most important factor that determines operational practices is labor. As explained in detail in Bushnell and Wolfram (2009) individual skills of key personnel could make a significant difference in the performance of generating plants.The Appendix Figure 22 highlights a few case studies of low-cost improvements. Power plant operators can control the production process in many small ways, with a big impact on overall efficiency. On the other hand, high-cost practices like improving the boiler, fuel feeder, and cooling system can lead to lower heat rates.

Improving the efficiency of the plant is also important for environmental considerations. The more efficiently a plant operates, the less fuel it requires, emitting lower local pollutants and GHG emissions. As a result, improving plant efficiency can be an effective tool to decrease local and global pollution.[12] The potential role of increasing power plant efficiency has been recognized by policymakers in the US. In the 2016 Clean Power Plan Act introduced by the Obama administration, improving the heat rate of existing power plants was proposed as the first building block to reduce

[12]For example, it has been estimated that 1.7 $GtCO_2$ could be saved annually by improving the efficiency of existing plants worldwide. In China, efficiency improvements by 4 percent could reduce SO_2 emissions by 1129 kt/y (Henderson 2003) and similarly in India a 4 - 5 percent net efficiency improvement could reduce SO2 emissions by 790 kt/y and NO_x emissions by 178 kt/y (Sloss 2011).

the carbon intensity of electricity generation.[13]

3 Data

This section briefly describes the key sources of data used in the empirical analysis. Our primary goal is to construct an hourly measure of generator efficiency and detailed ownership changes to examine the impacts of M&A on productivity.

The US electricity sector represents roughly 4 - 5 percent of total US GDP with over 11000 utility-scale power plants, providing nearly 2-3 million jobs across the US. For this study, an attractive feature of the power generation industry is that the industry is partially regulated at different levels. Therefore, data availability is much richer than in many other industries in terms of efficiency measures and ownership. We take advantage of this in our paper and create a unique dataset on ownership and production. We combine several datasets from the Federal Energy Regulatory Commission (FERC), Environmental Protection Agency (EPA), the Department of Energy's Energy Information Administration (EIA), S&P Global, and Velocity Suite at the firm, plant, and generator level for all coal and gas-fired power plants in the US between 2000-2020. This results in close to a billion data points with the hourly generation at the generator level. Appendix Section A provides additional information regarding the data, the construction of several variables, and their descriptive statistics.

Plant-Level Characteristics and Production

We use EIA Form 860 and 923 for detailed data on unit-level characteristics. These annual forms cover the universe of power plants in the US. We assembled information on age, fuel type, boiler type, capacity, location, ISO, cost, regulation status, and plant-level investment. Then, we merge this data to plant-level capital expenditure data from S&P Global, which is sourced from FERC Form 1.[14]

We utilize The EPA's Continuous Emissions Monitoring Systems (CEMS) for hourly generation and heat rate. The CEMS program was developed to monitor power plant emissions systematically to implement environmental controls. It provides hourly power output, emission, and heat rate of almost every fossil fuel power plant in the US.[15] To construct our final data, we merged the

[13] An analysis conducted by National Energy Technology Laboratory (NETL) supported this conclusion. Under a scenario where generation from coal is constant at the 2008 level, increasing the average efficiency from 32.5 to 36 percent reduces US GHG by 175 MMmt/year or 2.5 percent of total US GHG emissions in 2008. Moreover, NETL notes that "if each plant achieved their maximum efficiency each year, 5 percent reduction in CO_2" could result.

[14] Only power plants, whose parent company has an asset with regulated returns, must comply with FERC Form 1's requirements. Therefore roughly half of the capital expenditure data is missing.

[15] Every power plant in the US with larger than 25 MW capacity that burns fossil fuel must comply with EPA CEMS program. This sample represents $\approx$ 95 percent of the US fossil-fuel generating capacity.

production data from CEMS with the data from EIA. In some cases, generator names in the EIA dataset and CEMS do not match.[16] We use an EPA's Power Sector Data Crosswalk in those cases. We manually matched the retired and unmatched power plants using the same principles as the initial crosswalk. We restrict our sample to all the US fossil-fuel generators that comply with the CEMS program, except Alaska and Hawaii.

Mergers and Acquisitions Data

We construct the ownership panel data for the universe of fossil fuel power stations from two separate ownership and transaction datasets obtained from S&P Global. The ownership data includes the ownership structure of all power plants at the owner and parent company levels. We observe any firm that owns some shares of the power plant. Transaction data contains details about the transferred assets, deal size, buyer, seller, announcement and close date, conference call transcripts, and deal description. Since regulatory authorities must review all transactions, this data includes the universe of our transactions in our sample period.

Ownership and merger data often suffer from falsely identified ownership changes. Name changes of the subsidiary, restructuring of the parent company as an owner change sometimes show up as ownership changes. We utilize our transaction data to identify false ownership change cases. Transaction data provides details about assets sold and the time of the deal, whereas ownership data provides the timing of the ownership change. We identify the true ownership changes by cross-matching the transaction date and asset list. We also use corporate structure data to identify changes that are merely a restructuring within the same parent company. We later use those false ownership change cases in Section 8 for robustness checks. We also specified deregulation cases and excluded those cases from ownership change.

Personnel

We assembled panel data on personnel information for each plant in our sample.[17] Each power plant that complies with at least one of the EPA programs needs to submit personnel information at the plant level.[18] This results in a panel dataset where we can observe the exact data of personnel changes. Furthermore, to obtain more information on the personnel data, we matched roughly 70 percent of plant personnel names to Linkedin profiles, obtaining education and employment

[16] EPA uses boiler names as a unit, whereas EIA uses generator names.

[17] For instance, a generator that goes through M&A only at the parent company level tends to keep its subsidiary structure and the personnel.

[18] The personnel information is important for EPA, as a potential problem like leakage needs to be addressed fast and the responsible parties should be accountable. The reported personnel could, in principle, be a power plant manager, engineer, or regulatory compliance manager. We obtained the title of this personnel from Linkedin and confirmed that 80 percent of the reported personnel are plant managers. Therefore, we treat this personnel information as plant manager for the rest of the study.

history. This data is useful because even though most of the electricity output is correlated with the fuel input, the plant personnel plays an important role in controlling the process. Therefore understanding whether an ownership change leads to a personnel change is important.

Demand and Renewables

Since demand-side variations lead to expected or unexpected changes in power plant production, controlling for demand shocks is critical to understanding plant efficiency. The US electricity markets are organized primarily on balancing authority areas (BAA) or ISO Zones. FERC provides hourly demand data on each of these markets.[19] The marginal cost and emissions of electricity production for renewables are often very close to zero. Therefore market operators make use of available renewable electricity generation. As the most renewable generation is not dispatchable, availability of the renewable sources creates variation in the fossil-fuel supply needed to meet the demand. To control renewable generation, we gathered hourly data for solar and wind power generation from FERC and S&P Global for each BAA and ISO Zone.

4 Some Descriptive Facts about M&A in the US Power Generation

This section presents descriptive statistics about mergers and acquisitions in the fossil fuel power generation industry. Our goal is to document that the industry experienced a significant number of acquisitions with rich heterogeneity in terms of transaction size, acquirer and target firm types, and location. These facts allow us to study several aspects of how acquisitions affect efficiency, and they will be essential to keep in mind when we conduct our empirical analysis.

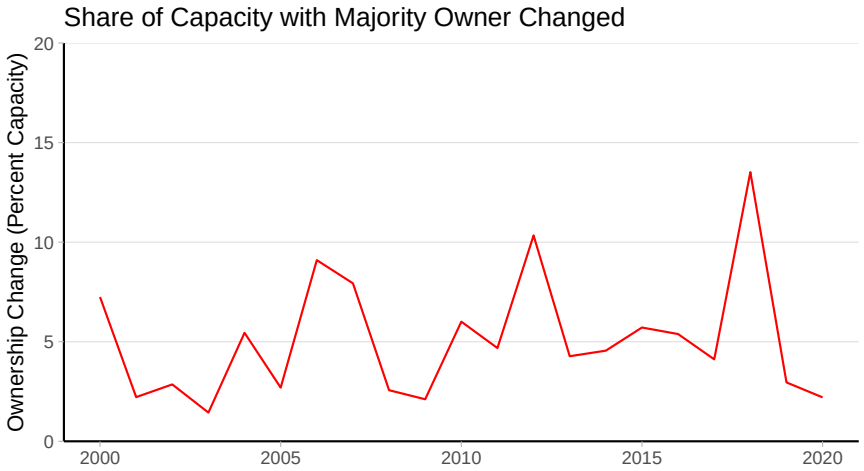
95 percent of Industry Capacity Changed Ownership Between 2000 - 2020. There has been a large number of mergers and acquisitions in the power generation industry. Figure 3 shows the percentage of fossil fuel electricity generation capacity that changed ownership from 2000 to 2020. We see that an average of 5 percent capacity changes ownership annually, with some fluctuations year-to-year.[20] Cumulatively, this corresponds to 95 percent of industry capacity during our sample period.[21] This is also reflected in the large number of power plants that changed ownership. Table 1 presents some summary statistics on plants, firms, and deal characteristics from the universe of acquisitions between 2000–2020. Our data includes 690 transactions involving 6044 generation

[19] Market in the electricity market is often segregated due to transmission congestion. Many reliability and generation planning happen at ISO zones or BAAs level.

[20] We define acquisition as an ownership change if a different firm owns the majority of the plant's shares after the acquisition. For a small number of plants, no firm owns more than 50 percent of shares. For those plants, an acquisition is defined as the change of the largest shareholder.

[21] This is cumulative capacity, so it double-counts the capacity of generators that have changed ownership multiple times. We observe that 2,200 generators change ownership at least once, corresponding to 50 percent of the industry's total capacity.

Figure 3: Share of Capacity with Majority Owner Change



Note : This figure shows the change in percentage cumulative ownership of fossil fuel plants in the US between 2000 - 2020

units and 2193 plants. In about 80 percent of these transactions, there is a plant whose majority owner changes, giving us a total of 4373 generators with an ownership change. These generators will constitute our primary sample. Finally, looking at the firm characteristics, we see 308 unique acquirer firms and 291 target firms in the data.

Most Acquisitions Reallocate Assets between Incumbent Firms. Most acquisitions are partial assets sales between two incumbent firms, but we also see some transactions where the target exits or the acquirer enters the industry. Columns 2 and 3 of Table 1 report the summary statistics by transactions where the acquirer firm enters, and the target firm exits the industry. In the rest of the transaction, a firm that already owns power plants acquires more power plants from another firm that has the remaining plants after the transaction. In these transactions, both firms have a presence in the industry pre-and post-acquisition. We see that in 20 percent of the transactions, the acquirer firm enters the market, and in about 20 percent of transactions, the target firm exits the market. Overall, these summary statistics suggest a significant reallocation of assets between the firms in the industry, which allows us to test some important hypotheses about the allocative effects of acquisitions.

Market Concentration is Stable. Despite the large number of acquisitions in our study period, we do not observe a meaningful change in market concentration. Figure 4 reports the national market shares of the largest 5, 10, 20, and 30 firms in terms of capacity owned. The figure shows some fluctuation over time; however, the concentration ratios are broadly stable in the sample period.[22]

[22]Note that these concentration ratios are not informative about the changes in market power due to the local nature

Table 1: M&A Summary Statistics

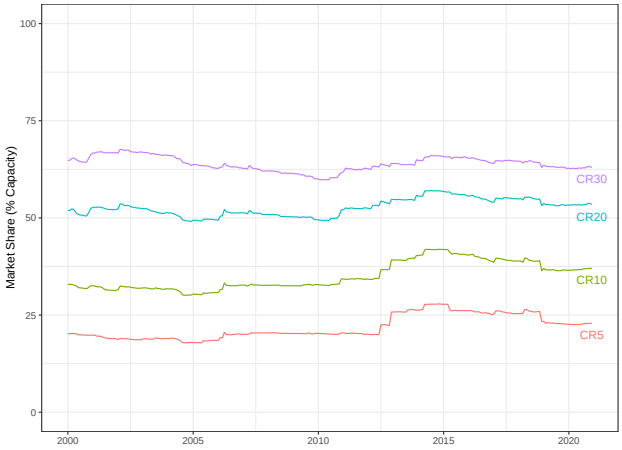
	(1)	(2)	(3)	(4)
	All	Acquirer Firm Enters Market	Target Firm Exits Market	Change in Majority Owner
		Unit Characteristics		
# of Units	4834	701	1692	4030
# of Plants	1567	268	482	1264
# of Unique Units	2365	585	1355	2198
# of Unique Plants	735	222	393	674
# of Acquirer Firms	267	126	107	234
# of Target Firms	266	99	148	229
% Gas	0.81	0.89	0.74	0.81
% Coal	0.13	0.09	0.18	0.13
% Oil	0.06	0.02	0.08	0.06
% Becomes Unregulated	0.04	0.06	0.03	0.04
% In Regulated State	0.24	0.25	0.39	0.24
% in ISO	0.77	0.76	0.71	0.76
		Firm Characteristics		
# of Units Target Owns	35.03	0.00	25.56	32.50
	(49.28)	(0.00)	(39.54)	(46.15)
# of Units Acquirer Owns	44.60	35.22	11.92	44.05
	(52.49)	(47.16)	(22.16)	(52.02)
Acquirer Firm Capacity	5459	0	4189	5055
	(8765)	(0)	(6883)	(8049)
Target Firm Capacity	7025	5312	1738	6912
	(9655)	(8314)	(3588)	(9453)
		Transaction Characteristics		
# of Deals	689	132	147	532
Deal Size in # of Units	7.0	5.3	11.5	7.6
	(14.7)	(8.9)	(21.8)	(16.0)
Deal Size in Capacity	1233	986	1922	1298
	(2640)	(1981)	(3798)	(2813)

Note: This table includes M&A activities that includes a fossil fuel generating units in the US between 2000 - 2020. Each column reports the counts and characteristics in the data at varying levels of sample restrictions. Column (1) reports data from all acquisitions. Column (2) and Column (3) presents data from transactions where the acquirer firm enters the market and the target firms exit the market, respectively. Column (4) reports data from majority acquisitions only.

This is because there is a considerable firm turnover in the industry, as suggested by a large number

of wholesale electricity markets. We report these changes at the national level to see whether large firms increase their dominance in this industry through acquisitions.

Figure 4: Change in Market Concentration



Note : This figures show change of the HHI in the overall US fossil fuel power plants market between 2000 - 2020

of acquirers and targets in Table 1. Some examples can be seen in Appendix Figures 19 and 20 where we report firms with the largest capacity increase and decrease between 2010 - 2020.[23]

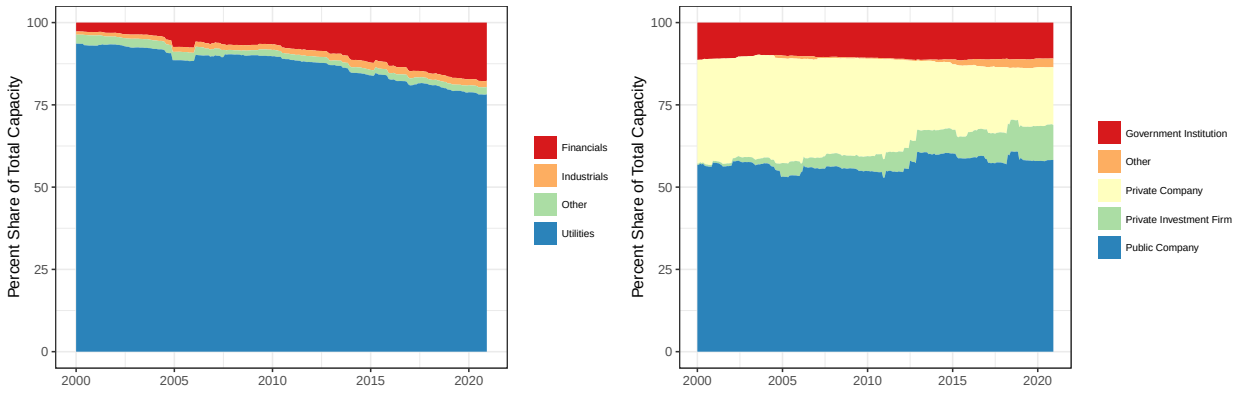
Asset Allocation from Utilities to Financial Firms. Figure 5a displays the change in ownership based on the primary activity of the ultimate owner (utilities, industries, financials), and Figure 5b displays the change in ownership by whether the ultimate owner is public. Starting with Panel 5a, we see an increasing presence of financial firms between 2000 and 2020 in the industry. The share of total capacity owned by financial firms goes from 3 percent in 2000 to 20 percent in 2020, suggesting substantial asset allocations from utilities to financial firms. Figure 5a highlights that public firms own most industry capacity, and the share of public firms remains stable over time. Finally, government institutions own twelve percent of the industry capacity. Except for the federally run Tennessee Valley Authority, these are local governments in rural areas that operate the power plant that supplies electricity to the public.

Most Acquisitions Occur in Deregulated Markets. As explained in the previous section, some states regulate the plant's returns from power generation. One might be concerned about the role of regulations as they might change merger motives and the incentive to improve productivity after an acquisition. To investigate this, Table 1 shows the fraction of acquisitions that occur in regulated vs. deregulated markets. We see that the majority of the ownership changes, 76 percent, occur in deregulated markets.[24] This is also reflected in the geographic variation of acquisitions. Appendix Figure 24 shows the regulation by state and capacity that changes ownership in every

[23]One reason for stable concentration ratios could be regulatory oversights as merger proposals are endogenous to stringency of antitrust policies.

[24]This is expected because, in most regulated markets, public ownership serves the local population.

Figure 5: Market Share by Firm Type



(a) Industry Type

(b) Owner Type

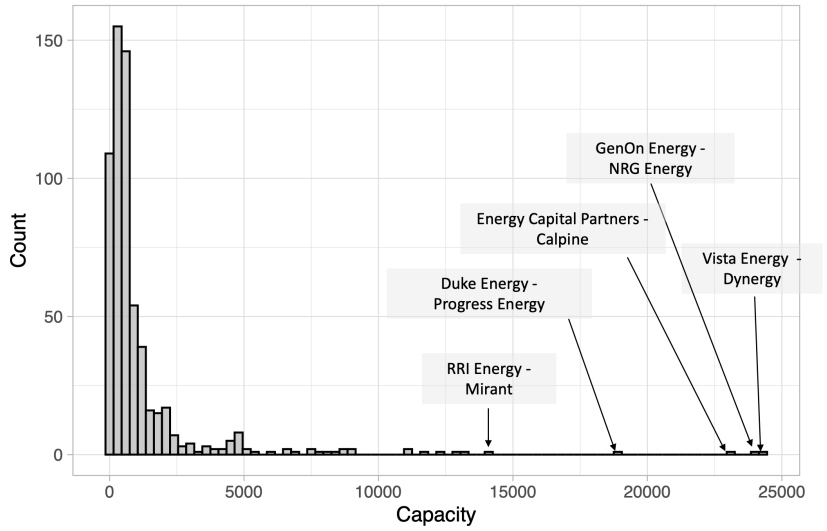
Note : These figures show change in market share of industry and owner types of fossil fuel plants in the US between 2000 - 2020

state. We see that change in ownership is concentrated in deregulated states suggesting that most of the acquired plants operate in a competitive market. One might also worry that ownership changes coincide with the divestitures that were required by restructuring. Even though most state restructuring happened in the 90s, some state restructuring has overlapped with our sample period. For this reason, we look at how many ownership changes coincide with restructuring divestitures. Table 1 reports that only a handful of deregulation happens after 2000, which we exclude from our acquisition sample.

Heterogeneity in Transaction Size. Our sample includes mega-mergers that involve hundreds of generators and small transactions that involve only minority owner change. In Figure 6, we report the distribution of capacity that changed ownership across 660 transactions. While most small transactions involve one or a few plants with small capacity, some moderate-size transactions include ownership change of 5000-10000 MWh capacity. Finally, our sample includes mega-mergers that involve more than 10000 MWh capacity. Observing this rich heterogeneity is useful because (i) our evidence does not come from a small number of large mergers, and (ii) we can test heterogeneity of the effect by transaction size. Moreover, in our data, we observe not only the majority of acquisitions, which involve more than 50 percent shares of the plant, but also minority acquisitions where the buyer acquires less than 50 percent of a power plant. The distribution of shares that change ownership is reported in Figure 7. Perhaps surprisingly, there is a large number of minority acquisitions. We use these minority acquisitions in placebo tests as one should expect no change in efficiency after a minority acquisition.

Ownership Changes at Different Level of Corporate Structure Ownership changes can mainly

Figure 6: Heterogeneity in Merger Size



Note: This figure shows the differences in the size of deals that includes fossil fuel plants in the US between 2000 - 2020

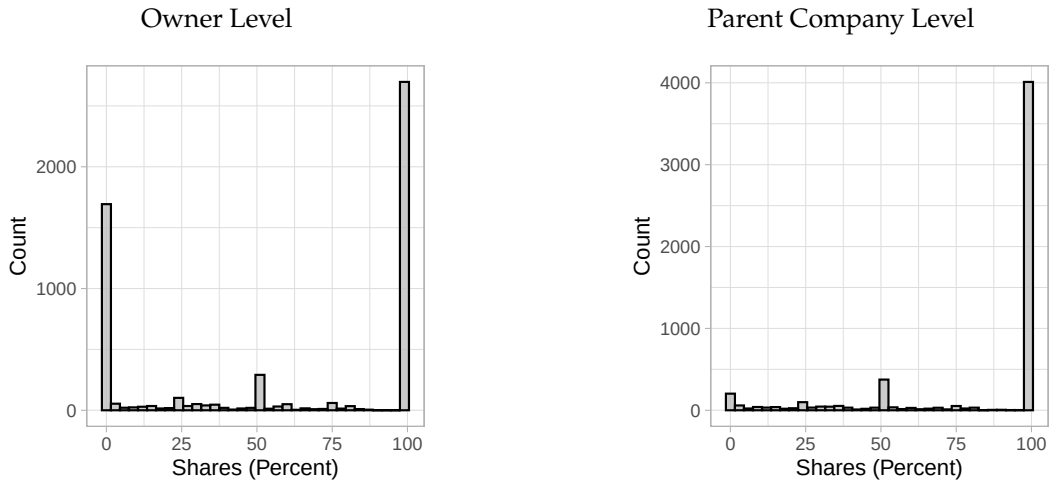
happen at two levels in a corporate structure: (i) at the owner level and (ii) at the parent company level. Typically, a subsidiary of a holding company owns the power plant, and the parent company owns that subsidiary. When a parent company acquires a subsidiary of another parent company, the entity that owns the power plant remains the same, but the parent company changes. On the other hand, if a subsidiary acquires a power plant, both the owner and parent company change. Figure 7 shows ownership changes at the owner and parent company level. The figure suggests that in around 1700 acquisitions, the owner remains the same, and the parent company changes. We will use this variation to study the efficiency effects of acquisition at different levels of corporate structures.

5 Empirical Results

Our empirical strategy aims to identify the causal effect of acquisitions on power plant productivity and study potential mechanisms. To do this, we compare productivity trends at acquired generators to productivity trends at the plant that did not directly involve in merger activity; we refer to these generators as 'control generators' or 'controls.' In most estimations, each observation is a unique combination of generator and week, with variables containing productivity, ownership, and several plant characteristics.

The main advantage of our empirical setting is that we observe a high-frequency measure of the productivity of power plants, allowing us to track the productivity immediately before and after

Figure 7: Ownership Change Types



Note : This figure shows the differences in the ownership level of deals that includes fossil fuel plants in the US between 2000 - 2020

the acquisition. As a result, we can identify the effects of acquisition within a short window, not years before or after the acquisition. This is in contrast to data availability in most manufacturing industries, where production data is typically at the annual level, and the researcher has to compare productivity trends years before and years after the acquisition. This unique data feature makes it possible to consider acquisitions as discrete events.

Before estimating our model, we make several additional sample restrictions. First, we eliminate generators that are inactive more than 90 percent of the time during their lifetime.[25] Second, we drop acquisition events that correspond to divestitures due to deregulation. Third, we require that target generators have at least one year of data before and after being acquired so that all in-sample acquired plants contribute to identifying variation in both the pre-merger and post-merger effect coefficients.

We find that acquisitions increase the productivity of power plants by four percent, but only when ownership changes both at the parent company and owner level. In contrast, ownership changes at the parent company level only lead to a one percent productivity increase. The productivity increase starts five months after the acquisition and reaches the new steady-state level after eight months. After documenting the evidence on efficiency, we close the section by examining whether heterogeneity is heterogeneous by acquirer firm type. To facilitate the exposition, we defer the detailed examination of mechanisms to Section 7.

[25] Lifetime is defined as the period the first and last time of production observed in the data.

5.1 Mergers and Efficiency

This section presents our main difference-in-differences results from estimating the effects of mergers on efficiency. To do this, we follow Braguinsky et al. (2015) and, we estimate a regression of the following form:

$$log(y_{it}) = \theta_1 \text{lpre_acq}_{it} + \theta_2 \text{epost_acq}_{it} + \theta_3 \text{lpost_acq}_{it} + X_{it} + \mu_t + \alpha_i + \eta_{it} \tag{5.1}$$

where y_{it} is the productivity of generator i at week t (measured as inverse heat rate), the controls, X_{it} include state-month fixed effects, time-varying generator characteristics such as age and fuel type, capacity, α_i is generator fixed effect and μ_t is week fixed effect. By controlling for state-month fixed effect, we flexibly account for changes in demand and the supply of non-fossil fuel electricity generators (mainly entry of renewables) at the state level. Although it happens rarely, the generators can change their capacity and fuel type, so to control for these, we include fuel type and capacity. Including generator and week fixed effects imply that merger effects are identified within-generator changes following a merger event. The regression includes three coefficients of interest: (i) $epost_acq$, an indicator variable for 1-6 months post-treatment, (2) $lpre_acq$ is an indicator variable for 1-6 months pre-treatment and (iii) $lpost_acq$ is an indicator variable for 7-12 months post-treatment. By including early and late post-acquisition time dummies, we aim to capture the dynamic effects and identify when productivity changes happen. We include $lpost_acq$ to see whether there are any productivity effects of the acquisition before the acquisition. This can happen due to anticipation effects or disruption in the production process as most acquisitions are announced months in advance. Finally, all standard errors are clustered at the firm level unless otherwise indicated.

It is important to highlight that our unit of analysis is a generator rather than a plant. While the same firm owns all the generators in a plant, they might have different production profiles and maintenance schedules, which would affect efficiency estimates if inputs and production are aggregated at the plant level. Therefore, we think the generator is the right level of analysis and maintain this throughout the paper.

Before moving to the results, in Table 2, we report the average characteristics of acquired power plants and power plants that have never been acquired. Treated and control groups look similar in terms of capacity and install year. There are slight differences in fuel type: acquired plants are more likely gas-powered than the control group. This difference is expected because there is a substantial policy uncertainty about the future of coal power plants, which deters potential buyers. Finally, regarding geographical distribution, we see that treated and control groups are similar.

Table 3 shows the results from estimating Equation (5.1) for the outcome variable of log productivity. It does so for the entire sample of acquisitions (All M & A) as well as different acquisitions events: (i) both the parent company and owner firm change, (ii) only the parent company changes, and the owner remains the same, (iii) minority acquisitions (iv) owner name changes. Estimates

Table 2: Balance Table

	Acquired	Never Acquired
% Coal	0.18	0.26
% Gas	0.74	0.67
% Oil	0.08	0.07
Capacity	179	176
Install Year	1987	1985
% in ISO	0.75	0.58
% in PJM	0.29	0.11
% in MISO	0.14	0.22
% in ERCOT	0.09	0.05
% in NY	0.09	0.05

Note : This figure shows the differences acquired and never acquired fossil fuel plants in the US between 2000 - 2020

Table 3: Regression Results

Dep var. Log Productivity	All M&A	Owner/Parent Company Change	Only Parent Company Change	Minority Sharehold Change	Name Changes
Late pre-acquisition	0.006	0.001	0.009	-0.012	0.003
	(0.003)	(0.006)	(0.005)	(0.007)	(0.008)
Early post-acquisition	0.007	0.008	0.009	-0.011	-0.003
	(0.003)	(0.004)	(0.005)	(0.01)	(0.009)
Late post-acquisition	0.022	0.034	0.01	0.012	-0.005
	(0.004)	(0.006)	(0.005)	(0.013)	(0.011)
Observations	1.7M	1.7M	1.7M	1.7M	1.7M
Adjusted R^2	0.579	0.579	0.579	0.512	0.498
# of Acquisitions	4012	1778	1913	512	612

Note: This table presents the coefficient estimates from estimating Equation (5.1). Standard errors are clustered at the generator level.

from (iii) and (iv) provide placebo tests, as discussed later.

The results in the first numerical column indicate that the generator's efficiency rise after the acquisition. The efficiency change in the early acquisition period is only 0.7 percent and marginally statistically significant, pointing out that there is no considerable change in efficiency immediately

after the acquisition. However, in the late post-acquisition period, 6-12 months after the acquisition, the efficiency increases by 2 percent above the pre-acquisition. Thus, acquired generators' efficiency levels improve following the acquisition, though it takes time for this to manifest itself fully.

The following two columns test whether different types of ownership change differ in efficiency impact. Column 2 estimates a difference-in-difference specification where treatment is defined as ownership change at the parent and owner levels. In contrast, in Column 3, a plant is treated when the parent company changes, but the owner firm remains the same after the acquisition. One might expect the efficiency effects of an acquisition to be different in these two cases because the owner firm typically has direct control over the operation and personnel of the power plant. In contrast, the parent company controls the power plant indirectly. Moreover, ownership changes at the parent level tend to be financial acquisitions. Comparing these two columns reveals significant heterogeneity in the treatment effect. The effect of the acquisition on efficiency is significantly larger when it occurs at the owner-company level than when it occurs at the company level. The effect is small and marginally significant when the owner company remains the same. These results confirm our intuition that what matters for operational changes of the power plant is the direct owner rather than the ultimate parent. A change in indirect control does not affect power plant productivity.

The last two columns of the table serve as placebo tests. For the first placebo test, we use the 512 minority acquisitions in the data. These are the transactions where the majority owner remains the same after a transaction. For the second placebo test, we identify 612 generators whose owner changes its name, but the generator is not involved in an acquisition. These are 'false' ownership changes that would have been classified as "acquisitions" from the ownership data, but cross-checking with the transaction data reveals no ownership change. We use these two types of events, minority acquisitions, and name changes, as placebo tests because we should not expect to see any impact on power plant efficiency. The results confirm our expectation that we do not see any significant change in power plant efficiency after these events. These placebo tests give us confidence that confounders do not drive our main results.

To interpret the results from the specification in Equation 5.1 as causal, we rely on the assumption that an acquisition creates a discontinuous change in power plant behavior. In particular, the acquisition creates a discrete change surrounding the event. In contrast, any efficiency trends that might lead to selection would be either common to the control plants or 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 include a rich set of control variables that account for industry-specific efficiency changes.[26]

[26]The average within power plant efficiency gain in the industry is 0.3 percent. Therefore, in power plant generation, we do not see a significant fluctuation in efficiency.

Threats to identification could be unobservable factors that differentially affect the efficiency trend of generators involved in acquisition versus generators in the control groups around the acquisition. For example, it could be that unobservable factors that would change efficiency in the absence of mergers are observed by acquirers and prompt them to acquire the plants. These unobservables will not bias our estimates unless they have a differential effect on efficiency during the pre-and post-acquisition period.[27] To explore this concern, we also estimate a model in which we pair each treatment generator with its closest match in the control group, as identified using a propensity score model. The results, reported in C, are broadly similar. We also look at how other important events, such as manager changes, affect efficiency in the absence of mergers, and we find minimal effects (Appendix Figure 21). Finally, we do a battery of robustness checks presented in Section 8 to show that our results are robust to several specifications.

After showing a significant impact of acquisitions on efficiency, we next turn to the dynamic effects of acquisition to identify more precisely when efficiency change occurs and whether there are any differences in pre-trends. For this purpose, we plot the power plant efficiency during the period around acquisition using the following regression specification:

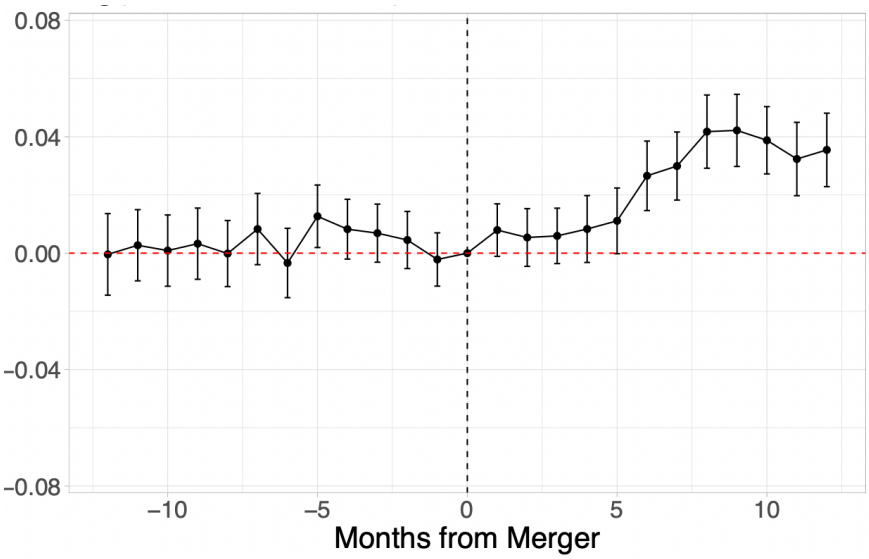
$$log(y_{it}) = \sum_{s\in(-12,12)} \delta^s D^{t-s} + X_{it} + \mu_t + \alpha_i + \eta_{ijt}, \tag{5.2}$$

where D^{t-s} is a dummy variable for generator i being acquired at month t and controls are the same as the regressions estimated above, including generator fixed effects. Because we identify the significant efficiency impact of ownership changes at the owner and parent company level, we study only those acquisitions hereafter.

The results from the dynamic effect regression suggest that there is no significant evidence of pre-treatment trends. For the treatment group, the coefficients on $t \in (-12, 0)$ are small and insignificant, suggesting that acquired plants do not have a different efficiency trend before the acquisition than those not acquired. The difference remains close to zero until five months after the acquisition, and after that, the efficiency of acquired plants and control plants diverges. The cumulative efficiency increase is 4 percent, similar to what we found in the previous empirical specification. The fact that plants experience efficiency gain five months after the acquisition suggests that it takes time for the new owner to make changes in power plant operations necessary for efficiency improvements. This finding is suggestive of how the efficiency gain occurs. Our interviews with power plant managers indicated that five months is not long enough to make costly capital investments and upgrades. This suggests that the 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.

[27] For example, the acquirer firm might observe that the target plant's manager will retire and decide to buy the plant with anticipation that the new manager will improve efficiency. Although we cannot rule out such anticipatory acquisitions, we can do different robustness checks.

Figure 8: Impact of Merger on Productivity



Note: The dynamic effects of acquisitions estimated from Equation 5.2. Standard errors are clustered at the generator level.

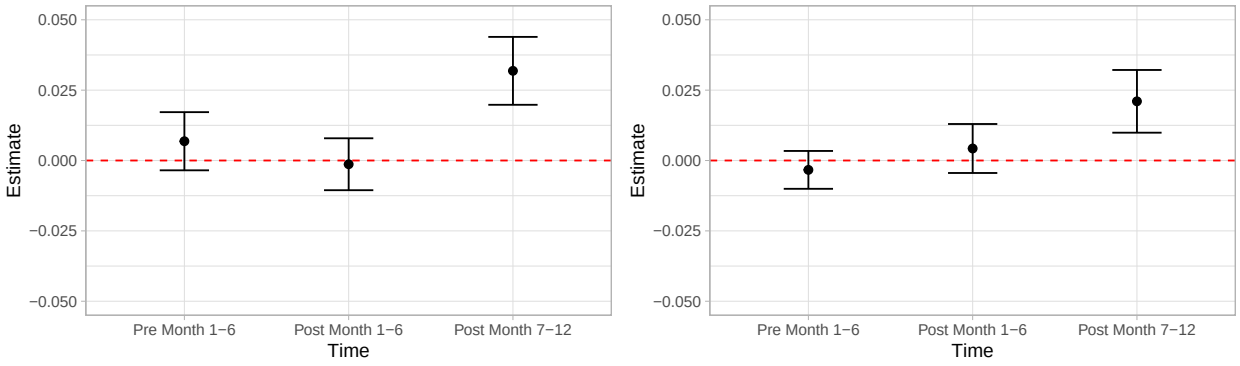
5.2 Discussion

How large is the average 4 percent efficiency gain after the acquisition, and what are the corresponding cost savings? In this section, we interpret our main findings and estimate private and social cost savings due to acquisitions.

To understand how large our finding is, we compare it to average within-plant productivity growth in the industry. In power generation, the contribution of within-plant productivity growth to aggregate productivity is small, as most of the productivity growth comes from plant entry and exit. To show this, Appendix Figure 23 plots the average year-to-year within-plant productivity growth for the plants that were not involved in an acquisition. The within-plant productivity growth fluctuates around 0, with an average 0.3 percent annual increase over the sample period. This minimal average productivity growth makes our result even more striking because it shows that in a single year, acquired plants achieve the level of productivity increase that an average plant achieves in twelve years

Next, we would like to understand how large the cost-saving is due to the efficiency increase after an acquisition? We calculate this number under three simplifying assumptions (i) acquired plants will keep the efficiency level after the acquisition, and (ii) acquired plants will maintain the same production level that we observed pre-acquisition, (iii) there is no redistribution of production across plants. Under these simplifying assumptions, we find that the total cost saving is six billion dollars. Whether these cost savings would be passed to consumers is more complicated.

Figure 9: Heterogeneity in Impact of Merger on Productivity



(a) **Financial Acquirers** (b) **Utility Acquirers**

Note: .

It depends on whether the acquired plants are marginal or infra-marginal and how much market power they have. Although we think this is an important point, it is outside the scope of this paper.

Finally, we also aim to estimate the social gains due to positive externalities resulting from a decline in fuel usage in electricity generation. For this estimation, we assume that (i) CO_2 emission is linearly increasing with heat rate, (ii) CO_2 emission is roughly 0.4 tons per MWh for gas power plants, and 1 ton per MWh for coal power plants. Under these assumptions, the total cumulative decline in CO_2 emission between 2000 - 2020 is roughly 50 million tons. This corresponds to emission reduction from replacing 125 TWh gas power plant with renewables.

5.3 Heterogeneity by Acquirer Type

Our results so far have clearly shown that new owners improve efficiency at newly acquired power plants. This section aims to understand whether this effect is different across acquirer types. As shown in Section 4, we primarily observe two types of acquirers: (i) financial acquirers, which are typically bank funds and private equities, and (ii) utilities. Recently, there has been growing interest on understanding how private equity ownership affects productivity and company performance (Kaplan and Stromberg (2009), Davis et al. (2014)). We aim to provide evidence for this important question by investigating heterogeneity across firm types.

To do this, we estimate Equation 5.1 separately for acquisitions by financial and utility acquirers. In particular, we define the plant as treated if it is acquired by a financial firm or utility separately. Figure 9 reports the coefficients from these regressions. Similar to our main regression, we report coefficients from the late pre-acquisition period, early post-acquisition period, and late post-acquisition period, normalizing the early pre-acquisition period to zero. The results show an

efficiency increase for both types of acquires. The effect is slightly larger when a financial firm acquires the plant, but the difference is not statistically significant. The results suggest that private equity firms that entered this industry in the last 20 years achieve efficiency gains as large as traditional utilities. This evidence is consistent with Davis et al. (2014) who finds an average of 2.1 percent TFP increase over the first two years of private equity buyouts.

6 Do Mergers Allocative Resources Efficiently?

Mergers and acquisitions represent a significant source of reallocation in the economy and account for vast flows of resources between firms. This reallocation can generate allocative efficiency gain in the economy if the assets are allocated from less productive firms to more productive firms or to firms that utilize the acquired assets more productively.[28] Our empirical setting provides an ideal opportunity to study the allocative efficiency effects of mergers because we observe hundreds of asset reallocations between incumbent firms. By utilizing our setting, in this section, we ask (i) are acquirers more productive than target firms, and (ii) do acquirer firms have a comparative advantage in utilizing the acquired assets over the target firm?

There are two main theories on how acquisitions raise aggregate productivity through resource reallocation. The first one, the Q theory of mergers (Jovanovic and Rousseau (2002)), posits that there are inherent productivity differences between firms and acquisitions transfer resources from low to high productivity firms. This implies a "high-buy-low" pattern in the merger market. According to the second theory, proposed by Rhodes-Kropf and Robinson (2008), there are no systemic productivity differences between firms, but assets and firms could be complementary. Therefore, firms could have different levels of ability to operate different assets. This implies a "like-buy-like" pattern as we expect to see mergers between complementary firms. A body of literature has tested these theories of merger gains (Maksimovic and Phillips (2001), Jovanovic and Rousseau (2008)) without a conclusive empirical evidence.

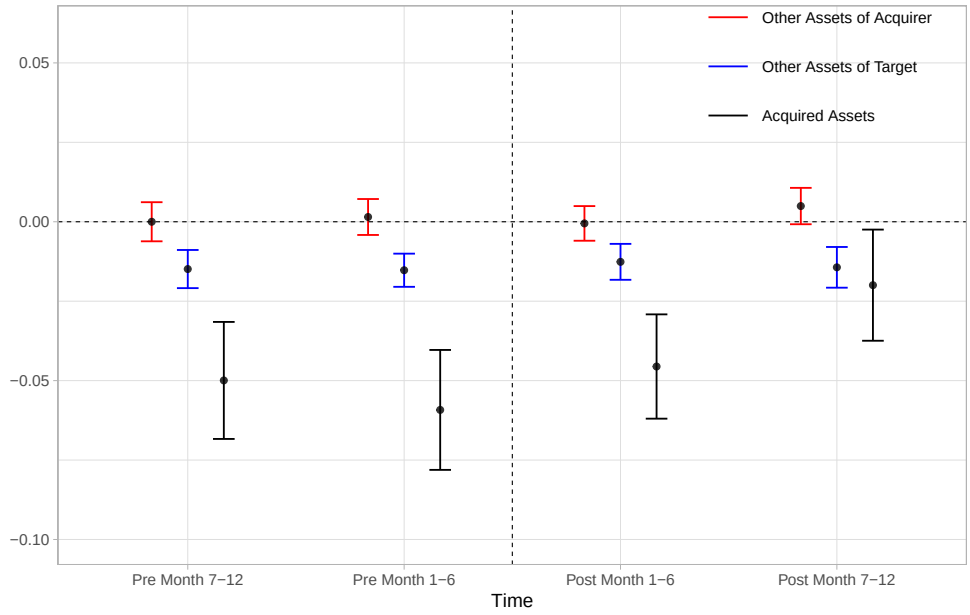
Even if mergers reallocate assets from low to high-productive firms, an important question remains: is efficiency transferable? It is well known that organizational challenges for integrating merged firms and dis-economies of scale at the senior management level could prevent firms from transferring best practices that improve productivity. In our empirical analysis, we also provide evidence for this important question. [29]

To understand how mergers allocate resources in the economy, we estimate a differences-in-differences specification where we study the efficiency level and change of three different types of

[28] Another view of the literature suggests that most acquisitions are undertaken for other motives, such as empire building and managerial hubris.

[29] The answer to this question is an important input to quantify efficiency gains in merger analysis. For example, in merger simulations of two firms with different marginal costs, it is an empirical question of what should be the marginal cost post-merger: is it the marginal cost of the efficient firm or a weighted average of two marginal costs.

Figure 10: Efficiency of Acquirer and Target's Plants



Note: Regression estimates from Equation (6.1). Error bars are 95 percent confidence intervals. Standard errors are clustered at the plant level.

assets: (i) acquired plants, (ii) plants of the acquirer not subject to the transaction, (iii) plants of the target not subject to the transaction. In particular, we estimate the following specification:

$$log(y_{it}) = \sum_j \left(\theta_1^j \text{epre_acq}_{it}^j + \theta_2^j \text{lpre_acq}_{it}^j + \theta_2^j \text{epost_acq}_{it}^j + \theta_3^j \text{lpost_acq}_{it}^j\right) + X_{it} + \mu_t + \eta_{it} \quad (6.1)$$

where $j \in \{\text{acquired, acquirer's other plants, target's other plants}\}$. This regression estimates the productivity level and change of the target's assets, acquirer's assets, and acquired assets separately around the acquisition. Equipped with these coefficients, we will be able to compare the efficiency levels of the target and acquirer firms at the time of acquisition and identify how the acquired plants perform relative to these plants. This regression does not include generator fixed effect because we are interested in estimating the level differences, not only change. We deal with potential endogeneity concerns due to the lack of generator fixed effects by including a very rich set of controls, including age, boiler type, fuel type, and capacity. Since the goal is to compare different plan types, we restrict the sample to the acquisitions where both the acquirer and target firms own other plants before and after the acquisition that are not subject to the transaction. Therefore, the sample size and the number of acquired generators are smaller than our main specification. We also normalize the efficiency level of acquirers' assets to zero in the early pre-acquisition period, so all other coefficients are estimated relative to θ_1^1.

Figure 10 reports the estimates of three sets of coefficients. The red color indicates the change of

efficiency of the existing assets of the acquirer; the blue color indicates the change in the efficiency of the existing assets of the target, and the black color shows how the efficiency of acquired assets changes. First, comparing the efficiency levels of acquirers' and targets' assets reveals several interesting findings. First, we see that the productivity level of both target's and acquirer's existing plants are constant.[30] This result provides evidence against target or acquirer level unobservables that lead to the selection. Second, comparing the efficiency level of the acquirer and target, we see that the acquirer is slightly more efficient than the target firm, about one percent. These estimates suggest that assets are allocated from high productive to low productive firms; however, the productivity differences are small.

We next compare the efficiency level of acquired assets with the other asset types. The first observation is that the assets sold by the target firm are underperforming relative to the other asset in the target's portfolio: the acquired asset's efficiency is four percent lower than the average efficiency of other assets in the target's portfolio. This suggests some heterogeneity in within-firm plant productivity, and furthermore, it shows that target firms keep their more productive plants and sell their least productive plants.

What happens to these underperforming assets after the acquisition? Consistent with the evidence we found in the previous section, the efficiency of these assets improves after the acquisition. The efficiency gain is about three percent, similar to what we found in the previous section, albeit estimated less precisely due to the decline in sample size. Comparing the post-merger efficiency of the acquired assets with the acquirer's portfolio, the acquired assets become almost as efficient as the acquired firm's other assets.

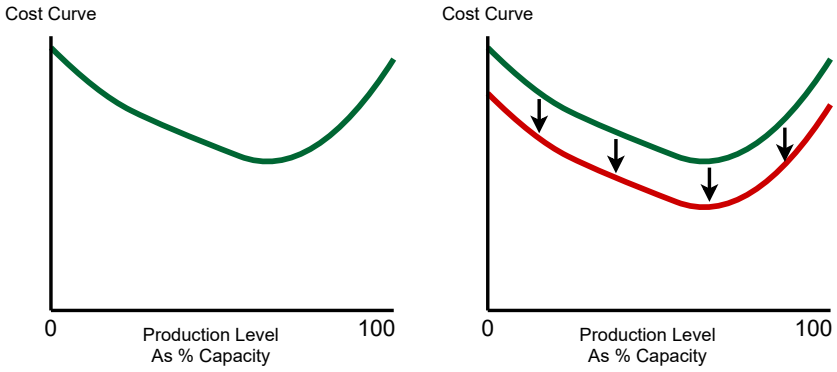
Overall, the empirical findings in the literature suggest that *high* productive firms buy underforming assets of *low* productive firms and make the acquired asset almost as productive as its existing assets after the acquisition. These results provide clear evidence for both merger efficiency gain hypotheses discussed above. In particular, we find evidence for the high-buy-low pattern as the acquirers are, on average, more efficient than the targets. We also find evidence for complementary asset theory in that acquirer firms have a higher ability to utilize acquired assets than the target firms as they make acquired assets more productive. These results overall are strong evidence for the allocative efficiency effects of acquisitions. As the assets are underutilized under target firm ownership and improve performance after the acquisition, we can say that acquisitions potentially contribute to aggregate productivity in the power generation sector.

7 Mechanisms

Our results in the previous section uncovered substantial improvements in the efficiency of acquired plants after the acquisition. An important question is what mechanisms generate this effi-

[30] Except for the slight bump in late post period of acquirer's assets which we will revisit later.

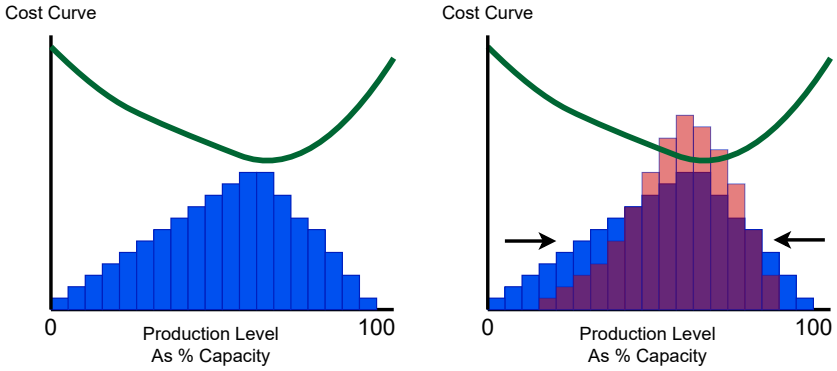
Figure 11: Productive Efficiency



(a) Pre-merger (b) Post-merger

Note :

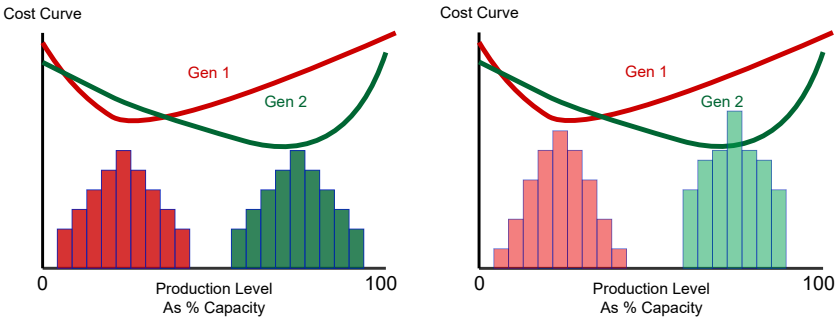
Figure 12: Improved Capacity Utilization



(a) Pre-merger (b) Post-merger

Note :

Figure 13: Portfolio Effects



(a) Pre-merger (b) Post-merger (1 Acquires 2)

Note: Illustrations of different efficiency gain mechanisms.

ciency gain. This is particularly important because we would like to draw broader lessons about the effects of mergers on productivity and extrapolate these findings to other industries. In this section, we aim to answer this question and provide two important findings. First, we find that most efficiency gains come from improvement in productive efficiency rather than portfolio efficiency. Second, firms achieve these efficiency gains with operational improvements rather than costly capital investments.

7.1 Mechanisms of Efficiency Improvements

In this subsection, we propose three mechanisms that could generate the increase in efficiency results we identified in the previous section (i) increase in productive efficiency, (ii) dynamic efficiency, and (iii) allocative efficiency. We first explain these mechanisms and then develop an empirical prediction for each mechanism that can be tested in the data. We find evidence consistent with each of the three mechanisms, but most of the efficiency gain comes from productive efficiency.

Increase in Productive Efficiency The first mechanism that generates efficiency chance is productive efficiency. Productive efficiency arises when the new owner of the plant owner adopts new operational and production processes that lower the production cost. This mechanism does not rely on synergies with other plants in the same market; it arises because the new owner knows how to run the plant more efficiently. An implication of productive efficiency is the decline in the cost curve at every production level, illustrated in Figure 11. Based on this implication, a distinct prediction of this mechanism is

PREDICTION 1: If firms improve efficiency by increasing productive efficiency, the cost curve of production will shift down.

Dynamic Efficiency The second mechanism that improves overall efficiency is dynamic efficiency. An important feature of power generation is that efficiency depends on the level of production as well as change in production level. As discussed in Section 2.3, there is typically an efficient scale above and below which efficiency declines and firms incur ramp-up and ramp-down costs. Since the demand is stochastic and not perfectly predictable, balancing production by taking into account ramp-up and ramp-down costs and the shape of the cost curve is not straightforward. For example, it requires coordination between the trading desk, which chooses a bidding strategy, and plant personnel, who observes marginal cost and decides on production. By optimizing these margins, a firm can produce more with less input by adjusting the production profile even if the cost curve remains identical pre-and post-acquisition. Figure 12 demonstrates this effect where the cost curve is identical pre-and post-acquisition, and production is more concentrated around the efficient scale, implying less ramp-up and ramp-down. This efficiency improvement would be more cost-effective than improving production efficiency as the plant operator can achieve it by

simply changing the production profile. A distinct prediction of this mechanism is

PREDICTION 2: If firms improve dynamic efficiency, the standard deviation of heat rate goes down.

Portfolio (Allocative) Efficiency The third mechanism to improve efficiency is portfolio effects. This mechanism arises when firms with multiple power plants in the same market can improve overall efficiency by allocating production optimally across power plants. According to this mechanism, having more power plants in the same market gives firms more flexibility to allocate production across power plants with different production costs. This effect is illustrated in Figure 13. Since this mechanism is present only if firms have other plants in the same market, a prediction for portfolio efficiency is

PREDICTION 3: Efficiency of the existing plants of the acquirer firm in the same market will improve.

After developing these testable predictions from three different mechanisms of efficiency gains, in the next section, we test these predictions.

7.2 Quantifying Sources of Efficiency Gains

We start by testing for the presence of productive efficiency using an empirical strategy guided by Prediction 1. In particular, we estimate the cost curve of production non-parametrically by flexibly controlling for ramp and production level:

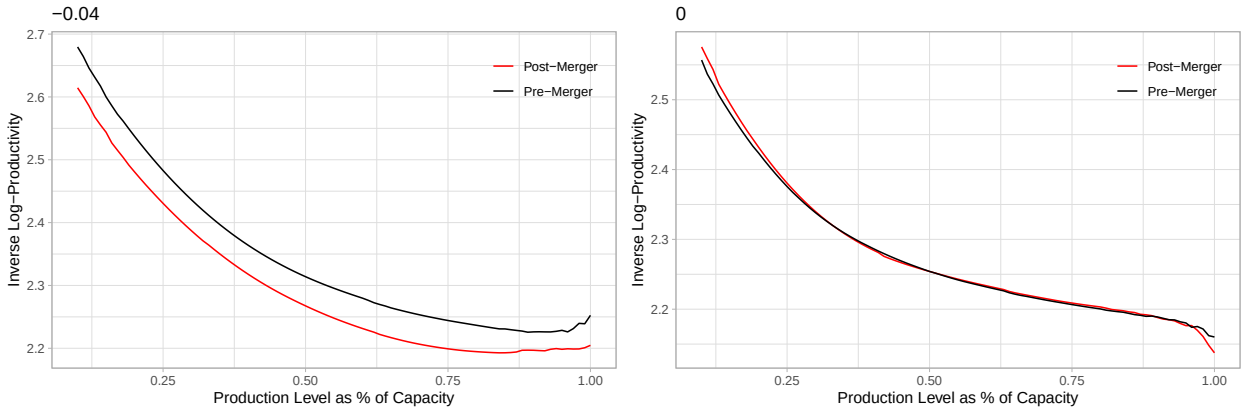
$$y_{it} = f_{i\tau}(pr_{it}, r_{it})$$

where y_{it} is heat rate, pr_{it} is production level as percentage of total capacity of generator i at time t, and r_{it} is the ramp defined as the percentage change in production relative to $t-1$. To control for heterogeneity across firms, we estimate this function for each acquired firm separately using data one year prior and one year after the acquisition. As a result, f_{i0} corresponds to the cost curve before the acquisition, and f_{i1} corresponds cost curve after the acquisition.[31]

It is worth highlighting two critical features of this regression. First, the estimated cost function is generator-specific, as indicated by the index i. Estimating the cost curve at the generator level is important to capture unobserved time-invariant differences across generators. Second, differently from our main specification, we estimate this regression using hourly data to be able to control for ramp accurately. Moreover, hourly level data allows us to estimate a cost function at the firm level since we have many observations from each firm. This estimation highlights the advantage of the

[31] We estimate these functions for generators that are operating more than 20 percent of the time in the window one-year pre-and post-acquisition. This excludes some peak generators that produce only during peak demand and some others that are not active before the acquisition.

Figure 14: Estimated Cost Curves



(a) Treated Group

(b) Control Group

Note: These figures shows estimates of average costs curves one year before the acquisition and one year after the acquisition. Panel (a) shows this for the treated group and panel B is for the control group.

rich data environment as traditional production function estimation requires aggregation at the industry level.

We estimate f_{i0} and f_{i1} for every i acquired during our sample period and ask how the cost curve changes after the acquisition. In particular, we quantify the productive efficiency gain in the following way:

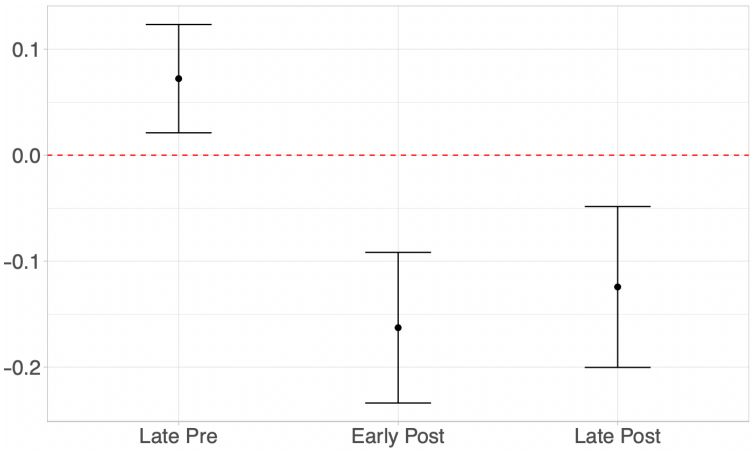
$$\Delta(pr) = c_{post}(pr) - c_{pre}(pr) = \sum_i f_{i1}(pr, 0) - \sum_i f_{i0}(pr, 0)$$

where $pr \in (0, 100)$, $c_{post}(pr_{it})$ is the average cost at production level pr after the acquisition, and $c_{pre}(pr)$ is the average cost at production level pr before the acquisition. The difference between these two functions give us changes in productive efficiency at production level pr.

Figure 14 displays $c_{pre}(pr)$ and $c_{post}(pr)$ for the treated plants and 14b displays the same curves for the control plants. Comparing the pre-and post-acquisition cost curve demonstrates that the cost curve shifts downs at every production level for the treated plants, and the cost curves are almost identical for the control plants. The difference between the cost curves for the treated group is slightly larger at production levels close to the efficient scale, but the difference is not statistically significant. These results provide direct and strong evidence that the acquirers improve the productive efficiency of the acquired plants.

This analysis also allows us to quantify the role of productive efficiency. To see this, we integrate the difference between the cost curves to quantify the total productivity gain from productivity

Figure 15: Change in Variation of Heat Rate



Note: Coefficient estimates from a regression of standard deviation of heat rate on treatment dummies. Error bars are 95percent confidence intervals.

efficiency:

$$\Delta = \int (c_{post}(pr_{it}) - c_{pre}(pr_{it}))dF(pr_{it}).$$

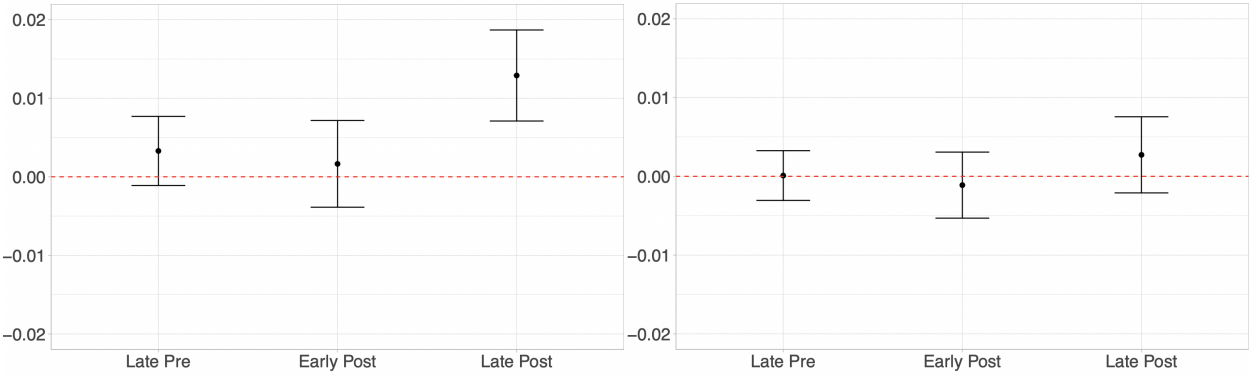
This calculation suggests the overall efficiency gain explained by productive efficiency is three percent, corresponding to 75 percent of the total efficiency gain identified in the previous section.

Next, we move to dynamic efficiency. According to our Prediction 2, an increase in dynamic efficiency should reduce the standard deviation of the heat rate after the acquisition. To test this hypothesis, we estimate the exact specification as in Equation 5.1, but use the standard deviation of heat rate as the outcome variable. Figure 15 shows the results from this specification. We find that the average standard deviation of heat rate goes down after the acquisition. Unlike the average heat rate, the decline in the volatility of heat rate is realized more rapidly where the firms make production more stable in the early post period, which remains the same in the late post period. From this regression, we conclude that the firms not only improve the production efficiency but allocate production more efficiently over time to reduce ramp-up and ramp-down costs.

Finally, we test the allocative efficiency effects of mergers. According to Prediction 3, allocative efficiency occurs only if the firm owns other power plants in the same market, and power plants in other markets do not affect allocative efficiency. To test this prediction, we estimate our main specification in Equation 5.1 on power plants that the acquirer firm owns, operate in the same market as the acquired asset, but are not involved in the acquisition. We assume power plants are in the same market if they are located in the same balancing authority.

Figure 16 presents results for these regressions. Panel 16a shows the change in heat rate of the

Figure 16: 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 treatment dummies. Error bars are 95% confidence intervals.

plants that are owned by the acquirer and located in the same market as the acquired plant, and Panel 16b shows the change in heat rate of the plants that are owned by the acquirer but located in different markets. We find that acquirers' power plants in the same market exhibit efficiency improvements by 1.3 percent, whereas acquirers' power plants in different markets show no change in average heat rate. On balance, these results suggest cost savings for the acquirers' power plants, but only if they are in the same market, consistent with allocative efficiency. Moreover, observe that the efficiency improvement of the acquirer's plants is much lower than the efficiency improvements of the acquired plants, 1.3 vs. 4 percent, suggesting that the scope for improvement through productive efficiency is larger than the scope of improvements through allocative efficiency.

To summarize this section, we find evidence for all three mechanisms we identified (i) productive efficiency, (ii) dynamic efficiency, and (iii) allocative efficiency. The largest mechanism of efficiency gain is productive efficiency explaining 80 percent of total efficiency gain, and the rest is explained by dynamic and allocative efficiency.

7.3 How do Firms Improve Productive Efficiency

So far, we have shown clear evidence of efficiency increase after the acquisitions, and this efficiency increase mostly comes from an increase in productive efficiency. The next natural question is what firms do to achieve this efficiency gain. In this section, we investigate this question.

In Section 2.3, we identified two primary sources of efficiency gains in the power generation industry. First are low-cost ways to achieve efficiency gains by making operational improvements or hiring more skilled personnel to control and monitor production more efficiently. Second, the

acquirer firm can make costly capital investments and capital upgrades. The mechanism of efficiency gain is important because if it is mainly through best practices, that would suggest knowledge transfer. However, if it is primarily through capital investment, that would point out financing constraints or heterogeneous returns to investment.

We will disentangle the sources of productive efficiency improvements in two ways, directly and indirectly. Our first test will use data from manager changes and capital expenditures. In particular, we will ask whether power plants experience personnel changes after the acquisition and whether there is any significant change in capital expenditures. Personnel changes would provide evidence for significant operational changes after the acquisition, and change in capital expenditures would provide direct evidence for the role of cost investment.[32] Our second test will be indirect and use the fact that capital expenditures often require significant downtime in the power plant. Therefore, we can look at downtime after the acquisition. The lack of downtime would suggest evidence for the absence of capital expenditures.[33]

To study whether power plant managers change after an acquisition, we estimate the dynamic differences-in-differences specification given in Equation 5.1. The outcome variable equals one if the power plant manager is replaced with a new one after the acquisition and zero otherwise. We include the same controls but estimate the regression at the monthly level. 17 reports the coefficient estimates. We see that the probability of management change jumps around the time of the acquisition, with 15 percent of acquired power plants changing their managers within one month and 30 percent changing their managers within two months. The cumulative change is 55 percent within 12 months after the acquisition.[34] These results suggest that the acquired firms make operational changes through new management, which could improve efficiency. The potential role of management changes in explaining productivity differences is plausible, given the recent findings of Bloom and Van Reenen (2010). They present empirical evidence that productivity measures correlate with various management practices, reflecting human resource (HR) practices and organizational design.

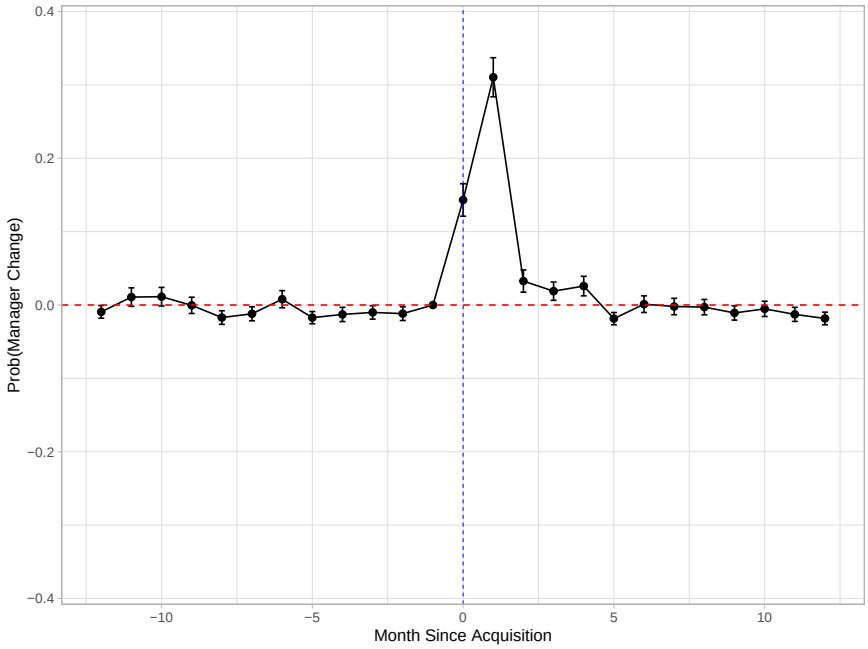
Next, we turn to results from capital expenditures and non-fuel variable costs, which are reported in Figure 18. Since we have these variables at the annual level, we estimate the differences-in-differences specification at the annual level. The results suggest no change in non-fuel variable costs and capital expenditures after the acquisition. However, these estimates are imprecise due to missing observables and annual frequency. These results suggest that firms do not just substitute

[32] As we explain in the Online Appendix, these personnel changes are self-reported. These personnel changes reflect changes in the organization where the representative changes even though the old representation is still in the company. This might not correspond to a personnel change but still points out important organizational changes that would be relevant for efficiency.

[33] One concern for this test is that firms schedule shutdowns for regular maintenance. If maintenance is more likely after the acquisition, we might see an increase in downtime even without capital investment. However, the downtime duration would be longer for capital investment than regular maintenance.

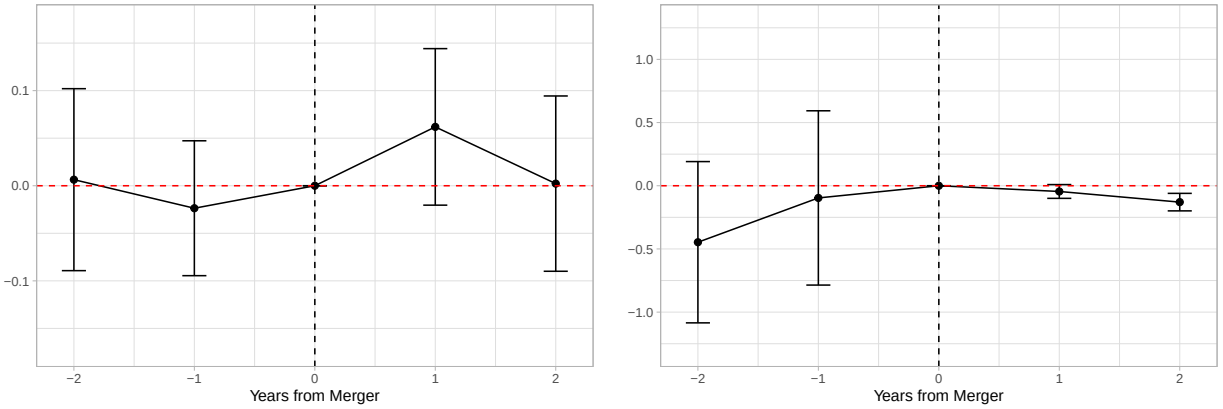
[34] Note that the unconditional probability of management change in a given year is only 10 percent.

Figure 17: Probability of Management Change



Note: Coefficient estimates from a regression of management change dummy on pre- and post-treatment variables. Error bars are 95% confidence intervals.

Figure 18: Change in Cost and Capital Expenditure



(a) Non Fuel Variable Cost

(b) Capital Expenditures

Note: Coefficient estimates from a regression of non-fuel variable cost and capital expenditures. Error bars are 95% confidence intervals.

one cost with another and do not achieve efficiency gains through costly capital investments.

8 Robustness Checks

In this section, we investigate the robustness of our results to alternative specifications.

8.1 First Acquisitions

In our estimations, we only use the first acquisitions of the plants that are acquired multiple times (about 25 percent of all plants). We did this because it was unclear how to properly construct the acquisition timing variables for plants acquired more than once. In this robustness check, we repeat our estimation procedure by including all acquisitions of plants acquired more than once in our sample period and estimate our main specifications. The results, reported in Appendix C, are broadly similar to our main results, with some decrease in precision due to the decline in the treated population.

8.2 Estimation with Daily and Hourly Data

Our main specification estimates the effects of mergers with data at the weekly level. Averaging at the weekly level provides computational benefits and also reduces noise. To understand how robust our results are to this choice, Appendix C shows the estimation results from daily and hourly data. We see that the results are robust to data frequency, with some increase in standard errors.

8.3 Differences in Differences Literature

Recent literature in econometrics has shown that the difference-in-differences method could yield a weighted average of all possible permutations of pairwise difference-in-differences estimators, where a pair is either the never-treated control group compared with the cohort treated at time t or a cohort treated at time t compared with a cohort treated later. (Goodman-Bacon (2021), Callaway and SantAnna (2021) and De Chaisemartin and dHaultfoeuille (2020)). To address this point, we estimate cohort-specific treatment effects using the never-treated group as a control group and then take weighted averages.

8.4 Matching Estimators

Our main specification uses standard differences-in-differences estimation estimated with two-way fixed effects. In Appendix C, we also consider a matching estimator. We match acquired power plants to power plants that were never (the "control" group) acquired during our sample period

based on generation MWh, and fuel type, location. We then apply a difference-in-differences adjustment to the bias-corrected matching estimator developed by Abadie and Imbens (2006). For each of our 2000 acquired plants, we identify the three nearest neighbors from our sample pool of 2500 control power plants. We match on log generation MWh, location, and fuel type using a least-squares metric to calculate the distances between power plants, with equal weights across the three variables. We scale up the fuel type distance so that roughly equal weight is put on fuel types across all potential matched pairs as the combination of the other three variables. We use our distance measure to select the three nearest neighbors for each acquired plant, allowing control plants to be matched to multiple acquired plants. Plants of the acquirer and target firms are excluded from the pool of potential control plants.

8.5 Weighted Estimations

In our main specification, we estimate average treatment effects without considering the different capacity sizes of acquired plants. An alternative estimation would be weighting observations by their production level or capacity, which would be a more accurate measure of total cost saving. We report estimates from this specification in Appendix C, and the results are broadly similar.

9 Concluding remarks

By allocating resources between firms, mergers and acquisitions affect a significant portion of the economy. Despite this importance, there is limited systematic evidence of their effect on productivity and market power. 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 2020. Our empirical results can be summarized into three principal findings. First, we find that acquired plants experience an average of four percent efficiency increase five to eight months after the acquisition, and most of this productivity increase is explained by improvement in productive efficiency. Second, our findings suggest that acquisitions reallocate assets to more productive uses: we find that high productive firms buy underperforming assets from low productive firms and make the acquired asset almost as productive as their existing assets after the acquisition. Finally, we find that the new owners improve productivity by changing operational processes rather than making costly capital investments.

The underlying source of our findings is using a large number of acquisitions in the power generation industry and taking advantage of high-frequency physical productivity measures obtained from physical input and output quantities. With physical measure and studying a homogeneous product, we can disentangle the productivity effects from other potential merger effects, such as market power, buyer power, and changes in quality. With high-frequency data, we can treat mergers as discrete events and compare firm productivity immediately before and after the acquisition.

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. Beyond antitrust, our results have important implications for the role of mergers on aggregate productivity growth. Our finding that mergers reallocate assets to more productive suggests that mergers contribute to aggregate productivity growth.

We believe that the availability of this high-frequency and high-quality data on power plant production can be useful for understanding other important issues for antitrust and productivity, such as quantifying total welfare effects by estimating price effects of mergers together with efficiency and studying how strategic firm behavior changes after a merger. These issues various could be a fruitful area for future research.

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A Data Appendix

A.1 Unit Level Data

We use EIA Form 860 and 923 for unit-level characteristics. These annual forms cover the universe of power plants in the US. We assembled information on age, fuel type, boiler type, capacity, location, ISO, cost, regulation status, and plant-level investment. We identify deregulation cases as changes in the regulation status at the plant level in Form 860. To find the exact month of the regulation change, we use Cicala (2022) for the cases until 2012, and for 2012 onwards, we rely on individual plant-level news regarding the status change.

Roughly 95 percent of fossil-powered generation in the United States from 2000-2020 is reported at the boiler-hour level in the EPA CEMS data. While the data availability started in 1995, the coverage was still low until 1999. We take out Alaska and Hawaii and drop outliers of heat rate if they are larger than 16 and lower than 5. Less than one percent of the observations fall outside of this range. We also eliminate inactive generators more than 90 percent of the time during their lifetime. We restrict our sample to all the US fossil-fuel generators that comply with the CEMS program, except Alaska and Hawaii.

In some cases, generator names in the EIA dataset and CEMS do not match as EPA uses boiler names as a unit, whereas EIA uses generator names. We use the EPA's Power Sector Data Crosswalk in those cases. We manually matched the retired and unmatched power plants using the same principles as the initial crosswalk.

EPA data do not provide capacity data. Therefore in the cases of mismatch between EIA Form 860 and CEMS, we need to determine the capacity. We first keep units that work more than two weeks' worth of hours in the whole year each year. Then we define the 99th percentile of the production level as the capacity for the unit every year. Suppose there is a significant variance between yearly capacity at units, with no apparent capacity change at EIA plant-level data. In that case, we take the max capacity of the unit for consecutive years. After cross-checking this capacity definition for the perfectly EPA-EIA matched unit's capacity from EIA, we find this criterion to match very well.

A.2 Load Data

Hourly data on electricity usage is obtained from FERC and S&P Global depending on the data available on Balancing Authority Areas (BAA) or ISO Zones. Until 2006, data was not in great shape, so we used data after 2006. We rely on EIA data's market definitions to match load data with plants. We have data on load for roughly 70 percent of the units.

A.3 Personnel Data

Each power plant that complies with at least one of the EPA programs needs to submit personnel information at the plant level quarterly. The personnel information is essential for EPA, as a potential problem like leakage needs to be addressed quickly, and responsible parties should be accountable. This data is self-reported and include a change date if there is any update for the plant representative.

We scraped EPA modules to identify unit level representative names [35]. Furthermore, to obtain more information on the personnel data, we individually matched roughly 70 percent of plant personnel names to Linkedin profiles, obtaining education and employment history. The reported personnel could, in principle, be a power plant manager, engineer, or regulatory compliance manager. We confirmed that 80 percent of the reported personnel are plant/general managers. Therefore, we treat this personnel information as plant managers in this study.

A.4 Capital Expenditures and Non-fuel Cost

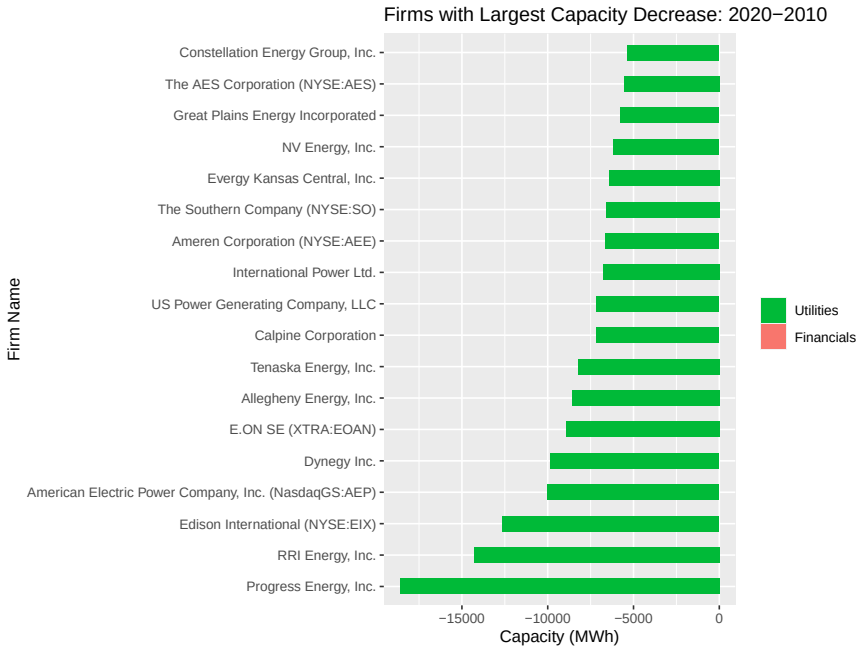
Then, we merge this data to plant-level capital expenditure data from S&P Global, which is sourced from FERC Form 1.[36]

[35] With only a few exceptions, unit and plant level representatives were the same.

[36] Only power plants, whose parent company has an asset with regulated returns, must comply with FERC Form 1's requirements. Therefore roughly half of the capital expenditure data is missing.

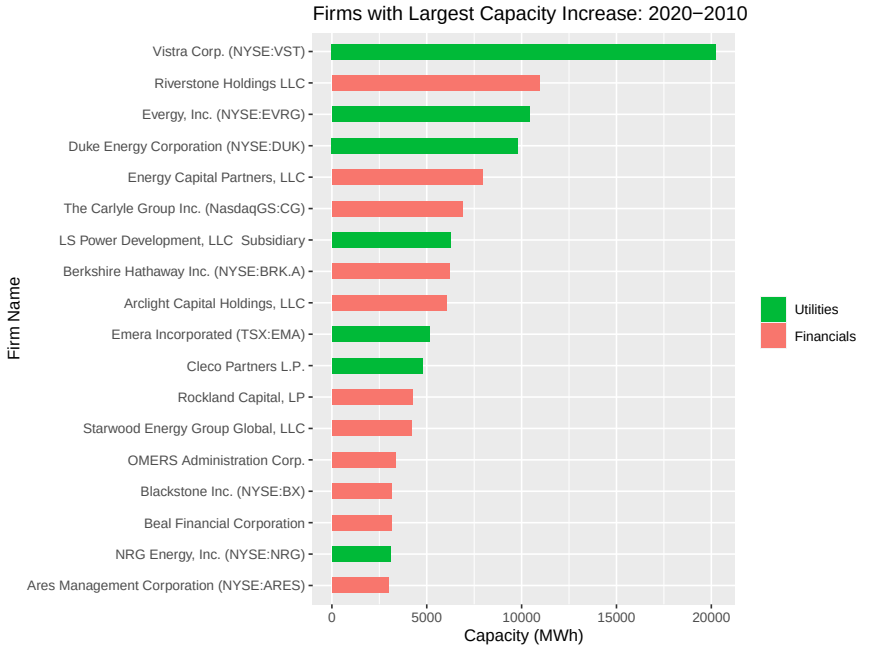
B Additional Figures and Tables

Figure 19: Firms with Largest Capacity Decrease: 2010-2020



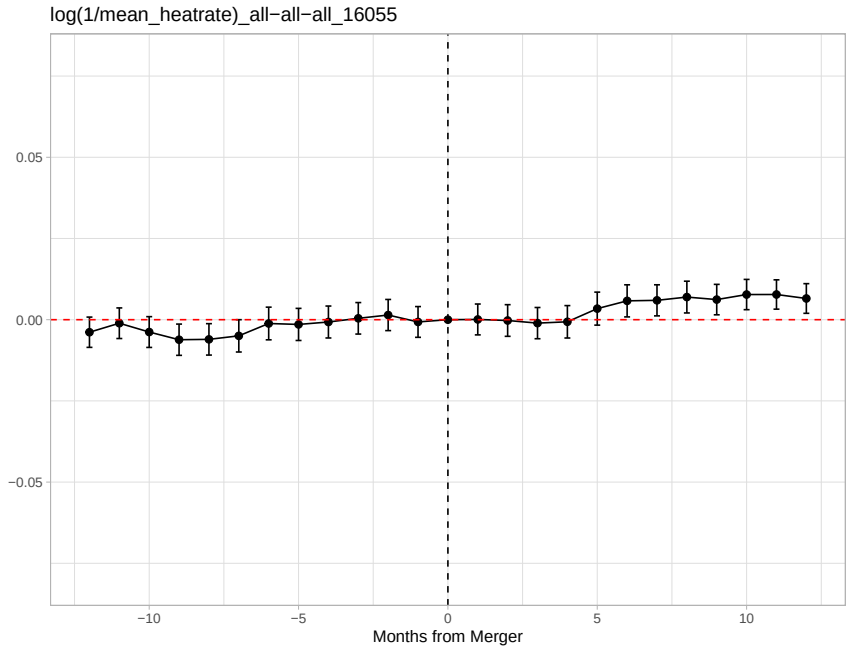
Note : This figure shows firms with the largest capacity decrease in fossil fuel plants in the US between 2000 - 2020

Figure 20: Firms with Largest Capacity Increase: 2010-2020



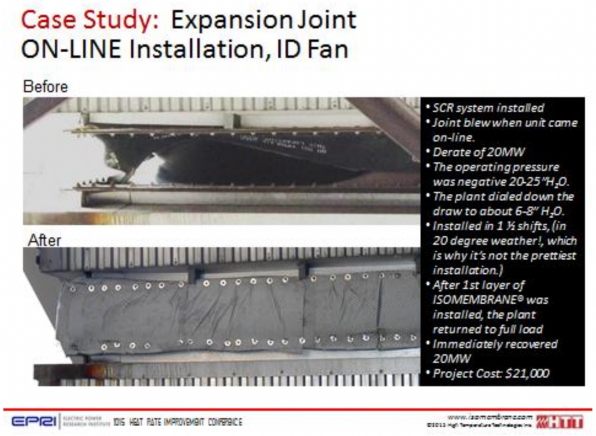
Note : This figure shows firms with the largest capacity increase in fossil fuel plants in the US between 2000 - 2020

Figure 21: Effects Of Manager Change without Mergers on Efficiency

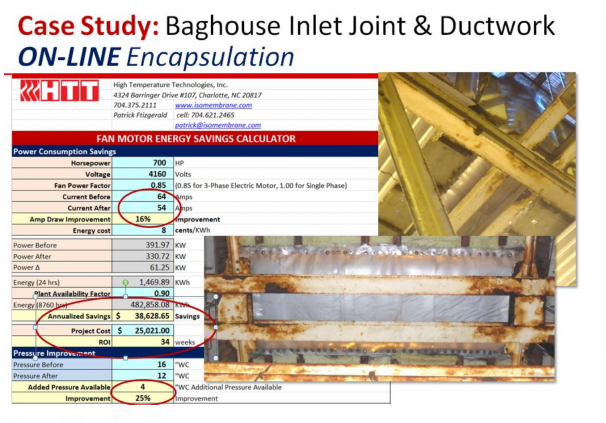


Note :

Figure 22: Case Studies of Heat Rate Improvement



(a) a



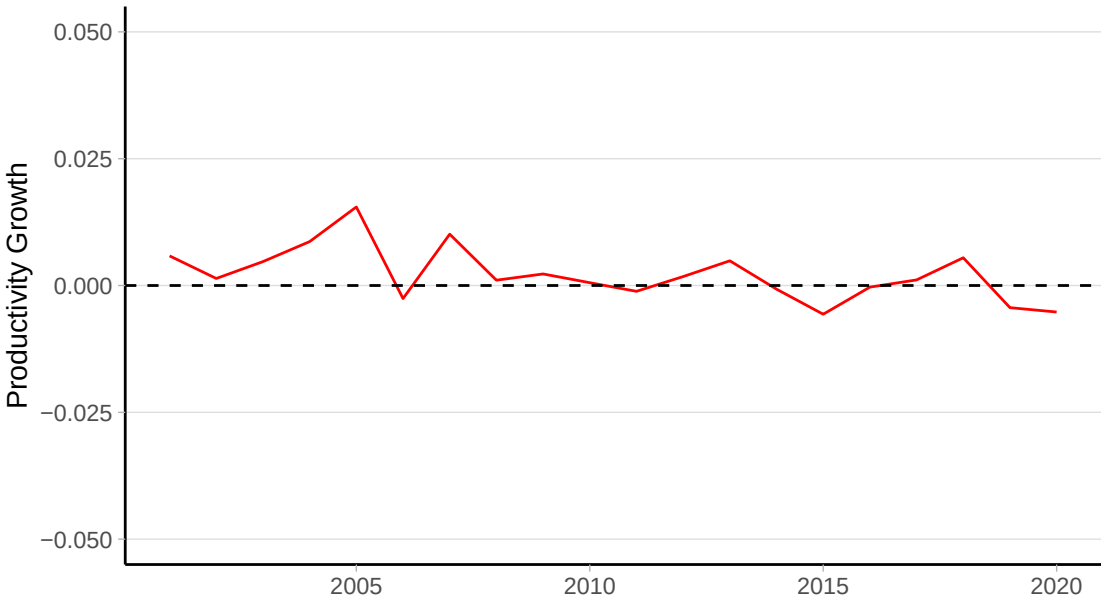
(b) a



(c) a

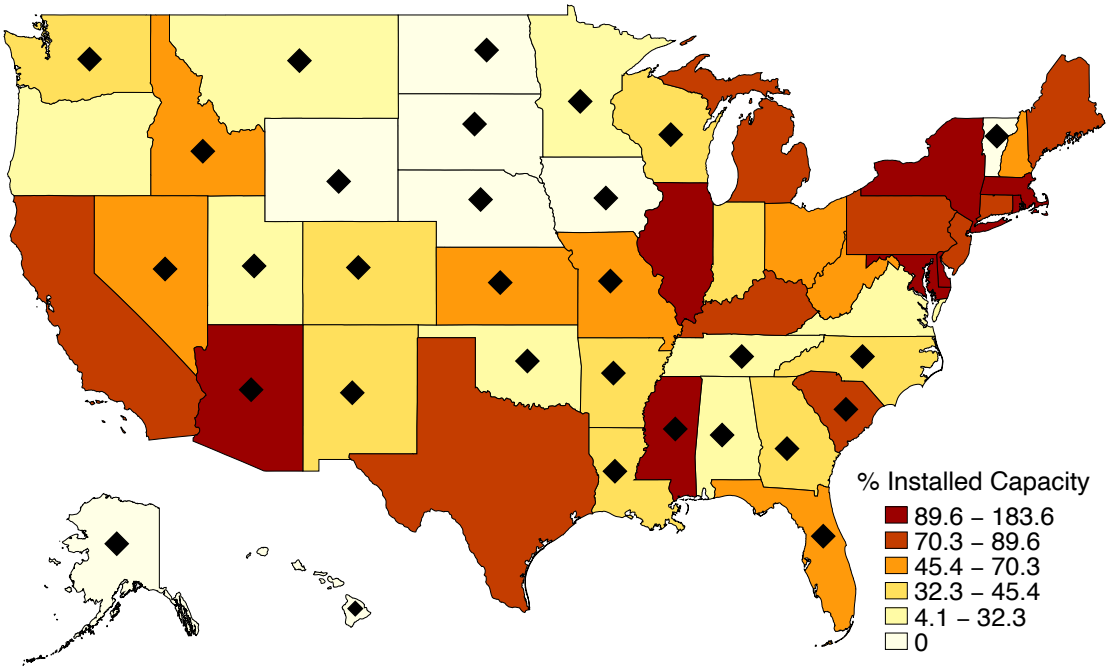
Note: These pictures demonstrate some methods that were implemented in power plants to improve heat rate.

Figure 23: Average Within-Plant Annual Productivity Change



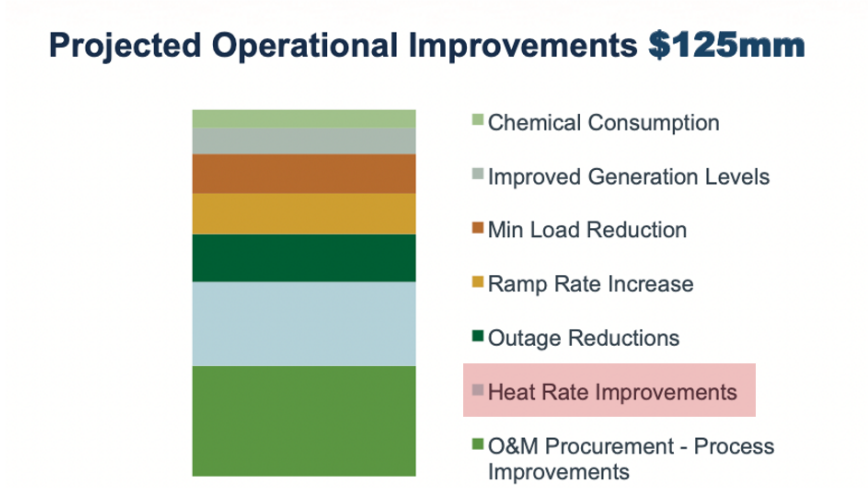
Note: This figure shows average year-to-year within-plant productivity growth for the plants that were not involved in an acquisition.

Figure 24: Change of Percentage of Fossil Fuel Generation Capacity



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

Figure 25: Acquiring Firms often make claims about Heat Rate improvement



Note : This figure is from the conference call of acquisition of Dynergy by Vista Energy (2018, $1.74 billion deal)

Table 4: Largest Acqusitions

Acquirer	Target	Year	Capacity	# of unit
NRG Energy, Inc.	GenOn Energy, Inc.	2012	26174	139
Investor group	Calpine Corporation	2018	22991	127
RRI Energy, Inc.	Mirant Corporation	2000	22748	140
Duke Energy Corporation	Progress Energy, Inc.	2012	19048	134
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 Incorporated	2018	12237	66
Investor group	TXU Corp.	2007	11116	45
Exelon Corporation	Constellation Energy Group, Inc.	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
Investor group	Engie SA	2017	8604	39
Reliant Resources, Inc.	Orion Power Holdings, Inc.	2002	8247	85
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 Company	NV Energy, Inc.	2013	7149	52
Astoria Generating Co.	EBG Holdings LLC	2007	7143	66

Note: Largest 10 acquisitions in the fossil fuel power generation industry between 2000–2020. The columns indicate the year the transaction occurs, total production capacity that changed ownership and the total number of units that changed ownership.

C Robustness Checks (TO BE ADDED)