Minimizing Costs, Maximizing Sustainability

Finance Working Paper N° 702/2020
June 2023

Yaniv Grinstein
IDC Herzliya, Cornell University and ECGI
Yelena Larkin
York University

ECGI Working Paper Series in Finance

Minimizing Costs, Maximizing Sustainability

Working Paper N° 702/2020
June 2023

Yaniv Grinstein
Yelena Larkin

we thank participants at the IDC summer conference 2019, the 2020 ECGI conference on Sustainable Finance and Corporate Governance, SFS Cavalcade North America 2021 conference, SELE 2021 conference, CSFN 2021 conference, FMCG 2022 conference, EFA 2022 conference, FMA 2022 conference, and seminar participants at Cornell University, Dalhousie Universi?

Abstract

Product market competition has been long considered an important driver of sustainability, motivating firms to cater to environmentally-conscious consumers. However, in the most polluting industries consumers cannot differentiate across products, rendering consumer channel ineffective. Can competition still improve environmental footprint of corporations absent consumer differentiation? We show that cost-cutting measures available to the firm are the key determinant of whether competition will reduce environmental impact. Only when cost-cutting measures have a positive impact on the environment the overall effect of competition is positive. * For helpful comments we thank participants at the IDC summer conference 2019, the 2020 ECGI conference on Sustainable Finance and Corporate Governance, SFS Cavalcade North America 2021 conference, SELE 2021 conference, CSFN 2021 conference, FMCG 2022 conference, EFA 2022 conference, FMA 2022 conference, and seminar participants at Cornell University, Dalhousie University, University of Oklahoma, University of South Florida, University of Waterloo, and York University. We also wish to thank Pat Akey, Aymeric Bellon, Roman Chychyla, Lauren Cohen, Chitru Fernando, Andrew Karolyi, Nadav Levy, Lavinia Regnone, Malgorzata Ryduchowska, Laura Starks, Margarita Tsoutsoura and Yishay Yafeh for helpful discussions. Guy Pincus has provided excellent research assistance. This research was supported by the Social Sciences and Humanities Research Council of Canada.

Yaniv Grinstein

IDC Herzliya, Cornell University and ECGI
Professor of Finance
IDC Herzliya
e-mail: grinstein@idc.ac.il

Yelena Larkin

York University
Associate Professor of Finance
York University, Schulich School of Business
e-mail: YLarkin@schulich.yorku.ca

Corporate Environmental Footprint and Product Market Competition*

Yaniv Grinstein[1] Yelena Larkin[2]

June 2023

Abstract

Product market competition has been long considered an important driver of sustainability, motivating firms to cater to environmentally-conscious consumers. However, in the most polluting industries consumers cannot differentiate across products, rendering consumer channel ineffective. Can competition still improve environmental footprint of corporations absent consumer differentiation? We show that cost-cutting measures available to the firm are the key determinant of whether competition will reduce environmental impact. Only when cost-cutting measures have a positive impact on the environment the overall effect of competition is positive.

* For helpful comments we thank participants at the IDC summer conference 2019, the 2020 ECGI conference on Sustainable Finance and Corporate Governance, SFS Cavalcade North America 2021 conference, SELE 2021 conference, CSFN 2021 conference, FMCG 2022 conference, EFA 2022 conference, FMA 2022 conference, and seminar participants at Cornell University, Dalhousie University, University of Oklahoma, University of South Florida, University of Waterloo, and York University. We also wish to thank Pat Akey, Aymeric Bellon, Roman Chychyla, Lauren Cohen, Chitru Fernando, Andrew Karolyi, Nadav Levy, Lavinia Regnone, Malgorzata Ryduchowska, Laura Starks, Margarita Tsoutsoura and Yishay Yafeh for helpful discussions. Guy Pincus has provided excellent research assistance. This research was supported by the Social Sciences and Humanities Research Council of Canada.

[1] Reichman University, Cornell University and ECGI. grinstein@runi.ac.il
[2] York University. ylarkin@schulich.york.ca

1. Introduction

Product market competition (hereafter, PMC) is often viewed as a mechanism to improve sustainability and environmental footprint. For example, the OECD Competition Committee 2021 meeting report notes that "competition supports environmental protection goals where consumers' preferences are oriented towards environmentally-friendly products or services" (p. 9).[3] This view is also shared by academic research: A large body of literature has demonstrated that in a competitive environment, firms can differentiate their products by becoming environmentally friendly in order to increase consumer demand and profits (Aghion et al., 2020; Albuquerque et al. 2019; Flammer, 2015; Servaes and Tamayo, 2013; Duanmu et al., 2018; Delmas et al., 2007).

Unfortunately, even in competitive markets, product differentiation is hard to obtain. One reason is that, often, consumers cannot verify whether environmental actions claimed by firms are actually attained (e.g., Larcker et al., 2022). Another reason is that products in the most polluting industries trade in centralized spot and futures wholesale markets (e.g., energy) – where exchanges and contracts are unified and are not differentiated by producer type. A third reason is that products in the most polluting industries are transported through complex distribution systems of grids, pipelines, transportation networks etc., which do not allow consumers to be matched with environmentally friendly suppliers. In an effort to circumvent these obstacles, regulators have recently started to introduce alternative programs that allow customers to support environmentally-friendly production in other ways (e.g., green tariffs, renewable energy certificates). However, the reality is that even with such systems and programs, most consumers do not participate in them.[4]

[3] https://one.oecd.org/document/DAF/COMP(2021)4/en/pdf

[4] For example, Heeter et al. (2021) report that in 2020, voluntary green energy purchase by retail customers accounted for only 5% of the retail electricity market in the US. In section 2 we provide more evidence in support of the argument that consumer differentiation channel does not seem to play a role when it comes to the most polluting sectors of the economy.

Can PMC reduce corporate environmental impact absent product differentiation? In this study, we address this question. We analyze the impact of PMC on corporate environmental footprint when firms cannot differentiate themselves as environmentally friendly producers. Our theoretical framework builds on the existing literature on competition, which shows that PMC forces firms to become more efficient. We identify two channels through which increased efficiency impacts the environment: within-firm actions to reduce costs of output produced (cost-cutting) and reallocation of production across competing firms (efficient allocation of resources). We then develop hypotheses as to how each of these channels affects corporate environmental footprint.

First, we consider the cost-cutting channel. We divide cost-cutting activities into three categories: (a) reduced spending on environmental protection, (b) change of inputs to achieve lower production costs, and (c) change of production process to achieve higher output per input. Some of these actions will have a negative impact on the environment (e.g., reduced spending on environmental protection), while others could have a positive impact (e.g., achieving higher output per input produced). Thus, depending on which source dominates, the cost-cutting channel could either have a positive or a negative effect on the environment.

Second, we consider the efficient allocation of production across competing firms. Competition is known to alter production decisions across firms in a way that re-allocates production from units with high marginal costs towards units with lower marginal costs. To the extent that units with high marginal costs also pollute more, the efficient allocation of resources across firms will have a positive impact on the environment.

We empirically examine the relation between environmental footprint and competition by focusing on the staggered restructuring of the electric utility industry in the US – the nation's largest emitter of toxic chemicals and greenhouse gases. The electric utility industry is a classic example of a setup with limited product differentiation. In the pre-restructuring environment, every plant operated as a local monopoly, so that consumers could not choose their electric provider. States that restructured their electric utility markets, opened them to competition at the wholesale level, where power plants compete to sell electricity to local distributers through centralized market mechanisms such as power exchanges. In such a system, final customers, who buy their electricity from local distributors, do not know the identity of their suppliers.[5]

In support of the cost-cutting channel, we provide three sets of results. First, we find a significant cut in abatement investment and expenses in restructured states compared with non-restructured states. Second, we find that plants in restructured states have decreased costs by switching to a cheaper input mix. Specifically, the affected plants shifted from oil (the most expensive) towards cheaper fuels - natural gas and coal. In addition, within the coal category, plants increased their reliance on cheaper and more polluting types. Our third finding is that plant input utilization, as measured by the ratio between electricity output and heat input, increased in restructured states in comparison to plants in non-restructured states.

We also provide evidence that supports the efficient allocation of resources channel. Specifically, we show that capacity factor declined in affected plants, which suggests that competition reduced the production of local plants in favor of incumbent competing plants.

After establishing the existence of the cost-cutting channel and the efficiency-allocation-of-resources channel, we proceed to examine the impact of these channels on the environment. The heterogeneity of plant production characteristics in our sample allows us to confirm the

[5] While all restructured states have allowed electricity generators to compete in the wholesale market, a very small portion have also opened their markets to retail sales access, which would enable end-users to choose their electricity providers. Excluding these cases (around 1% of our sample) does not affect our results.

existence of both outcomes. First, we focus on a subset of plants where the impact of the cost-cutting channel on the environment is unambiguously positive. This subset includes all the plants that do not have the technology to produce electricity with coal. Those plants switch from petroleum to gas, reducing emission as a byproduct of this cost-cutting action.[6] In support of our predictions, we find a negative and statistically significant effect of restructuring on the amount of emitted toxic chemicals among the subset of non-coal operating plants.

Second, we contrast these predictions with the predictions regarding the rest of the sample – plants that have the capacity to switch to coal. In this subset, the impact of the cost-cutting channel is likely to be negative as these plants move towards more-polluting inputs, increasing the level of emission. Consistent with our priors, we find a positive and statistically significant effect of restructuring on the amount of emitted toxic chemicals among the subset of coal operating plants.

In the last part of the study, we validate the role of PMC as the driver of our results by performing several additional tests. First, we examine whether our results are driven by state characteristics, correlated with state decisions to restructure. To this end, we explore differences between Independently Owned Utilities (IOUs) and Municipal Utilities (*Muni*s) within states; primarily, the latter were largely exempt from restructuring. We find that only IOUs have reduced their production following the restructuring, whereas *Muni*s did not. We also directly analyze the restructuring determinants across states and find that the decision was driven solely by high electricity prices and is unrelated to pollution or fuel mix available at the state. Finally, we verify econometric validity of our difference-in-difference (DiD) framework. We perform a parallel trend

[6] Since abatement expenses are aimed at the more polluting fuel, reduction in abatement expenses associated with the move to gas should not have a material effect on pollution.

test, and also ensure that our results are not subject to staggered DiD bias (Baker et al., 2022) or count data bias (Cohn et al., 2022).

The study examines the relation between pollution and efficiency channels in the 1990s, but its implications are ever so relevant today. Fossil-fuel-based electricity still accounts for almost two-thirds of the overall electricity generated nationwide and the Electric Utility industry remains the number one source of carbon dioxide pollution (CO2), responsible for global warming and climate change. The contribution of coal to the carbon dioxide generation is particularly alarming: As of 2021, coal-based electricity generation accounted for 59% of CO2 emissions from the sector. Moreover, due to significant economic growth in China in India over the past two decades, coal-based electricity generation has doubled around the world.[7] At the same time, policy initiatives focusing solely on investment in renewable energy have been too slow to affect the environment in the short-run: in 2021, green energy accounted for only 13% of total energy consumption in the world.[8] Our study demonstrates that given the slow implementation of zero-carbon solutions, market mechanisms that incentivize firms to alter their fossil fuel mix towards gas can contribute to the reduction in CO2. Although natural gas-based production is not emission-free, it emits only half the amount of carbon dioxide as coal. In fact, the Environmental Protection Agency (EPA) lists switching to natural gas as the first example of greenhouse gas reduction opportunities for power plants.[9]

Our study offers several contributions to the literature. First, we highlight the fact that product differentiation is not easily obtained in the most polluting industries and that product market competition might not reduce environmental impact absent product differentiation. This

[7] https://www.carbonbrief.org/mapped-worlds-coal-power-plants/
[8] https://ourworldindata.org/renewable-energy
[9] https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

finding stands in contrast to the common view that product market competition is good for the environment. Relatedly, a large body of literature has emphasized the benefits of catering to environmentally, socially, and governance conscious consumers. Among the benefits are higher consumer loyalty during crises (Lins et al., 2017; Albuquerque et al., 2020), higher sales growth (Dai et al., 2021) higher valuation (Servaes and Tamayo, 2013), and lower overall systematic risk (Albuquerque et al., 2019). We argue that these benefits are hard to obtain in industries that lack product differentiation.

Within the product differential strand of literature, the closest to our work is the study by Delmas et al. (2007), who examine the effect of opening the electricity market to competition on green electricity production. However, their study wrongfully assumes that the restructuring legislation has led to retail competition, and therefore allowed for product differentiation. In reality, retail access during that time was virtually non-existent: only few states implemented retail access during their sample period, and even in those states, retail access among residential and small commercial customers has been disappointingly low (Joskow (2003)). Our study shows that the impact of restructuring on the environment was driven by efficiency, rather than by product differentiation incentives.

Relatedly, Duanmu et al. (2018) examine the effect of product market competition on environmental footprint among Chinese firms in response to China's opening to international competition in 2001. Their study also focuses on the differentiation channel and analyzes firms that, in response to the shock, choose to differentiate through advertising. In contrast, our study focuses on an industry that does not have product differentiation. While Duanmu et al. (2018) show the tension between differentiation and efficiency, they assume away any positive effect of improving efficiency on the environment. As a result, their study erroneously concludes that efficiency motives can have only a negative impact on the environment.

The results of our paper are also relevant to non-environmental dimensions of corporate social responsibility (CSR). The inability to differentiate among environmentally-friendly and unfriendly producers can be extended to other dimensions of CSR, such as social and governance components. For example, in the absence of a standardized reporting system (similar to that of EPA, which sets clear criteria of emission reporting and makes the data publicly available), it is unclear how to measure other aspects of social responsibility of a firm, such as diversity, employee relationship and impact on the community. In support of this argument, recent literature has demonstrated that the correlation among various indices that measure CSR is extremely low. We note that the shortcomings of CSR measurement further impede the effectiveness of consumer differential channel as the major market force behind promoting CSR.

Finally, our work also belongs to a growing strand of the finance literature whose methodology entails placing a single industry at the core of its empirical design to provide precise inferences regarding the forces that shape corporate policies (e.g., Benmelech, 2009; Benmelech and Bergman, 2011; Gilje et al., 2020; Décaire et al., 2020). The detailed data allows us to identify different actions to increase efficiency and the effect of each one of them on environmental footprint. It also quantifies the means by which the efficiency is achieved (fuel choice, usage and quality, resource allocation) and the precise environmental impact of each one of these decisions. Moreover, we note that efficiency channels that we identify in our empirical analysis are general and apply to other industries and production processes.

The rest of the study continues as follows. Section 2 discusses the role of consumer channel in the most polluting industries. Section 3 provides a summary of the electric utility industry and its restructuring. Section 4 presents the data and outlines the empirical design. In Section 5 we validate the existence of efficiency channels, and in Section 6 we test the impact of these channels on emission. Section 7 discusses the findings in light of the different hypotheses, and Section 8 concludes.

2. Consumer Channel in Polluting Industries

The literature in economics and finance highlights the strategy of firms in competitive industries to single themselves out by investing in corporate social responsibility (CSR). When competition is high, firms strive to cater to CSR-conscious consumers by enhancing their CSR policy, thereby increasing consumer demand for their products and their profits (Albuquerque et al., 2019; Flammer, 2015; Servaes and Tamayo, 2013). A related strand of literature focuses on the environmental aspect of CSR policy and also demonstrates that in a competitive environment, firms invest in environmental policy and clean technology in order to cater to consumers (Aghion et al., 2020; Duanmu et al., 2018; Delmas et al., 2007).

An essential condition for consumer channel effectiveness is the ability to distinguish between environmentally friendly and non-friendly suppliers. Empirical studies have shown the importance of this key condition. For example, using size-adjusted advertising expense as a measure of product differentiation and customer awareness, Servaes and Tamayo (2013), Albuquerque et al. (2019) and Albuquerque et al. (2021) show that shareholder value is higher and firm risk is lower among socially responsible firms only when firms are able to differentiate their products.

By design, the ability of consumers to differentiate among firms highly depends on the industry in which firms operate, since differentiation is done vis a vis other products and other producers in the same industry. How economically important is product differentiation in the most pollutive industries?

To answer this question, we conduct the following exercise. We first identify the most pollutive industries in the US as of 2019 by calculating the relative share of each industry out of the nationwide pollution. Next, we evaluate the extent to which firms in these industries differentiate themselves. Following past studies, we use advertising expenses to measure differentiation and focus our attention on publicly traded firms from the Compustat universe. We identify all Compustat firms in these industries as of 2019 and calculate the fraction within each industry that reports advertising expenses.

The results are presented in Table 1. In Panel A our pollution measure is the level of greenhouse gas (GHG) emission. We obtain the facility-level data on greenhouse emissions in the US from the EPA's greenhouse gas reporting program (GHGRP) and aggregate the information at the 3-digit NAICS level.

The table shows that out of a total 2.86 billion metric tons of GHG produced by US facilities, about 58% come from Electric Utilities, followed by Oil and Gas Extraction (8.7%) and Petroleum (7.8%). Together, these three industries are responsible for almost three quarters of the nationwide emission.

Interestingly, the table shows that 98% of Compustat firms that belong to the Electric Utility industry have no advertising expenses. In fact, in three of the nine most polluting industries, advertising expenses are zero in over 97% of the firms. Thus, relying on advertising as an established measure of differentiation, we find that in the industries responsible for almost 70% of US greenhouse gases in 2019 there is practically no product differentiation.

To ensure that we do not capture a size effect (i.e., only larger, more important firms advertise) we calculate a percentage of advertising firms weighted by asset size. We find that the pattern is not driven by small firms. To verify that our results are not specific to the methodology of measuring pollution, we repeat the same exercise using the data from the Toxic Release Inventory (TRI) program, also managed by the Environmental Protection Agency (EPA). The results, reported in panel B, support the same conclusions.

Why don't firms in industries such as Electric Utilities and Oil Extraction differentiate themselves? We argue that these industries have a particular design that prevents producers from differentiating themselves. Importantly, the inability to differentiate themselves is despite the fact that some of these industries have high levels of product market competition.

Consider first the electric utility industry. In this system, distributers receive electricity from multiple providers and deliver the output to the final consumers through a network of power grids. Regional dispatch centers monitor the distributed energy and control its flow from power stations to the end user to ensure a steady supply at any point of time. As a result, the structure of distribution system makes delivery from a specific electricity provider to a specific customer very difficult. A series of industry restructuring reforms, conducted throughout the 1990s in the US, has resulted in the development of wholesale electricity markets in which generators compete to sell electricity and related services to distributors. However, the majority of final consumers still face one large distributor in their region and cannot shift their demand from one distributor to another, based on distributor environmental norms.[10]

[10] As of today, only 13 states and the District of Columbia have active, statewide residential retail choice programs. Moreover, eligible consumers have been passive about exercising their right to choose electricity providers, so that the total participation rate in these programs amounts to around 13% of total residential customers.

Consider next oil extraction and metal production. Products in these industries are traded in centralized markets (e.g., exchanges). Although the markets impose certain product quality requirements, these requirements do not apply to environmental characteristics. As a result, it is impossible to differentiate between environmentally friendly and non-friendly producers within the exchange. Any attempt by a producer to differentiate itself requires that she closes deals outside the exchange and uses storage, distribution systems, and verification systems unique to its product. These requirements entail large fixed costs and are difficult to implement. [11]

In an effort to cater green energy to consumers, regulators intervene in these markets in various ways. Some require verification systems such as renewable energy tracking systems (e.g., Menz and Vachon 2006), allowing for the development of the market for renewable electricity certificates (REC).[12] Other regulators mandate utilities to offer utility green power options so that consumers can choose to buy green power (EPA, 2018). Despite the efforts to overcome the above obstacles and create differentiation, only about 5% of retail consumers in the US choose green power today (Heeter et al., 2021). Note also that these initiatives apply to green energy only and do now allow customers to choose more environmentally-friendly ways of electricity generation among fossil-fuel plants, which currently accounts for almost two-thirds of total electricity production in the US. Finally, the existing initiatives are limited to electricity and do not extend to oil and gas sectors.

To summarize, our evidence shows that among the most pollutive industries in the US, the offering of green products is done mainly through regulatory means and has limited effectiveness.

[11] One can argue that these industries do not advertise because they use business-to-business model, and corporate customers are able to differentiate across suppliers even absent advertising. However, we point out that industry design can prevent differentiation even within business-to-business model. This happens when product delivery is based on a centralized system (grids, pipelines, etc.), as well as when customers and suppliers are matched in centralized markets, such as spot and forward markets.

[12] Renewable energy certificates are allocated to producers of electricity from renewable resources. These certificates can then be sold to consumers who wish to claim the right for renewable sources on the electricity they consume.

This begs the question whether competitive forces can push polluting industries to offer green products. Can competition encourage firms in these industries to become environmentally friendly? We examine this question in the rest of the study.

3. The Electric Utility Industry in the US

This section provides a brief summary of the US electric utility industry. It consists of an explanation of how electricity is generated (Section 3.1) and how its environmental impact is regulated (Section 3.2). Section 3.3 describes the restructuring process of electric utilities.

3.1 Electric Generation

The focus of our study is electric plants that are powered by fossil fuel. This type of plant was responsible for generating approximately 70% of all US electricity during our sample period, and its prevalence has remained high until today. For example, in 2020, 61% of total electricity in the US was generated from fossil fuels.[13]

Electricity generation in steam turbines starts with burning fossil fuels to heat a boiler and create steam to rotate a turbine. The turbine is connected to a generator that rotates through opposing magnetic fields. The rotation induces the flow of electricity, which then travels to its final destination through a network of power grids. The steam that leaves the turbine is cooled and fed into the boiler again.

Three main types of fossil fuels are used to generate heat in steam turbine electric plants: coal, petroleum, and gas. These fossil fuels differ in their heat content as measured by the amount

[13] https://www.eia.gov/tools/faqs/faq.php?id=427&t=3.

of fossil fuel required to generate one unit of heat. Fossil fuels also differ in cost and environmental impact.

Overall, the main environmental concern associated with steam generating plants is the hazardous gases emitted when burning fossil fuels.[14] A chief byproduct is sulfur dioxide (SO_2), which causes acid rain and worsens respiratory illnesses and heart diseases in humans. Other hazardous byproducts include nitrogen oxides (NOx), which contribute to ground-level ozone and irritate and damage human lungs; carbon monoxide and particulate matter, which results in hazy conditions in cities and scenic areas, as well as small amounts of heavy metals such as mercury. Finally, as Table 1 indicates, electric plants emit large quantities of carbon dioxide, or greenhouse gas. While not as toxic as other byproducts, it contributes to the greenhouse effect responsible for global warming.

Among the three fuels used for steam power-plants operation, coal has the most damaging emissions content, followed by petroleum and natural gas. For example, burning coal to generate one billion British Thermal Units (BBTU) of heat is associated with approximately 2,600 pounds of SO_2. A typical power plant uses 22,000 BBTU per year, resulting in approximately 57 million pounds of SO_2. In contrast, generation of the one BBTU of heat by burning petroleum is associated with 1,122 pounds of SO_2. Finally, burning natural gas is associated with one pound of SO_2 for one BBTU.

[14] Other environmental concerns include (i) the use of nearby water resources to produce steam and provide cooling (ii) discharges of water that is hotter than the natural temperature of the water body (thermal pollution); (iii) solid, including hazardous, waste; (iv) land use for fuel production, power generation, and transmission and distribution lines. While these factors are also part of the overall environmental impact, they have a less hazardous immediate impact and are more challenging to quantify.

3.2 Pollution Abatement and Environmental Regulation

To mitigate the environmental effects of burning fuel, electric plants can employ three main strategies. First, they can burn less polluting fossil fuel: rely on natural gas or less pollutive coal, or pretreat the coal. Second, plants can capture the pollutants during the fuel burning process, which can be done in several ways. The most efficient one requires an apparatus called a flue-gas desulfurization unit (FGD), or scrubber. Scrubbers remove about 90% of the pollution in the flue gas, but are expensive (Baasel, 1988). Third, plants can increase fuel efficiency, resulting in less fuel required to produce the same amount of electricity. Efficiency can be increased, for example, by replacing older equipment with newer boilers, turbines, and generators.

Electric utilities are required to abide by the emissions standards of the Clean Air Act, which the US introduced in 1970 and significantly amended in 1990. The most relevant amendment for electric utilities was Title IV, which was specifically directed at SO_2 and NOx emissions from utility power plants. The amendment was implemented in two phases: Phase I, which became effective January 1, 1995, required 110 listed power plants of greater than 100 MW electrical capacity and with high emissions levels to considerably reduce their emissions ("Table 1 Units").[15] Phase II, implemented in 2000, targeted all units with capacity of at least 75 MW. Phase II has affected the majority of US electric plants.

3.3 Restructuring of the Electric Utility Industry

This subsection briefly summarizes the restructuring process of the electric utility industry in the US. For more detailed explanations see, e.g., Warwick (2002) and Joskow (1997).

[15] Those units were referred to as "Table 1 units" because they were listed in Table 1 of the allowance allocation regulation, 40 CFR 73.10. Additional 182 units were allowed to substitute for "Table 1 Units" in reducing overall utility emissions levels.

Historically, electric utilities operated mostly as vertically-integrated regulated monopolies, owning generation, transmission, and distribution of electricity within their localized geographic market. The majority of plants in the US are owned by private investors and denoted as investor-owned utilities (*IOU's*). A minority of the plants are owned by the public government or local municipalities, as well as member-owned cooperatives across municipalities (*Munis*).

State regulators used to set the price of electricity based on utility costs in a process called a rate case, a lengthy and complex procedure for determining both the electricity price level and the price design. A utility generally initiates a rate case only when it needs to increase revenues or believes that it needs a higher rate of return to attract investment capital. Rate cases are examined by the regulator on a periodic basis, usually every several years.

By the early 1990s it became apparent that electric industry regulatory approaches were not working. The demand for electricity increased, attempts to build new plants faced regulatory constraints, and the process of rate case reviews was time-consuming and expensive. As a result, states began adopting different versions of industry restructuring in the early 1990s. The restructuring involved opening the electricity utilities to competition both within the state and outside the state. In the restructured supply system, generation and distribution became unbundled and power plants were free to compete with each other through a market mechanism to sell electricity to distributors or customers. Purchasing of power is done via market mechanisms like the power exchange, and transmission scheduling is conducted by an independent body known as the Independent System Operator (ISO).

Between 1990 and 1999, a total of 23 states plus the District of Columbia restructured their electric utility industry. The regulation affected primarily the IOUs. Munis were not compelled to restructure and were permitted to rely on their own production and distribution systems in their own localized markets.

The economics literature analyzing the competitiveness of the electricity industry after restructuring has established that electricity price levels have generally become competitive (see, e.g., the Federal Energy Regulatory Commission (FERC) report to Congress, 2011). Bushnell et al. (2017) conclude that "despite the notable isolated failures of competition, US electricity markets are now found to be reasonably competitive overall…" (page 13).

4. Data and Methodology

4.1 Plant Data

The main dataset for the analysis consists of annual plant-level data of fossil-fuel electric utilities in the US. The dataset combines three different sources: EIA, Utility Data Institute (UDI), and EPA, as described in Appendix A.

Table 2 summarizes key variables in our sample. An average plant generates approximately 3.4 terawatt-hours of electricity a year, so that the combined production of our sample plants accounts for close to 60% of the total electricity generated in the United States during that time. Consistent with the fact that only a small fraction of municipal utilities has a capacity of 100 MW and higher, 80% of our plants are investor-owned. Regarding emissions, plants allocate on average around $2 million a year on pollution abatement activities; however, significant variation occurs across plants. Finally, our plants also differ substantially in the types of input they use. An average plant uses coal as the primary fuel in two-thirds of its operating boilers, compared to 27% and 11% reliance on gas and petroleum, respectively.[16]

[16] To account for differences in operating time across boilers within a given plant-year we use a weighted average. The weights correspond to the total hours under load of each boiler.

4.2 Restructuring and Difference-in-Differences Methodology

The restructuring reform affected 23 states plus the District of Columbia. The reform in each state began with several rounds of formal hearings prior to establishing the laws in question. The process took between two and three years; therefore, identifying the specific year that captures the economic impact of the reform is challenging. To address this issue, we follow the assignment method proposed by Fabrizio et al. (2007), and for the reform implementation year we use the year of the formal hearing initiation in those states that passed restructuring legislation by the end of our sample period.

Figure 1 shows the states that restructured their utility industry and the restructuring year. New York was the first state to begin the restructuring process in 1993, followed by eight additional states in 1994 and a further nine states in 1995. Two states and the District of Columbia restructured their utilities industries in 1996, and three additional states followed suit in 1997.

In our empirical design we do not expand our analysis beyond 1999 for two reasons. First, in the aftermath of the California energy crisis in 2000, several states have postponed restructuring.[17] Second, starting from 2000, Phase II of the Clean Air Act has been implemented. It has imposed stricter sulfur dioxide emission restrictions and has allowed market participants to

[17] Specifically, electricity prices in California skyrocketed in 2000–2001, due to market manipulation and the shortage of electricity. As a result, the state of California suspended its restructuring; five additional states (Oklahoma, Arkansas, New Mexico, Nevada, and Montana) postponed restructuring; and other states began debating whether to continue with the restructuring process at all. Those developments contaminate our difference-in-differences setting in the post-1999 period. For example, it is not clear whether a state that began and then postponed restructuring following the California crisis should be assigned into a treated or control group. Also, a significant delay implementing already initiated restructuring processes undermines our assumption that the impact of the reform starts at the hearings stage; a delay further prevents identifying the true year of the reform for the treated states. Finally, it is not clear whether the states that did not initiate the restructuring process did so because they had originally decided against this policy or because they were waiting to see the resolution of the energy crisis for other states. Consequently, to ensure that we accurately capture the causal effect of competition on the outcomes of interest, we restrict our data to the years before 2000.

trade emissions permits in the open market. As a result, in the post-2000 environment most polluting firms had to consider not only the effect of competition on efficiency but also the effect of efficiency on pollution constraints and on the cost of pollution permits. Importantly, our focus is on the impact of product market competition on the environmental footprint *in the absence* of regulatory intervention. We therefore focus on the 1985-1999 period where the emission restrictions have not been a significant constraint for the plants.[18]

To ensure the validity of our method to establish the timing of reform implementation, we perform a parallel-trends analysis. Specifically, we re-run the estimation of total electricity output, as measured by total MWh, while replacing the restructuring indicator variable with a vector of time dummies for years $t-4$ to $t+4$ relative to the first year of restructuring. If the restructuring increased competition by allowing plants from out-of-state and independent power producers to enter the market, we should expect to see significantly negative coefficients, but only from year t and onward. Moreover, we should see the effect occurring primarily among IOUs and not Munis, which were free to choose whether to comply with the restructuring or not, and among larger plants. We report the coefficients and their significance interval in Figure 3. Panels A and B of Figure 3 confirm the validity of these predictions. The impact of time dummies on emissions increases in magnitude and becomes statistically significant only after the restructuring (Panel A). At the same time, we observe no significant change in emissions among Muni plants around the

[18] Specifically, during the 1985-1999 period, plants that were built before 1978 and represent 88% of our sample, did not have any meaningful restrictions in place. The 1977 legislation has required the cap of 1.2 lb of sulfur dioxide (SO_2) per Million British Thermal Units (MMBTU) for coal-fired plants (and 0.8 lb for petroleum-fired) but has applied it only to plants built after 1978. The vast majority of these new plants in our sample plants had sufficient room to increase emission without being worried about hitting the 1.2lb emission cap.

restructuring (Panel B), further confirming the differential impact of the restructuring on plants of different ownership type.[19]

Finally, we ensure that our empirical design is not subject to a potential bias, stemming from the staggered DiD design. Baker et al. (2022) show that when treatment effects change over time and across treatment groups, staggered DiD treatment effect estimates can actually obtain the opposite sign of the true estimates, even with a randomized treatment assignment. To address this issue, we replicate all our tests based on the sample that uses only the plants that belong to the first state to initiate the restructuring (New York) as the treatment group. Our control group consists of plants that operate in the states that have never initiated restructuring during our sample period. This alternative empirical design (a) solves the problem of heterogeneous effect of restructuring across states as the condition that treatment effects are distributed identically across treatment groups and periods holds automatically in the classical two-group, two-period setting (Gardner (2021)); (b) mitigates the issue of using plants that have been treated earlier in time as controls; and (c) avoids truncation problem: since New York state has initiated restructuring in 1993, we have six post-restructuring years to trace the impact of the ruling. For the sake of brevity, in Appendix Table A-6 we only report the estimation of the restructuring on the emission. Our results are qualitatively similar when we employ the same methodology for the other tests of the paper.

4.2.a Determinants of Restructuring

The economics literature points to high electricity prices as the main driver of a given state's decision to restructure its electric utility industry (Joskow 1997; White 1996; Fabrizio et

[19] To further establish the differential impact of the restructuring on IOU versus *Muni* plants, we re-estimate all of the paper's findings after splitting the restructuring indicator variable into *Restructured*IOU* and *Restructured*Muni*. The results, presented in Tables A-1 through A-5 of the Internet Appendix, indicate that restructuring only affected efficiency channels and pollution policy of the IOU plants, whereas its impact on *Muni* plants is mixed and statistically insignificant.

al., 2007). An important question is whether the restructuring decision was driven (either directly or indirectly) by changes in pollution levels in the industry. To test the validity of this argument, in Table 3 we examine the determinants of states' choice to restructure. To that end, we run a logit regression where the dependent variable is a dummy variable that equals one if the state restructured its utility industry between 1993–1999, and zero otherwise. The independent variables are electricity prices during the three-year period prior to the first restructuring initiation, as well as additional controls.[20]

The specification in Table 3 Column 1 confirms the conjecture that electricity prices are an important driver of restructuring in a state. To further evaluate the extent to which electricity prices explain the restructuring decision, we re-estimate the regression using OLS and find the adjusted R-squared of 20% (unreported for the sake of brevity). In Table 3 Column 2 we also control for the fuel mix. Variations in endowments of fossil reserves across states may be related to state-level economic factors (e.g., the prices of fuel and electricity, employment in mining, oil refinery, and transportation, etc.), and play an additional role in the state's restructuring decision. We augment our estimation with the quantities of each of the fuel types used (measured in logs of their physical quantities). Because the total quantity of fuel used is significantly affected by state electricity consumption, we scale each fuel quantity variable by total electricity produced by all of our sample plants in a given state-year. The inclusion of fuel quantities improves the overall explanatory power of the regression, as measured by pseudo R-squared. However, none of the fuel variables is statistically significant. Importantly, the negative coal quantity coefficient and the positive coefficient on gas indicate that the decision to restructure is unlikely to be driven by high state-level pollution. In Table 3 Columns 3 and 4, we explore the potential role of pollution in a

[20] Annual state-level electricity prices were obtained from EIA at https://www.eia.gov/electricity/data/state/avgprice_annual.xlsx.

more direct way and include the state-level amount of emissions, scaled by MWh, as another independent variable.[21] We find that the level of SO_2 has no significant explanatory power, and the price of electricity remains the only statistically significant variable. To summarize, our analysis of the restructuring determinants indicates that the reforms were driven primarily by high electricity prices and are unlikely to be triggered by the emission levels in a given state.

4.3 Empirical Framework

In the first set of tests, we establish the existence of each competition-driven efficiency channel.

Our baseline OLS regression tests the impact of a competition shock on each efficiency channel using difference-in-differences (DiD) framework. Our specification takes the following form:

$$(1) \qquad Efficiency_{i,s,t} = \beta_1 * Restructure_{s,t} + \beta_2 Scrubber_{i,s,t} + \beta_3 PhaseI_{i,s,t} + \alpha_i + \delta_t + \varepsilon_{i,s,t}$$

where the dependent variable is the efficiency-driven action undertaken by plant *i* under the jurisdiction of state *s*, in year *t*.[22] $Restructure_{s,t}$ is a dummy variable that equals one for every plant in a state that eventually passed the restructuring law, starting from the year of the first restructuring hearing and onward, and zero otherwise. We also include a set of control variables to capture technological and regulatory differences across plants that can subsequently affect both plant efficiency and emissions levels. The first variable, $Scrubber_{i,s,t}$, is an indicator variable that takes on a value of one if the plant has at least one FGD unit in operation (operating status "OP")

[21] Since SO_2 variable is measured with gaps, we can only include year 1990 in the pre-restructuring period.
[22] Two percent of the sample consists of plants that are geographically located in one state but fall under the jurisdiction of another state. This could happen if, for example, a plant is geographically located in one state but belongs to a company with exclusive service territory in a different state. Excluding these cases does not change any of our main results in a material way.

in a given year, and zero otherwise. The second variable, $PhaseI_{i,s,t}$, is a dummy variable for whether the plant had at least one unit that was specifically required to participate in the Acid Rain program (i.e., belongs to "Table 1 Units"). As discussed in Section 3, beginning in 1995, the Acid Rain program imposed stringent requirements on a subset of the most polluting plants. About 6% of the plants in our sample were identified under the Act.[23]

In a variant of Specification 1, we also control for the net electricity generation at the plant level.[24] Because efficiency is significantly affected by the amount of output produced, a change in output following the restructuring could have been the driver of the results.

Lastly, we include plant-epoch fixed effects (α_i) and year fixed effects (δ_t). Plant fixed-effects absorb unique plant production characteristics, as well as regional characteristics, such as demand for electricity, weather conditions, proximity to input factors, etc. We follow Fabrizio et al. (2007) and use plant-epoch, rather than just plant fixed effects as a more refined way to capture key production characteristics of a facility, as well as to neutralize the effect of deregulation on plant-level capacity. Specifically, if the capacity of a plant changes by more than 15%, we consider it a new entity epoch. Time-fixed effects account for common industry factors such as production shocks driven by economic conditions, country-wide weather profile that could affect demand, etc. Standard errors are double clustered by year and plant-epoch.[25]

[23] The program also allowed this subset of plants to trade their emission allowances in what was called cap-and-trade program. To ensure that our results are not driven by these confounding rules we also ran all our analysis with the remaining plants. Our results are similar to those for the entire sample.
We also note that the Acid Raid program included Phase II, which has targeted smaller plants. Since implementation of Phase II has started in 2000, right after the end of our sample-period, there is no need to include an additional control variable for that phase.

[24] Plants use a small portion of the electricity they produce as part of the operation process. Net generation refers to the electricity generated in excess of the amount of electricity consumed by the plant in the production process.

[25] Clustering instead by state-year does not change any of the results in a material way.

5. Results

5.1 Cost Cutting Channel

Electricity generation technology allows to cut costs in one of the following ways. First, plants can cut abatement expenses, both in terms of ongoing labor and material expenses, and in terms of investment in pollution-reducing equipment. Second, plants can change the composition of the fuel used to generate a certain heat level. Third, increasing input utilization and optimizing existing controls can also achieve a reduction in emissions rate by reducing the overall amount of heat input needed for electricity generation. In the remainder of the section, we analyze the impact of restructuring on each of these mechanisms.

5.1.a Pollution abatement

We start by analyzing the effect of restructuring on investment in equipment to reduce pollution, as well as on expenses towards material and labor in order to reduce pollution. Plants may invest in control technology, such as scrubbers or fluidized bed combustion (FBC) boilers, or they can increase expenses on collection and disposal of byproducts.

We first focus on capital expenditures, measured in dollars, and examine the effect of restructuring on the investment in pollution abatement. The results reported in Table 4 Column 1 demonstrate that the level of capital expenditure among restructured utilities dropped measurably following restructuring: the average affected facility reduced its log investment in emissions 82%. In Table 4 Column 2 we refine the definition of investment by focusing on scrubbers.[26] The results demonstrate that plants have not increased reliance on scrubbers following the reform. The only significant variable in this specification is the Phase I dummy, indicating that installing scrubbers

[26] We estimate an OLS regression because our estimation includes plant-epoch fixed effects, and the logit estimation is not feasible in this type of setting.

was one emissions-reduction method employed by facilities subject to the first stage of the acid rain program.

Next, we look at pollution abatement expenses measured by expenditures on material and labor costs, as well as equipment operation and maintenance. In Table 4 Column 3 we consider abatement costs across all categories of chemicals, including ash, flue gas, and other potentially hazardous chemicals. In Table 4 Column 4 we consider only expenses associated with the collection and disposal of the sulfur byproducts. In both cases, we find that restructured plants cut their costs in these categories.

It is possible that the results of a decline in emissions collection expenditures are driven by a shift from coal to less polluting fossil fuels following restructuring. Although we explore the effect of restructuring on fuel mix in greater detail below, we conclude this subsection by expanding the analysis of pollution abatement expenses to control for the amount of coal used in the electricity generation process. Table 4 Panel B shows that the reduction of air cleaning expenses is not attributed to the move from coal to cleaner fuel sources, and the impact of restructuring on abatement expenses remains negative and statistically significant.

In panel C we show the specification in panel B, but this time we include only non-coal operating plants. Non-coal plants use either natural gas or petroleum to generate electricity.[27] Since gas produces almost no SO_2 pollution, we expect these plants to spend more on pollution abatement when they use petroleum. To control for fuel mix, we include the quantity of petroleum used to produce electricity. Consistent with the results in panel B, the results in this specification also show a reduction in both capital expenditure and abatement expenses following the restructuring.

[27] Since these plants do not use coal, they don't have FGD, so we do not include dummy for scrubber here or use it as a control.

5.1.b Fuel mix

We next examine whether, subsequent to restructuring, plants started using cheaper inputs. We first estimate regressions where the dependent variable is the fraction of all the plant's operating boilers that rely on coal (coal-fired), gas (gas-fired), or petroleum (petroleum fired) as their primary fuel in a given year, as weighted by the number of hours under load of each boiler in that year. We present the results in Table 5 Panel A. The fraction of coal-fired boilers increased on average by 0.7% compared to nonaffected plants, and the fraction of gas-fired boilers increased by 3.4. In contrast, the fraction of oil-fired units decreased by 4.3%. We find similar results when we measure the use of coal, gas, and petroleum by the log of (one plus) the physical quantity of each fuel (Table 5 Columns 4–6).

To test more directly the extent to which fuel-changing actions may be driven by cost-cutting considerations, we exploit a cross-sectional variation in plants' production technology. To this end, we compare the subset of plants that do not have the capacity to use coal to the subset of plants that have this capacity. Our hypothesis is as follows: If cost-minimizing incentives are responsible for the change in fuel mix, the group of non-coal users should switch from petroleum (the more expensive of the two inputs) to gas (the cheaper one).[28] At the same time, for the second group – coal-operating plants – we anticipate that the propensity to use petroleum (the most expensive input) will decrease, whereas the propensity to use coal (the cheapest input) will increase. The impact of the restructuring on gas use is less clear in this subset.

Panel B of Table 5 presents the results of estimating the use of inputs within the subset of plants with no coal-based production technology. Consistent with our predictions, these plants

[28] One may argue that modifying existing technology by adding coal-operating capacity may be another way to cut costs. However, existing literature shows that adding fuel switching capabilities to a plant is an expensive and lengthy process. Adding switching capabilities that allow petroleum and gas boilers to operate on coal is particularly costly to implement (Mallory III, 1978).

have changed their fuel mix away from more expensive petroleum towards cheaper gas input. In contrast, in Panel C of Table 5 we find that changes in fuel mix are moderate within the sample of coal users. At the same time, the increase in gas use among coal-operating plants is small and statistically insignificant, suggesting that the overall increase in gas usage, presented in Panel A, is driven by the sample of non-coal plants. The increase in use of coal is positive, but marginally significant in coal operators.

Although affected plants may have not significantly changed the overall amount of coal used, coal-operating plants could have switched to cheaper and more polluting coal types. To analyze this possibility, in Table 5 Panel D we look at the sulfur and ash content of the coal used (as measured by the percentage amount of sulfur or ash times the amount of coal used, in tons). We find that plants switched to coal with higher sulfur content (Column 1), and the results remain similar when we consider differences in production technology and directly control for the amount of coal used. In Columns 3 and 4 we also analyze the ash content of coal. Higher ash content indicates more residue after the coal is burned, which is another indication of low coal quality and price. We find that following the reform, affected plants saw an increase in ash content in coal, although the effect is not statistically different from zero.

To summarize, our findings confirm the existence of another mechanism through which cost-cutting channel affects production.

5.1.c Input Utilization

Finally, we test whether the change in emissions rates may be driven by better input utilization. Plants may have reduced the overall fuel costs by generating the same amount of electricity with a smaller energy input. Higher input utilization can be achieved by a smoother and more continuous operation that avoids starting and stopping the plant. Smaller improvements, such as changes to equipment maintenance practices, may also play a role.

We perform the analysis of fuel utilization by examining whether the heat input, measured in log units of heat (BTU), declined following the restructuring. Table 6 demonstrates that, after controlling for the amount of generated electricity, an affected plant reduces its BTU input by approximately 1.2%. This finding confirms the existence of the third cost-cutting method – increased input utilization – employed in response to restructuring.

5.2 Efficient Allocation of Resources Channel

A primary reason for restructuring across states was the inability to meet peak electricity demands, which has led to increased electricity prices (Warwick, 2002). We should therefore expect plants prior to restructuring to have been subject to high loads and lower efficiency. Following restructuring many utilities started to compete for electricity across states. Electric utilities operating at close to maximum capacity sustain higher costs and cannot compete with utilities that operate below full capacity. Because peak demands are not fully correlated with one another, electricity restructuring has the potential to improve production and efficiency. In addition, the entry of nonutility electricity suppliers further increases the supply of electricity and potentially reduces loads across existing utilities.

To test whether utilities reduced their production after the restructuring, we examine plant-level capacity factor in affected plants. To measure capacity factor, we scale total annual generation, *Net MWh*, by overall plant capacity (Gross MWh multiplied by 8,760 annual number of hours). We then estimate capacity factor as a function of deregulation and control variables.

Consistent with the argument above, we find a decrease following restructuring of about 2.4% in the capacity factor of plants in the restructured states (Table 7 Column 1). In Table 7 Column 2 we use an alternative way to capture capacity and examine whether overall plant-level production has declined following restructuring. We find that the decline in the capacity factor translates into a decrease of about 16.6% in the log amount of electricity produced over time by the utilities.

Overall, the findings of this subsection are consistent with efficient allocation of resources channel: Competition led to a reduction in the production of local plants with overcapacity in favor of incumbent competing plants.

6. Emission and Restructuring

After establishing all the efficiency channels through which PMC has affected the electricity production process, we turn to analyzing the impact of these channels on the environment. This is not a trivial step, since, as indicated earlier, the cost-cutting channel could have either a positive or a negative impact on the environment. First, reduction in abatement expenses has a negative impact on environment, whereas the production efficiency channel and efficient allocation of resources - positive, so it is not clear what unique predictions we could obtain in this case. Second, the incentives to alter fuel mix vary across plants depending on the available production technology, which can also generate opposite predictions regarding the impact of this specific channel on environment.

To gauge the effect of the efficiency channels, triggered by changes in product market competition, on emission in an unambiguous way, we again turn to a cross-sectional analysis. Our goal is to test the impact of restructuring on emission within subsamples of plants where we can precisely establish the impact of the cost-cutting channel on emission. Since the major source of differential predictions is the type of fuel used, we split the sample into a group of plants that have the capacity to use coal, and those that do not. Our hypothesis is as follows. As we have established that the group of non-coal users should switch from petroleum to gas, this change in fuel mix should also reduce emission as a byproduct. Since abatement expenses are also less crucial for non-coal operating plants (for example, FGD equipment cannot be installed on a gas-operating plant), we anticipate that the restructuring will have more positive overall impact on environment compared to the rest of the sample. At the same time, for the second group – coal-operating plants – that started to use more coal, as well as coal of lower quality, we anticipate that the input mix channel will increase environmental footprint, offsetting the benefits of other channels of efficiency. As a result, we expect the impact of PMC on emission to be less positive (more negative) among coal plants compared to non-coal operating plants.

To test this idea empirically, we estimate our main specification using the natural logarithm of sulfur dioxide emission, as the dependent variable. The results on the impact of restructuring on emissions are presented in Table 8. In Table 8 Column 1, we find that the restructuring has a positive and statistically significant impact on emissions levels of coal-operating plants. At the same time, the impact of restructuring on non-coal operating plants is negative and also statistically significant. These results are consistent with our hypothesis regarding the impact of efficiency channels on emission: plants in which the cost-cutting technology was also the environmentally friendly one, have experienced the largest reduction in their environmental impact. At the same time, plants that have switched to cheaper and post polluting input source, have become more polluting.

To better understand the specific channels of efficiency that have shaped the differential response of coal and non-coal operating plants to restructuring, we include all the efficiency proxies in an alternative specification and present the results in columns (2) and (4), respectively. The results reveal several notable patterns. First, the inclusion of efficiency channels reduces the magnitudes of restructuring coefficients by 75%-90% and eliminates their statistical significance. Second, the changes in fuel mix and the capacity factor are the ones with highest statistical significance. Specifically, the coefficient of sulfur content is positive and statistically significant in explaining emission of coal-operating plants (column 2), whereas petroleum quantity has a positive and significant impact on emission among gas-operating plants.

One may wonder how the reduction in petroleum can result in sizeable changes to pollution given that the use of oil by power plants during our sample period was economically small (around 5% of the total US electricity production). Our findings that restructured plants had a 60% average reduction in pollution among non-coal plants (column (4)) is due to the fact that, in these plants, the non-petroleum source of production generated almost no sulfur dioxide emission. Therefore, even if only a small fraction of electricity in these plants is produced with petroleum, cutting that production by a substantial amount would result in a large percentage reduction in pollution. Nevertheless, the switch away from petroleum leads to an economically meaningful total reduction in pollution. Translating the regression results to actual reduction in annual emission of plants in our sample, we find that it is in the order of 4% of total emission across all plants.[29]

[29] To obtain this value, we re-estimate the emission volume of non-coal plants in tons (that is, without converting the numbers into logs) as a function of restructuring and controls (unreported). We find that the coefficient on deregulation is roughly equal to the mean emission of non-coal plants, which, on average, generate 4% of total emission in our sample. Thus, the regression implies that the post-restructured non-coal plants have essentially eliminated all their SO_2 emission, thereby reducing the overall emission by utilities nation-wide by 4%.

Taken together, these findings indicate that cost-cutting consideration plays an important role and depends on the available technology. Thereby, the existence of cheaper and environmentally friendly production options can be critical to evaluate the impact of product market competition on environmental footprint. Finally, capacity factor also plays an important role, as efficient allocation of production across competing plants has a positive impact on the environment.

To ensure the robustness of our findings, we perform several additional tests. As mentioned in section 3, we modify our DiD design to include only NY-based plants as treated units and all plants in never-restructured states as control units. The results, presented in Table A-6, remain similar to the ones reported in Table 8. We also consider an alternative econometric approach to estimation of count-like data such as emissions. Following Cohn et al. (2022), we re-estimate Table 8 using Poisson regression and report the results in Table A-7. The results remain similar when using this alternative econometric model.

7. Exploring Other Channels

Although our evidence is consistent with efficiency considerations of plants affected by the restructuring, it is possible that other economic forces helped shape this decision. In this section we explore additional potential channels, which could also be consistent with efficiency and pollution patterns that we document in our data. These channels were offered by finance literature to explain a given firm's choice to enhance their corporate social responsibility (CSR). We discuss the extent to which these channels could drive our findings.

7.1 Investor channel

The pollution reduction we found may be driven by investors of public utilities interested in protecting the environment. Shareholder activism has increased in recent decades, and Dimson et al. (2015) and Naaraayanan et al. (2020) demonstrate that, aside from traditional activism, active owners engage target firms in socially responsible practices. Therefore, investors may have responded to restructuring by pushing firms to reduce pollution. We note that this channel, while consistent with our trend in emissions overall, cannot explain the cross-sectional variations found in our study. For example, we find that coal-based plants have increased their emissions levels, while gas-based plants have reduced emissions. Moreover, this argument relies on the assumption that investors would have had a hard time engaging firms in pollution-reduction activities before restructuring. Because restructuring has changed the electricity price setting mechanism by abandoning the cost-of-sale process through which utilities were essentially guaranteed a certain level of profits, the new system has created more risk. Therefore, we cannot conclusively posit why investors choose to compel the utility to increase expenses during the more vulnerable post-restructuring period but did not do so when the utility was regulated, and less risk would have been involved.

7.2 Legal channel

Finally, we address the possibility that industry restructuring has led to greater legal uncertainty. Restructuring essentially involves changes in rulings that are yet to be challenged in a court of law. Moreover, other types of legislation, such as possible amendments to the Clean Air Act, could potentially interact with restructuring rules in ways not predicted by utilities. As a result, reducing environmental risk may be a value-enhancing strategy in such a setting. Consistent with this rationale, Sharfman and Fernando (2008) find that low environmental risk reduces firms' cost of capital, and Fernando, Sharfman, and Uysal (2017) and Koh et al. (2014) find that a decrease in environmental risk enhances firm value. In addition, from a legal standpoint, behavioral benefits may accrue to environmentally friendly policy. For example, Hong et al. (2019) demonstrate that regulators act favorably towards environmentally friendly firms.

If legal risk considerations are the effective channel, then we should expect an increase in environmentally friendly behavior in a restructured environment. However, the legal channel cannot explain the variation in our findings between plants that rely on coal, and those that do not. Table 8 demonstrates that coal-reliant plants have increased their pollution levels. Coal plants are likely to be subject to higher scrutiny by regulators because they are the most polluting agents across all categories of toxic emissions. Consistent with this notion, Phase I of the Acid Rain Program has deliberately targeted the largest polluters—old coal-operating plants—and required them to reduce pollution. We therefore conclude that the legal channel cannot be the driver of our findings.

7.3 Managerial entrenchment channel

Past studies have shown that managers may attempt to become environmentally friendly because of nonpecuniary motives, and these actions are a manifestation of agency conflicts. For example, Cheng et al. (2019) show that, consistent with the agency channel, the passage of shareholder-rights proposals leads to less environmentally friendly policies. Similarly, Masulis and Resa (2015) show that corporate philanthropy is a manifestation of agency conflicts that reduce firm value. If this is the case, then we should expect to find regulated plants more susceptible to agency conflicts. However, to the extent that product market competition spurs alignment of incentives (e.g., Hart, 1983; Schmidt, 1997; Chhaochharia et al., 2017), managers of less competitive industries are more likely to be involved in environmentally friendly policies. Therefore, our findings stand in contrast to the managerial entrenchment argument, as we find that managers of restructured utilities have decreased pollution. Our findings are instead consistent with the agency view that well-governed firms could engage more actively in CSR (Ferrell et al., 2016).

8. Conclusion

In this paper we examine the impact of efficiency incentives, triggered by an increase in product market competition, on corporate environmental footprint. We outline a theoretical framework, which establishes that product market competition incentivizes firms to become more efficient, and higher efficiency affects environment through two channels: cost-cutting and efficient allocation of resources. While the efficient allocation of resources channel unambiguously reduces pollution, the impact of cost-cutting channel depends on the set of cost-cutting actions, available to the firm.

Our empirical strategy takes advantage of a staggered passage of restructuring legislation in the electric utilities industry across the US during the 1990s. We first confirm that plants in restructured states have indeed become more efficient. We then examine the impact of the efficiency channels on the environment by exploiting the heterogeneity of plant production characteristics in our sample. Focusing on a subset of plants that do not have the technology to produce electricity with coal, we establish a positive impact of PMC on the environment. The reason is that all cost-cutting actions of the plants in this subset lead, as a by-product, to environmentally-friendly production. In contrast, we find that the impact of PMC on the environment is negative among plants that can use coal as part of their electric-generating process. Taken together, our findings indicate that cost-cutting measures available to the firm are the key determinants of whether competition will lead to environmentally-friendly outcome.

Overall, our study contributes to a growing finance research that analyzes the determinants of corporate environmental footprint. We augment the literature by studying the role of PMC when product differentiation is not at play – a setting that applies to the most polluting sectors in the economy. In addition, it is commonly believed that strong incentives to cut costs lead firms to neglect negative externalities, as firms reduce their abatement expenses. We stress that pollution abatement is not the only economic mechanism, and the changes in the firm's production function in response to competition can also play an important role in reducing environmental impact. As a result, cost-cutting incentives can be environmentally friendly and bring about lower negative externalities, reducing emission as a byproduct. Moreover, we also show another potentially important side effect of competition largely overlooked in the literature: Product market competition can lead to more efficient allocation of resources across competing plants which, in turn, further reduces the negative impact of corporate production activity on the environment.

Finally, this work adds to the literature that studies the consequences of a decline in product market competition. A number of finance papers have recently pointed to a trend in the form of an increase in product market concentration and a decline in competition in the US (Grullon et al., 2019; Gutierrez and Philippon, 2019), which, in turn, has implications for investment (Barkai, 2020), labor markets (Benmelech et al., 2022), and entrepreneurship (Decker et al., 2014, 2016)). Our work contributes to this strand of research by exploring environmental implications of changes in a competitive landscape. Consequently, we believe the findings of this study would interest both environmental and antitrust regulators.

References

Aghion, P., Benabou, R., Martin, R., and Roulet, A., 2020. Environmental preferences and technological choices: Is market competition clean or dirty? National Bureau of Economic Research Working Paper #26921.

Albuquerque, R., Koskinen, Y., and Zhang, C., 2019. Corporate social responsibility and firm risk: theory and empirical evidence, *Management Science* 65, 4451–4949.

Albuquerque, R., Koskinen, Y., Yang, S., and Zhang, C. 2020. Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies*, 9, 593–621.

Baasel, W. D., 1988. Capital and operating costs of wet scrubbers, *JAPCA* 38, 327–332.

Baker, A. C., Larcker, D. F., and Wang, C. H. C., 2022. How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370–295.

Barkai, S., 2020. Declining labor and capital shares, *Journal of Finance* 75, 2421–2463.

Benmelech, E., 2009. Asset salability and debt maturity: evidence from nineteenth-century American railroads, *Review of Financial Studies* 22, 1545–1584.

Benmelech, E., Bergman, N., 2011. Bankruptcy and the collateral channel, *Journal of Finance* 66, 337–378.

Benmelech, E., N. Bergman, and Kim, H., 2022. Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources* 75, S200–S250.

Bushnell, J., Mansur, E.T., and Novan, K., 2017. Review of the economics literature on US electricity restructuring, *Working Paper*.

Cheng, I-H, Hong, H. G., and Shue, K., 2019. Do managers do good with other people's money? *Working Paper*, Dartmouth College.

Chhaochharia, V., Grinstein, Y., Grullon, G., and Michaely, R., 2017. Product market competition and internal governance: evidence from the Sarbanes-Oxley Act, *Management Science* 64, 1405–1424.

Cohn, J. B., Liu, Z., and Wardlaw, M., 2022. Count (and count-like) data in finance, *Journal of Financial Economics* forthcoming.

Dai, R., Liang, H., and Ng, L., 2021. Socially responsible corporate customers, *Journal of Financial Economics* 142, 598–626.

Décaire, P. H., Gilje, E.P., and Taillard, J.P., 2020. Real option exercise: empirical evidence, *Review of Financial Studies* 33, 3250–3306.

Decker, R., Haltiwanger, J., Jarmin, R., and Miranda, J., 2014. The role of entrepreneurship in U.S. job creation and economic dynamism, *Journal of Economic Perspectives* 28, 3−24.

Decker, R., Haltiwanger, J., Jarmin, R., and Miranda, J., 2016. Where has all the skewness gone? The decline in high-growth (young) firms in the U.S., *European Economic Review* 86 (2016), 4−23.

Delmas, M., Russo, M. V., and Montes-Sancho, M. J., 2007. Deregulation and environmental differentiation in the electric utility industry. *Strategic Management Journal*, *28*, 189–209.

Dimson, E., Karakaş, O., and Li, X., 2015. Active ownership, *Review of Financial Studies* 28, 3225–3268.

Duanmu, J., Bu, M., and Pittman, R., 2018. Does market competition dampen environmental performance? Evidence from China. *Strategic Management Journal*, 39, 3006–3030.

Fabrizio, K., Rose, N. L., and Wolfram, C.D., 2007. Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency, *American Economic Review* 97, 1250–1277.

Fernando, C. S., Sharfman, M. P., and Uysal, V. B., 2017. Corporate environmental policy and shareholder value: following the smart money, *Journal of Financial and Quantitative Analysis* 52, 2023–2051.

Ferrell, A., Liang, H., and Renneboog, L., 2016. Socially responsible firms, *Journal of Financial Economics* 122, 585–606.

Flammer, C., 2015. Does product market competition foster corporate social responsibility? Evidence from trade liberalization, *Strategic Management Journal* 36, 1469–1485.

Gardner, J., 2021. Two-stage differences in differences, Working Paper.

Gilje, E. P., Loutskina, and E., Murphy, D., 2020. Drilling and debt, *Journal of Finance* 75, 1287–1325.

Grullon, G., Larkin, Y., and Michaely, R., 2019. Are U.S. industries becoming more concentrated? *Review of Finance* 23, 697–743.

Gutiérrez, G., and T. Philippon, 2016. Investment-less growth: An empirical investigation, National Bureau of Economic Research Working Paper 22897.

Hart, O., 1983. The market as an incentive mechanism, *Bell Journal of Economics* 14, 336–382.

Heeter, J., O'Shaughnessy, E., and Burd, R., 2021 *Status and Trends in the Voluntary Market (2020 Data)*. Renewable Energy Markets Conference, Report No. NREL/PR-6A20-81141.

Hong, H. G., Kubik, J. D., Liskovich, I., and Scheinkman, J., 2019. Crime, punishment and the value of corporate social responsibility, *Working Paper,* Columbia University.

Joskow, P. L, 1997. Restructuring, competition and regulatory reform in the U.S. electricity sector, *Journal of Economic Perspectives* 11, 119–138.

Joskow, P.L., 2003. The difficult transition to competitive electricity markets in the U.S., MIT Center for Energy and Environmental Policy Research paper.

Koh, P. S., Qian, C., and Wang, H., 2014. Firm litigation risk and the insurance value of corporate social performance, *Strategic Management Journal* 35, 1464–1482.

Larcker, D. F., Tayan, B. and Watts, M. 2022. Seven myths of ESG. *European Financial Management*, 28, 869-882.

Lins, K. V., Servaes, H., and Tamayo, A. 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance,* 72, 1785–1824.

Mallory III, C.K, 1978. The phasing out of oil and gas used for boiler fuel: constraints, *Tulsa Law Review* 13, 702–713.

Masulis, R. and Resa, S. W., 2015. Private benefits and corporate investment and financing decisions: the case of corporate philanthropy, *Review of Financial Studies* 28, 592–636.

Naaraayanan, S. L., Sachdeva, K., and Sharma, V., 2020. The real effects of environmental activist investing, *ECGI Finance Working Paper No. 743/2021*.

Schmidt, K., 1997. Managerial incentives and product market competition, *Review of Economic Studies* 64, 191–213.

Servaes, H. and Tamayo, A., 2013. The impact of corporate social responsibility on firm value: the role of customer awareness, *Management Science* 59, 1045–1061.

Sharfman, M. P., and Fernando, C. S., 2008. Environmental risk management and the cost of capital, *Strategic Management Journal* 29, 569–592.

Warwick, W. M., 2002. “A primer on electric utilities, deregulation, and restructuring of U.S. electricity market,” *U.S. Department of Energy Federal Energy Management Program, Office of Energy Efficiency and Renewable Energy Program.*

White, M. W., 1996. Power struggles: Explaining deregulatory reforms in electricity markets. *Brookings Papers on Economic Activity. Microeconomics*, 201-267.

Appendix A: Data sources

Our main source of information for this study is the US Energy Information Administration (EIA). EIA is a statistical and analytical agency within the US Department of Energy, which collects comprehensive data covering a full spectrum of elements related to the energy generation process, including sources, uses, technologies, and distribution. The information is usually available at a plant level.[30]

The majority of the EIA information in our project comes from Form EIA-767. Specifically, the data on capital investment in pollution abatement as well as expenditures associated with the collection and disposal of byproducts during the generation process, are obtained from Form EIA-767 files. Information on plant equipment characteristics, such as boilers and flue-gas desulfurization (FGD) units, are also collected from this form. Next, we include data on quantities of fuel-by-fuel type (coal, natural gas, or petroleum). This information is collected in Form EIA-423 (we sum up monthly fuel use by each fuel type within each calendar year). Finally, we rely on Form EIA-861 to obtain information on electricity sales and prices, which we also convert into annual frequency.

The second dataset is collected from the Utility Data Institute (UDI) Operations and Maintenance (O&M) Production Cost Database, which combines data from the following publicly available resources: The Federal Energy Regulatory Commission (FERC); the US Energy Information Administration (EIA); and the Rural Utilities Service (RUS). The dataset contains basic plant characteristics such as plant ownership, age, location, and capacity. The dataset

[30] Some reports provide more granular information (e.g., at a unit, boiler, or generator level). In these cases, we aggregate information at a plant level; the data are available online at www.eia.gov and are categorized into topics (each topic corresponds to a specific form the plant needs to fill out).

additionally contains production-related factors, including (i) energy output measured in net Megawatt hours (MWh); (ii) energy input measured in British thermal units (BTUs) of fuel consumption; (iii) number of employees; (iv) fuel; and (v) nonfuel expenses. Nonfuel expenses primarily consist of operation and maintenance expenses, as well as wage and salary expenses. Fabrizio et al. (2007) have combined these variables into one dataset and have made it available for researchers. Their data spans the period 1981–1999 and contains all large fossil-fuel steam and combined-cycle gas turbine generating plants with a capacity of 100 megawatt hours (MWh) and higher.[31]

Finally, we obtain emissions data from the Environmental Protection Agency (EPA). Electric utilities are required by law to monitor and disclose their emission levels. Within the EPA platform, our emission data comes from two sources. First, we rely on data from the Emissions & Generation Resource Integrated Database (eGRID). The eGRID database is based on plant-specific data for all US electricity generating plants that provide power to the electric grid and report data to the US government. The information on emissions starts from 1996 and, according to the EPA, is a comprehensive source of data on the environmental characteristics of almost all electric power generated in the US. Data reported include mass emissions of carbon dioxide (CO_2), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and other chemicals. The eGRID database reports this information on an annual basis and rely on the same type of plant identifier as EIA (namely the Office of Regulatory Information Systems Plant Location (ORISPL)), making the merge of the two databases straightforward.

Since eGRID does not cover the pre-restructuring years for most states, we supplement the eGRID information with historical information on emissions from a different platform, Air

[31] The dataset is available on the website of the American Economic Association at: https://www.aeaweb.org/articles?id=10.1257/aer.97.4.1250.

Markets Program Data (AMPD), which is also managed by the EPA.[32] The US government began gathering SO_2 emissions data as early as the 1980s, and AMPD provides information on emission levels of SO_2 for the years 1980, 1985, 1990, and annually from 1995. We therefore combine our eGrid data with information on SO_2 emissions for the years 1985, 1990, and 1995.[33] The only complete available time-series are for SO_2 emissions. Therefore, we focus on this pollutant in our analysis. However, as we will elaborate in the analysis section, our findings extend also to other chemicals involved in the production of electricity. Overall, for the 599 facilities that appear in the Fabrizio et al. (2007) dataset in all the years that overlap with EPA data we were able to find data on 572 facilities with nonmissing SO_2 information in the eGRID or Air Markets Program datasets.

[32] https://ampd.epa.gov/ampd/.
[33] Air Markets Program Data also reports statistics on NO_x, but these data start in 1995. We therefore focus our analysis on SO_2 pollution.

Figure 1:
Restructured States

The figure depicts the U.S. map where restructured states are shaded. Each color corresponds to a specific restructuring year (see legend).

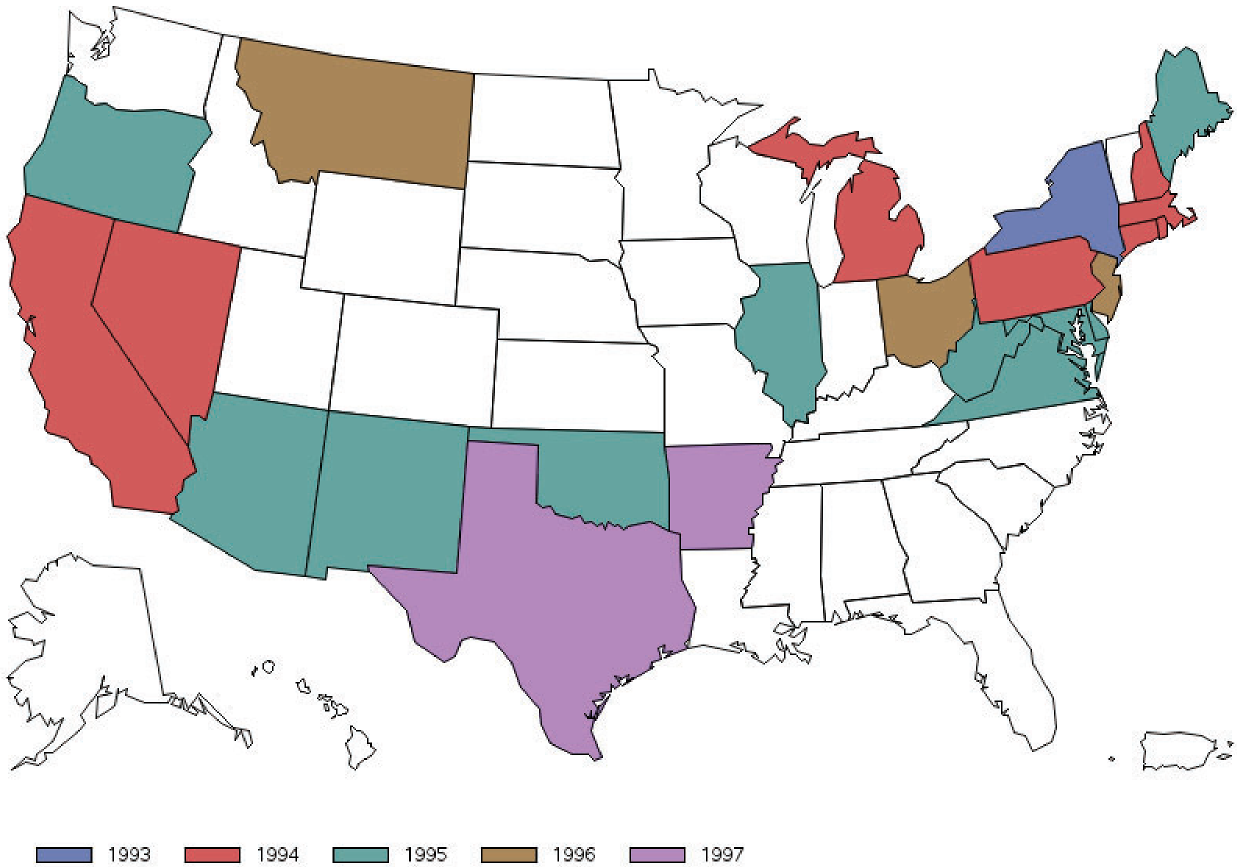


Figure 2:
Average Fuel Prices Over Time

The figure depicts average prices of coal, petroleum and gas, all in cents per million BTU, based on information reported in Form EIA-861 for plants in our sample. To aggregate the data across plants, for every fuel type and year we calculate the average of fuel prices, weighted by total MWh generated by each plant. To mitigate the impact of outliers, prices of each fuel type at the plant-year level are winsorized at 1% and 99% of their empirical distribution prior to averaging.

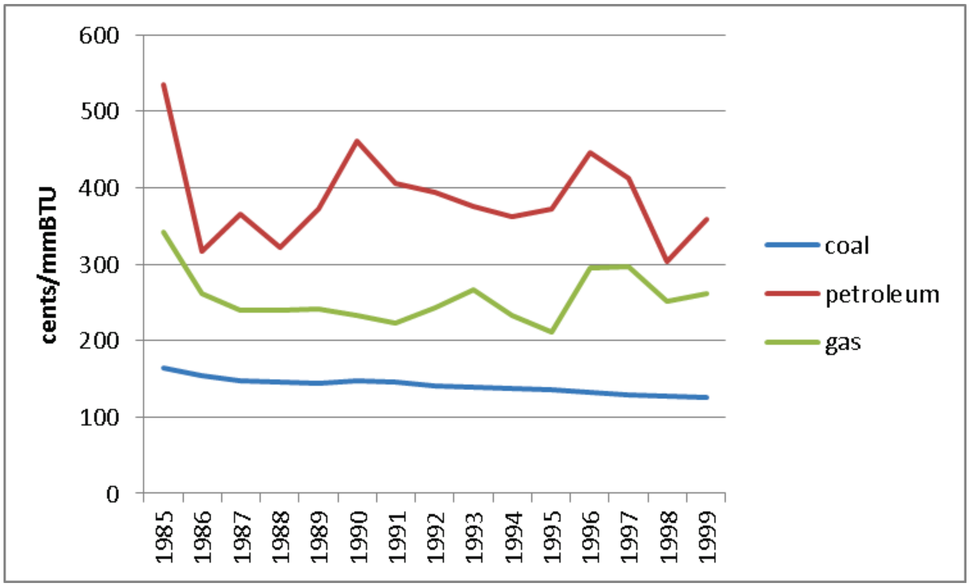
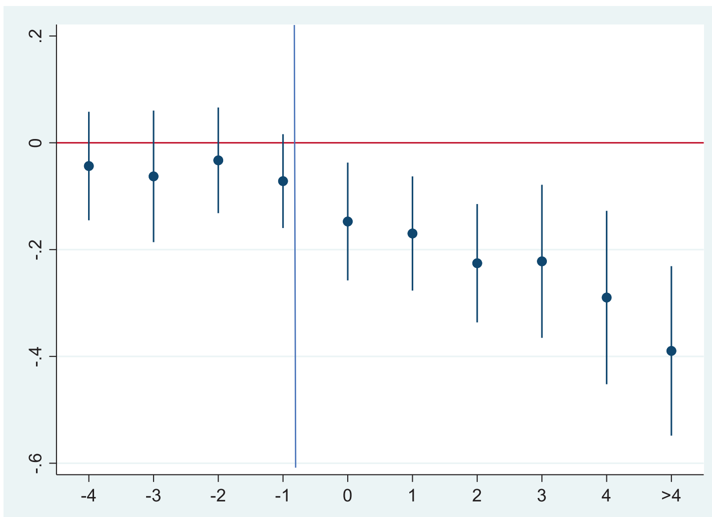


Figure 3:
Parallel Trends

This graph reports point estimates and 95% confidence intervals of panel regressions of total output, as measured by natural log of plant-level Net MWh, for investor-owned (*IOU*) versus municipal (*Muni*) plants. The sample consists of all firms in the EIA-Fabrizio et al. (2007) sample over the following years: 1985–1999. All regressions include also *Phase I* and *Scrubber* indicator variables. *IOU* is an indicator variable which equals one if the plant belongs to an investor-owned utility firm. *Muni* is an indicator variable which equals one if the utility firm is owned by government, municipality, or members of a co-op. The regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions. The x-axis reports year relative to the restructuring year.

Panel A: Regression of MWh, *IOU* plants



Panel B: Regression of MWh, *Muni* plants

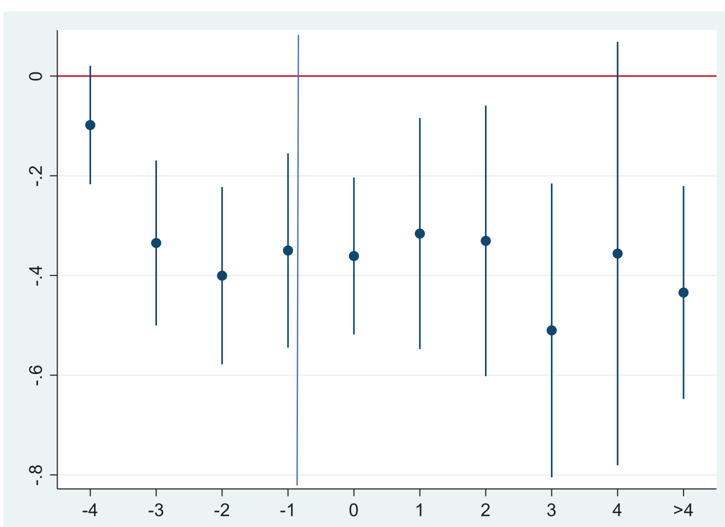


Table 1
Product Differentiation Among Largest Emitters

The table shows aggregate waste release in 2019 by the most pollutive industries (defined at a 3-digit NAICS code) in the US. Panel A measures pollution based on emission of greenhouse gases and equivalent. The data is obtained from GHGRP, managed by the EPA. In Panel B we define the most pollutive industries based on the Toxic Release Inventory (TRI) database, also from EPA. Each panel presents the most polluting industries in the descending order. For each of the industries, we also present the number of Compustat firms in 2019, and the fraction of firms with positive advertisement expenses. In the last columns of each table we the fraction of firms with positive advertisement expenses is weighted by the book value of assets.

Panel A: GHG emission

NAICS	Industry	% of nationwide GHG emission	Number of Compustat firms	% Compustat firms with positive advertising expenses	% Compustat firms with positive advertising expenses (asset-weighted)
221	Electric Utilities	57.8%	201	2.0%	2.4%
211	Oil and Gas Extraction	8.7%	248	0.8%	0.1%
324	Petroleum	7.3%	40	15.0%	2.8%
325	Chemicals	7.0%	1,149	14.1%	43.9%
327	Concrete Gypsum	3.7%	27	37.0%	14.4%
562	Hazardous Waste	3.5%	24	29.2%	18.4%
331	Primary Metals	3.0%	51	15.7%	18.1%
486	Pipeline Transportation	2.3%	38	0.0%	0.0%
212	Metal Mining	1.7%	366	2.7%	0.0%
	Total	95%	2,144	9.7%	

Panel B: Toxic releases

NAICS	Industry	% of nationawide toxic waste emission	Number of Compustat firms	% Compustat firms with positive advertising expenses	% Compustat firms with positive advertising expenses (asset-weighted)
212	Metal Mining	41.2%	366	2.7%	0.0%
325	Chemicals	14.9%	1,149	14.1%	43.9%
331	Primary Metals	10.1%	51	15.7%	18.1%
221	Electric Utilities	8.5%	201	2.0%	2.4%
322	Paper	4.7%	36	16.7%	26.8%
311	Food	4.6%	85	55.3%	57.2%
562	Hazardous Waste	4.1%	24	29.2%	18.4%
324	Petroleum	2.4%	40	15.0%	2.8%
	Total	90%	1,952	12.8%	

Table 2
Descriptive Statistics

The table presents descriptive statistics for the merged EPA-EIA- Fabrizio et al. (2007) plant-year sample for the period of 1985–1999. *Restructured* is an indicator variable that takes on a value of one for every plant in a state that passed the restructuring legislation starting from the year of the first restructuring hearings and onward. Net annual MWh measures the amount of electric energy produced, in Megawatt hour. *Gross MW Capacity* is the maximum electric power a plant can produce, in Megawatt. *Installation year* is the year when the oldest unit in the plant was installed. *Heat input* is the amount of heating energy used as an input in the generation of electricity and is measured in billions of British thermal units (BBTUs); *Capacity factor* is the ratio of total net energy produced by the plant to its maximal capacity (defined as Gross *MW* Capacity, multiplied by number of hours per year). *IOU* is an indicator variable which equals one if the plant belongs to an investor-owned utility firm. SO_2 is the annual emission of sulfur dioxide, in tons. *Scrubber* is an indicator variable that equals 1 if the plant has at least one flue-gas desulfurization (FGD) system in operating status, and zero otherwise. *Phase I* is an indicator variable for whether the plant was subject to Phase I of the Acid Rain program. The indicator takes on the value of 1 for all affected plants starting from 1995 and onward, and zero otherwise. *Abate. Capex* measures all pollution abatement capital expenditures for new structures and/or equipment made during the reporting year, in thousand dollars. *Abate. Costs* cover all material and labor costs including equipment operation and maintenance costs (such as particulate collectors, conveyers, hoppers, etc.) associated with the collection and disposal of the byproducts, including fly and bottom ash collection, FGD collection, and other pollution collection. *SO_2 Costs* variable covers the FGD expenses. Fuel quantities (Coal, Gas, and Petroleum) are total annual amount of each input used, measured in its respective units. %boilers with primary fuel – coal [gas, petroleum] measures the fraction of boilers in a given plant-year that use coal [gas, petroleum] as their primary fuel, weighted by each boiler's total hours under load.

Table 2 (cont.)

Variable	Obs	Mean	Std. Dev.	Min	p25	Median	p75	Max
Dummy (Restructured=1)	7,940	0.15	0.36	0	0	0	0	1
Plant Characteristics								
Total output (Net annual MWh)	7,940	3,447,705	3,726,115	886	819,218	2,167,528	4,691,988	22,000,000
Gross Capacity (MW)	7,940	807	665	100	304.00	588.96	1,137.60	3,969
Installation year	7,940	1962	12	1918	1953	1960	1972	1997
Heat input (BBTU)	7,940	35,441	37,254	15	9,068	22,706	48,042	229,489
Capacity factor	7,940	0.44	0.22	0.00	0.26	0.45	0.62	0.98
Dummy (IOU=1)	7,940	0.80	0.40	0	1	1	1	1
Pollution and Abatement								
SO_2 emission, ton	3,467	24,345	39,024	0	497	10,847	28,112	374,920
Dummy (Phase I=1)	7,940	0.06	0.24	0	0	0	0	1
Dummy (Scrubber=1)	7,940	0.16	0.37	0	0	0	0	1
Abate. Capex, ($1,000)	7,810	731	6,139	0	0	0	117	304,014
Abate. Costs, total ($1,000)	7,810	1,369	4,163	0	0	17	979	95,656
SO_2 Costs ($1,000)	7,810	643	2,810	0	0	0	149	56,236
Fuel Inputs								
Coal quant. ('000 short tons)	7,788	1,457	2,024	0	0	628	2,116	14,108
Gas quant. ('000 cubic ft.)	7,788	4,509,418	11,000,000	0	0	8,300	2,780,975	107,000,000
Petroleum quant. ('000 barrels)	7,788	282	1,009	0	1	9	44	13,617
% boilers with primary fuel - coal	7,598	0.62	0.46	0.00	0.00	1.00	1.00	1.00
% boilers with primary fuel - gas	7,598	0.27	0.43	0.00	0.00	0.00	0.67	1.00
% boilers with primary fuel - petroleum	7,598	0.11	0.29	0.00	0.00	0.00	0.00	1.00

Table 3
Determinants of Restructuring

This table reports estimates of logit regressions where the dependent variable is an indicator variable that takes on a value of one if the state has passed restructuring legislation at any point between 1993 and 1999. The sample in Specifications 1 and 2 consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1990–1992. The sample of the independent variables in specifications (3) and (4) consists of all plants in the EIA-EPA-Fabrizio et al. (2007) sample in 1990. *Cents/KWh* is annual state-level electricity prices. Net annual MWh measures the aggregate amount of electric energy produced by all the plants in our sample at a given state-year, measured in Megawatt hour. SO_2 is the annual emission of sulfur dioxide, in tons, aggregated across all plants in a given state-year. Fuel quantities (Coal, Gas, and Petroleum) are the total annual amount of each input used, measured in its respective units, aggregated across all plants in a given state-year. Robust standard errors are reported in parentheses below coefficient estimates and are clustered by state in Specifications 1 and 2. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) 1990–1992	(2) 1990–1992	(3) 1990	(4) 1990
Cents/KWh	0.720**	0.645	1.064***	0.669*
	(0.313)	(0.431)	(0.317)	(0.390)
ln(SO_2/Net MWh)			-0.668	-0.617
			(0.506)	(0.529)
ln(Coal Quant./Net MWh)		-0.292		-0.252
		(0.415)		(0.464)
ln(Gas Quant./Net MWh)		0.053		0.038
		(0.067)		(0.062)
ln(Pet Quant./Net MWh)		0.274		0.302
		(0.280)		(0.321)
N	141	138	46	46
pseudo R^2	0.166	0.299	0.233	0.299
SE Clustered by State	Yes	Yes	No	No

Table 4
Cost-Cutting Channel: Emission Cleaning Expenditure

This table reports estimates of panel regressions of plant-level capital expenditures, as well as of operations and management costs associated with emission abatement, as a function of restructuring and control variables. The sample in Panel A consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999. The sample in Panel B is refined to include only plants with positive coal input in a given year. The sample in Panel C is refined to include only plants with zero coal input in a given year. All variables are as described in Table 2. Each dependent variable, except *Scrubber* indicator, is converted into natural logs (a value of one is added before the transformation). All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: All Plants

	(1) ln(Abate. CapEx)	(2) Dummy (Scrubber=1)	(3) ln(Abate. Costs, total)	(4) ln(SO_2 Costs)
Restructured	-0.823***	-0.005	-0.436*	-0.614**
	(0.217)	(0.010)	(0.224)	(0.232)
ln(Net MWh)	0.216*	0.000	-0.009	0.225*
	(0.116)	(0.004)	(0.111)	(0.115)
Dummy (Scrubber=1)	0.117		4.839***	1.427**
	(0.671)		(0.872)	(0.540)
Dummy (Phase I=1)	-0.323	0.124***	-1.550***	0.732*
	(0.287)	(0.033)	(0.414)	(0.348)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7810	7940	7810	7810
adj.R^2	0.42	0.95	0.76	0.59
adj.R^2 within	0.01	0.07	0.06	0.02

Panel B: Coal Plants

	(1) ln(Abate. CapEx)	(2) Dummy (Scrubber=1)	(3) ln(Abate. Costs, total)	(4) ln(SO_2 Costs)
Restructured	-0.791**	-0.003	-0.619***	-0.588*
	(0.280)	(0.016)	(0.199)	(0.307)
ln(Coal quant.)	0.195	0.003	-0.008	0.264
	(0.203)	(0.010)	(0.167)	(0.196)
Dummy(Scrubber=1)	0.054		5.136***	1.291**
	(0.679)		(0.786)	(0.545)
Dummy(Phase I=1)	-0.503	0.123***	-0.672**	0.488
	(0.321)	(0.034)	(0.301)	(0.364)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5169	5169	5169	5169
adj.R^2	0.35	0.94	0.79	0.54
adj.R^2 within	0.01	0.06	0.10	0.01

Panel C: Non-Coal Plants

	(1) ln(Abate. CapEx)	(2) ln(Abate. Costs, total)	(3) ln(SO_2 Costs)
Restructured	-0.620**	-1.201**	-0.191
	(0.211)	(0.406)	(0.268)
ln(Petroleum quant.)	0.122**	0.053	0.127**
	(0.057)	(0.050)	(0.051)
Dummy(Phase I=1)	-1.280*	-2.654**	-1.887
	(0.645)	(1.212)	(1.306)
Plant-Epoch FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2618	2618	2618
adj. R^2	0.46	0.55	0.50
adj. R^2 within	0.02	0.05	0.02

Table 5
Cost-Cutting Channel: Fuel Mix

This table reports estimates of panel regressions of plants' reliance on different fuel types in the production process as a function of restructuring and control variables. The sample in Panel A, as well as Panel D (Specifications 1 and 3) consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999; the sample in Panel B (Panel C) consists of non-coal (coal) plants only. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. Panel C does not have a *Prim. Petrol.* estimation because there are no coal plants in our sample with boilers that use petroleum as primary fuel. The sample in Panel D Specifications 2 and 4 includes only plants with positive coal input in a given year. ln(Sulf. Coal) is one plus the amount of sulfur in coal used for burning, in tons. ln(Ash) is one plus the amount of ash, produced in the process of coal burning, measured in the same way as the amount of sulfur. All the remaining variables are as described in Table 2. When converting variables into natural logs, a value of one is added before the transformation. All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Fuel Mix – All Plants

	(1) Prim. Coal	(2) Prim. Gas	(3) Prim. Petrol.	(4) ln(Coal Quant.)	(5) ln(Gas Quant.)	(6) ln(Pet. Quant.)
Restructured	0.007*	0.032**	-0.043***	0.012	0.590**	-0.415***
	(0.004)	(0.013)	(0.013)	(0.030)	(0.228)	(0.104)
ln(BTU)	0.003	0.002	-0.008	0.359***	0.608***	0.350***
	(0.002)	(0.009)	(0.009)	(0.039)	(0.124)	(0.074)
Dummy (Scrubber=1)	-0.002	-0.006	0.008*	0.025	-0.191	-0.129
	(0.005)	(0.007)	(0.004)	(0.044)	(0.494)	(0.154)
Dummy (Phase I=1)	0.000	-0.008	0.008	0.015	0.232	0.216*
	(0.006)	(0.007)	(0.006)	(0.027)	(0.240)	(0.112)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7598	7598	7598	7788	7788	7788
adj.R^2	0.99	0.94	0.88	0.99	0.94	0.86
adj.R^2 within	0.00	0.01	0.01	0.16	0.01	0.04

Panel B: Fuel Mix – Non-Coal Plants

	(1) Prim. Gas	(2) Prim. Petrol.	(3) ln(Gas Quant.)	(4) ln(Pet. Quant.)
Restructured	0.082**	-0.091***	0.870**	-0.818***
	(0.031)	(0.029)	(0.351)	(0.231)
ln(BTU)	0.011	-0.015	0.854***	0.507***
	(0.014)	(0.014)	(0.160)	(0.112)
Dummy (Phase I=1)	0.107	-0.099	9.622***	0.003
	(0.116)	(0.115)	(1.675)	(0.585)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2523	2523	2603	2603
adj. R^2	0.85	0.86	0.85	0.86
adj. R^2 within	0.02	0.02	0.07	0.07

Panel C: Fuel Mix –Coal Plants

	(1) Prim. Coal	(2) Prim. Gas	(3) ln(Coal Quant.)	(4) ln(Gas Quant.)	(5) ln(Pet. Quant.)
Restructured	0.011*	0.005	0.065	0.285	-0.108
	(0.006)	(0.006)	(0.038)	(0.272)	(0.084)
ln(BTU)	0.007	0.004	0.959***	0.294	-0.058
	(0.006)	(0.006)	(0.047)	(0.174)	(0.063)
Dummy (Scrubber=1)	-0.002	-0.002	0.011	-0.062	-0.172
	(0.005)	(0.005)	(0.020)	(0.485)	(0.139)
Dummy (Phase I=1)	0.001	-0.004	0.017	0.202	0.058
	(0.006)	(0.006)	(0.022)	(0.236)	(0.088)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	5075	5075	5185	5185	5185
adj. R^2	0.92	0.85	0.95	0.91	0.87
adj. R^2 within	0.00	0.00	0.43	0.00	0.00

Panel D: Coal Quality

	(1) ln(Sulf.)	(2) ln(Sulf.)	(3) ln(Ash)	(4) ln(Ash)
Restructured	0.093**	0.128**	0.045	0.051
	(0.037)	(0.045)	(0.038)	(0.034)
ln(Net MWh)	0.263***		0.311***	
	(0.030)		(0.036)	
ln(Coal Quant.)		0.752***		0.932***
		(0.040)		(0.019)
Dummy(Scrubber=1)	0.412***	0.407***	0.136**	0.117***
	(0.097)	(0.087)	(0.052)	(0.039)
Dummy(Phase I=1)	-0.455***	-0.446***	-0.093**	-0.090***
	(0.062)	(0.065)	(0.032)	(0.029)
Intercept	-0.583	-0.577*	0.178	0.319**
	(0.432)	(0.283)	(0.521)	(0.138)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7788	5169	7788	5169
adj. R^2	0.99	0.95	0.99	0.96
adj. R^2 within	0.16	0.38	0.11	0.52

Table 6
Cost-Cutting Channel: Input Utilization

This table reports estimates of a panel regression of heat input as a function of restructuring and control variables. The sample consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999. All variables are as described in Table 2. The regression is estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) ln(BTU)
Restructured	-0.012**
	(0.005)
ln(Net MWh)	0.914***
	(0.008)
Dummy(Scrubber=1)	0.007
	(0.007)
Dummy(Phase I=1)	-0.002
	(0.005)
Plant-Epoch FE	Yes
Year FE	Yes
N	7940
adj.R^2	0.997
adj.R^2 within	0.947

Table 7
Efficient Allocation of Resources Channel

This table reports estimates of panel regressions of plant-level measures of efficient resource allocation as a function of restructuring and control variables. The sample consists of all plants in the EIA- Fabrizio et al. (2007) sample over the period of 1985–1999. All variables are as described in Table 2. All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(2) Capacity Factor	(3) ln(Net MWh)
Restructured	-0.056***	-0.166***
	(0.010)	(0.032)
Dummy(Scrubber=1)	0.009	0.007
	(0.025)	(0.061)
Dummy(Phase I=1)	-0.009	-0.053
	(0.011)	(0.036)
Plant-Epoch FE	Yes	Yes
Year FE	Yes	Yes
N	7940	7940
adj.R^2	0.853	0.941
adj.R^2 within	0.026	0.015

Table 8
Restructuring and Emissions, by Production Technology Groups

This table reports estimates of panel regressions of plant-level SO_2 emission amounts as a function of restructuring and other control variables. The sample consists of all firms in EPA-EIA-Fabrizio et al. (2007) sample over the following years: 1985, 1990, 1995–1999. The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. *Heat rate* is the ratio of total heat input to net output (MMBTU/Net MWh). All other variables are as described in Table 2. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. Since *Scrubber* is not used in plants with no coal-based operation, and *Sulfur* is a feature of coal input only, the two variables are excluded in Specifications 3 and 4. The regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) Coal Plants	(2) Coal Plants	(3) Non-Coal Plants	(4) Non-Coal Plants
Restructured	0.179*	0.048	-0.716**	-0.077
	(0.081)	(0.036)	(0.213)	(0.147)
ln(Sulfur)		0.557**		
		(0.206)		
ln(Petroleum Quant.)		0.037		0.652***
		(0.031)		(0.044)
ln(Heat Rate)		-0.038		-0.149
		(0.393)		(0.231)
Capacity Factor		0.974**		1.936***
		(0.356)		(0.369)
ln(Abate. Expenses)		-0.004		0.024
		(0.008)		(0.022)
ln(Abate. Investment)		-0.002		-0.003
		(0.003)		(0.013)
ln(Net MWh)	0.886***		0.692***	
	(0.074)		(0.130)	
Dummy(Scrubber=1)	-0.854***	-1.094***		
	(0.199)	(0.232)		
Dummy(Phase I=1)	-0.554***	-0.305*	0.245	-0.260
	(0.059)	(0.130)	(0.342)	(0.379)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2317	2315	1116	1111
adj. R^2	0.92	0.94	0.87	0.93
adj. R^2 within	0.35	0.48	0.12	0.52

Internet Appendix
Table Appendix A-1
Cost-Cutting Channel: Emission Cleaning Expenditure

This table reports estimates of panel regressions of plant-level capital expenditures, as well as of operations and management costs associated with emission abatement, as a function of restructuring and control variables. The sample in Panel A consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999. The sample in Panel B is refined to include only plants with positive coal input in a given year. The sample in Panel C is refined to include only plants with zero coal input in a given year. All variables are as described in Table 2. Each dependent variable, except *Scrubber* indicator, is converted into natural logs (a value of one is added before the transformation). All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: All Plants

	(1) ln(Abate. CapEx)	(2) Dummy (Scrubber=1)	(3) ln(Abate. Costs, Total)	(4) ln(SO_2 costs)
Restructured*IOU	-0.935***	-0.007	-0.648**	-0.635**
	(0.228)	(0.010)	(0.239)	(0.238)
Restructured*Muni	-0.054	0.009	1.005**	-0.470
	(0.495)	(0.020)	(0.356)	(0.454)
ln(Net MWh)	0.221*	0.001	0.001	0.226*
	(0.116)	(0.004)	(0.109)	(0.115)
Dummy (Scrubber=1)	0.093		4.793***	1.422**
	(0.673)		(0.873)	(0.537)
Dummy(Phase I=1)	-0.279	0.125***	-1.468***	0.740*
	(0.287)	(0.033)	(0.411)	(0.351)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7810	7940	7810	7810
adj. R^2	0.42	0.95	0.76	0.59
adj. R^2 within	0.01	0.07	0.07	0.02

Panel B: Coal Plants

	(1) ln(Abate. CapEx)	(2) Dummy (Scrubber=1)	(3) ln(Abate. Costs, total)	(4) ln(SO_2 Costs)
Restructured*IOU	-0.951***	-0.007	-0.855***	-0.627*
	(0.294)	(0.017)	(0.195)	(0.323)
Restructured*Muni	0.529	0.029	1.334**	-0.260
	(0.772)	(0.042)	(0.487)	(0.683)
ln(Coal quant.)	0.216	0.003	0.023	0.270
	(0.203)	(0.010)	(0.163)	(0.197)
Dummy (Scrubber=1)	0.012		5.074***	1.280**
	(0.683)		(0.788)	(0.539)
Dummy(Phase I=1)	-0.435	0.124***	-0.570*	0.505
	(0.321)	(0.034)	(0.298)	(0.369)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5169	5169	5169	5169
adj. R^2	0.35	0.94	0.79	0.54
adj. R^2 within	0.01	0.06	0.12	0.01

Panel C: Non-Coal Plants

	(1) ln(Abate. CapEx)	(2) ln(Abate. Costs, total)	(3) ln(SO_2 Costs)
Restructured*IOU	-0.676**	-1.347***	-0.193
	(0.231)	(0.424)	(0.274)
Restructured*Muni	-0.330	-0.436	-0.184
	(0.457)	(0.562)	(0.497)
ln(Petroleum quant.)	0.122*	0.053	0.127**
	(0.057)	(0.051)	(0.051)
Dummy(Phase I=1)	-1.235*	-2.536*	-1.886
	(0.641)	(1.202)	(1.304)
Plant-Epoch FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2618	2618	2618
adj. R^2	0.46	0.55	0.50
adj. R^2 within	0.02	0.06	0.02

Table Appendix A-2
Cost-Cutting Channel: Fuel Mix

This table reports estimates of panel regressions of plants' reliance on different fuel types in the production process as a function of restructuring and control variables. The sample in Panel A, as well as Panel D (Specifications 1 and 3) consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999; the sample in Panel B (Panel C) consists of non-coal (coal) plants only. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. Panel C does not have a *Prim. Petrol.* estimation because there are no coal plants in our sample with boilers that use petroleum as primary fuel. The sample in Panel D Specifications 2 and 4 includes only plants with positive coal input in a given year. ln(Sulf. Coal) is one plus the amount of sulfur in coal used for burning, in ton. ln(Ash) is one plus the amount of ash, produced in the process of coal burning, measured in the same way as the amount of sulfur. All the remaining variables are as described in Table 2. When converting variables into natural logs, a value of one is added before the transformation. All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Fuel Mix

	(1) Prim. Coal	(2) Prim. Gas	(3) Prim. Petrol.	(4) ln(Coal Quant.)	(5) ln(Gas Quant.)	(6) ln(Pet. Quant.)
Restructured*IOU	0.008*	0.039***	-0.047***	0.019	0.695**	-0.404***
	(0.004)	(0.013)	(0.014)	(0.032)	(0.255)	(0.100)
Restructured*Muni	0.002	-0.017	-0.013	-0.032	-0.126	-0.493
	(0.004)	(0.030)	(0.011)	(0.039)	(0.164)	(0.284)
ln(BTU)	0.003	0.002	-0.007	0.359***	0.603***	0.350***
	(0.002)	(0.009)	(0.009)	(0.039)	(0.124)	(0.074)
Dummy (Scrubber=1)	-0.001	-0.004	0.007	0.027	-0.168	-0.126
	(0.005)	(0.007)	(0.004)	(0.044)	(0.496)	(0.155)
Dummy(Phase I=1)	0.000	-0.011	0.010	0.013	0.192	0.211*
	(0.006)	(0.007)	(0.006)	(0.027)	(0.241)	(0.111)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7598	7598	7598	7788	7788	7788
adj. R^2	0.99	0.94	0.88	0.99	0.94	0.86
adj. R^2 within	0.00	0.01	0.01	0.16	0.02	0.04

Panel B: Non-Coal Plants

	(1) Prim. Gas	(2) Prim. Petrol.	(3) ln(Gas Quant.)	(4) ln(Pet. Quant.)
Restructured*IOU	0.100***	-0.101***	1.051**	-0.811***
	(0.031)	(0.031)	(0.406)	(0.232)
Restructured*Muni	-0.020	-0.035	-0.072	-0.855*
	(0.059)	(0.023)	(0.233)	(0.422)
ln(BTU)	0.011	-0.015	0.855***	0.507***
	(0.014)	(0.014)	(0.158)	(0.112)
Dummy(Phase I=1)	0.093	-0.092	9.477***	-0.003
	(0.115)	(0.115)	(1.661)	(0.598)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2523	2523	2603	2603
adj. R^2	0.85	0.86	0.85	0.86
adj. R^2 within	0.02	0.02	0.07	0.07

Panel C: Coal Plants

	(1) Prim. Coal	(2) Prim. Gas	(3) ln(Coal Quant.)	(4) ln(Gas Quant.)	(5) ln(Pet. Quant.)
Restructured*IOU	0.012	0.006	0.071*	0.348	-0.109
	(0.007)	(0.007)	(0.040)	(0.299)	(0.087)
Restructured*Muni	0.002	-0.002	0.013	-0.233	-0.095
	(0.007)	(0.007)	(0.048)	(0.199)	(0.271)
ln(BTU)	0.006	0.004	0.959***	0.287	-0.058
	(0.006)	(0.006)	(0.047)	(0.174)	(0.062)
Dummy (Scrubber=1)	-0.001	-0.002	0.013	-0.046	-0.172
	(0.005)	(0.005)	(0.021)	(0.485)	(0.139)
Dummy(Phase I=1)	0.000	-0.005	0.014	0.175	0.059
	(0.006)	(0.006)	(0.023)	(0.237)	(0.086)
Intercept	0.727***	-0.089	-22.555***	-4.891	4.142*
	(0.174)	(0.173)	(1.460)	(5.403)	(1.932)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	5075	5075	5185	5185	5185
adj. R^2	0.92	0.85	0.95	0.91	0.87
adj. R^2 within	0.00	0.00	0.43	0.00	0.00

Panel D: Coal Quality

	(1) ln(Sulf.)	(2) ln(Sulf.)	(3) ln(Ash)	(4) ln(Ash)
Restructured*IOU	0.102**	0.136**	0.053	0.053
	(0.038)	(0.047)	(0.040)	(0.035)
Restructured*Muni	0.030	0.065	-0.004	0.035
	(0.049)	(0.065)	(0.048)	(0.059)
ln(Net MWh)	0.262***		0.310***	
	(0.030)		(0.036)	
ln(Coal Quant.)		0.751***		0.932***
		(0.040)		(0.019)
Dummy(Scrubber=1)	0.414***	0.409***	0.137**	0.117***
	(0.097)	(0.087)	(0.052)	(0.039)
Dummy(Phase I=1)	-0.458***	-0.450***	-0.096**	-0.091***
	(0.062)	(0.066)	(0.032)	(0.029)
Intercept	-0.576	-0.570*	0.183	0.321**
	(0.432)	(0.282)	(0.520)	(0.136)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7788	5169	7788	5169
adj. R^2	0.99	0.95	0.99	0.96
adj. R^2 within	0.16	0.38	0.11	0.52

Table Appendix A-3
Cost-Cutting Channel: Input Utilization

This table reports estimates of a panel regression of heat input as a function of restructuring and control variables. The sample consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999. All variables are as described in Table 2. The regression is estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) ln(BTU)
Restructured*IOU	-0.013**
	(0.005)
Restructured*Muni	-0.008
	(0.025)
ln(Net MWh)	0.914***
	(0.008)
Dummy (Scrubber=1)	0.007
	(0.007)
Dummy(Phase I=1)	-0.001
	(0.005)
Plant-Epoch FE	Yes
Year FE	Yes
N	7940
adj. R^2	0.997
adj. R^2 within	0.947

Table Appendix A-4
Efficient Allocation of Resources Channel

This table reports estimates of panel regressions of plant-level measures of efficient resource allocation as a function of restructuring and control variables. The sample consists of all plants in the EIA-Fabrizio et al. (2007) sample over the period of 1985–1999. All variables are as described in Table 2. All regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(2) Capacity Factor	(3) ln(Net MWh)
Restructured*IOU	-0.056***	-0.157***
	(0.011)	(0.032)
Restructured*Muni	-0.057***	-0.225***
	(0.015)	(0.068)
Dummy (Scrubber=1)	0.009	0.009
	(0.025)	(0.060)
Dummy(Phase I=1)	-0.009	-0.057
	(0.011)	(0.036)
Plant-Epoch FE	Yes	Yes
Year FE	Yes	Yes
N	7940	7940
adj. R^2	0.853	0.941
adj. R^2 within	0.026	0.015

Table Appendix A-5
Restructuring and Emissions, by Production Technology Groups

This table reports estimates of panel regressions of plant-level SO_2 emission amounts as a function of restructuring and other control variables. The sample consists of all firms in EPA-EIA-Fabrizio et al. (2007) sample over the following years: 1985, 1990, 1995–1999. The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. *Heat rate* is the ratio of total heat input to net output (MMBTU/Net MWh). All other variables are as described in Table 2. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. Since *Scrubber* is not used in plants with no coal-based operation, and *Sulfur* is a feature of coal input only, the two variables are excluded in Specifications 3 and 4. The regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) Coal Plants	(2) Coal Plants	(3) Non-Coal Plants	(4) Non-Coal Plants
Restructured*IOU	0.187*	0.047	-0.770**	-0.097
	(0.088)	(0.040)	(0.232)	(0.162)
Restructured*Muni	0.115	0.060	-0.434	0.017
	(0.117)	(0.106)	(0.297)	(0.149)
ln(Sulfur)		0.557**		
		(0.206)		
ln(Petroleum Quant.)		0.037		0.652***
		(0.031)		(0.044)
ln(Heat rate)		-0.037		-0.162
		(0.390)		(0.227)
Capacity Factor		0.974**		1.926***
		(0.358)		(0.366)
ln(Abate. Expenses)		-0.004		0.023
		(0.008)		(0.022)
ln(Abate. Investment)		-0.002		-0.002
		(0.002)		(0.014)
ln(Net MWh)	0.885***		0.693***	
	(0.074)		(0.126)	
Dummy(Scrubber=1)	-0.852***	-1.094***		
	(0.200)	(0.231)		
Dummy(Phase I=1)	-0.557***	-0.304*	0.299	-0.245
	(0.059)	(0.129)	(0.392)	(0.415)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2317	2315	1116	1111
adj. R^2	0.92	0.94	0.87	0.93
adj. R^2 within	0.35	0.48	0.12	0.52

Table Appendix A-6
Restructuring and Emissions: Addressing Staggered DiD Bias

This table reports estimates of panel regressions of plant-level SO_2 emission amounts as a function of restructuring and other control variables. The sample consists of all firms in EPA-EIA-Fabrizio et al. (2007) sample over the following years: 1985, 1990, 1995–1999. We further restrict the sample to plants that operate either in NY state, or in one of the states that have not initiated restructuring hearing by 1999. The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. *Heat rate* is the ratio of total heat input to net output (MMBTU/Net MWh). All other variables are as described in Table 2. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. Since *Scrubber* is not used in plants with no coal-based operation, and *Sulfur* is a feature of coal input only, the two variables are excluded in Specifications 3 and 4. The regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) Coal Plants	(2) Coal Plants	(3) Non-Coal Plants	(4) Non-Coal Plants
Restructured	0.515**	0.003	-1.608*	-0.437
	(0.191)	(0.129)	(0.803)	(0.484)
ln(Sulfur)		0.825***		
		(0.120)		
ln(Petroleum Quant.)		0.079		0.758***
		(0.048)		(0.089)
ln(Heat rate)		-0.092		-0.857
		(0.278)		(0.645)
Capacity Factor		0.616**		1.409**
		(0.170)		(0.556)
ln(Abate. Expenses)		-0.009		-0.007
		(0.007)		(0.020)
ln(Abate. Investment)		0.000		0.002
		(0.004)		(0.013)
ln(Net MWh)	0.917***		0.523**	
	(0.119)		(0.177)	
Dummy(Scrubber=1)	-0.897***	-1.263***		
	(0.231)	(0.296)		
Dummy(Phase I=1)	-0.679***	-0.205	0.674	-0.242
	(0.082)	(0.122)	(0.903)	(0.434)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1387	1385	369	367
adj.R2	0.91	0.94	0.87	0.94
adj.R2 within	0.34	0.58	0.09	0.60

Table Appendix A-7
Restructuring and Emissions: Poisson Estimation

This table reports estimates of Poisson panel regressions of plant-level SO_2 emission amounts as a function of restructuring and other control variables. The sample consists of all firms in EPA-EIA-Fabrizio et al. (2007) sample over the following years: 1985, 1990, 1995–1999. The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. *Heat rate* is the ratio of total heat input to net output (MMBTU/Net MWh). All other variables are as described in Table 2. *Coal Plants* are plants that have used a positive amount of coal input at least once throughout our sample period. *Non-Coal Plants* are plants that have used zero coal input throughout our sample period. Since *Scrubber* is not used in plants with no coal-based operation, and *Sulfur* is a feature of coal input only, the two variables are excluded in Specifications 3 and 4. The regressions are estimated with an OLS model and include plant-epoch- and year-fixed effects. Standard errors are double clustered by plant-epoch and year dimensions and are reported in parentheses below coefficient estimates. Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

	(1) Coal Plants	(2) Coal Plants	(3) Non-Coal Plants	(4) Non-Coal Plants
Restructured	0.152**	0.046	-0.717***	-0.336**
	(0.062)	(0.041)	(0.203)	(0.138)
ln(Sulfur)		0.552**		
		(0.253)		
ln(Petroleum Quant.)		-0.011		0.674***
		(0.017)		(0.094)
ln(Heat rate)		-0.346		-0.539***
		(0.287)		(0.189)
Capacity Factor		0.470		1.267***
		(0.423)		(0.399)
ln(Abate. Expenses)		-0.011		0.004
		(0.011)		(0.017)
ln(Abate. Investment)		-0.003		0.001
		(0.005)		(0.015)
ln(Net MWh)	0.761***		0.728***	
	(0.091)		(0.114)	
Dummy(Scrubber=1)	-0.984***	-1.146***		
	(0.312)	(0.338)		
Dummy(Phase I=1)	-0.550***	-0.295**	-0.103	-0.308
	(0.056)	(0.132)	(0.158)	(0.299)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2317	2315	1116	1111
adj.R2	N/A	N/A	N/A	N/A
adj.R2 within	N/A	N/A	N/A	N/A

About ECGI

ECGI is an international non-profit membership organisation that provides a platform for debate and dialogue among academics, policymakers, and business leaders, with a focus on major corporate governance, ESG, and stewardship issues.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

www.ecgi.global