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 4% efficiency increase five to eight months after acquisition. Three-quarters of this efficiency gain is explained by increased productive efficiency; the rest comes from dynamic efficiency 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-productivity* firms buy *underperforming* assets from *low-productivity* firms and make the acquired assets almost *as productive as* their existing assets after 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

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

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

In this paper, we provide a detailed and large-scale analysis on the efficiency effects of mergers while tackling these issues. In particular, we ask: (i) Do mergers and acquisitions improve efficiency? (ii) What are the mechanisms? (iii) How do mergers reallocate assets between firms?

We focus on the mergers in the US electricity generation industry between 2000 and 2020. Four distinct features of this industry and available rich data allow us to overcome the challenges of estimating the efficiency effects of mergers. First, we observe, at the hourly frequency, the physical quantity of output and the physical quantity of the largest single input, the consumption of fuel (80% of variable cost). With this high-frequency production data, we construct an efficiency measure and analyze how it changes around the time of acquisition. Second, electricity is a homogeneous product, ruling out potential quality changes that could confound our analysis. Third, the efficiency measure relies mainly on accurate input and output sensor measurements rather than survey responses,

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

as in many other industries. Finally, and most importantly, the power generation industry experienced a significant number of mergers and acquisitions during the sample period. We identified 689 transactions with 4,834 ownership changes between 2000 and 2020, corresponding to an average of 5% of industry capacity annually. These ownership changes exhibit significant heterogeneity by transaction, firm, and plant characteristics, which we use to study the mechanisms of efficiency gains.

Our analysis starts by employing a difference-in-differences estimator to compare the efficiency of acquired plants to those not involved in an acquisition. Our first finding is that the efficiency of the acquired plants increases by 4% on average after acquisition. The efficiency increase starts five months after acquisition, and it 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 a total cost saving of 6 billion dollars, and a total decline of roughly 50 million tons of CO_2 emissions between 2000 and 2020.

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

We start by analyzing the characteristics of acquired plant, acquirer, and transaction that are correlated with efficiency gains. For plant characteristics, we consider fuel type (gas or coal), plant age, generation capacity, regulation status, and whether the plant is infra-marginal. We find that the efficiency gain is higher if the plant is older, unregulated, larger, and infra-marginal. In these plants with higher efficiency gains, the acquirer has more incentive to make efficiency gains, so the results are consistent with ex-ante predictions based on firm incentives.[2] Regarding firm characteristics, we find that large acquirers and serial acquirers lead to more efficiency gains, suggesting that experience, both in plant operations and acquisitions, plays an important role in generating efficiency gains. Finally, looking at transaction characteristics, efficiency gains are higher if the acquired capacity is high and the acquirer's capacity in the acquisition market is high.[3]

We next ask how mergers allocate assets between firms. There are two main theories on

[2]There is more room for efficiency improvements in older plants due to degradation in performance over time. In unregulated plants, any cost savings will be retained as profit. In infra-marginal and larger plants, production is higher, so marginal cost improvements would lead to a higher return.

[3]The heterogeneity results from the acquirer's capacity in the market suggest the potential role of synergies in efficiency gains, which we investigate later in detail.

the 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-buys-like" pattern (Rhodes-Kropf and Robinson, 2008), in which firms have no systemic productivity differences, but there are complementaries between assets and firms. According to this theory, assets are allocated to firms with a higher ability to utilize those assets. Quantifying the role of these theories helps us understand whether mergers put assets to more productive uses and contribute to productivity growth.

Our findings suggest that acquisitions reallocate assets to more productive uses; we find that *high-productivity* firms buy *underperforming* assets from *low-productivity* firms and make the acquired asset almost *as productive as* their existing assets after acquisition. Acquirers are, on average, 1% more productive than the target firms, and the target firms are selling the underperforming assets relative to their other assets. This finding suggests that assets are allocated to firms with both relative and absolute advantages in utilizing those assets. Thus, we find evidence for both "high-buys-low" and "like-buys-like" hypotheses.

We then move to study the mechanisms that generate efficiency gains. A firm can improve the overall efficiency of a power plant via three distinct mechanisms: (i) increasing its productive efficiency, (ii) better allocating production dynamically within a plant (dynamic efficiency), and (iii) better allocating production across plants (portfolio efficiency). We develop predictions for each of these mechanisms and test them empirically. The test for productive efficiency involves comparing generator-specific cost curves separately for pre- and post-acquisition periods. In dynamic efficiency, the production profile of acquired plants would be less volatile, whereas portfolio efficiency would suggest that the acquirer's existing plants in the same markets see efficiency improvements. Testing these predictions in the data, we find that productive efficiency explains 75–80% of the total efficiency gain. There is also evidence for dynamic and portfolio efficiency, but they play a minor role in explaining the total efficiency gain.

After establishing the role of productive efficiency, the next question is what firms do to improve productive efficiency. There are two alternatives: (i) low-cost process improvements, which involve adopting best practices and hiring more skilled personnel, and (ii) high-cost capital investments, which involve equipment upgrades. Process improvements indicate information transfers after acquisition (Atalay et al., 2014); capital upgrades indicate credit constraints of the former owner. To distinguish between these two hypotheses, we augment the efficiency data with two different datasets: (i) data on plant managers and (ii) annual non-fuel costs, capital expenditures, and number of employees for a sub-

set of plants. Starting with the manager data, we find that 55% of acquired power plants change managers within three months of acquisition. These managers are 5 percentage points more likely to have a master's degree and 4 percentage points more likely to have a bachelor's degree than non-merger manager changes. In contrast, we find no evidence of an increase in capital expenditures after acquisition. These findings suggest that the new owner of the power plant improves efficiency through operational improvements rather than high-cost capital investment.

As in all retrospective merger analyses, an important concern in our paper is the endogeneity of mergers. We include three additional analyses to address this concern. 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 empirical specification, acquisition definition, and data frequency. 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 and find that management change leads only to a 0.8% efficiency gain, in contrast to 4% 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 might be different from production in other industries in terms of the roles of labor and energy input. While we focus on a single industry to take advantage of the available data and numerous acquisitions, we provide detailed evidence for mechanisms to draw broader lessons from this study. Second, our efficiency measure is fuel efficiency rather than total factor productivity (TFP), which is most commonly used in productivity literature. While it is possible to estimate TFP for power plants at the annual frequency, analyzing fuel efficiency provides a richer analysis due to its availability at high frequency. Nevertheless, to understand the potential role of other inputs, we look at how non-fuel costs and the number of employees change after acquisition and find no significant change. Therefore, the increase in fuel efficiency does not arise at the expense of other inputs.

We 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. Moreover, the efficiency effects identified in this paper may not be generalizable to other industries for merger analysis, especially those with significantly different production techniques from electricity generation. Our view is that more research is needed to understand the net effects of mergers from different

industries, and we provide a detailed analysis of the efficiency effects from a large and important industry.

1.1 Literature

This article contributes to several bodies of literature. The first is the literature studying the effects of mergers and acquisitions on productivity. Since many merger retrospectives focus on price effects, there are a limited number of papers that study the productivity effects of mergers (Braguinsky et al., 2015; Blonigen and Pierce, 2016; Kulick, 2017). Blonigen and Pierce (2016) use the methods of De Loecker and Warzynski (2012) to separately identify markup power and productivity for manufacturing plants in the US and study how mergers affect them. Their findings suggest significant effects of mergers on market power, but no evidence for a productivity effect. Kulick (2017) studies mergers in the ready-mix concrete industry. He finds evidence for price increase due to a rise in market power post-merger despite a 6% productivity increase in acquired plants. This 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 higher capacity utilization. After acquisition, the acquirer improves capacity utilization in the acquired plant, raising the productivity level by almost 13%.[4]

This article also contributes to the literature studying efficiency in the power generation industry. This literature has primarily focused on how restructuring that started in the 1990s affected efficiency (Knittel, 2002; Bushnell and Wolfram, 2005; Fabrizio et al., 2007; Davis and Wolfram, 2012). These papers compare the performance of plants in states that pursued restructuring against plants in states that did not. Overall, the results point to a positive influence of restructuring on the operations of plants.[5]

We contribute to the literature studying the allocative efficiency effects of mergers (McGuckin and Nguyen, 1995; Jovanovic and Rousseau, 2002; Schoar, 2002; Jovanovic

[4]Evidence of cost savings from other industries includes meat products (Nguyen and Ollinger, 2006), railroads (Bitzan and Wilson, 2007), electricity distribution (Clark and Samano, 2020; Chen, 2021), radio (Jeziorski, 2014), banking (Focarelli and Panetta, 2003), and healthcare (Dranove and Lindrooth, 2003; Harrison, 2011; Schmitt, 2017). Another literature provides evidence on efficiency effects by analyzing a single merger. Some examples are the Molson and Coors merger (Grieco et al., 2018), Miller and Coors merger (Ashenfelter et al., 2015), and Boeing-McDonnell Douglas merger (An and Zhao, 2019)

[5]A particularly related paper is by Bushnell and Wolfram (2005), who study whether ownership change during deregulation provides additional efficiency gains and find no evidence. Differently from Bushnell and Wolfram (2005), we study mergers without deregulation in a later period, so our ownership change sample and time period are different.

and Rousseau, 2008; Rhodes-Kropf and Robinson, 2008). 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, this paper is related to a recent wave of papers that use retrospective merger analyses to understand how mergers affect firm behavior. The insights from this growing literature advance the understanding of cross-market mergers (Lewis and Pflum, 2017; Dafny et al., 2019), monopsony power (Prager and Schmitt, 2021), buyer power (Craig et al., 2021), quality (Eliason et al., 2020), product availability (Atalay et al., 2020), firm entry (Fan and Yang, 2020), and the price effects of mergers (Luco and Marshall, 2020; Bhattacharya et al., 2022). We complement this literature by studying how mergers affect firm efficiency and providing evidence on the mechanisms.

2 Institutional Background and Plant Productivity

This section starts by providing an institutional background of the power generation sector and an overview of mergers and acquisitions in the industry. We then explain the construction of efficiency measures for power plants.

2.1 Power Sector

The US electricity sector represents about 2% of the US GDP, providing 2.6 million direct and indirect jobs (Bradley Associates, 2017). Until the early 1990s, US electricity generation was overwhelmingly supplied by regulated and vertically integrated investor-owned utilities or government-owned utilities (municipal and state-owned). Typically, these entities served a specific territory and owned all components of the power sector: generation, transmission, distribution, and retailing. The returns of these utility services were regulated through rate-of-return on capital investments and cost-of-service regulation. This highly regulated market structure left little incentive for efficiency improvements, generating significant inefficiencies (Fabrizio et al., 2007; Cicala, 2015).

After the 1990s, the industry went through significant deregulation. Electricity generation was decoupled from transmission and distribution, and most generators began to be paid for through a market mechanism. This deregulation was accompanied by the creation of independent system operators (ISOs) (EIA, 2003).[6] ISOs organize the wholesale

[6]Throughout this paper, we will use ISO as an umbrella term for both ISOs and regional transmission

electricity market and meet electricity demand by running high-frequency auctions where power plants bid their willingness to produce. In 2020, roughly 70% of US electricity demand was met through seven ISOs.[7]

The deregulation also led to a change in the electricity generation technology mix with a significant number of entries and exits. In the 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, gas-fired generation became competitive with coal-fired plants, each providing roughly one-third of the market supply in 2015. Today, gas-fired generation has reached twice the size of coal-fired generation (EIA, 2020).

2.2 Mergers and Acquisitions in the Power Sector

Large utility companies are usually organized into several subsidiaries under a big parent company, serving different locations and segments of the power sector. The structure of the subsidiaries tends to follow the boundaries of the legacy vertically integrated utilities. Parent companies typically own assets in generation, transmission, and distribution in the same region, with some parent companies having subsidiaries serving different parts of the country. After the 1990s wave of deregulation, significant merger and acquisition activity occurred between these entities. Moreover, financial firms, predominantly private equities and bank funds, started to invest in the power generation sector.

Mergers and acquisitions in the power sector can be divided into three main groups: (i) asset sales, (ii) subsidiary acquisitions (divestitures), and (iii) mergers. In asset sales, a firm sells part of its power plant portfolio while maintaining its corporate structure. In this case, the acquired assets fall under the ownership of a subsidiary of the acquirer. In subsidiary acquisitions, a parent company acquires a subsidiary of another firm with all its assets. The plant's owner (subsidiary) remains the same in these cases, but the parent owner changes. The third type is a merger between two firms, where two companies merge and form a new company. Appendix Figure 26 provides a visual representation of these acquisition types.

All proposed plant acquisitions in the US electricity sector must be reviewed by the Federal Energy Regulatory Commission (FERC), the Department of Justice (DOJ), and state Public Utility Commissions (PUCs) (Niefer, 2012). The FERC reviews mergers under Section 203 of the Federal Power Act, determining whether mergers are consistent with

organizations.

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

the public interest. The DOJ's review investigates the potential anticompetitive effects of mergers.[8] If either the DOJ, FERC, or state PUC concludes that the acquisition harms consumers, they either block it or require remedies, which are typically asset divestitures.[9] Despite extensive reviews by three government agencies, most proposed mergers in the US electricity sector have been approved, with only a few challenged mergers in the last two decades.[10]

There are several merger motives in the electricity industry, and efficiency improvement in power plants is one of them.[11] Merging firms often argue that mergers will generate synergies between assets, citing enhanced financial flexibility, increased cash flow benefits, and complementarities between different assets, such as those in distribution and generation.[12] Since fuel represents an important part of operational costs, fuel efficiency improvements are often cited as an important source of cost savings post-merger. As an example, Appendix Figure 25 shows a slide from the investor presentation of the 2018 Dynegy and Vista Energy merger, in which merging parties argue that heat rate improvements will lead to 125 million dollars in cost savings.

2.3 Electricity Production and Construction of the Efficiency Measure

A significant challenge when studying the efficiency effects of mergers is the lack of suitable data, as most industries do not have reliable measures of cost and physical productivity. The power generation industry is unusual in this respect because detailed and high-frequency efficiency data is publicly available. This section describes the efficiency measures used in this study and explains production in power plants.

A power plant is an industrial facility that generates electricity. In 2020, there were

[8] The FERC relies on the 1996 revision of the Horizontal Merger Guidelines (HMG) and puts more emphasis on market concentration levels (Niefer, 2012), whereas the DOJ's review relies on the 2010 HMG.

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

[10] Our review of a list of large mergers provided by FERC between 2000 and 2020 and merger press releases suggest that only a few of them were challenged.

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

[12] Some examples of merger motives from past mergers are: (i) AES-DPL merger, which argues that their earlier merger IPL led to improvements in management; (ii) NRG-GenOn merger, which argues measurable and actionable cost synergies of $175 million per year; (iii) Mirant-RRI Energy merger, which claims $150 million in annual cost savings; (iv) Vistra-Dynegy mentions geographic, fuel, market, and earnings diversification benefits. Other cited reasons are increasing the consumer base, diversifying the portfolio across technologies and regions, and accelerating efforts to meet potential future environmental regulations.

11,070 utility-scale electric power plants in the US (EIA, 2020). A typical power plant includes multiple generators, which transform a form of energy (mainly heat, wind, or solar) into electricity using different production technologies. Our research focuses on fossil fuel power plants, a type of thermal plant, because their efficiency is easy to measure. Fossil fuel power plants use the energy of heat obtained from burning gas or coal to make electricity.[13] In this process, the total input is measured as the heat content of the fuel used in electricity generation. This leads to a widely used and natural efficiency measure, called *heat rate*, which specifies how much heat input is used to produce a given amount of electricity. Our primary measure of efficiency is the inverse of this measure, defined as the ratio of energy output and input:

$$\text{Fuel Efficiency (Inv. Heat Rate)} = \frac{\text{Energy Output (MWh)}}{\text{Energy Input (MMBtu)}}. \tag{2.1}$$

The heat rate characterizes how efficiently fuel is converted into electricity. It is expressed as the ratio of the fuel's heat content, a million British thermal units (MMBtu), and the plant's electricity output, megawatt-hour (MWh). Heat rate is the most important determinant of power plant efficiency since fuel is the major input, representing roughly 80% of operating costs (Fabrizio et al., 2007). For this reason, heat rate is a standard efficiency measure in the industry, widely used by regulatory agencies and firms.

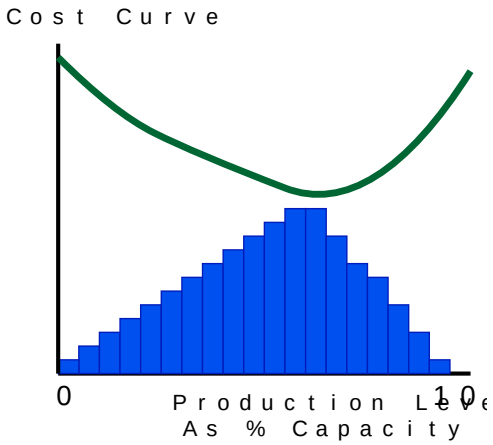
Most importantly for this paper, fuel efficiency provides important advantages to studying the effects of mergers and acquisitions on productivity. First, it is a quantity-based efficiency measure obtained from quantity input and output, not directly affected by buyer or market power changes. Second, electricity is a homogeneous product, so there are no potential quality changes or demand response after acquisition. Finally, the efficiency measure relies mainly on accurate sensor measurements of input and output rather than survey responses, as in many industries.[14]

Several factors affect the heat rate in a power plant. Figure 1 displays a hypothetical example of a heat rate curve, where the green line shows efficiency (inverse heat rate) and the blue bars show a typical production distribution by percentage of capacity. First, a power plant's cost curve depends on the production level, which typically has an efficient

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

[14] It is worth noting that our efficiency measure is fuel efficiency rather than TFP, and does not take into account non-fuel inputs. Although we believe that in electricity generation, the role of other inputs is not as significant as in other manufacturing industries and substitution from fuel to other inputs is limited, we study them in Section 7.3.

Figure 1: Representative Heat Rate Curve



Note: The green line represents the marginal cost of producing electricity at a given capacity without potential ramping costs. The blue bars represent the distribution of production levels.

scale around 90–95% capacity. Second, the production profile is an important determinant of efficiency. Since electricity cannot be stored at scale and demand is volatile, power plants often need to adjust their production rapidly. The associated cost with this adjustment is called ramp-up and ramp-down cost. Therefore, power plants whose production varies a lot tend to produce electricity less efficiently. These determinants of power plant efficiency depend on the skills and expertise of power plant personnel who monitor and control production (Bushnell and Wolfram, 2009).[15]

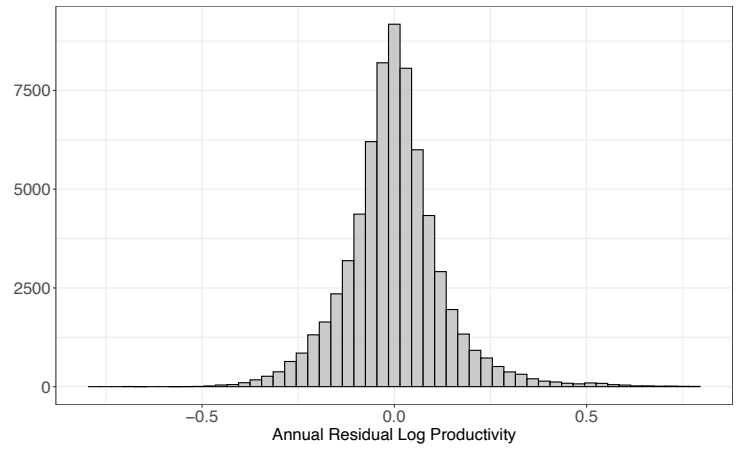
Although the electricity generation process seems relatively mechanical, there is considerable heterogeneity in power plant productivity in the US. Figure 2 shows the distribution of yearly residual log efficiency of power plants in the US after controlling for a rich set of observables that include production profile, plant age, fuel type, technology, capacity, generator manufacturer, and generator model.[16] The difference between the 10th and 90th percentiles is 0.32, indicating that plants in the top decile of the productivity distribution are more than twice as productive as plants in the bottom decile of the productivity distribution.[17] This heterogeneity in productivity has also been observed by others (Sar-

[15]Finally, 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. Even within a fuel type, there could be small differences in efficiency depending on the processing of the fuel. For example, using different coal types can lead to different efficiency levels due to factors like moisture content and pulverization procedures. Since we observe fuel and quality (for coal), we can control for changes in fuel type.

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

[17]This dispersion is slightly smaller than the dispersion identified in other manufacturing industries

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 and 2020 after controlling for production profile, plant age, fuel type, technology, capacity, generator manufacturer, and generator model, and other characteristics.

gent & Lundy, 2009; Staudt and Macedonia, 2014).[18] The large dispersion in productivity conditional on a large set of observables highlights the role of unobserved heterogeneity in efficiency, indicating potential room for improvement in many power plants.

Improving the heat rate curve of a power plant is a complex process that can be done in two main ways: (i) low-cost operational improvements and (ii) costly capital upgrades. Low-cost practices, such as process optimization, personnel training, and efficient maintenance, can significantly improve heat rate. Every year, power plant managers gather at the Heat Rate Improvement Conference to discuss these practices (EPRI, 2022).[19] An important determinant of operational practices is labor input.[20] As documented in detail in Bushnell and Wolfram (2009), individual skills of key personnel could make a significant difference in the performance of generating plants. A second way to improve plant efficiency is by upgrading critical equipment, such as boilers, fuel feeders, and cooling

(Syverson, 2011).

[18] Sargent & Lundy (2009) report commissioned by the EPA found that coal-fired power plants' heat rate range from 5 MMBtu/MWh to 32.7 MMBtu/MWh. Staudt and Macedonia (2014) examine factors that contributed to heat rate, including facility size, capacity factor, emission controls, steam cycle, and coal type. They determine that each factor is essential to the generator's heat rate, but there is considerable unexplained variability in the data.

[19] Appendix Figure 26 highlights a few case studies of low-cost improvements from this conference.

[20] As an example, Bushnell and Wolfram (2009) highlight the operator's impact with the following quote: "the act of balancing all of these input parameters was described by one manager as playing the piano and one star operator was considered a virtuoso on the instrument."

systems, as old equipment degrades and new technology becomes available.

Improving the efficiency of a 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 pollution, which policymakers have recognized 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 the carbon intensity of electricity generation (EPA, 2018).[21]

3 Data

Our primary goal is to construct an hourly measure of generator efficiency and the universe of ownership changes to examine the efficiency of acquisitions. An attractive feature of the power sector is that it has richer data on production and ownership than most industries. We take advantage of this attribute and create a unique dataset on ownership and production.

We combine several datasets from the FERC, EPA, Department of Energy's Energy Information Administration (EIA), S&P Global, Velocity Suite, and S&P Capital IQ Pro at the firm, plant, and generator level for coal- and gas-fired power plants in the US between 2000 and 2020. This section briefly describes the data sources. Appendix A provides a more detailed description of the data sources, construction of variables, and descriptive statistics.

Generator and Plant Level Data We use Velocity Suite, S&P Global, and EIA Forms 860 and 923 to construct detailed data on generator-level and plant-level characteristics for all power plants in the US. For generators, we assemble information on fuel type, technology, capacity, boiler model, and boiler manufacturer. For plants, we construct data on plant age, regulation status, location, ISO, and FERC region. For about half of the plants in the sample, we also have annual information on the number of employees, non-fuel costs, and capital expenditures between 2008 and 2020.[22]

Production and Efficiency Data We utilize the EPA's Continuous Emissions Monitoring

[21] 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 average efficiency from 32.5 to 36% reduces US GHG by 175 million metric tons per year, or 2.5% of total US GHG emissions in 2008. Moreover, NETL notes that "if each plant achieved their maximum efficiency each year, 5% reduction in CO_2 could result" (Campbell, 2013).

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

Systems (CEMS) for hourly generation and input data. The CEMS program monitors power plant emissions to implement environmental control policies. It provides hourly power output, power input, emission, and heat rate for almost every fossil fuel power plant in the US.[23] We merge this dataset with the unit characteristics data from other datasets using plant and generator names.[24] We restrict the sample to all US fossil-fuel generators that comply with the CEMS program, except those in Alaska and Hawaii.

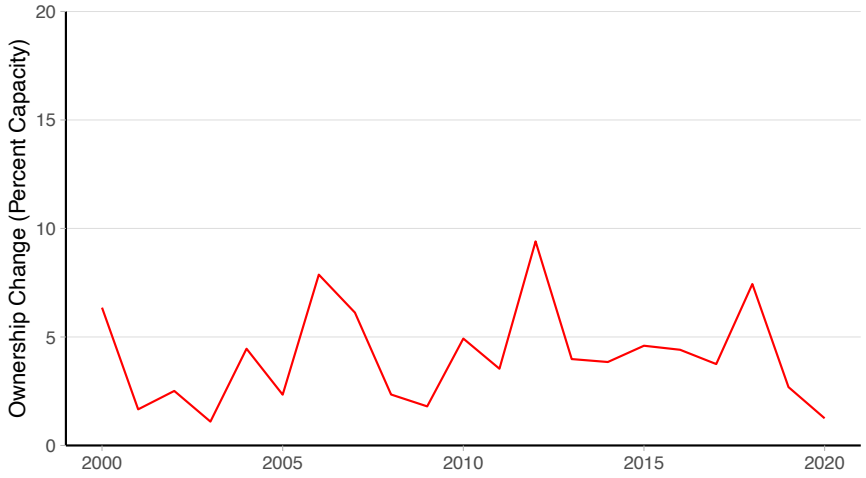
Mergers and Acquisitions Data We construct data on the universe of fossil fuel power plant ownership changes from ownership and transaction datasets obtained from S&P Global. The ownership data includes the ownership structure of all power plants at the subsidiary and parent company levels for all shareholders. The transaction data provides detailed information about the transferred assets and transactions, such as acquired power plants, deal size, buyer, seller, announcement and close dates, conference call transcripts, and deal descriptions. Since regulatory authorities must review all transactions, this data is available for the universe of transactions during the sample period. Ownership datasets can suffer from falsely identified ownership changes because firm name changes and company restructuring sometimes appear as ownership changes. We identify false ownership changes by cross-matching the transaction data with the ownership data. We also use corporate structure data to identify changes that are merely restructuring within the same parent company. We use those false ownership changes for placebo tests. We also identify ownership changes that are divestitures due to deregulation in the early 2000s and exclude them from the sample.

Personnel Data Since plant personnel is an important determinant of efficiency, we assemble panel data on plant personnel from the EPA. The EPA has this information because each power plant that complies with an EPA program must submit a plant representative to the EPA. This data includes the representative's name, start and end date of their tenure, and contact information. To obtain more information about the personnel, we match 70% of them to their LinkedIn profiles, obtaining their title, education, and employment history. From LinkedIn data, we confirm that 78% of the reported personnel are plant managers, and the rest are mostly environmental compliance personnel and key engineers. Therefore, we treat these personnel as plant managers for the rest of the study.

[23] Every power plant in the US with more than 25 MW capacity that ignites fossil fuel must comply with the EPA CEMS program. This sample represents approximately 95% of the US fossil fuel generating capacity.

[24] In some cases, generator names in the EIA dataset and CEMS do not match because the EPA uses boiler names as a unit, whereas EIA uses generator names. For most cases, we rely on the EPA's Power Sector Data Crosswalk. Finally, we manually match the retired and unmatched power plants using the principles described in Appendix A.

Figure 3: Share of Capacity with Ownership Change



Note: This figure shows the percent of capacity of fossil fuel plants that change ownership annually in the US between 2000 and 2020.

Other Datasets We gather hourly data for solar and wind power generation from FERC and S&P Global for each Balancing Authority Area (BAA) and ISO Zone. We also obtain information about firm characteristics, such as asset size, market cap, and industry information from S&P Capital IQ Pro.

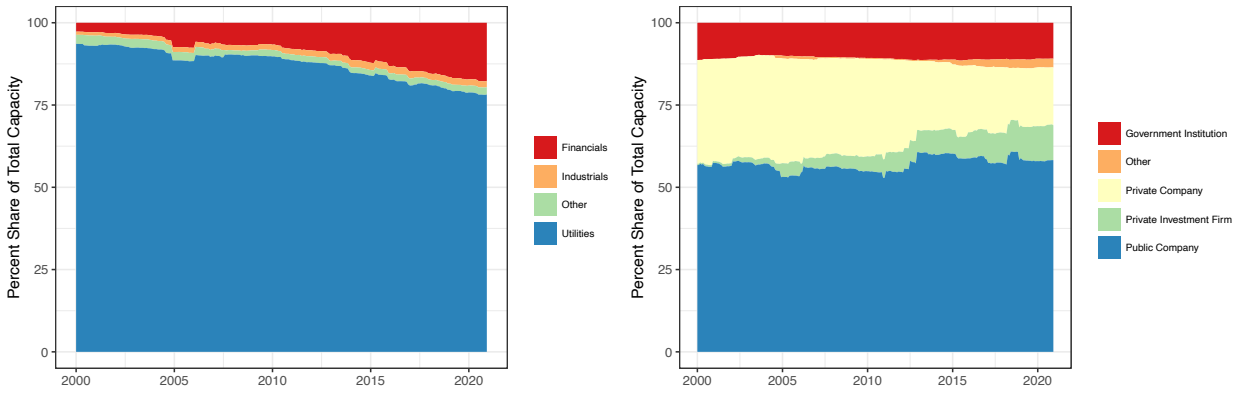
4 Descriptive Statistics on M&A in the US Power Industry

This section presents descriptive statistics about mergers and acquisitions of fossil fuel power plants in the US. We demonstrate that the industry experienced a significant number of acquisitions with large heterogeneity in terms of transaction size, acquirer and target firm types, and plant characteristics. These facts allow us to study several aspects of how acquisitions affect efficiency, and they are essential to keep in mind when we conduct the empirical analysis.

95% of Industry Capacity Changed Ownership between 2000 and 2020. There has been a large number of mergers and acquisitions in the US fossil fuel power generation industry between 2000 and 2020. Figure 3 shows the percentage of fossil fuel electricity generation capacity that changed ownership from 2000 to 2020. An average of 5% capacity changed ownership annually, with some fluctuations year-to-year.[25] Cumulatively, this

[25]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% of shares. For those plants,

Figure 4: Market Share by Firm Type



(a) Industry Type

(b) Owner Type

Note: This figure shows the change in the market share of industry and owner types of fossil fuel plants in the US between 2000 and 2020.

corresponds to 95% of industry capacity during the sample period.[26] This is also reflected in the large number of power plants that changed ownership. Table 1 presents summary statistics on plants, firms, and deal characteristics from acquisitions. The data includes 690 transactions involving 4,834 generation units and 1,567 plants. About 80% of these transactions involve a generator whose majority owner changes, resulting in 4,030 generators with majority acquisitions. Finally, looking at the firm characteristics, there are 267 unique acquirer firms and 266 unique target firms in the data.

Despite many acquisitions in the study period, there has been no significant change in market concentration in the US. Appendix Figure 20 reports the national market shares of the largest 5, 10, 20, and 30 firms in terms of capacity owned. The concentration fluctuates over time; however, it is broadly stable in the sample period.[27] This is because there is a considerable firm turnover in the industry, as suggested by the large number of acquirers and targets in Table 1.[28]

To show the composition of firms in the industry over time, Figure 4a displays the

an acquisition is defined as change in the largest shareholder.

[26]This is cumulative capacity, so it double-counts the capacity of generators that have changed ownership multiple times. We observe that 2,365 unique generators change ownership at least once.

[27]Note that these concentration ratios are not informative about the changes in market power due to the local nature of wholesale electricity markets. We report these changes at the national level to see whether large firms increase their dominance in this industry in the US through acquisitions.

[28]Some examples can be seen in Appendix Figures 21 and 22, where we report firms with the largest capacity increase and decrease between 2010 and 2020.

evolution of ownership by the primary activity of the parent company (utilities, industries, financials), and Figure 4b displays the evolution of ownership by company type. Figure 4a indicates an increasing presence of financial firms in the industry between 2000 and 2020.[29] The share of total capacity owned by financial firms increases from 3% in 2000 to 20% in 2020, suggesting substantial asset allocations from utilities to financial firms. Figure 4b highlights that public firms own half of industry capacity, and their share remains stable over time. Finally, government institutions own 12% of industry capacity. Except for the federally run Tennessee Valley Authority, these are local governments in primarily rural areas that operate power plants.

Most Acquisitions Reallocate Assets between Incumbent Firms. Most acquisitions are partial asset sales between two incumbent firms, but there are also transactions where the target exits or the acquirer enters the industry. Columns 2 and 3 of Table 1 report the summary statistics separately for transactions where acquirer enters and target exits. In 19% of the transactions, the acquirer firm enters the market; in 21% of transactions, the target firm exits the market. The rest of the transactions occur between incumbent firms, which have a presence in the industry pre- and post-acquisition. Overall, these summary statistics suggest a significant asset reallocation between incumbent firms, which we use to test important hypotheses about how efficiently mergers allocate assets between firms.

Transaction Sizes Exhibit Large Heterogeneity. In Figure 5, we report the distribution of capacity that changed ownership across 689 transactions. While most transactions involve a few plants, there are some moderate-size transactions with an ownership change of 5,000–10,000 MWh capacity, as well as mega-mergers involving more than 10,000 MWh capacity.[30] Observing this heterogeneity is helpful because it indicates that our results do not come from a small number of large mergers, and we can test the heterogeneity of the effect by transaction size.

Ownership Changes Occur at Different Levels of Corporate Structure. Ownership changes can occur at two levels in a corporate structure: (i) the subsidiary level and (ii) the parent company level. Typically, a subsidiary of a parent company is the legal entity that owns the power plant, and the parent company owns that subsidiary. When a parent company acquires a subsidiary from another parent company, the subsidiary owner remains the same, but the parent owner changes. On the other hand, if a subsidiary acquires a power plant in a partial asset sale, both the subsidiary owner and parent owner change. Figure

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

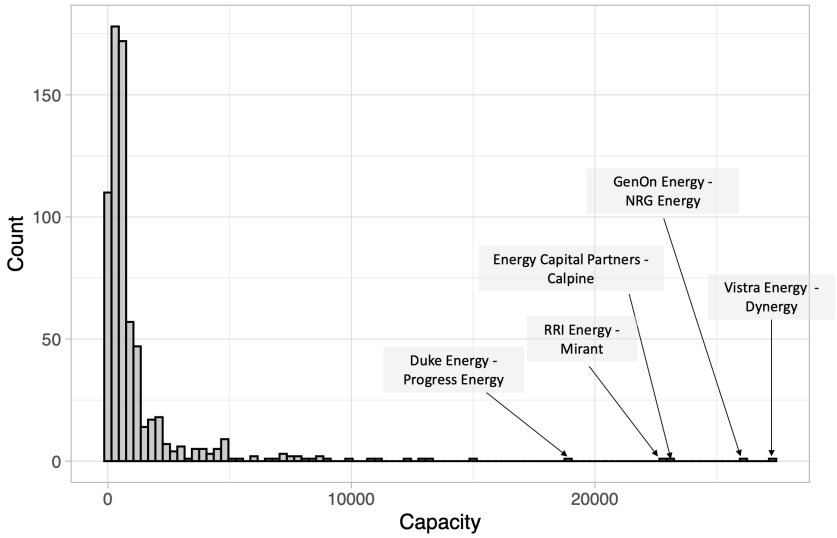
[30] Table 5 lists the largest 25 mergers during the sample period.

Table 1: Acquisitions 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 (Pre-merger)			
Avg. # of Units Acquirer Owns	35.03	-	25.56	32.50
	(49.28)	-	(39.54)	(46.15)
Avg. # of Units Target Owns	44.60	35.22	11.92	44.05
	(52.49)	(47.16)	(22.16)	(52.02)
Avg. Acquirer Firm Capacity	5459	-	4189	5055
	(8765)	-	(6883)	(8049)
Avg. Target Firm Capacity	7025	5312	1738	6912
	(9655)	(8314)	(3588)	(9453)
	Transaction Characteristics			
# of Deals	689	132	147	532
Avg. Deal Size in # of Units	7.0	5.3	11.5	7.6
	(14.7)	(8.9)	(21.8)	(16.0)
Avg. Deal Size in Capacity	1233	986	1922	1298
	(2640)	(1981)	(3798)	(2813)

Note: This table includes summary statistics on M&A that include fossil fuel-generating units in the US between 2000 and 2020. Each column reports the data's counts and characteristics at varying sample restriction levels. Column (1) reports data from all acquisitions. Column (2) and column (3) present data from transactions where the acquirer firm enters, and the target firm exits the market, respectively. Column (4) reports data from the majority acquisitions only. The numbers in parentheses reports standard deviation. The unit of capacity is MWh.

Figure 5: Distribution of Transaction Size

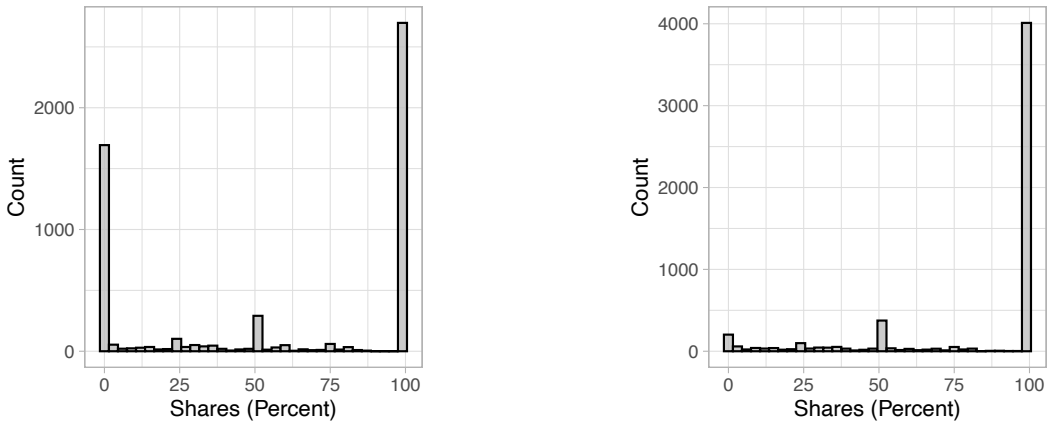


Note: This figure shows the distribution of deal size by fossil fuel generation capacity in the US between 2000 and 2020. The unit of observation is a transaction. The largest five transactions are labeled.

6 shows the percent of shares that change in transactions at the subsidiary and parent company levels separately. The left panel shows that, in around 1,700 acquisitions, the subsidiary owner remains the same and only the parent owner changes. We will use this variation in ownership type to study the efficiency effects of ownership changes at different levels of corporate structure. Moreover, the right panel shows that there are many minority acquisitions where the buyer acquires less than 50% of a power plant. We use these minority acquisitions as placebo tests, as one should expect no change in efficiency after a minority acquisition.

Some states regulate power plants' returns from power generation. One might be concerned about the role of regulations, as they might change the incentives to improve productivity after an acquisition. To investigate this, Table 1 shows the fraction of acquisitions that occur in regulated vs. deregulated markets. Most ownership changes (76%) occur in deregulated markets, which is also reflected in the geographic variation of acquisitions (Appendix Figure 24). Another concern could be that ownership changes coincide with divestitures due to deregulation (Fabrizio et al., 2007). Even though most state restructuring took place in the 1990s, some state restructuring overlaps with our sample period. For this reason, we look at how many ownership changes were due to forced divestitures. Table 1 reports that only 4% of acquisitions coincide with deregulation after 2000, which

Figure 6: Percent Change in Shares by Ownership Type



(a) Subsidiary Level

(b) Parent Company Level

Note: This figure shows the percentage of shares that change ownership in transactions between 2000 and 2020 by ownership type. The unit of observation is a generator.

we exclude from the sample.

5 Empirical Results

Our empirical strategy aims to identify the causal effect of acquisitions on power plant efficiency and study potential mechanisms. To do this, we compare productivity trends at acquired generators (2,365 generators) to those that were never acquired (2,882 generators) during the sample period.[31] We refer to the latter type as "control generators." In most estimations, each observation is a combination of generator and week, with variables containing productivity, ownership, and several generator characteristics. The main advantage of our empirical setting is the availability of a high-frequency measure of generator efficiency, which allows us to track productivity immediately before and after acquisition in a short time frame. This allows us to treat acquisitions as discrete events.

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

[31] When we estimate the effects of acquisition on a subsample of acquired units, we always exclude the other acquired units from the regression, so the control group is always the group of never-treated generators.

and post-merger effect coefficients. Fourth, we focus only on the first acquisition if a unit is acquired multiple times (51% of treated units). We remove the observations of units after the post-treatment period if they are acquired multiple times so that other acquisitions are not included in the sample. Fifth, we remove all treated units if they are acquired again during post-treatment period of first acquisition (10 months). We provide several robustness checks for these sample restrictions in Section 8.

We find that acquisitions increase the productivity of power plants by 4%, but only when ownership changes both at the subsidiary and parent owner level. In contrast, ownership changes only at the parent company level do not lead to a significant productivity increase. The productivity increase starts five months after the acquisition and reaches the new steady-state level after eight months. We conclude the section by studying the heterogeneity of the effects. To facilitate the exposition, we defer the detailed examination of mechanisms to Section 7.

5.1 Mergers and Efficiency

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

$$\log(y_{it}) = \theta_1 \text{late_pre}_{it} + \theta_2 \text{early_post}_{it} + \theta_3 \text{late_post}_{it} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \tag{5.1}$$

where y_{it} is the efficiency of generator i at week t (measured as inverse heat rate given in Equation (2.1)); the controls, X_{it}, include state-month fixed effects, time-varying generator characteristics such as age and fuel type (for coal), capacity, and indicators for whether the unit is connected to the grid and whether it is an internal generator. α_i is the generator and μ_t is the week fixed effects.[32] By controlling for the state-month fixed effect, we flexibly account for changes in the supply of non-fossil fuel electricity generators (mainly entry of renewables) and demand at the state level. Although it happens rarely, generators can change their capacity and fuel type; we include fuel type and capacity to control for these cases. Including generator and week fixed effects implies that merger effects are identified within generator changes following an acquisition event.

The regression includes three variables of interest: (i) late_pre, a monthly indicator variable for 1 to 5 months pre-treatment, (ii) early_post, an indicator variable for 1 to 5

[32] We estimate our main specification at the weekly level for computational reasons and to reduce noise in the hourly data. We provide estimations at the daily and hourly level as robustness checks in Section C.2

Table 2: Balance Table

	Acquired	Never Acquired
Coal Unit	0.18	0.26
Gas Unit	0.74	0.67
Oil	0.08	0.07
Capacity (MWh)	179	176
Install Year	1987	1985
Unit in ISO	0.75	0.58
# of Units	2365	2882

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

months post-treatment, and (iii) late_post, an indicator variable for 6 to 10 months post-treatment. By including early and late post-acquisition treatment indicators, we aim to capture the dynamic effects of mergers and identify when efficiency changes occur. We include late_pre to check whether there are any productivity effects of the acquisition before the acquisition. This could happen due to anticipation effects or disruption in the production process, as most acquisitions are announced months in advance. Finally, we cluster all standard errors at the plant level.

It is important to highlight that the unit of analysis is a generator rather than a plant. While the same firm typically own all generators in a plant, generators 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 proper level of analysis, and it is maintained throughout the paper unless otherwise stated. Before moving to the results, Table 2 reports 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 installation year. There are some differences in fuel type: acquired plants are more likely to be gas-fired than the control group. This difference is expected since there is substantial policy uncertainty about the future of coal-fired power plants, which deters potential buyers. Finally, acquired plants are more likely to operate in an ISO.

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 for different acquisition events: (i) both the parent and subsidiary owner change; (ii) the parent owner changes and the subsidiary owner remains the same; (iii) minority acquisitions;

Table 3: Regression Results

	All M&A (i)	Subsidiary/Parent Owner Changes (ii)	Only Parent Owner Changes (iii)	Minority Owner Changes (Placebo) (iv)	Name Changes (Placebo) (v)
Late pre-acquisition	0.002	-0.003	-0.003	-0.004	-0.007
	(0.005)	(0.007)	(0.007)	(0.008)	(0.006)
Early post-acquisition	0	0.005	-0.002	-0.008	-0.004
	(0.005)	(0.007)	(0.007)	(0.020)	(0.043)
Late post-acquisition	0.014	0.039	-0.006	0.001	0.007
	(0.006)	(0.012)	(0.007)	(0.01)	(0.01)
Adj. R^2	0.622	0.635	0.622	0.652	0.635
# of Obs.	1.79M	1.38M	1.4M	1.12M	1.22M
# of Acq.	1760	897	921	405	456
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

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

and (iv) owner name changes. Estimates from (iii) and (iv) provide placebo tests, as discussed later. The results in the first numerical column of Table 3 indicate that efficiency rises after the acquisition. The efficiency change in the early acquisition period is zero, underscoring that there is no considerable change in efficiency immediately after acquisition. However, in the late post-acquisition period, 6 to 10 months after acquisition, the efficiency increases by 1.4% above the pre-acquisition level. Thus, acquired generators' efficiency levels improve following acquisition, though it takes time to fully manifest.

Columns (ii) and (iii) of Table 3 test whether the type of ownership change affects efficiency differently. Column (ii) estimates a difference-in-differences specification, where treatment is defined as ownership change both at the parent and subsidiary levels. In contrast, in column (iii), a plant is treated when the parent owner changes, but the subsidiary owner remains the same after acquisition. One might expect the efficiency effects of an acquisition to be different in these two cases because the subsidiary owner typically has direct control over the operation and personnel of the power plant. In contrast, the parent owner controls the power plant indirectly.[33] Comparing these two columns reveals

[33]Moreover, ownership changes at the parent level tend to be financial acquisitions, in which the motive is to achieve diversification or safe returns.

considerable heterogeneity in the efficiency effect. There is no significant effect when the subsidiary owner remains the same, whereas it is 4% if both the subsidiary and parent owner change. These results confirm that the direct owner plays a more important role than the parent for operational changes to occur in a power plant.

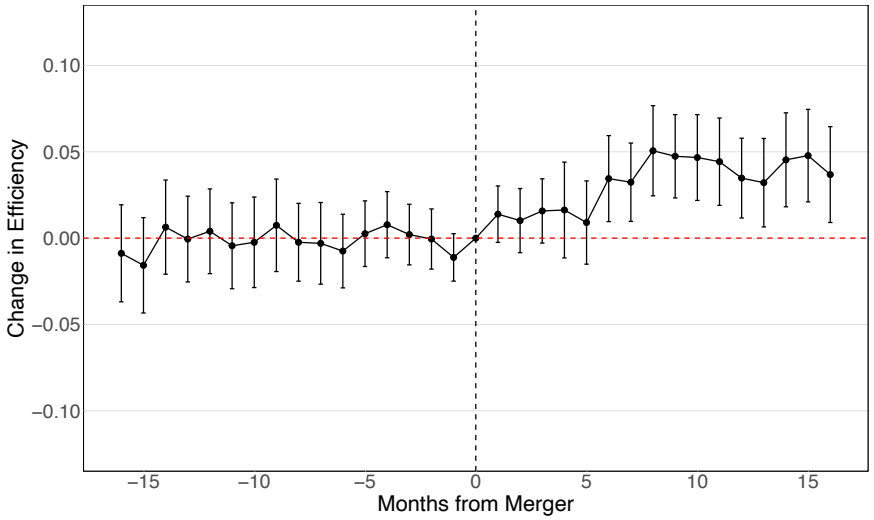
The last two columns of the table serve as placebo tests. For the first placebo test, we use the 512 minority acquisitions in the data. These are transactions where the majority owner remains the same after acquisition. For the second placebo test, we identify 612 changes due to corporate restructuring or name changes, 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 actual ownership change. We use these two types of events as placebo tests because these events are unlikely to affect power plant efficiency. The results confirm our expectation that there is no significant change in power plant efficiency after these events. These placebo tests give us confidence that confounders are not likely to drive the 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 contrast, any efficiency trends that might lead to selection would be gradual enough to be distinguished from the more discrete direct effect. This assumption is likely to hold in our setting as we observe production at short intervals and include a rich set of control variables and month-state fixed effects that account for potential efficiency trends in the industry.[34] Still, mergers are of course not random, and unobservable factors could change efficiency in the absence of mergers. If those factors are observed by the acquirers, they can lead to selection, violating the assumptions for causality. For example, the acquirer might observe that the target plant's manager will retire soon and decide to buy the plant, anticipating that the new manager will improve efficiency. To address such a concern, we estimate the effects of manager changes on efficiency in the absence of mergers and find that the efficiency increase is only 0.6% (Appendix Figure 17). Finally, we do a battery of robustness checks, presented in Section 8, including matching estimators, Callaway and SantAnna (2021) estimator, and estimation with daily and hourly data, to show that the results are robust to several specification choices.[35]

[34]The 4% efficiency gain that is realized in 4–5 month period is not easily explained by other mechanisms. The average annual within-power plant efficiency gain in the industry is only 0.3%, with very little fluctuation in efficiency.

[35]We also want to point out that our estimates report the average effects on treated, i.e., the efficiency effects of the proposed and approved mergers. These mergers clearly are not random, and we will show

Figure 7: Impact of Merger on Productivity



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

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

$$\log(y_{it}) = \sum_{s\in(-16,16)} \delta_s D_{i(t-s)} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \tag{5.2}$$

where $D_{i(t-s)}$ is an indicator variable that equals 1 for generator i if the generator is acquired at time t and zero otherwise. We include the same control variables as in Equation (5.1). Since we found efficiency effects for ownership changes at the subsidiary and parent owner levels, we restrict our attention to those acquisitions hereafter.

The results from the dynamic effect regression in Figure 7 suggest no significant evidence of differential pre-treatment trends. The coefficients on $s \in (-16, 0)$ are small and not significant, suggesting that acquired plants do not have a different efficiency trend before acquisition than those not acquired. The difference remains close to zero until five months post-acquisition. After that, the efficiency of acquired and control units diverges, leading to a cumulative efficiency increase of 4%. The fact that plants experience efficiency

later that target firms sell their assets strategically. However, the average treatment effects on treated plants is the policy-relevant object of interest because we aim to identify the efficiency effects of the proposed acquisitions, as merging firms randomly is not a viable policy.

gain five months after acquisition suggests that it takes time for the new owner to improve efficiency.[36]

5.2 Discussion

How significant is the average 4% efficiency gain after acquisition, and what are the corresponding cost savings? To answer these questions, it is helpful to compare our estimates to average within-plant productivity growth. In the power generation industry, within-plant productivity growth is small, only 0.3% annually, as most aggregate productivity growth comes from plant entry and exit.[37] This small within-plant productivity growth makes the efficiency gain after acquisitions more even striking.

Next, we quantify the cost savings 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; (ii) acquired plants will maintain the same production level observed pre-acquisition; and (iii) there is no redistribution of production across plants.[38] Under these simplifying assumptions, we find that the total cost saving amounts to 6 billion dollars. Given this finding, an important question is whether these cost savings would be passed to consumers. The answer to this question is complicated, as it depends on whether the acquired plants are marginal or infra-marginal and how much market power they have. Though this is an important question, it is beyond the scope of this paper.

Finally, we also estimate the social gains due to CO_2 emissions resulting from a decline in fuel usage in electricity generation. Under the assumptions detailed in Appendix B.3, the total cumulative decline in CO_2 emissions due to acquisitions between 2000 and 2020 is roughly 50 million tons. This corresponds to emission reduction from replacing 110 TWh electricity generation of gas-fired power plants with renewables.

5.3 What Predicts Efficiency Gains: Heterogeneity Analysis

Estimating the average effects of past mergers is important to understand the overall impacts of mergers. However, to draw broader lessons from this industry and guide merger

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

[37] We show this in Appendix Figure 19, which 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% annual increase over the sample period.

[38] Details of this calculation are provided in Section B.3.

policy, it is crucial to learn the underlying mechanisms that lead to post-merger changes and understand what merger and firm characteristics predict them. Thus, the next set of analyses examines what merger characteristics predict efficiency effects.

Our rich data and a large number of ownership changes allow us to study the relationship between efficiency gains and several plant, firm, and transaction characteristics. For this purpose, we estimate the following regressions:

$$\log(y_{it}) = \theta_1 D_{it} + \theta_2 D_{it} \times Z_{it} + X_{it} + \mu_t + \alpha_i + \epsilon_{it}, \tag{5.3}$$

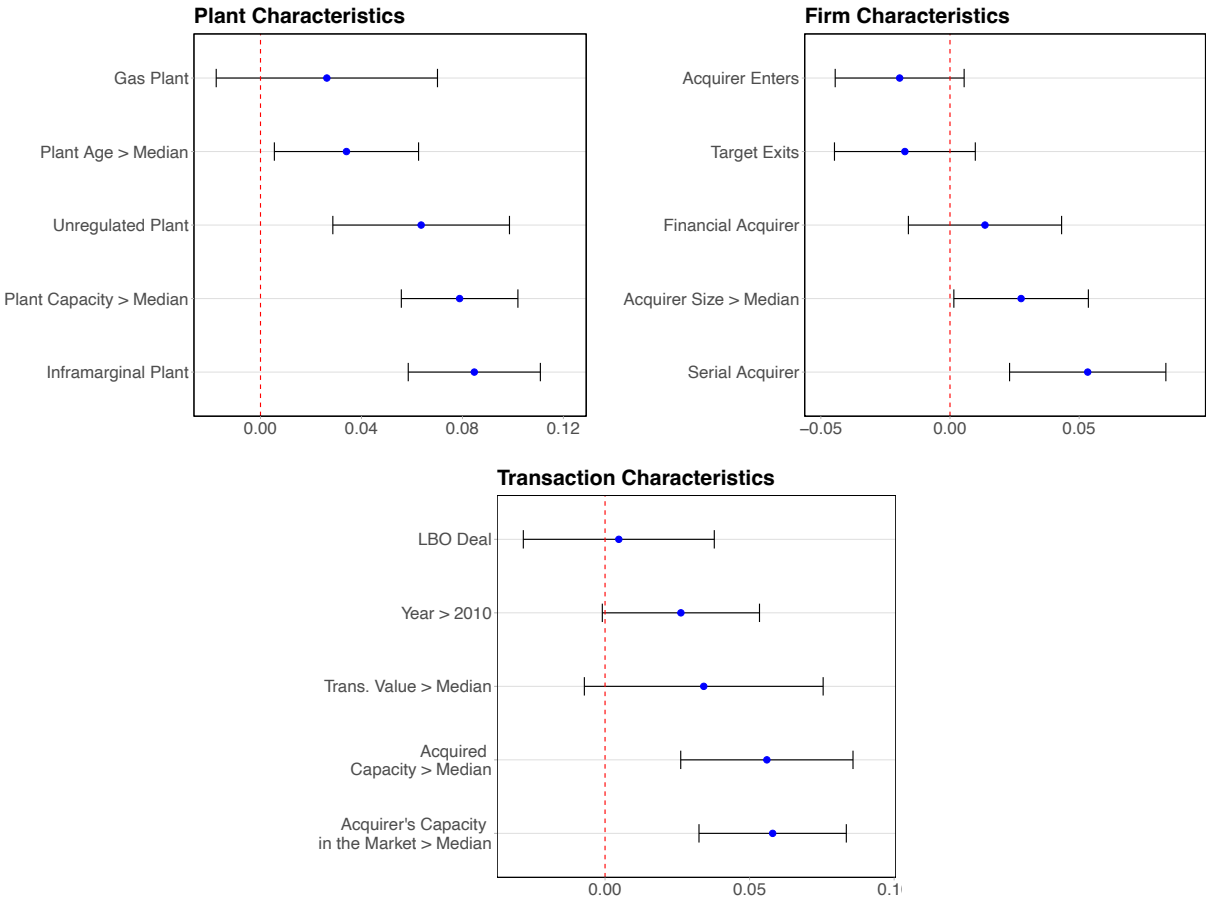
where D_{it} is an indicator variable for treatment and Z_{it} is a plant, firm, or transaction characteristic. We separately estimate this equation for many plant, firm, and transaction characteristics and report the estimates of θ_2. The details of the estimation procedure for this analysis and how subsamples are constructed are provided in Appendix B.

The results from this estimation are reported in Figure 8. We consider five plant characteristics: fuel type (natural gas or coal), age, regulation status, capacity, and whether the plant is infra-marginal or marginal. Because only a small number of coal-fired power plants were acquired during the sample period, heterogeneity result by fuel type is noisy, with no significant heterogeneity effect. However, there is a significant heterogeneity based on other power plant characteristics. The efficiency impact of mergers is higher in older power plants, which is expected because there is more room for efficiency improvements in older plants due to degradation in performance over time. The efficiency improvements are also higher if the plant is unregulated, larger, and infra-marginal. In all of these cases, the new owner has more incentive to improve power plant efficiency. This is because, in unregulated plants, any cost savings will be retained as profit. In infra-marginal and larger plants, production is higher, so efficiency improvements would lead to a higher return.

Next, we look at which firm characteristics predict efficiency gains. We focus on transactions where the target firm exits the market, the acquirer enters the market, the acquirer is a financial firm, the acquirer is large, and it is a serial acquirer. We do not detect significant heterogeneity when the target firm exits, the acquirer firm enters, and the acquirer is a financial firm. However, efficiency improvement is 2% higher when the acquirer is large (in total fossil fuel capacity) and is 5% higher when the acquirer is a serial acquirer. These results are consistent with the interpretation that a firm's experience in plant operations and acquisitions is an important predictor of efficiency increase after acquisition.

Finally, we study five transaction characteristics: deal value (which includes non-generation

Figure 8: Heterogeneity of the Merger Effects on Productivity



Note: Estimates of θ_2 from Equation (5.3) along with the 95% of confidence intervals. Standard errors are clustered at the plant level. Details about the heterogeneity variables are provided in Appendix B.4. The corresponding coefficient estimates and standard errors can be found in Appendix Tables 7–9.

assets), transaction year (after 2010), the acquirer's existing capacity in the market, transaction size (acquired fossil fuel capacity), and whether the transaction is a leveraged buyout (LBO). First, larger transactions by deal size and LBO deals do not lead to a higher efficiency increase. Transactions after 2010 lead to a slightly higher efficiency gain, suggesting that the results are not specific to acquisitions that occur in a particular time frame.[39] The acquirer's total capacity in the US and the capacity in the market are correlated with higher efficiency improvements.

[39]One alternative explanation for the efficiency gains could be industry-wide improvements in efficiency after the deregulation wave in the late 1990s and early 2000s. Even though we exclude forced divestitures from acquisition events, this result provides evidence that the effect is not due to deregulation.

The analysis in this section suggests that the magnitude of efficiency gains are correlated with many plant, firm, and deal characteristics. Even though these findings are not necessarily causal (the true driver of heterogeneity could be other factors), we still believe they are valuable for merger policy. Predicting the efficiency effects of mergers through counterfactual simulations is particularly difficult as most merger simulations focus on predicting price effects. Therefore, evidence on the efficiency effects of mergers conditional on a merger's attributes provides valuable information to assess which mergers could lead to efficiency gains ex-ante.

6 Do Mergers Allocate Resources Efficiently?

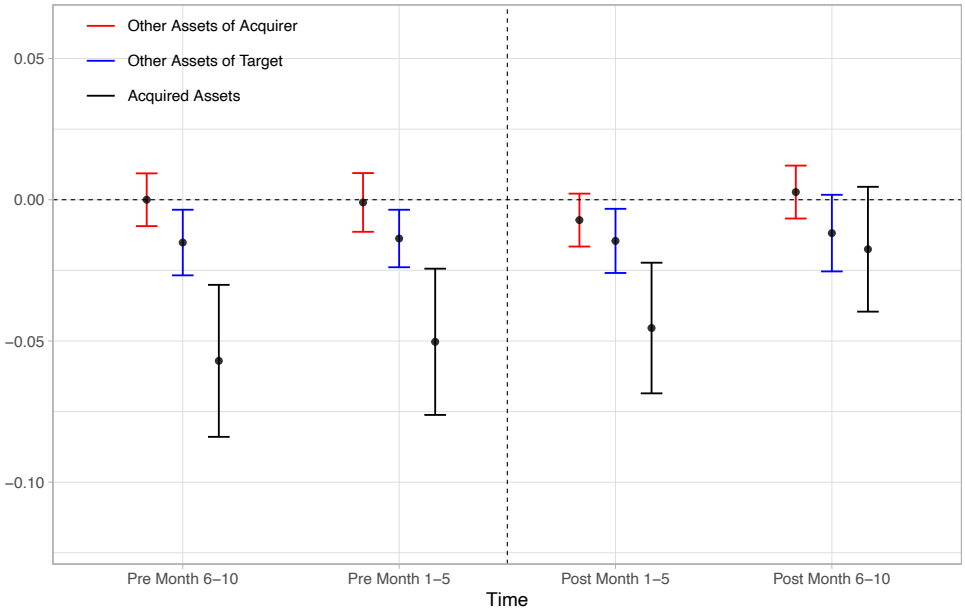
Mergers and acquisitions represent a significant source of reallocation in the economy and account for vast flows of resources between firms. This reallocation can generate allocative efficiency gains if the assets are allocated from less productive firms to more productive firms or if acquirers utilize the acquired assets more productively.[40] Our empirical setting provides an opportunity to study the allocative efficiency effects of mergers as we observe hundreds of asset reallocations between incumbent firms. Motivated by this, this section investigates whether (i) acquirers are more productive than target firms and (ii) acquirers have a comparative advantage in utilizing the acquired assets over target firms.

There are two main theories on how acquisitions raise productivity through resource reallocation. The first, 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-buys-low" pattern. 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-buys-like" pattern, indicating mergers between complementary assets.

The answers to these questions are also an important input to merger analysis. In merger simulations of firms with different marginal costs, what researchers should assume for the post-merger marginal cost is unclear (Farrell and Shapiro, 1990). In other words, one needs to know whether efficiency is transferable from one firm to another. 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 prac-

[40] Another view of the literature suggests that most acquisitions are undertaken for other motives, such as empire building and managerial hubris (Jensen, 1986; Roll, 1986).

Figure 9: Efficiency of Acquirer and Target's Plants



Note: Regression estimates from Equation (6.1). Red, blue and black bars show the change in the existing assets of the acquired, existing assets of the target and the acquired assets, respectively. Error bars indicate 95% confidence intervals. Standard errors are clustered at the plant level.

tices that improve productivity (Weber and Camerer, 2003; Malmendier et al., 2018). In our empirical analysis, we also provide evidence for this question.

To understand how mergers allocate resources in the economy, we estimate a difference-in-differences specification where we analyze the efficiency of three different types of assets: (i) acquired plants, (ii) the acquirer's existing plants not involved in the transaction, and (iii) the target's existing plants not involved in the transaction. In particular, we estimate the following specification:

$$\log(y_{it}) = \sum_{j=1}^{3} \left(\theta_1^j \text{early_pre}_{it}^j + \theta_2^j \text{late_pre}_{it}^j + \theta_3^j \text{early_post}_{it}^j + \theta_4^j \text{late_post}_{it}^j\right) + X_{it} + \mu_t + \epsilon_{it}, \quad (6.1)$$

where j represents the three different assets types listed above. This regression aims to estimate the level and change of efficiency separately for the target's assets, acquirer's assets, and acquired assets around the time of acquisition. With these estimates, one can compare the efficiency of the target and the acquirer's existing assets and identify how they perform relative to acquired plants. Note that this regression does not include generator fixed effects because we are interested in estimating level differences, not only changes.

We deal with potential endogeneity concerns due to the lack of generator fixed effects by including a rich set of controls, including age, boiler type, fuel type, boiler model, boiler manufacturer, and generator capacity. We restrict the acquisition sample to those where the acquirer and target firms own plants not involved in the transaction pre- and post-acquisition, which corresponds to 60% of all acquisitions. We remove other acquisitions from the sample, so they are not included in the control group. We also normalize the efficiency of acquirers' assets to zero in the early pre-acquisition period, so all other coefficients are estimated relative to θ_1^1.

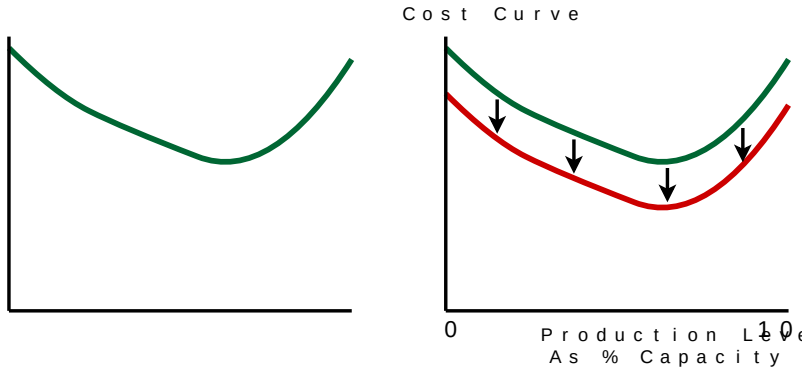
Figure 9 reports the estimates of three sets of coefficients. The red, blue, and black colors indicate the efficiency of the existing assets of the acquirer, the existing assets of the target, and the acquired assets, respectively. Comparing the efficiency levels of the acquirer and the target's assets reveals two interesting findings. First, the productivity levels of the target and the acquirer's existing plants are roughly constant around the acquisition time. Second, the acquirer is 1% more efficient than the target firm. These estimates suggest that assets are allocated from high-productivity to low-productivity 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 the assets sold by the target firm are underperforming relative to other assets in the target's portfolio by 4%. This suggests target firms sell their underperforming plants in their portfolio. What happens to these underperforming assets after acquisition? The efficiency of these assets improves after acquisition by 4%, and they become almost as efficient as the acquired firm's other assets.[41]

Overall, the empirical findings in this section suggest *high-productivity* firms buy underperforming assets of *low-productivity* firms and make the acquired asset almost *as productive as* its existing assets after acquisition. These results provide clear evidence for the two merger efficiency gain hypotheses discussed above. In particular, we find evidence for the high-buys-low pattern, as the acquirers are more efficient than the targets. We also find evidence for complementary asset theory, in that acquirer firms can improve the productivity of the underperforming assets of the target firm. Because the acquired assets are underutilized under the target's ownership and improve performance under the acquirer's ownership, acquisitions contribute to aggregate productivity in the power generation sector.

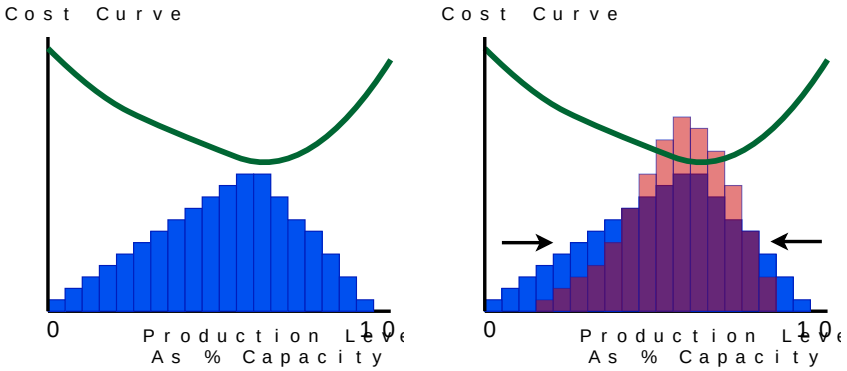
[41] This effect is similar to what we found in the previous section; however, it is estimated less precisely due to the decline in sample size.

Figure 10: Productive Efficiency



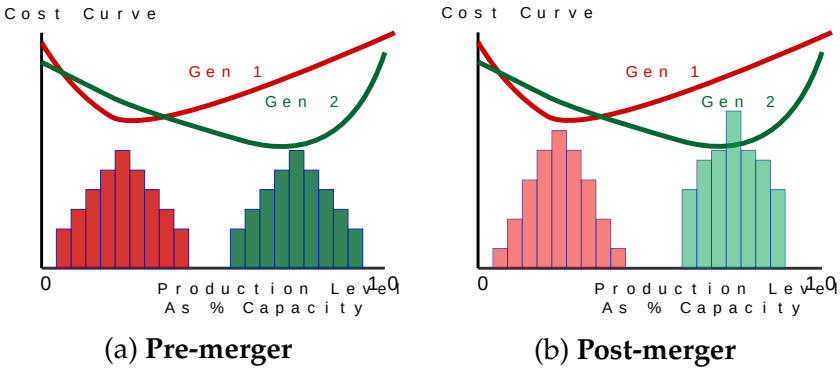
(a) **Pre-merger** (b) **Post-merger**

Figure 11: Dynamic Efficiency



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

Figure 12: Portfolio Efficiency



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

Note: Illustration of different efficiency gain mechanisms introduced in Section 7.

7 Mechanisms

The results so far show large improvements in the efficiency of acquired plants after acquisition. This section investigates the potential mechanisms of efficiency gains and provides two major findings: (i) most efficiency gains come from improvement in productive efficiency within a generator, and (ii) firms achieve these efficiency gains with operational improvements rather than costly capital investments.

7.1 Mechanisms of Efficiency Improvements

We propose three mechanisms that could generate the estimated efficiency gain: (i) productive efficiency, (ii) dynamic efficiency, and (iii) portfolio efficiency. We first explain these mechanisms and then develop a prediction for each mechanism that can be tested in the data.

Productive Efficiency. The first mechanism that could generate efficiency change is productive efficiency. Productive efficiency arises when the plant's new owner adopts operational processes that lower production costs or invests in new equipment. This mechanism does not rely on synergies with other plants or changes in production profile; it arises because the new owner makes the plant more efficient. An implication of productive efficiency is the decline in the cost curve at every production level, illustrated in Figure 10. Based on this implication, a prediction of this mechanism is:

Prediction 1: If acquirers improve productive efficiency, the cost curve of production shifts down.

Dynamic Efficiency. The second mechanism is dynamic efficiency, which arises due to better production allocation over time. As discussed in Section 2.3, an important feature of power generation is that efficiency depends on both the level of production and the change in production. Plants with large production shifts incur ramp-up and ramp-down costs, which reduces overall efficiency. Since the demand is stochastic and not predictable, balancing production by considering 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 personnel, who choose a bidding strategy, and plant personnel, who observe marginal cost and control production. Optimizing these margins allows a firm to produce more with less input by adjusting the production profile even if the cost curve remains identical pre- and post-acquisition. Figure 11 demonstrates this effect where production is more concentrated around the efficient scale post-acquisition, implying less ramp-up

and ramp-down. A prediction of this mechanism is:

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

Portfolio Efficiency. The third mechanism to improve efficiency is portfolio effects. Plant owners solve complex optimization problems with thousands of parameters as they face stochastic demand and time-varying transmission constraints. Having multiple power plants with different production costs in the same market can give firms more flexibility and improve efficiency by allocating production optimally across power plants. This effect is illustrated in Figure 12. Since this mechanism is present only if firms have other plants in the same market, a prediction for portfolio efficiency is:

Prediction 3: The efficiency of the existing plants of the acquirer firm in the same market improves, but in other markets they remain the same.

7.2 Quantifying Mechanisms of Efficiency Gains

We start by testing for productive efficiency using an empirical strategy guided by Prediction 1. In particular, we estimate the cost curves as a function of production level and ramp (change in production):

$$y_{it} = f_{i\tau}(Q_{it}, r_{it}), \tag{7.1}$$

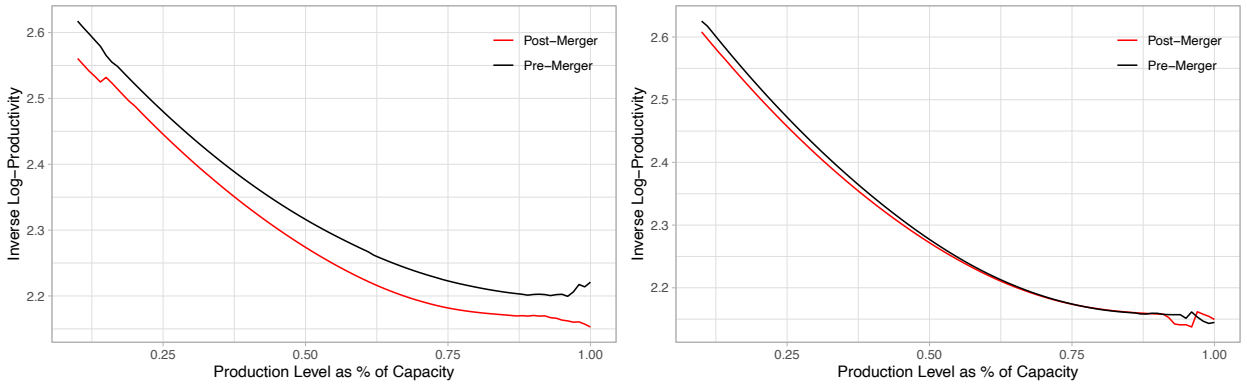
where y_{it} is heat rate, Q_{it} is production level as a percentage of the total capacity of generator i at time t, r_{it} is the ramp defined as the percentage change in production relative to $t-1$, and τ equals 1 in post-merger periods and 0 otherwise. We estimate the cost function for each generator separately using data one year prior to and one year after acquisition.[42] As a result, f_{i0} corresponds to the cost curve before the acquisition, and f_{i1} corresponds to the cost curve after the acquisition.[43]

It is worth highlighting two critical features of this exercise. 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 heterogeneity in production technology across generators. Second, different from our main specification, we estimate this regression using

[42]Since we find that efficiency increase starts a few months after acquisition, we exclude the first three months post-acquisition from the sample.

[43]We estimate these functions for generators that are operating more than 20% of the time in the window one year pre- and post-acquisition to improve precision in unit-specific cost curves. This excludes some generators that produce only during peak demand and others that are not active before acquisition. The results are robust to this sample restriction. The details of the estimation procedure are provided in Appendix B.2.

Figure 13: Estimated Average Cost Curves



(a) Treated Group (b) Control Group

Note: This figure shows estimates of average costs curves one year before acquisition and one year after acquisition. Panel (a) shows this for the treated group, and panel (b) is for the control group. The details of the estimation procedure is provided in Section B.2 and confidence band is shown in Appendix Figure 18.

hourly data to control for ramp. In addition, hourly level data makes it possible to estimate generator-specific cost functions, since the hourly data includes thousands of observations for each generator pre- and post-acquisition in a one-year window. This estimation highlights the advantage of the data-rich environment, as the traditional production function literature typically imposes a functional form at the industry level due to data limitations.

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

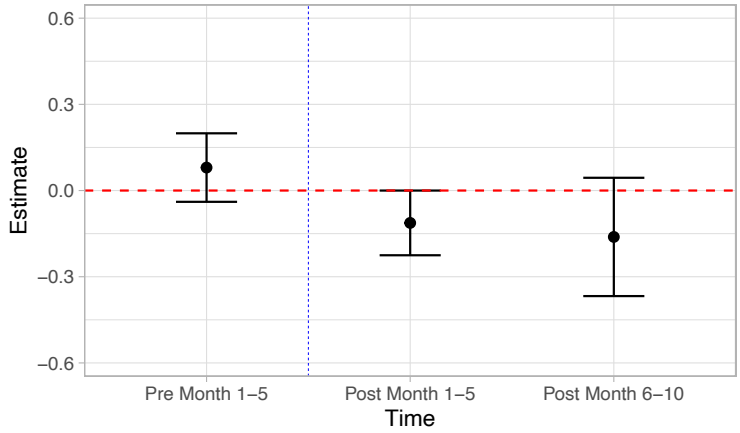
$$\Delta C(Q) = c_{post}(Q) - c_{pre}(Q) = \frac{1}{N_{acq}} \sum_{i}^{N_{acq}} f_{i1}(Q, 0) - \frac{1}{N_{acq}} \sum_{i}^{N_{acq}} f_{i0}(Q, 0),$$

where N_{acq} is the number of acquired generators, $Q \in (0, 100)$, and $c_{pre}(Q)$ and $c_{post}(Q)$ are the average cost at production level Q before and after acquisition. We set ramp level to zero to exclude the effects of ramp. The difference between these two functions gives us changes in productive efficiency at every production level.

Figure 13a displays $c_{pre}(Q)$ and $c_{post}(Q)$ for the acquired generators, and Figure 13b displays the same curves for the control generators.[44] Comparing the pre- and post-acquisition

[44]We construct the control group by matching treated generators to never treated ones on capacity, age and fuel type. The details of how the control units are constructed are given in Appendix B.2. We also provide

Figure 14: Change in Variation of Heat Rate



Note: Coefficient estimates from a regression of standard deviation of heat rate on treatment dummies using Equation (5.1). Error bars show 95% confidence intervals.

cost curves demonstrates that the average cost curve shifts down at every production level for the treated plants, but it does not change 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 it is not statistically significant. These results provide direct evidence that 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:

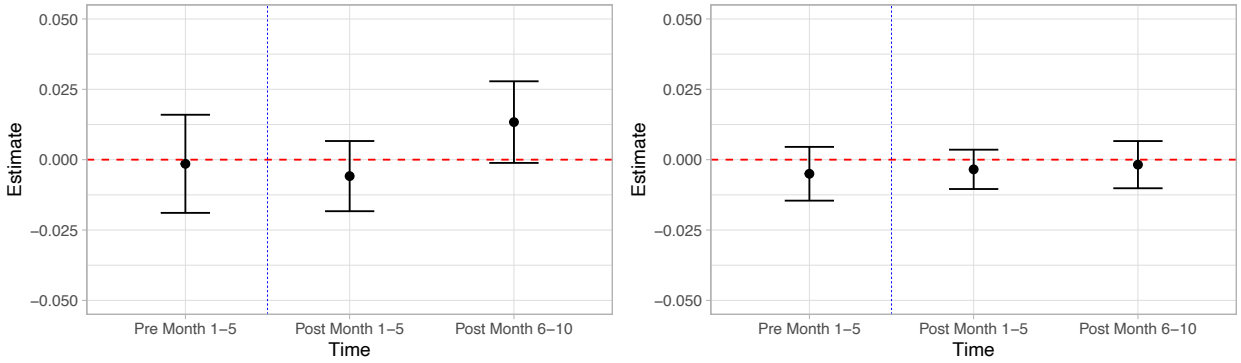
$$\Delta = \frac{1}{N_{acq}} \sum_{i}^{N_{acq}} \int \big(f_{i1}(Q,0) - f_{i0}(Q,0)\big) dF_i(Q),$$

where $dF_i(Q)$ is the distribution of production level of generator i before acquisition. This calculation yields an efficiency gain of 3.3%, corresponding to roughly 75% of the total efficiency gain identified in the previous section. Therefore, we conclude that most efficiency gains come from productive efficiency.

Next, we move to dynamic efficiency. According to Prediction 2, an increase in dynamic efficiency should reduce the standard deviation of heat rate after acquisition. To test this hypothesis, we estimate the same specification as in Equation (5.1), but use the weekly standard deviation of heat rate as the outcome variable. This regression includes

the bootstrapped standard errors for the difference between the two cost curves in Appendix Figure 18.

Figure 15: 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 where existing units of the acquirer in the acquisition market are treated. Panel (b) shows the results from the same regression, except that existing units of the acquirer in the different markets are treated. Error bars show 95% confidence intervals. Standard errors are clustered at the plant level.

acquisitions in which the acquirer does not have any existing plant in the same market to rule out portfolio efficiency. Figure 14 shows the results from this estimation. We find that the average standard deviation of the heat rate goes down after acquisition, but unlike the efficiency gain, the decline in the volatility of heat rate is realized more rapidly. Therefore, the acquirers not only improve production efficiency but also dynamically allocate production more efficiently over time to reduce ramp-up and ramp-down costs.[45]

Finally, we test the portfolio efficiency effects of acquisitions. According to Prediction 3, portfolio efficiency occurs only if the acquirer owns other plants in the same market, and plants in other markets should not be affected by portfolio efficiency. To test this prediction, we estimate Equation (5.1) twice, once where we treat the acquirer's generators in the acquisition market and once where we treat the acquirer's generators in different markets.[46] Figure 15 presents results for these regressions. Figure 15a shows the efficiency change of the generators owned by the acquirer and located in the same market as the acquired plant. Figure 15b shows the efficiency change of the generators 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%, whereas acquirers' power plants in different markets show no change in efficiency. This result indicates an efficiency increase for

[45]It is important to point out that the dynamic efficiency channel might not be mutually exclusive from the predictive efficiency channel. A marginal generator whose efficiency increases after acquisition will be infra-marginal more often and, therefore, experience less ramp.

[46]We assume power plants are in the same market if they are located in the same balancing authority.

acquirers' existing power plants, but only if they are in the same market, consistent with the portfolio efficiency mechanism. Moreover, we 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%, 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 mechanism with the largest effect is productive efficiency, explaining the majority of the total efficiency gain. The rest is explained by the combination of dynamic and allocative efficiency.

7.3 How Do Firms Improve Productive Efficiency?

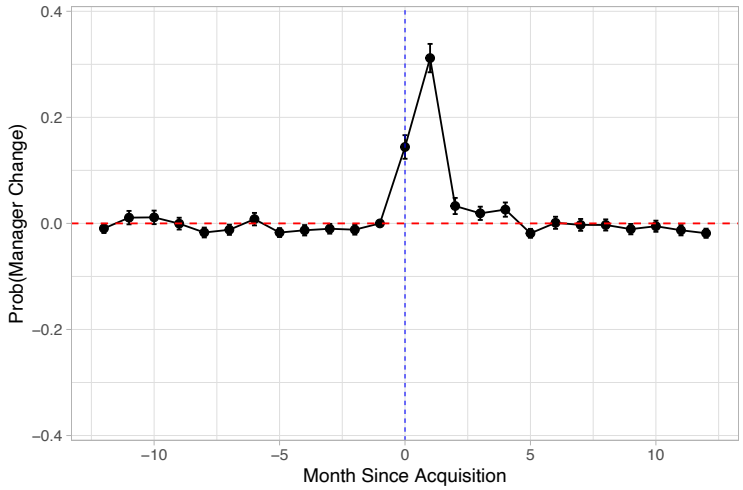
So far, we have provided evidence of an efficiency increase after ownership changes, and this efficiency increase primarily comes from an increase in productive efficiency. The next natural question is how firms achieve this efficiency gain. In this section, we investigate this question.

In Section 2.3, we posited two potential ways to improve productive efficiency of a plant. The first is that acquirers make operational improvements in the acquired plants. This mechanism would indicate knowledge transfer from the acquirer to the acquired generator. The second is large-cost capital investments, where acquirers upgrade the capital. If efficiency improvements occur this way, it would suggest that the previous owner has credit constraints or does not have incentives to make efficiency-improving capital investments. Disentangling these two sources of efficiency gains is important for antitrust policy because efficiency gains must be merger-specific to be considered cognizable.[47] Efficiency increases due to relaxing capital constraints are not merger-specific, as they can be accomplished without a merger, such as subsidizing capital investment. However, knowledge transfer is merger-specific since organizational knowledge is transferred between merging entities and is unlikely to be accomplished without a merger.

We disentangle the sources of productive efficiency improvements with additional datasets on manager changes and capital expenditures. In particular, we ask whether power plants experience personnel changes after acquisition and whether there is any significant change in capital expenditures. Personnel changes would provide suggestive evidence for significant operational changes after the acquisition, and changes in capital expenditures would provide direct evidence for the role of capital investment. Note that

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

Figure 16: Probability of Manager Change



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

the capital expenditure information is available only for investor-owned utilities between 2008 and 2020 because it is sourced from FERC Form 1.

We estimate the dynamic difference-in-differences specification given in Equation (5.2) to study whether power plant managers change after an acquisition. The outcome is an indicator variable that equals 1 if the power plant manager is replaced in a given month and 0 otherwise. We include the same control variables as before but estimate the regression at the monthly level. Results in Figure 16, show that the probability of management change jumps with the acquisition, with 15% of acquired power plants changing their managers within 1 month and 30% changing their managers within 2 months. The cumulative change is 55% within 12 months after acquisition.[48] These results suggest that acquired firms make operational changes through new management, potentially affecting efficiency. The potential role of management changes in explaining productivity differences is consistent with the findings in the literature. Macchiavello and Morjaria (2022) find that foreign acquirers improve the performance of coffee mills in Rwanda by implementing management changes, and Bloom and Van Reenen (2010) show that productivity measures correlate with various management practices.

We also investigate whether the characteristics of new managers after mergers differ from those of new managers without mergers. For a subset of managers, we observe

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

Table 4: Effects of Mergers on Non-fuel Costs

Dep. Var:	Non-fuel Cost	Number of Employees	Capital Expenditures
	(i)	(ii)	(iii)
Post-Merger × Treat	-0.068	-0.054	-0.020
	(0.053)	(0.031)	(0.032)
# of Acq	655	584	678
# of Obs	29325	26866	29418
R^2	0.62	0.92	0.86
Unit FE	X	X	X
Year FE	X	X	X

Note: This table presents the coefficient estimates from estimating the effects of mergers on non-fuel cost, number of employees and capital expenditures with annual data. Standard errors are clustered at the plant level.

whether the manager has a master's degree or a bachelor's degree. We find that these managers are 5 percentage points more likely to have a master's degree and 4 percentage points more likely to have a bachelor's degree compared to manager changes without mergers.[49,50]

Next, we turn to results from capital expenditures reported in Table 4. Since this variable is at the annual level, we estimate the difference-in-differences specification with yearly data. The coefficient estimate is negative and not significant, providing evidence that efficiency improvements do not occur due to increased capital expenditure. The timing of the efficiency effects also provides indirect evidence against the capital expenditure hypothesis. Large capital expenditures often take a long time to implement; therefore, it is not consistent with our findings that efficiency starts to increase five months after acquisition. Overall, the evidence in this section suggests that firms achieve productive efficiency through operational improvements rather than costly capital expenditures. This is consistent with the findings of Atalay et al. (2014), which finds evidence for transfers of intangible inputs rather than physical inputs in vertical mergers.

Finally, we turn to non-fuel variable inputs. In this paper, we measure the efficiency of a generator using fuel efficiency by ignoring other potential variable inputs such as labor,

[49] Another important question is whether mergers with manager changes explain the efficiency gain entirely. For this, we look at whether mergers with manager changes lead to larger efficiency gains. The results suggest that the effect is 2 percentage points larger, but it is not statistically significant.

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

water, and chemicals. A potential concern could be that plants substitute fuel for other variable inputs, improving fuel efficiency but reducing the efficiency of other inputs. Even though this is unlikely in power generation because inputs are generally not substitutable, it is still important to address. For this purpose, we also investigate how other inputs, labor and non-fuel cost, change after acquisition. The results, reported in columns (i) and (ii) of Table 4, indicate no significant increase in other inputs following an acquisition.

A natural question that follows our findings is why do not the previous owners implement these operational improvements. Since our study is an industry-level analysis rather than a case study, we cannot give an exact answer to this question. However, we want to emphasize that this result is not surprising considering the large evidence of persistent productivity differences across firms in many industries (Syverson, 2011; Gibbons and Henderson, 2012). Our reading of the evidence provided in this paper is that some firms develop intangible capital over time to operate power plants more efficiently, and this within-organization knowledge is transferable only through ownership changes. Therefore, mergers and acquisitions provide a channel for the intangible capital to spread across plants, which is unlikely to happen in other ways.

8 Robustness Checks

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

8.1 Acquisition Sample

In our estimations, we only use the first acquisitions of generators if they are acquired multiple times (63% of all treated generators). We take this approach because it is unclear how to correctly estimate the event study with generators acquired more than once. In this robustness check, we repeat our estimation procedure by including all acquisitions of generators if they are acquired more than once in our sample period. The results are broadly similar to our main results.

8.2 Estimation with Daily and Hourly Data

Our main specification estimates the effects of acquisitions with data at the weekly level because aggregation at the weekly level decreases computation time and reduces noise in the hourly data. To understand how robust our results are to this choice, we repeat

the estimation with daily and hourly data. The results are robust to estimation frequency, with some increase in standard errors.

8.3 Staggered Difference-in-Differences

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 the control unit in the pair could be a unit that is treated at a different time (De Chaisemartin and dHaultfoeuille, 2020; Callaway and SantAnna, 2021; Goodman-Bacon, 2021). To address this point, we estimate cohort-specific treatment effects using the Callaway and SantAnna (2021) method and find similar results.

8.4 Matching Difference-in-Differences

Our main specification uses standard difference-in-differences estimation estimated with two-way fixed effects. As a robustness check, we also consider a matching estimator. The matching estimator matches acquired generators to a similar generator and calculate generator-specific treatment effects by comparing them to match plants. We implement this estimation by identifying the three nearest neighbors from our sample pool of about 2,882 control (never-treated) units. We match on capacity, age, fuel type and heat rate at the time of the acquisition using a least-squares metric to calculate the distances between generation units, with weights inversely proportional to the standard deviation of each variable. We use our distance measure to select the three nearest neighbors for each acquired unit, allowing control units to be matched to multiple acquired plants. We exclude the generators in the same market from the pool of potential control plants due to potential spillover effects. This estimation method provides a robustness check against the mean reversion hypothesis because we match units based on their pre-treatment productivity level.

8.5 Weighted Difference-in-Differences

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 capacity, which would be a more accurate measure of total cost savings. The results from this specification suggest slightly higher efficiency effects, suggesting that the evidence does not primarily come from small units.

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 effects on productivity. This study provides detailed empirical analyses of the efficiency effects of mergers by examining a large sample of power plant mergers and acquisitions between 2000 and 2020. Our empirical results can be summarized into three principal findings. First, we find that acquired plants experience an average of 4% efficiency increase in five to eight months after acquisition, and most of this productivity increase is explained by improvements in productive efficiency. Second, our findings suggest that acquisitions reallocate assets to more productive uses: we find that high-productivity firms buy underperforming assets from low-productivity firms and make the acquired asset almost as productive as their existing assets after acquisition. Finally, we find that the new owners improve productivity by changing operational processes rather than by 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 measures 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 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. However, we want to emphasize that our results do not give a conclusive answer to the overall impact of mergers on consumer harm, as we identified only one factor going into the welfare analysis. Moreover, our efficiency results can not be generalizable to industries where the production process differs significantly from electricity generation, such as service industries. 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 firms suggests that mergers contribute to aggregate productivity growth in the power sector.

References

An, Yonghong and Wei Zhao (2019). "Dynamic Efficiencies of the 1997 Boeing-McDonnell Douglas Merger". *The RAND Journal of Economics* 50.3, pp. 666–694.

Ashenfelter, Orley C, Daniel S Hosken, and Matthew C Weinberg (2015). "Efficiencies Brewed: Pricing and Consolidation in the US Beer Industry". *The RAND Journal of Economics* 46.2, pp. 328–361.

Atalay, Enghin (2014). "Materials Prices and Productivity". *Journal of the European Economic Association* 12.3, pp. 575–611.

Atalay, Enghin, Ali Hortaçsu, and Chad Syverson (2014). "Vertical integration and input flows". *American Economic Review* 104.4, pp. 1120–48.

Atalay, Enghin et al. (2020). "Post-Merger Product Repositioning: An Empirical Analysis". *Federal Reserve Bank of Philadelphia Working Paper, WP 20-36*.

Bhattacharya, Vivek, Gaston Illanes, and David Stillerman (2022). "Have Mergers Raised Prices? Evidence from US Retail". *Working Paper*.

Bitzan, John D and Wesley W Wilson (2007). "Industry Costs and Consolidation: Efficiency Gains and Mergers in the US Railroad Industry". *Review of Industrial Organization* 30.2, pp. 81–105.

Blonigen, Bruce A. and Justin R. Pierce (2016). "Evidence for the Effects of Mergers on Market Power and Efficiency". *NBER Working Paper, 22750*.

Bloom, Nicholas and John Van Reenen (2010). "Why do Management Practices Differ Across Firms and Countries?" *Journal of Economic Perspectives* 24.1, pp. 203–24.

Bradley Associates, LLC (2017). "Powering America: The Economic and Workforce Contributions of the U.S. Electric Power Industry".

Braguinsky, Serguey et al. (2015). "Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry". *American Economic Review* 105.7, pp. 2086–2119.

Bushnell, James B. and Catherine Wolfram (2005). "Ownership Change, Incentives and Plant Efficiency: The Divestiture of US Electric Generation Plants". *Working Paper*.

— (2009). "The Guy at the Controls: Labor Quality and Power Plant Efficiency". *International Differences in the Business Practices and Productivity of Firms*. University of Chicago Press, pp. 79–102.

Callaway, Brantly and Pedro HC SantAnna (2021). "Difference in Differences with Multiple Time Periods". *Journal of Econometrics* 225.2, pp. 200–230.

Campbell, Richard J (2013). "Increasing the Efficiency of Existing Coal-fired Power Plants". *Congressional Research Service Washington, DC, USA*.

Chen, Yanyou (2021). "Network Structure and Efficiency Gains from Mergers: Evidence from US Freight Railroads". *Working Paper*.

Cicala, Steve (2015). "When does Regulation Distort costs? Lessons from Fuel Procurement in US Electricity Generation". *American Economic Review* 105.1, pp. 411–44.

— (2022). "Imperfect Markets versus Imperfect regulation in US Electricity Generation". *American Economic Review* 112.2, pp. 409–41.

Clark, Robert and Mario Samano (2020). "Incentivized Mergers and Cost Efficiency: Evidence from the Electricity Distribution Industry". *Available at SSRN 3703127*.

Craig, Stuart V, Matthew Grennan, and Ashley Swanson (2021). "Mergers and Marginal Costs: New Evidence on Hospital Buyer Power". *The RAND Journal of Economics* 52.1, pp. 151–178.

Dafny, Leemore, Kate Ho, and Robin S Lee (2019). "The Price Effects of Cross-Market Mergers: Theory and Evidence from the Hospital Industry". *The RAND Journal of Economics* 50.2, pp. 286–325.

Davis, Lucas W. and Catherine Wolfram (2012). "Deregulation, Consolidation, and Efficiency: Evidence from US Nuclear Power". *American Economic Journal: Applied Economics* 4.4, pp. 194–225.

De Chaisemartin, Clément and Xavier dHaultfoeuille (2020). "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects". *American Economic Review* 110.9, pp. 2964–96.

De Loecker, Jan and Frederic Warzynski (2012). "Markups and firm-level export status". *American Economic Review* 102.6, pp. 2437–71.

Dranove, David and Richard Lindrooth (2003). "Hospital consolidation and costs: another look at the evidence". *Journal of Health Economics* 22.6, pp. 983–997.

EIA (2003). "Status of State Electric Industry Restructuring Activity".

— (2020). "Annual Energy Outlook 2020".

Eliason, Paul J. et al. (2020). "How Acquisitions Affect Firm Behavior and Performance: Evidence from the Dialysis Industry". *The Quarterly Journal of Economics* 135.1, pp. 221–267.

EPA (2018). "Fact Street: Overview of the Clean Power Plan".

EPRI (2022). "Proceedings: 2022 EPRI heat-rate improvement conference".

Fabrizio, Kira R., Nancy L. Rose, and Catherine D. Wolfram (2007). "Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on US Electric Generation Efficiency". *American Economic Review* 97.4, pp. 1250–1277.

Fan, Ying and Chenyu Yang (2020). "Merger, product variety and firm entry: The retail craft beer market in California". *Available at SSRN 3681556*.

Farrell, Joseph and Carl Shapiro (1990). "Horizontal Mergers: An Equilibrium Analysis". *The American Economic Review*, pp. 107–126.

— (2010). "Antitrust Evaluation of Horizontal Mergers: An Economic Alternative to Market Definition". *The BE Journal of Theoretical Economics* 10.1.

Fitzgerald, Patrick and Jenifer Gelorme (2015). "Thermal Cycling, Air In-Leakage Impact On Heat Rate, Emissions and Cost of Compliance". *2015 Heat Rate Improvement Conference*.

Focarelli, Dario and Fabio Panetta (2003). "Are mergers beneficial to consumers? Evidence from the market for bank deposits". *American Economic Review* 93.4, pp. 1152–1172.

Foster, Lucia, John Haltiwanger, and Chad Syverson (2008). "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98.1, pp. 394–425.

Gibbons, Robert and Rebecca Henderson (2012). *What do managers do?: Exploring persistent performance differences among seemingly similar enterprises*. Citeseer.

Goodman-Bacon, Andrew (2021). "Difference-in-Differences with Variation in Treatment Timing". *Journal of Econometrics* 225.2. Publisher: Elsevier, pp. 254–277.

Grieco, Paul, Joris Pinkse, and Margaret Slade (2018). "Brewed in North America: Mergers, Marginal Costs, and Efficiency". *International Journal of Industrial Organization* 59, pp. 24–65.

Harrison, Teresa D (2011). "Do Mergers Really Reduce Costs? Evidence from Hospitals". *Economic Inquiry* 49.4, pp. 1054–1069.

Jensen, Michael C (1986). "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers". *The American Economic Review* 76.2, pp. 323–329.

Jeziorski, Przemysław (2014). "Estimation of Cost Efficiencies from Mergers: Application to US Radio". *The RAND Journal of Economics* 45.4, pp. 816–846.

Jovanovic, Boyan and Peter L. Rousseau (2002). "The Q-Theory of Mergers". *American Economic Review* 92.2, pp. 198–204.

— (2008). "Mergers as Reallocation". *The Review of Economics and Statistics* 90.4. Publisher: The MIT Press, pp. 765–776.

Knittel, Christopher R. (2002). "Alternative Regulatory Methods and Firm Efficiency: Stochastic Frontier Evidence from the US Electricity Industry". *Review of Economics and Statistics* 84.3, pp. 530–540.

Kulick, Robert B (2017). "Ready-to-Mix: Horizontal Mergers, Prices, and Productivity". *US Census Bureau Center for Economic Studies Paper No. CES-WP-17-38*.

Lewis, Matthew S and Kevin E Pflum (2017). "Hospital Systems and Bargaining Power: Evidence from Out-of-Market Acquisitions". *The RAND Journal of Economics* 48.3, pp. 579–610.

Luco, Fernando and Guillermo Marshall (2020). "The Competitive Impact of Vertical Integration by Multiproduct Firms". *American Economic Review* 110.7, pp. 2041–64.

Macchiavello, Rocco and Ameet Morjaria (2022). "Acquisitions, Management, and Efficiency in Rwanda's Coffee Industry".

Malmendier, Ulrike, Enrico Moretti, and Florian S Peters (2018). "Winning by losing: Evidence on the long-run effects of mergers". *The Review of Financial Studies* 31.8, pp. 3212–3264.

McGuckin, Robert H. and Sang V. Nguyen (1995). "On Productivity and Plant Ownership Change: New Evidence from the Longitudinal Research Database". *The RAND Journal of Economics*, pp. 257–276.

Mercadal, Ignacia (2022). "Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Players". *American Economic Journal: Microeconomics* 14.3, pp. 665–699.

Nguyen, Sang V and Michael Ollinger (2006). "Mergers and Acquisitions and Productivity in the US Meat Products Industries: Evidence from the Micro Data". *American Journal of Agricultural Economics* 88.3, pp. 606–616.

Niefer, Mark J (2012). "Explaining the Divide Between DOJ and FERC on Electric Power Merger Policy". *Energy LJ* 33, p. 505.

Nocke, Volker and Michael D Whinston (2022). "Concentration Thresholds for Horizontal Mergers". *American Economic Review* 112.6, pp. 1915–48.

Prager, Elena and Matt Schmitt (2021). "Employer Consolidation and Wages: Evidence from Hospitals". *American Economic Review* 111.2, pp. 397–427.

Rhodes-Kropf, Matthew and David T. Robinson (2008). "The Market for Mergers and the Boundaries of the Firm". *The Journal of Finance* 63.3, pp. 1169–1211.

Roll, Richard (1986). "The Hubris Hypothesis of Corporate Takeovers". *Journal of business*, pp. 197–216.

Sargent & Lundy, LLC (2009). "Coal-Fired Power Plant Heat Rate Reductions". *LLC Sargent & Lundy*.

Schmitt, Matt (2017). "Do Hospital Mergers Reduce Costs?" *Journal of health economics* 52, pp. 74–94.

Schoar, Antoinette (2002). "Effects of Corporate Diversification on Productivity". *The Journal of Finance* 57.6, pp. 2379–2403.

Setzler, Bradley (2022). *DiDforBigData: A Big Data Implementation of Difference-in-differences Estimation with Staggered Treatment*. R package version 0.1. URL: https://github.com/setzler/DiDforBigData.

Staudt, James E. and Jennifer Macedonia (2014). "Evaluation of Heat Rates of Coal Fired Electric Power Boilers". *Power Plant Pollutant Control âĂIJMEGAâĂİ Symposium*, pp. 19–21.

Syverson, Chad (2011). "What Determines Productivity?" *Journal of Economic Literature* 49.2, pp. 326–365.

Weber, Roberto A and Colin F Camerer (2003). "Cultural Conflict and Merger Failure: An Experimental Approach". *Management science* 49.4, pp. 400–415.

Williamson, O (1968). "Economies as an Antitrust Defense: The Welfare Tradeoffs". *American Economic Review*, pp. 18–36.

Appendix - For Online Publication

A Data Appendix

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

A.1 Unit-Level Data

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

Generation Most fossil fuel power plants are required under the EPA regulations for continual compliance determinations of environmental regulation. For this purpose, EPA collects boiler-level hourly production data (heat rate, input, and output) from power plants and makes this data publicly available. The coverage of this data corresponds to roughly 95% of fossil-powered generation in the US. While this data is available starting in 1995, the data quality is poor before 2000. For this reason, we restrict the study period from 2000 to 2020. We also eliminate generators that are not active for more than 10% of their lifetime based on weekly operations. With these restrictions, the final data includes all US fossil fuel generators that comply with the CEMS program, except those in Alaska and Hawaii and those that are active less than 10% of their lifetime. This procedure results in an hourly unit-level dataset on generation fuel input and heat rate between 2000 and 2020. We aggregate this data to daily to weekly levels in some of the analyses employed in the paper.

Heat rate observation is calculated by dividing the total heat input by the total electricity output for an hour. If there are significant changes in the production within the hour, the heat rate could be very high or very low. This sometimes generates noise in hourly heat rates, especially at small production levels. To account for this, we winsorize heat rates above 16 or below 6 MMBtu per MWh. This winsorization affects less than 1% of all observations.

We match unit-level generation data from CEMS to unit-level data from the other data sources mentioned above. While most units are easily matched using the unit name, some do not match as EPA uses boilers as a unit, whereas EIA uses generator names. For those cases, we rely on the EPA's Power Sector Data Crosswalk available on the EPA's website.[51] This crosswalk does not include units that retired before 2020. We manually match those retired and other unmatched units based on capacity, installation year, and retirement year information.

Gross vs. Net Generation The generation and heat rate provided by the EPA are based on gross generation, including the ancillary services, other non-market products, and consumption at the unit, such as scrubbers. For our study, gross generation is the relevant variable for understanding the overall efficiency of power plants since we study how fuel is transformed into electricity, not revenue obtained from net generation.

Capacity EPA data does not provide capacity data. Therefore, we need to assign a capacity for those units that do not exactly match the EIA and CEMS data. We infer yearly capacity from their generation using the following algorithm for these units. For each year, we keep generators that operate cumulatively for more than two weeks each year. Then, we obtain the annual hourly generation distribution and use the 99th percentile of the generation as the capacity for the unit every year. This algorithm yields generator capacity that is stable over time for most units. However, for some units, there is a significant variation year-to-year with no apparent capacity change at the EIA plant-level data. We take the unit's maximum capacity for consecutive years in these cases. To check the accuracy of this algorithm, we run it for the units that have a perfect match in the EPA and EIA, for which we have the true capacity information. We find that capacity generated from the EPA data aligns with those provided by the EIA.

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

A.2 Plant-Level Data

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

Regulation To identify ownership changes due to deregulation, we use Cicala (2022)'s deregulation list from 2000 to 2012. After 2012, we rely on EIA Form 860's regulation status for plants. Using this dataset, we flag ownership changes that coincide with a change in the regulation status, and we exclude those from the merger sample. This results in a total of 181 plants between 2000 and 2020 that we remove from the merger sample.

A.3 Load Data and Market Definition

We collect data on hourly demand and market definition. Market definition in electricity markets is more complex than in other industries due to nodal pricing and time-varying congestion. An accurate time-varying market definition is particularly important for market power considerations (Mercadal, 2022). Since we do not study the market power effects of mergers and need market definition only for accounting for potential synergies, we define ISO as market and rely on Velocity Suite for plants' corresponding ISOs. This simple market definition could potentially understate any evidence of the portfolio effects of mergers, so our estimate will be conservative.

Hourly data on electricity usage (load) is obtained from S&P Global either at the Balancing Authority Areas (BAA) or ISO Zone level, depending on data availability. We also use FERC Form 714 to obtain data on the fuel composition of total generation. FERC Form 714 treats Power Control Areas (PCA) as markets; the PCA market definition overlaps with our ISO market definitions for the deregulated plants and gives further granularity to regulated plants. Before 2006, data from FERC Form 714 was incomplete, so we assembled data on load after 2006. We rely on the EIA's market definitions to match load data with plants, resulting in data on load for roughly 70% of the plants.

A.4 Personnel Data

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

This procedure results in monthly plant-level panel data on plant managers. In this data, we know the manager's start and end date of tenure, employment history, and education history.

A.5 Ownership Data

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

The first dataset includes all shareholders (name and company ID) of a generator, the percent of shares owned by each shareholder, and the date of the ownership change. This dataset is updated for a given generator when there is a change in the generator's owners. In particular, for every ownership change, we observe previous and new shareholders. We turned this data into a month-generator panel dataset and included the largest three shareholders of every generator in this panel. This panel data includes the ownership history of each generator between the installation date and the retirement date (if any). Another advantage of this dataset is that it provides information on the subsidiary that owns the generator and the parent company that owns the subsidiary. Therefore, we can

see the corporate structure of the owner of this power plant. S&P Global backfills any company name change, so firm name changes do not affect the ownership structure significantly over time. To summarize, this procedure results in a month-generator panel data with the following information: the largest three shareholders of the generator, the parent company of each shareholder, and the percentage of the power plant owned by each shareholder.

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

Next, we merged the two datasets using transaction ID and company names, which gives us a complete picture of ownership changes, including new and previous owners and important merger characteristics. After merging these datasets, we removed the ownership changes we identified as false ownership changes from the transaction data. This gave us the final sample of data on ownership changes.

A.6 Firm Data

Even though the transaction data provides useful information about buyers and sellers, we used Capital IQ to obtain more information about companies involved in transactions. For this purpose, we merged company balance sheet data from Capital IQ with the ownership data from S&P Global. This data merge is straightforward for about 80% of the companies since S&P Global and Capital IQ use the same company ID for them. For the rest of the companies, we manually searched for company names in Capital IQ and matched those to the ownership data. We could match all company names except for a few companies that went bankrupt or were company funds. This firm data provides information such as industry, year founded, asset size, and various balance sheet information.

A.7 Sample Restrictions

Before employing the empirical analysis, we made some other sample restrictions. This section describes those restrictions. We first took month-unit level ownership data for fossil fuel generators from S&P Global between 2000 and 2020, which rely on EIA data for unit definitions. We removed a few power plants with missing ownership data for the entire study period.

Since S&P Global uses the EIA definition of units and our production data is based on the CEMS definition of units, we need to match the ownership data to CEMS data. This match is mostly straightforward because all generators operating in a power plant are typically owned by the same companies. We rarely observed that different units in a plant are owned by different companies. For those cases, we used the matching procedure described above. After the match, we removed units in S&P Global that are missing in CEMS data. Some units in CEMS data produce only steam. Moreover, some units still need production data in our observation period. We remove these units from our sample in both cases.

B Estimation Details

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

B.1 Estimation of Residual Productivity

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

We estimate regressions with a rich set of observables and fixed effects to obtain residual productivity. In particular, in the first step, we use weekly heat rate data aggregated from hourly data and regress the logarithm of the inverse heat rate on time-varying observed plant characteristics and unit-year indicators. These time-varying variables include week fixed effects, state-month fixed effects, regulation status, total load, the number of idle hours, the standard deviation of heat rate, and the number of times the production increases by more than 2% and 5% in that week. By controlling for these factors, we account for the potential effects of production profiles on efficiency. In the second step, we take the estimated unit-year fixed effects and regress them on time-invariant unit characteristics that include capacity, fuel type, boiler manufacturer, and generator model.[52] The second regression accounts for productivity differences that are explained by observable generator characteristics. We use the estimated residuals from this second regression and plot them in Figure 2. The time-varying observables in the first-step regression explain 45% of the variation in weekly heat rate, and the time-invariant observables explain 42% of the remaining variation in the second step.

B.2 Cost Curve Estimation

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

We estimate the cost curves for treated and control groups separately. We use the sample of acquired generators used to estimate in Equation (5.2) for the treated group. Then, we take the production profile of these generators one year preceding the merger and one

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

year following the merger. We remove generators from the sample if a generator is inactive more than 80% of the time, either during the pre-period or post-period. The results are robust to this restriction, but they are unstable because, for rarely active generators, the cost curve is noisy. With this sample, we non-parametrically estimate the cost curve using Local Polynomial Regression Fitting in R. In particular, we use the loess function in R with the default tuning parameters.

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

We estimate the confidence band for the difference between pre-and post-acquisition cost curves for the treated generators using a bootstrap procedure. We re-sample the treated generators with replacement and estimate the cost curve for the sample. We repeat this 200 times and report the 0.025 and 0.975 percentiles of the bootstrap distribution.

B.3 Calculation of Fuel and CO_2 Emission Savings

To quantify the impact of the efficiency gains resulting from the mergers, we calculate the changes in fuel usage and CO_2 emissions. First, we assume that after the merger, generators would produce the same amount of electricity than they would have if they had not been acquired. Second, we assume that CO_2 emissions are linearly increasing with heat rate, and CO_2 emissions are roughly 0.4 tons per MWh for gas-fired power plants and 1 ton per MWh for coal-fired power plants. Lastly, for natural gas, we assume 3$ per MMBtu and for coal 50$ per ton; both are conservative estimations of average fuel prices in the US.

Given the set of assumptions, we first calculate the fuel savings for acquired power plants. We calculate the total MMBtu in natural gas and ton in coal fuel savings separately. We find a cumulative 6 billion dollars in savings in fuel costs. For the CO_2 calculation, we first calculate the fuel savings for the acquired units, ignoring the potential extra emission savings due to ramp up and ramp down. For the 10% change in production, we conservatively assume that the production would have been replaced by natural gas generators rather than coal-fired power plants. With this set of assumptions, the total cumulative decline in CO_2 emissions between 2000 and 2020 is roughly 50 million tons. This corresponds to the emission reduction from replacing 110 TWh generation from fossil plants with renewables, assuming 80% of the savings came from natural gas and the rest from coal-fired

power plants. With the assumption of a 30% utilization rate of wind power plants, this is roughly equal to 2 GW capacity investment in wind power plants from 2000 to 2020.

B.4 Heterogeneity Analysis

This section provides the estimation details for the heterogeneity analysis that are presented in Section 5.3.

To increase the power in detecting heterogeneity, we consider a standard event study setting where we include a post-treatment dummy variable and interact with the variable for which we want to understand heterogeneity. In particular, we estimate the following specification:

$$\log(y_{it}) = \theta_1 D_{it} + \theta_2 \text{Treat}_{it} D_{it} \times Z_{it} + X_{it} + \mu_t + \alpha_i + \epsilon_{it},$$

where y_{it} is the efficiency of generator i at week t (measured as inverse heat rate given in Equation (2.1), the controls, X_{it}, include state-month fixed effects, time-varying generator characteristics such as age and fuel type (for coal), capacity, indicators for whether the unit is connected to the grid and whether it is an internal generator. α_i is generator fixed effect and μ_t is week fixed effect. Z_{it} is a plant, firm, or transaction characteristic for which we would like to test heterogeneity. The results report the estimates of θ_3.

B.4.1 Plant Characteristics

- **Gas Plant:** An indicator variable that equals 1 if the acquired unit is powered by natural gas and 0 otherwise. Since most of the acquired natural gas-fired power plants, this variable equals 1 for 90% of transactions.
- **Plant Age $>$ Median** An indicator variable that equals 1 if the age of the acquired unit is larger than the median. We consider all the units in our main specification to calculate the median age and find the median value.
- **Unregulated Plant:** An indicator variable that is 1 if the plant is unregulated and 0 otherwise.
- **Unit Capacity $>$ Median:** An indicator variable that equals 1 if the age of the acquired unit is larger than the median. To calculate the median capacity, we consider all the units in our main specification and find the median capacity.

- **infra-marginal Plant:** An indicator variable that equals 1 if the acquired plant is infra-marginal and 0 otherwise. This categorization is provided by Velocity Suite, which classifies plants as base load or peaker units.

B.4.2 Firm Characteristics

- **Target Exits:** An indicator variable that equals 1 if the target firm owns no fossil fuel power plants post-transaction and zero otherwise.
- **Acquirer Enters:** An indicator variable that equals 1 if the acquirer firm owns no fossil fuel power plants pre-transaction and 0 otherwise.
- **Financial Aquirer:** An indicator variable that equals 1 if the acquirer is a financial firm and zero otherwise. The firm classification is obtained from Capital IQ Pro.
- **Acquirer Size $>$ Median:** An indicator variable that equals 1 if the total capacity of the acquirer pre-transaction is larger than the median capacity of firms that have been involved in a transaction between 2000 and 2020.
- **Serial Acquirer:** An indicator variable that equals 1 if the total capacity acquired by the acquirer between 2000 and 2020 is larger than the median of the total capacity acquired by firms between 2000 and 2020.

B.4.3 Deal Characteristics

- **Deal Value $>$ Median:** An indicator variable that equals 1 if the total transaction value (including assets other than power plants) and 0 otherwise.
- **Year$>$2010** An indicator variable that equals 1 if the acquisition occurs later after 2010 and 0 otherwise.
- **Acquirer's Capacity in the Market$>$Median:** An indicator variable that equals 1 if the acquirer's capacity in the ISO where the plant is located is greater than the median capacity.
- **Acquired Capacity $>$ Median:** An indicator variable that equals 1 if the total fossil fuel plant acquired capacity in the transaction is larger than the median.
- **LBO Deal:** An indicator variable that equals 1 if the transaction is a leveraged buy-out.

C Robustness Checks

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

C.1 Acquisition Sample

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

The first robustness check includes all acquisitions except those within 32 months of each other. We drop these acquisitions because the post- and pre-acquisition periods overlap. Using this sample, we estimate Equation (5.1) with the following differences. First, for each event, we include post-treatment indicator variables 16 months following the acquisition, and we include pre-treatment indicator variables 16 months before the acquisition. The treatment variables are set to 0 for 16 months after acquisition and 16 months before the next acquisition. Therefore, we assume that treated plants follow the same trend as the control group between the two acquisitions. The results from this estimation procedure are reported in Appendix Figure 30 and Table 13. The estimates are similar to the results from our main specification.

C.2 Data Frequency

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

Estimation with daily data follows the same steps as the estimation in weekly data. We aggregate fuel input and electricity output to a daily level and define daily efficiency as total daily electricity input divided by total daily fuel input. The treatment variables are monthly indicator variables for each month 16 months before and 16 months after acquisition. We estimate the same specification as in Equation (5.1), but include the day of the

week as an additional control variable. Since the day of the week is a strong determinant of electricity demand, estimation with daily data controls for demand fluctuations more accurately. The results from this estimation are reported in Appendix Table 10 and Figure 27. The effect of ownership changes on efficiency is similar to what we found with the weekly data.

In the estimation with hourly data, we use the raw data obtained from CEMS, hourly electricity output, and fuel input without any processing. We consider the same specification as weekly and daily data, but the hour of the day as an additional control. Since the hour of the day is a strong determinant of electricity demand, the hourly specification controls for electricity demand much more precisely than daily and hourly data. The results from this estimation are reported in Appendix Table 11 and Figure 28. The effect of mergers on efficiency is similar to the results with weekly data. However, estimates are less precise since hourly data is noisier than weekly and daily data.

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

C.3 Staggered Difference-in-Differences

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

To implement the procedure, we use the R package DiDforBigData (Setzler, 2022), which provides a big-data-friendly and memory-efficient difference-in-differences estimator for staggered treatment contexts. The results, which are similar to our main set of estimates, are reported in Appendix Figure 32.

C.4 Matching Difference-in-Differences

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

We match each of our 2,365 acquired units to the three nearest neighbors from the pool of 2,882 control units that have never been acquired during our sample period. For each treated unit, we first find the never-treated active units during the acquisition time with the same fuel type and in a different ISO (to prevent spillovers). This never-treated sample constitutes the pool of candidate control units for that unit. Then, we find the nearest neighbor units on capacity and age using a least-squares metric to calculate the distances between generation units. The weights in the metric are inversely proportional to the standard deviation of the corresponding variable. We allow control units to be matched to multiple acquired plants. Using these nearest neighbors, we calculate the unit-specific treatment effect as follows:

$$\widehat{\Delta} Y_{it} = Y_{it}(1) - \widehat{Y}_{it}(1), \tag{C.1}$$

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

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

The results from this estimation are reported in Appendix Figure 29. We find that results are qualitatively similar to our main specification.

C.5 Observation Weights

In our regressions, we weighted units equally. A natural alternative to this is to weigh them by generator capacity, which would be robust to a potential concern that all efficiency gains come from small units. Moreover, it would be more informative about the total production affected by efficiency gains. To investigate this, we estimate Equations (5.1) and (5.2) by weighting units by their capacity in that year. The results from this estimation are reported in Appendix Table 12 and Figure 31. We find that the efficiency effect is slightly larger when we weigh units by capacity, which is consistent with the findings reported in Figure 8 that the efficiency effect is larger for larger units. This finding also indicates that

acquisitions of small units do not drive our main results.

D Additional Tables and Figures

Table 5: Largest 25 Acqusitions by Fossil Fuel Power Plant Capacity

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

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

Table 6: Regression Results for Identifying Mechanisms of Efficiency Gains

	Owner's Existing Assets in the Same Market (i)	Owner's Existing Assets in Different Market (ii)	Standard Deviation of Heat Rate (iii)
Late-Pre	0.004	0	0.08
	(0.006)	(0.003)	(0.061)
Early-Post	-0.004	-0.002	-0.113
	(0.005)	(0.003)	(0.057)
Late-Post	0.015	0.001	-0.161
	(0.006)	(0.004)	(0.105)
R2	0.628	0.625	0.514
# of Obs	1.4M	1.68M	1.22M
# of Acq	897	897	583
Unit FE	X	X	X
State by Month FE	X	X	X
Week FE	X	X	X

Note: This table presents the coefficient estimates from estimating Equation (5.1) for different outcome variables and samples. Column (i) estimates the effects of acquisitions on productivity by treating the acquirer's existing plants that are in the acquisition market. Column (ii) estimates the effects of acquisitions on productivity by treating the acquirer's existing plants that are in different markets. When estimating these equations, we remove all other acquired plants from the sample so the control group is the never-treated group. In column (iii) we estimate the effects of acquisitions on the weekly standard deviation of heat rate calculated from hourly data. This regression excludes acquisitions in which the acquirer has any existing plant in the same market to rule out portfolio effects. All standard errors are clustered at the plant level.

Table 7: Heterogeneity Coefficients: Plant Characteristics

	Gas Plant	Plant Capacity > Median	Unregulated Plant	Plant Age > Median	Infra-marginal Plant
Post x Treat	0.007	-0.017	-0.023	0.015	-0.01
	(0.022)	(0.007)	(0.016)	(0.009)	(0.007)
Post x Treat x Z	0.026	0.079	0.064	0.034	0.085
	(0.022)	(0.012)	(0.018)	(0.015)	(0.013)
# of Acquired Units	897	897	897	897	897
# of Units with ($Z = 1$)	809	448	777	416	297
# of Obs (M)	1.19	1.19	1.19	1.19	1.19
Adj. R2	0.638	0.638	0.638	0.638	0.638
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

Note: Estimates of θ_2 from Equation (5.3) for plant characteristics. Standard errors are clustered at the plant level.

Table 8: Heterogeneity Coefficients: Firm Characteristics

	Financial Acquirer	Serial Acquirer	Target Exits	Acquirer Enters	Acquirer Size > Median
Post x Treat	0.029	0.011	0.039	0.037	0.016
	(0.009)	(0.008)	(0.01)	(0.009)	(0.007)
Post x Treat x Z	0.014	0.053	-0.017	-0.019	0.028
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
# of Acquired Units	897	897	897	897	897
# of Units with ($Z = 1$)	199	430	393	236	421
# of Obs (M)	1.19	1.19	1.19	1.19	1.19
Adj. R2	0.638	0.638	0.638	0.638	0.638
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

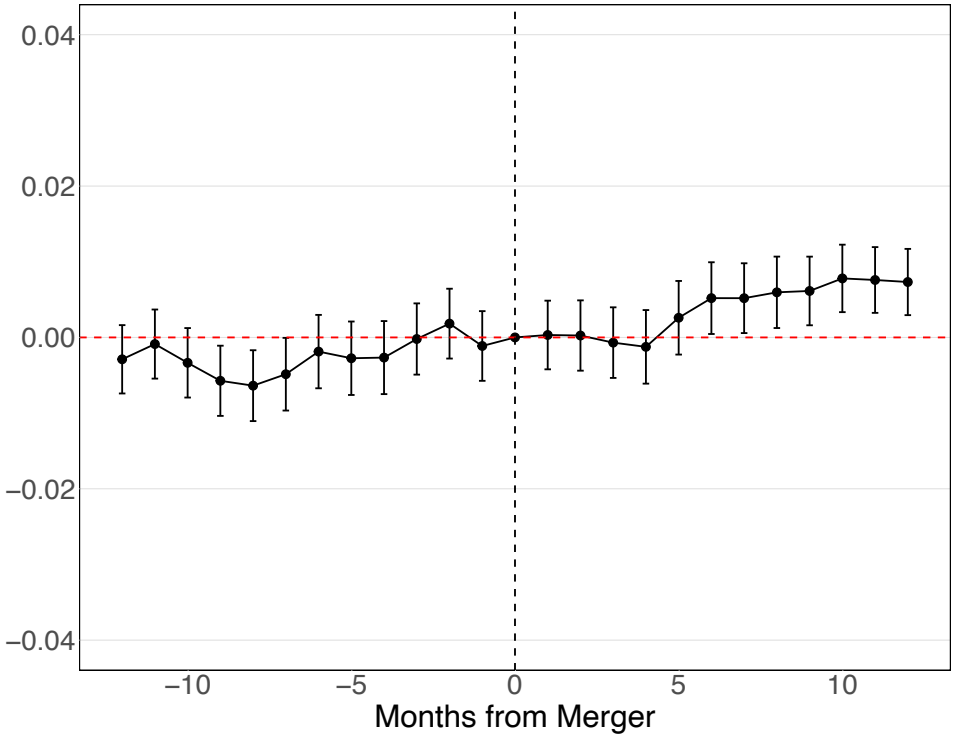
Note: Estimates of θ_2 from Equation (5.3) for firm characteristics. Standard errors are clustered at the plant level.

Table 9: Heterogeneity Coefficients: Transaction Characteristics

	Acquired Capacity $>$ Median	Acquirer's Capacity in the Market $>$ Median	LBO Deal	Year $>$ 2010	Trans. Value $>$ Median
Post x Treat	0.009	-0.001	0.031	0.016	0.023
	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)
Post x Treat x Z	0.056	0.058	0.005	0.026	0.034
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
# of Acquired Units	897	897	897	897	897
# of Units with ($Z = 1$)	448	407	60	374	193
# of Obs (M)	1.19	1.19	1.19	1.19	1.19
Adj. R2	0.638	0.638	0.639	0.638	0.638
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

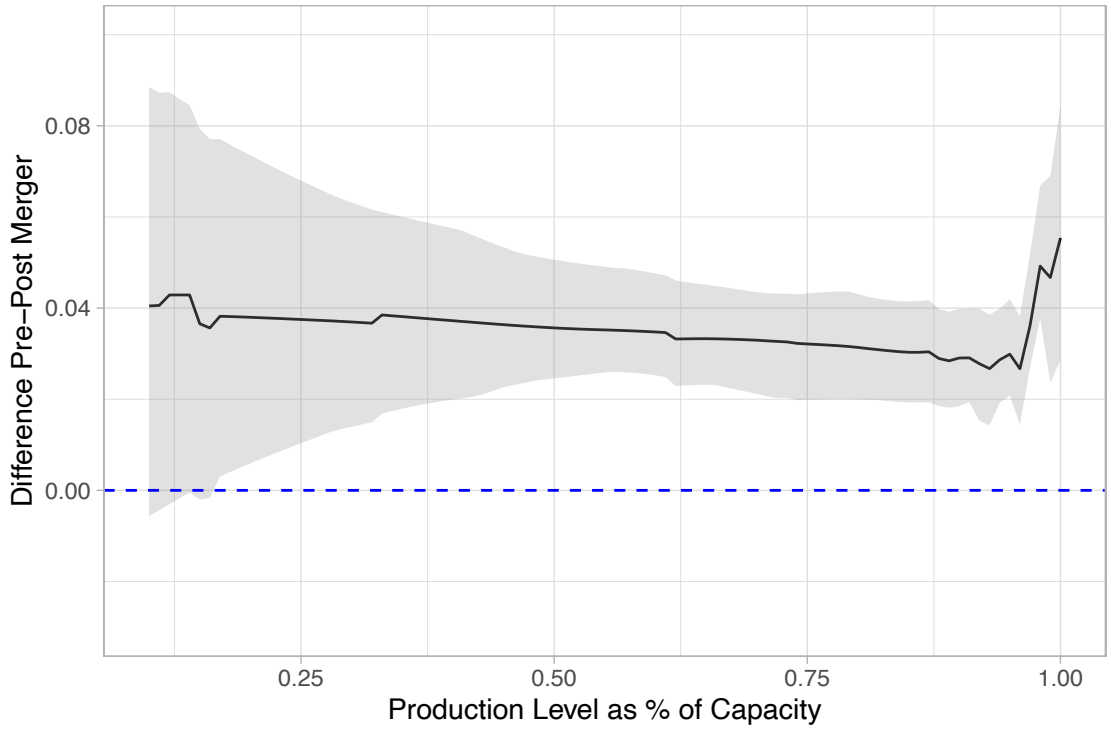
Note: Estimates of θ_2 from Equation (5.3) for transactions characteristics. Standard errors are clustered at the plant level.

Figure 17: The Effect of Manager Change without Mergers on Efficiency



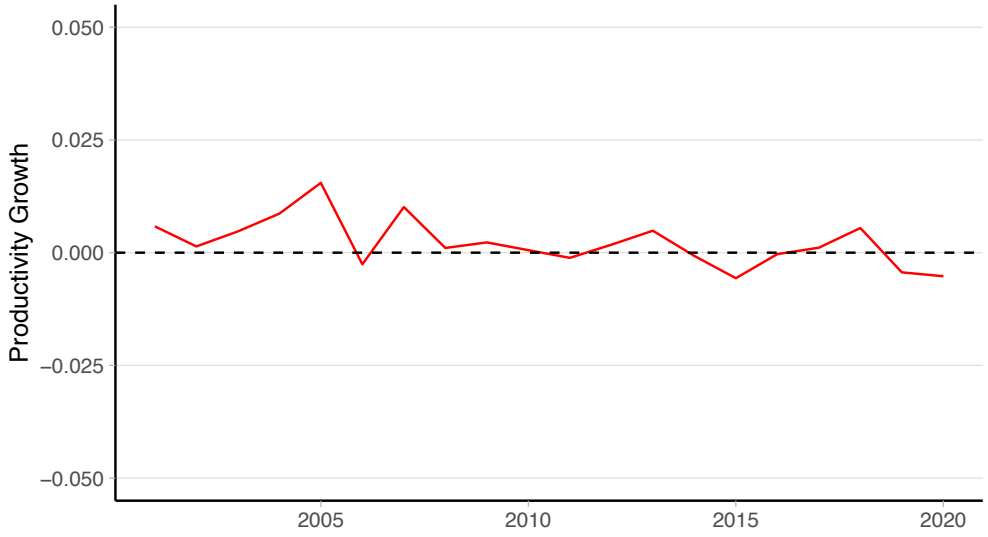
Note: This figure shows the effects of manager change on efficiency estimated using the specification given in Equation (5.2). In particular, we treat a unit if the manager of that unit changes and there is no acquisition in the three months preceding and following the manager change.

Figure 18: Confidence Band for Cost Curve Differences



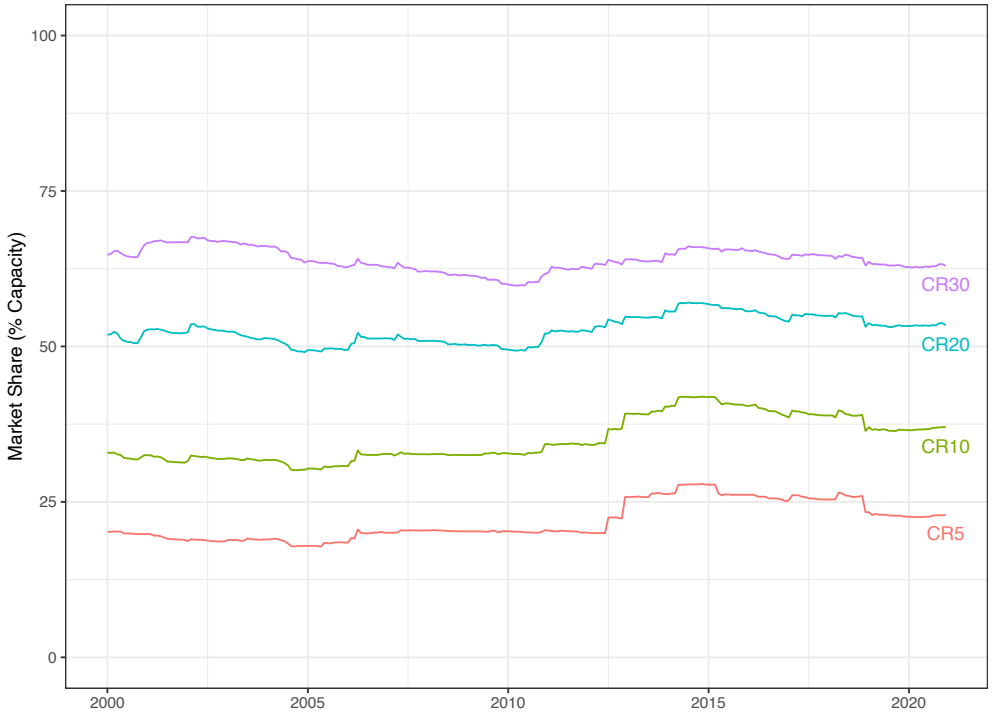
Note: This figure shows the 95% confidence interval for the difference between treated firms' cost curves pre- and post-merger, as reported in Figure 13a. The estimates are reported from 200 bootstrap replications.

Figure 19: Average Within-Plant Annual Productivity Change



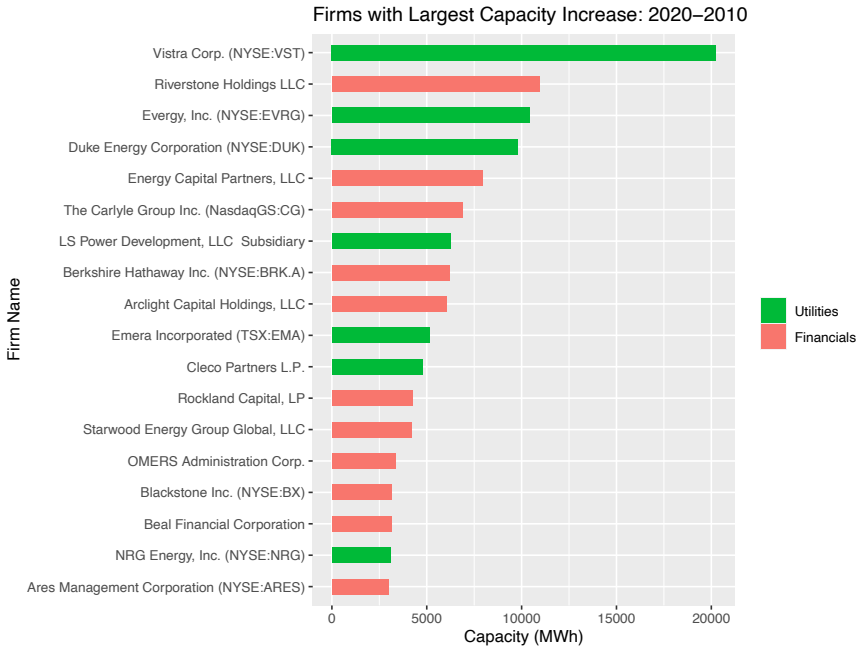
Note: This figure shows average year-to-year within-plant productivity growth for the plants that were not involved in an acquisition.

Figure 20: Change in Market Concentration



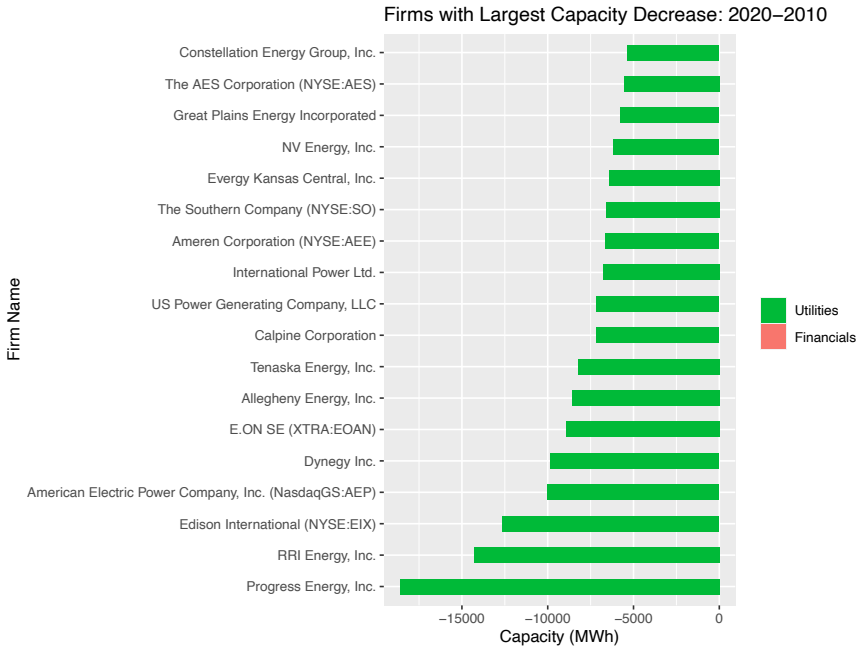
Note: This figure shows the change of national concentration ratios in the overall US fossil fuel power plant market between 2000 and 2020. For every concentration ratio, we calculate the total fossil fuel capacity of the largest corresponding number of firms in the US and divide that by the total fossil fuel capacity in the US.

Figure 21: Firms with Largest Capacity Increase, 2010–2020



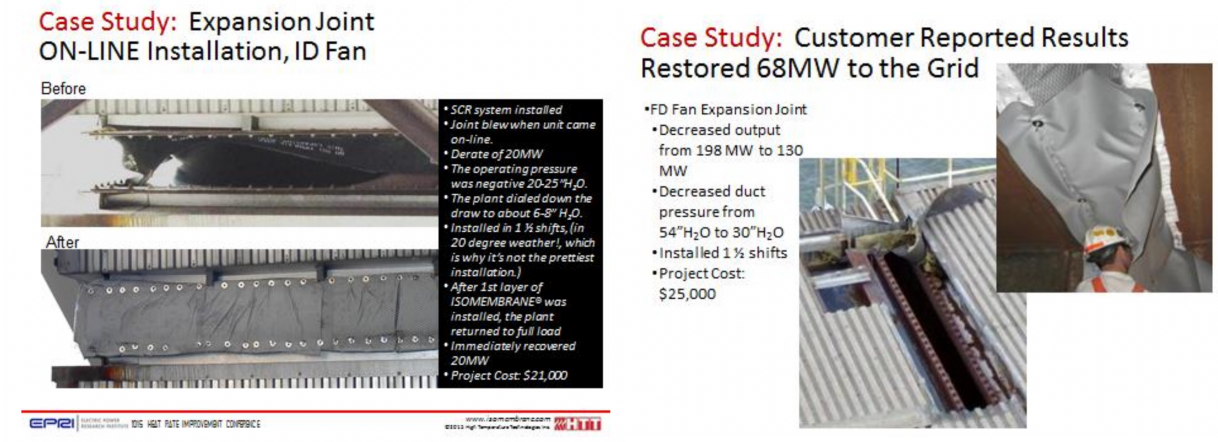
Note: This figure shows firms with the largest capacity increase in fossil fuel generation capacity in the US between 2010 and 2020.

Figure 22: Firms with Largest Capacity Decrease, 2010–2020



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

Figure 23: Case Studies of Heat Rate Improvement

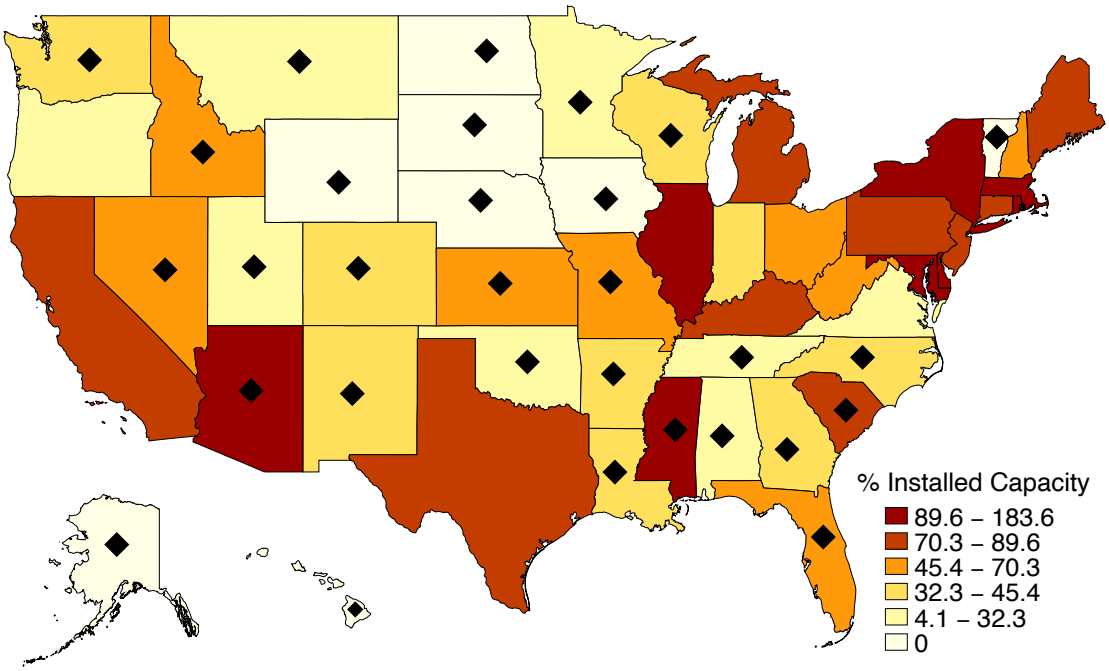


(a) Case Study 1

(b) Case Study 2

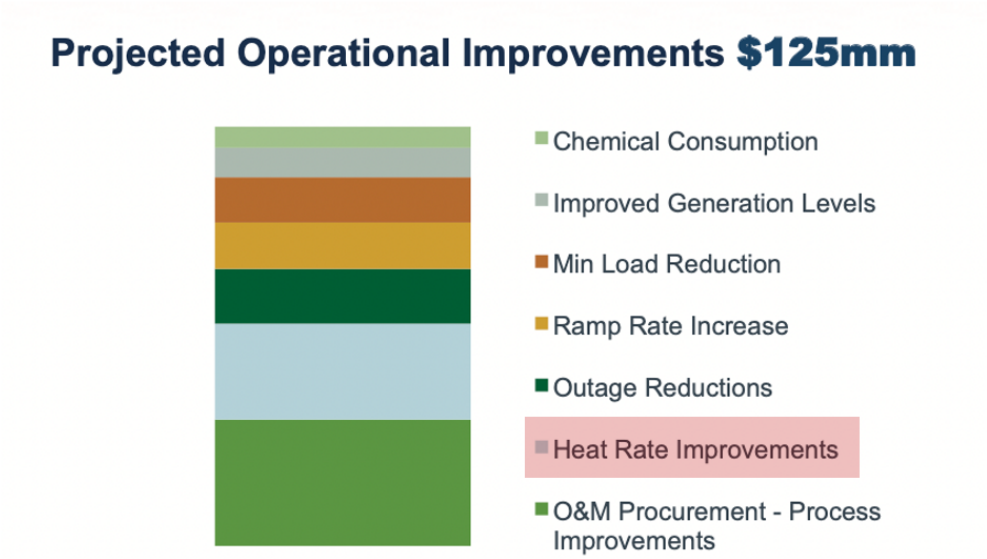
Note: These pictures demonstrate some methods that were implemented in power plants to improve heat rate. Source: Fitzgerald and Gelorme (2015).

Figure 24: Change of Percentage of Fossil Fuel Generation Capacity



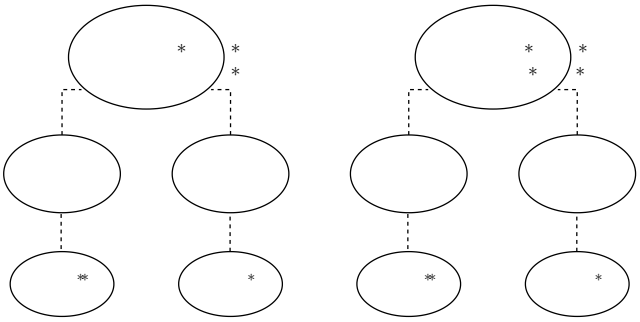
Note: Geographical distribution of power plant acquisitions by capacity. The diamond indicates the regulated states.

Figure 25: Heat Rate Improvement Claim From Merging Firms

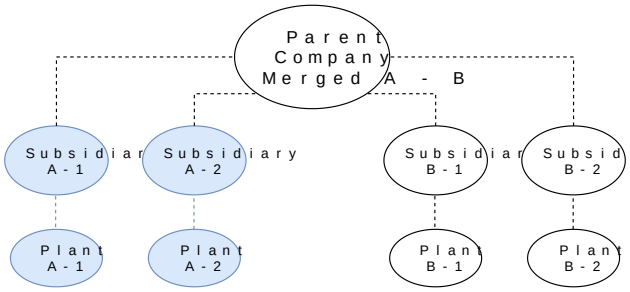


Note: This figure is from a slide deck presented in the conference call of the acquisition of Dynegy by Vista Energy (2018, $1.74 billion deal).

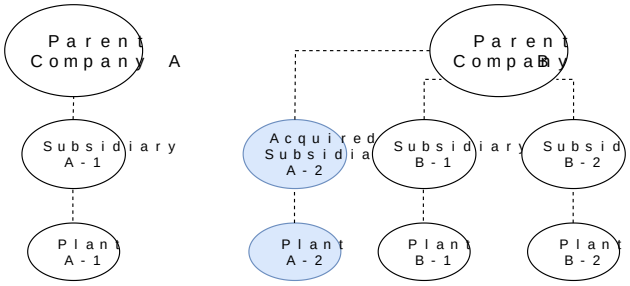
Figure 26: Ownership Change Types



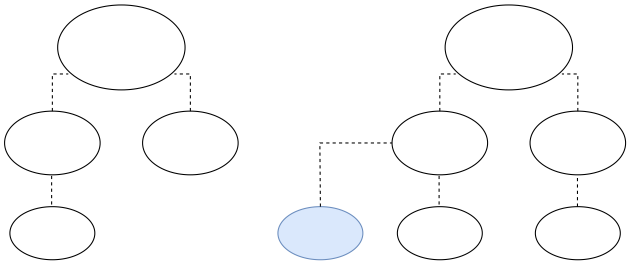
(a) Before



(b) Asset Sales



(c) Subsidiary Acquisitions



(d) Mergers

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

E Robustness Checks Results

Table 10: Impact of Merger on Productivity (Daily Data)

	All M&A	Owner/Parent Company Changes	Only Parent Company Changes	Minority Owner Changes (Placebo)	Name Changes (Placebo)
Late pre-acquisition	0.001	-0.003	-0.004	-0.005	-0.006
	(0.005)	(0.007)	(0.006)	(0.007)	(0.009)
Early post-acquisition	0	0.005	-0.003	-0.01	-0.003
	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)
Late post-acquisition	0.012	0.034	-0.004	-0.007	0.006
	(0.006)	(0.012)	(0.006)	(0.01)	(0.01)
Adj. R^2	0.645	0.652	0.642	0.663	0.655
# of Obs.	8.3M	6.26M	6.48M	5.12M	5.77M
# of Acq.	1760	897	921	405	456
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

Note: This table presents the coefficient estimates from estimating Equation (5.1) using daily data as described in Section C.2. Standard errors are clustered at the plant level.

Table 11: Impact of Merger on Productivity (Hourly Data)

	All M&A	Owner/Parent Company Changes	Only Parent Company Changes	Minority Owner Changes (Placebo)	Name Changes (Placebo)
Late pre-acquisition	0.001	0	-0.008	-0.01	-0.003
	(0.005)	(0.008)	(0.006)	(0.011)	(0.011)
Early post-acquisition	-0.004	0.005	-0.008	-0.023	-0.001
	(0.006)	(0.008)	(0.008)	(0.011)	(0.008)
Late post-acquisition	0.02	0.042	0.001	-0.021	0.005
	(0.008)	(0.017)	(0.007)	(0.013)	(0.012)
Adj. R^2	0.353	0.365	0.348	0.358	0.373
# of Obs.	146.06M	111.61M	122.03M	99.15M	109M
# of Acq.	1760	897	921	405	456
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

Note: This table presents the coefficient estimates from estimating Equation (5.1) using hourly data as described in Section C.2. Standard errors are clustered at the plant level.

Table 12: Impact of Merger on Productivity (Weighted Regressions)

	All M&A	Owner/Parent Company Changes	Only Parent Company Changes	Minority Owner Changes (Placebo)	Name Changes (Placebo)
Late pre-acquisition	0.001	0.002	-0.009	-0.007	-0.012
	(0.005)	(0.008)	(0.007)	(0.008)	(0.009)
Early post-acquisition	0.002	0.01	-0.006	-0.015	-0.003
	(0.005)	(0.009)	(0.006)	(0.009)	(0.007)
Late post-acquisition	0.014	0.045	-0.01	0.001	0.012
	(0.007)	(0.013)	(0.008)	(0.01)	(0.01)
Adj. R^2	0.599	0.62	0.599	0.631	0.613
# of Obs.	1.79	1.38	1.4	1.12	1.22
# of Acq.	1760	897	921	405	456
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

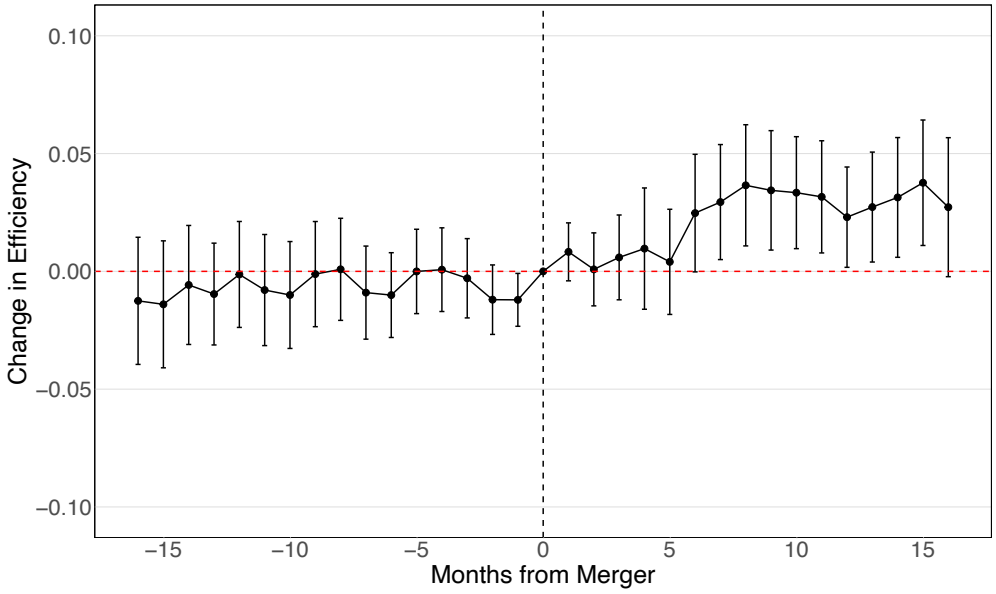
Note: This table presents the coefficient estimates from estimating Equation (5.1) by weighting observations by capacity as described in Section C.5. Standard errors are clustered at the plant level.

Table 13: Impact of Merger on Productivity All Acquisitions

	All M&A	Owner/Parent Company Changes	Only Parent Company Changes	Minority Owner Changes (Placebo)	Name Changes (Placebo)
Late pre-acquisition	0.002	0.003	-0.003	-0.005	-0.011
	(0.004)	(0.007)	(0.006)	(0.008)	(0.008)
Early post-acquisition	0.002	0.007	0.002	-0.009	0
	(0.004)	(0.007)	(0.006)	(0.007)	(0.005)
Late post-acquisition	0.016	0.036	0.003	0.001	0.011
	(0.01)	(0.009)	(0.01)	(0.008)	
Adj. R^2	0.622	0.635	0.622	0.652	0.635
# of Obs.	1.79	1.38	1.4	1.12	1.22
# of Acq.	2913	1202	1198	430	677
Unit FE	X	X	X	X	X
State by Month FE	X	X	X	X	X
Week FE	X	X	X	X	X

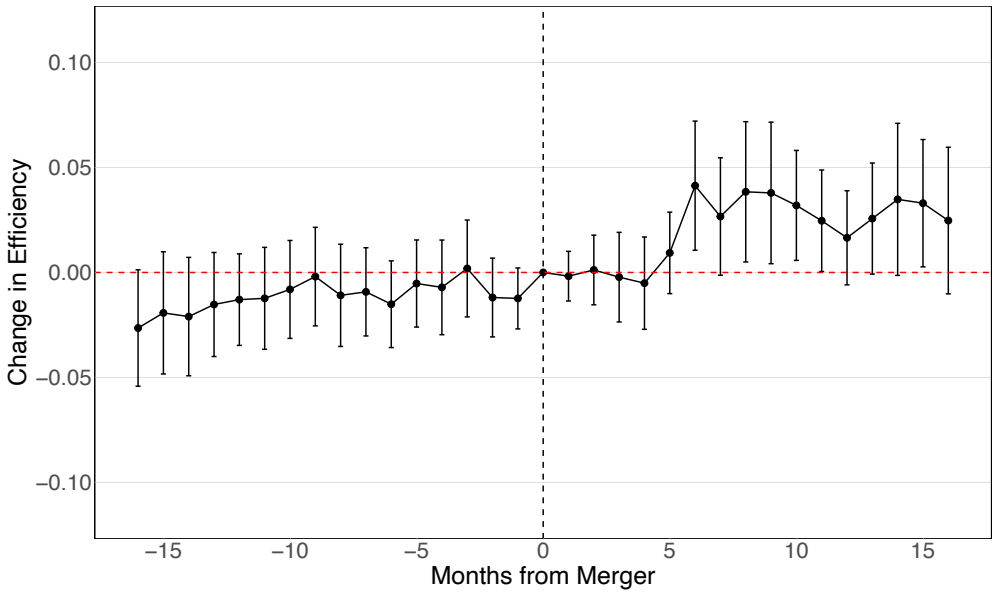
Note: This table presents the coefficient estimates from estimating Equation (5.1) using all acquisitions. The acquisition sample is described in Section C.1. Standard errors are clustered at the plant level.

Figure 27: Impact of Merger on Productivity (Daily Data)



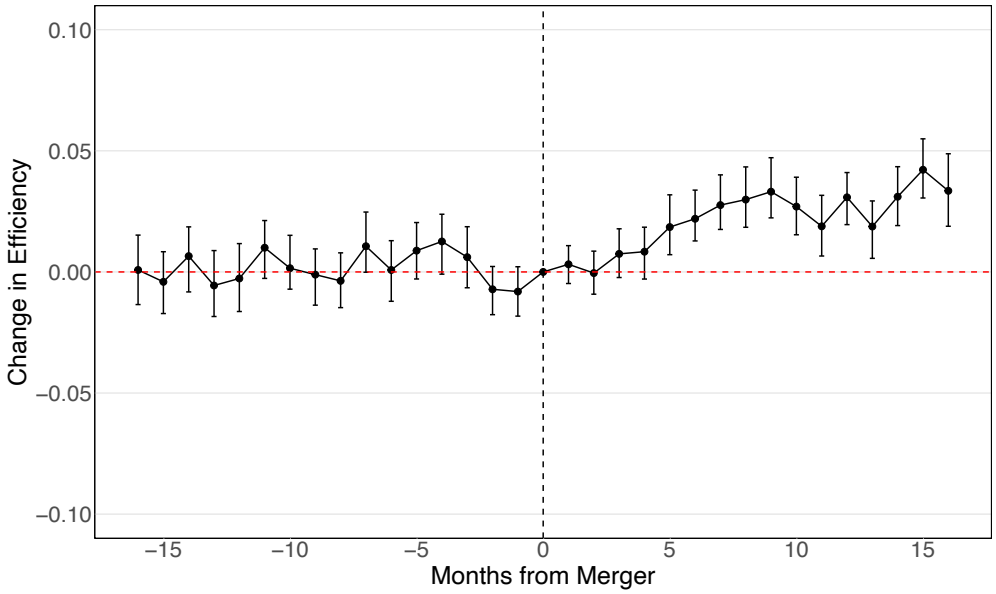
Note: The dynamic effects of acquisitions estimated from Equation (5.2) using daily data as described in Section C.2. Standard errors are clustered at the plant level.

Figure 28: Impact of Merger on Productivity (Hourly Data)



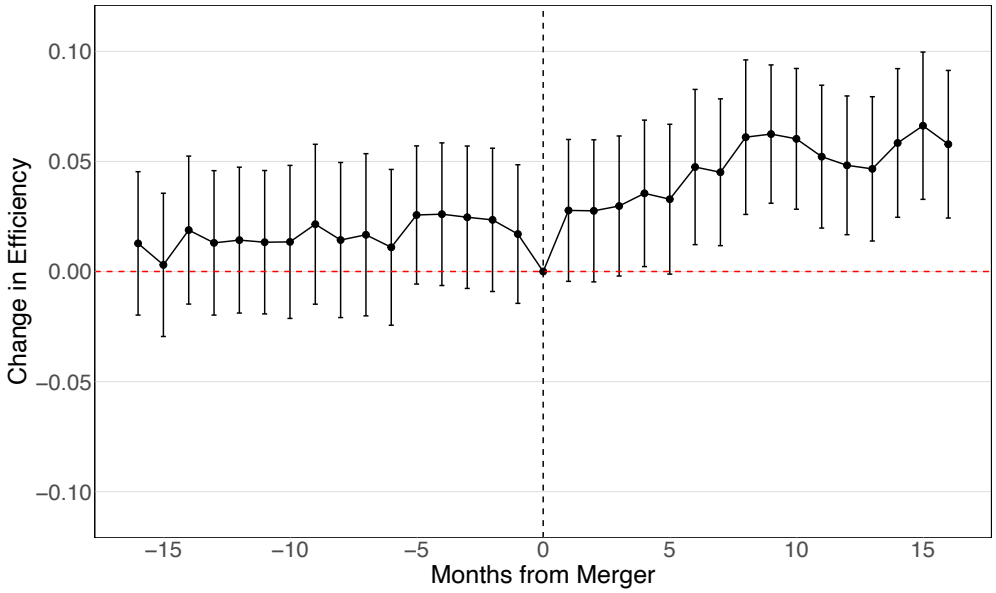
Note: The dynamic effects of acquisitions estimated from Equation (5.2) using hourly data as described in Section C.2. Standard errors are clustered at the plant level.

Figure 29: Impact of Merger on Productivity (Matching Estimator)



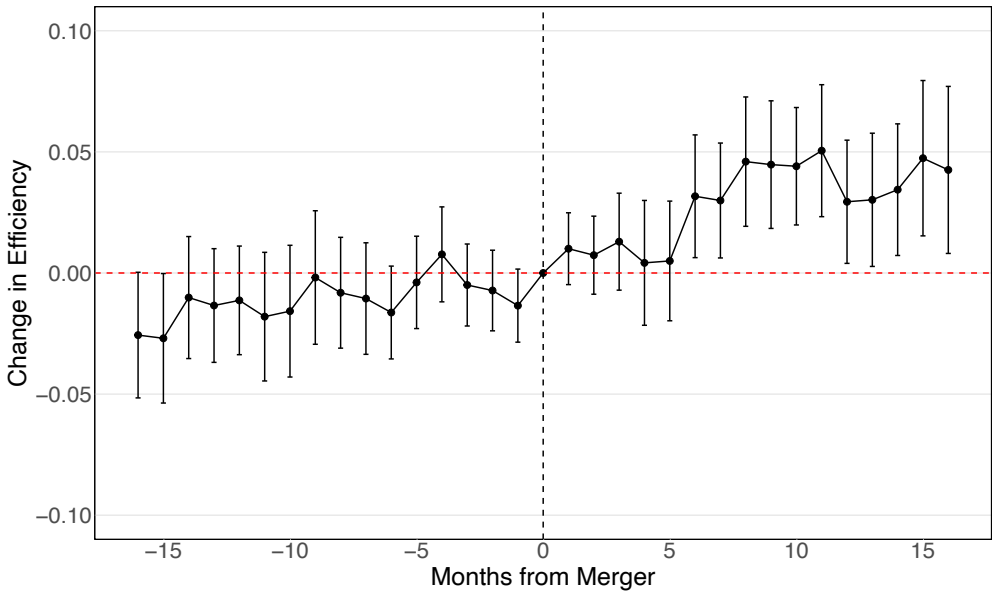
Note: The dynamic effects of acquisitions estimated using the matching method described in Section C.4

Figure 30: Impact of Merger on Productivity (All Acquisitions)



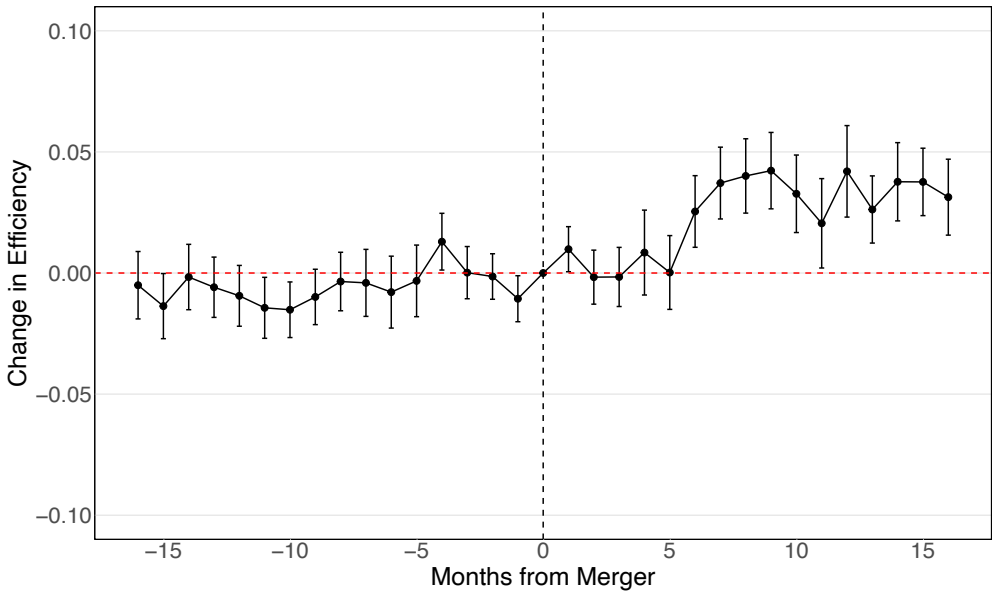
Note: The dynamic effects of acquisitions estimated from Equation (5.2) using all acquisitions. The acquisition sample is described in Section C.1. Standard errors are clustered at the plant level.

Figure 31: Impact of Merger on Productivity (Weighted By Capacity)



Note: The dynamic effects of acquisitions estimated from Equation (5.2) by weighting observations by capacity as described in Section C.5. Standard errors are clustered at the plant level.

Figure 32: Impact of Merger on Productivity (Staggered Difference-in-Differences)



Note: The dynamic effects of acquisitions using the method of Callaway and SantAnna (2021) method. The details are provided in Section C.3. Standard errors are clustered at the plant level.