Corporate Environmental Policy and Product Market Competition*

Yaniv Grinstein[1] Yelena Larkin[2]

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Abstract

Researchers and policy makers point to product market competition as a mean to improve corporate environmental policy, encouraging firms to compete over customers with high environmental awareness. Unfortunately, many environmentally important industries sell their output through centralized markets, making it hard for customers to differentiate across firms. We show that in these cases competition affects environmental policy through its impact on firms' incentives to become more efficient. Depending on available technology, the effect can have both positive and negative impact on the environment. We empirically establish both effects using fossil-fuel plants in the US electric utility industry.

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[1] IDC Herzliya, Cornell University and ECGI. grinstein@idc.ac.il
[2] York University. ylarkin@schulich.york.ca

Recent studies have shown that market forces play a significant role in promoting environmental policies among firms, which can ultimately substitute for regulation. A particular emphasis has been put on product market competition (hereafter, PMC), which incentivizes firms to compete over customers with high levels of sustainability awareness. A large body of literature has demonstrated that in a competitive environment firms differentiate their product by becoming environmentally friendly in order to increase consumer demand and their profits (Aghion, Benabou, Martin, and Roulet, 2020; Flammer, 2015; Duanmu, Bu, and Pittman, 2018; Delmas, Russo, and Montes-Sancho, 2007; Servaes and Tamayo, 2013).

A necessary condition for the effectiveness of the differentiation channel is that customers can distinguish between environmentally friendly and non-friendly suppliers. Unfortunately, for products in the most polluting industries, customers can have a hard time contracting their demand on the type of supplier. The reason is that products in polluting industries are often commodities that trade in centralized spot and futures wholesale markets (e.g., agriculture and energy) – where, for efficiency reasons, exchanges and contracts are unified and based on product quality characteristics rather than suppliers' environmental impact. Another reason is that products in polluting industries are often transported through complex distribution systems that rely on system of grids, pipelines, transportation networks etc. The delivery of the product through such centralized system can provide another obstacle for the customer to be matched with environmentally friendly supplier.[3]

[3] Theoretically, it is possible to set up contracts based on environmental characteristics of suppliers. However, implementing such contracts is costly, especially when the customers cannot differentiate among suppliers by simply examining the final product. For example, if a customer wants to buy oil that wasn't produced using fracking technologies, he needs a certification from the distributor that oil delivered is not based on fracking. To provide such certificate, the distributor will then have to set up a verification mechanism that (a) ensures that the oil delivered was bought from a particular supplier and (b) the supplier has, indeed, not used fracking technologies in the extraction process. The absence of such certifications in reality suggest that will be costly to implement.

How does product market competition promote corporate environmental policy when firms cannot single themselves out as environmentally friendly suppliers? Absent direct incentives to cater to environmentally friendly customers it is not clear that PMC will positively affect environmental policy. In fact, since a competitive environment raises the pressure to cut costs, and environmental policy is often costly to implement, it could lead to worse environmental policy.

In this study we analyze the impact of PMC on corporate environmental policy when firms cannot differentiate themselves as environmentally friendly producers. We show that PMC forces firms to become more efficient and then study the effect of the efficiency channel on environmental policy. To this end, we decompose efficiency into within-firm actions to reduce input per output produced (cost-cutting) and the effect of competition on efficient allocation of production across competing firms (efficient allocation of resources). We then ask how each of these channels affects environmental policy.[4]

First, we consider the cost-cutting channel. According to economics literature, protecting the environment is costly. Therefore, cost-minimizing production policy is often associated with less environmentally friendly policy. However, at the same time, more efficient production processes also make a better use of production factors, generating more output for a given amount of input used. It is therefore possible that product market competition will lead to higher protection of the environment by simply making the production process more efficient. We therefore argue that cost-cutting considerations could have either a negative or a positive effect on environmental policy.

[4] An additional effect of competition is through higher levels of production due to increased demand in response to lower prices in competitive environment. In the empirical setting we consider the demand is highly inelastic, so this is not a concern.

The second effect is the effect of product market competition on allocation of production across competing entities. Competition is known to alter production decisions across firms in a way that re-allocates production from overloaded units with high marginal costs towards underloaded units with lower marginal costs. Such shift will reduce the average amount of input needed per unit of production.[5] To the extent that environmental impact of a firm is an increasing function of the total input amount used, the efficient allocation of resources across firms will have a positive impact on the environment.

After establishing the conceptual framework, we turn to empirically gauging the environmental impact of the efficiency channels of competition. Analyzing the effect of increased efficiency on environmental policy is empirically challenging for several reasons. First, we need to identify the space of potential actions that firms can take to become environmentally friendly. Second, we need to be able to quantify the costs and benefits that each action entails. Third, we need to disentangle efficiency incentives driven by product market competition from other economic forces that affect corporate sustainability.

We address the empirical challenges by focusing on fossil-fuel plants in the US electric utility industry – the nation's largest emitter of toxic chemicals and greenhouse gases. This industry set-up provides numerous advantages, allowing us to overcome each of the empirical challenges above. First, electric generation process is homogeneous across fossil-fuel plants. As a result, the space of all possible production and investment decisions that, in turn, affect the environment is well-understood. Second, data regarding corporate decisions in this industry are rich and detailed, allowing us to quantify the benefits and costs of each action. Specifically, we are able to obtain plant-level data of public and private plants, including quantities and prices of

[5] Consider, for example, opening markets to international competition. If country-level demand shocks are imperfectly correlated, competition will help allocate excess supply in one country to meet excess demand in another country.

inputs and outputs. We can also measure environmental policy in a precise manner by focusing on pollution levels and pollution abatement expenses. Third, we take advantage of the staggered passage of restructuring across US utilities during the 1990s which has opened the market to competition. This setup mitigates endogeneity concerns and allows us to identify cause and effect between efficiency incentives and pollution. Finally, electric utility industry is a classic example of a setup where customers have a hard time differentiating among different suppliers. In the pre-restructuring environment, every plant operated as a local monopoly, so that customers could not choose their provider. In the restructured supply system, power plants sell electricity through a centralized market mechanism such as power exchange. As a result, final customers do not know the identity of suppliers that they receive their electricity from, and often times the electricity received comes from multiple different providers.[6]

We next use the uniquely detailed data of utilities to empirically establish the existence of each competition-driven efficiency channel. For the cost-cutting channel, the technology of electricity generation permits plant managers to undertake three types of efficiency-enhancing actions that also have an environmental impact: (i) cutting pollution abatement; (ii) changing input mix towards cheaper input factors; and (iii) increasing production efficiency (i.e., lower energy input per unit of electricity generation produced). To establish the efficient allocation of resources channel we examine plants' capacity factor: the ratio of total net energy produced by the plant to its maximal capacity. Electric utilities operating at close to maximum capacity sustain higher costs and cannot compete with utilities that operate below full capacity. We ask whether the

[6] 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 does not affect our results.

restructuring has reduced plants' capacity factor in a way that also resulted in reduced the amount of input per output produced.

Our findings support the cost cutting incentive channel. We find a significant cut in abatement expenses and abatement investment in restructured states compared with non-restructured states. For the average plant in the restructured states, investment in pollution-reducing equipment decreased by 55% following the restructuring, as compared with plants in nonrestructured states. Additionally, plants in restructured states decreased their overall abatement expenses by 35% as compared with plants in nonrestructured states.

Additionally, we find that plants in restructured states have increased their efficiency by switching to a cheaper input mix. In the case of electric utilities, fuel is the main input, and fossil-fuel plants employ three main inputs: petroleum (the most expensive), gas, and coal (the cheapest fuel during our sample period). We find that the affected plants shifted from oil towards cheaper fuels - natural gas and coal. In addition, plants increased their reliance on cheaper, but more polluting types of coal. To further pinpoint the cost-cutting mechanism, we explore the sensitivity of the affected plants' fuel choice to their pre-restructuring production costs. We find that the tendency of plants in restructured states to adopt cost-efficient fuels increased among affected plants whose cost structure was particularly high prior to restructuring.

Our third finding is that plant production efficiency, as measured by the ratio between electricity output and heat input, increased in restructured states in comparison to plants in nonrestructured states.

Our fourth and last evidence supports the efficient allocation of resources channel. Specifically, we establish that the actual energy production relative to the total plant capacity (known as capacity factor) declined in affected plants, which is consistent with the argument that

competition led to a reduction in the production of local plants with overcapacity in favor of incumbent competing plants. We also find that the decrease in the capacity factor following restructuring explains the improvement in the efficiency gap between restructured plants and regulated plants.

After establishing the existence of efficiency gains, we next analyze their impact on the environment. The total impact of PMC on pollution is a-priori unclear, since, as indicated earlier, efficiency channels could have either a positive or a negative impact on the environment. On the one side, reduction in abatement and switch to more polluting coal should translate into a negative impact of competition on environment. On the other side, higher reliance on natural gas, as well as improved production efficiency both within and across plants should have a positive impact on environment.

To gauge the prediction regarding the impact of the efficiency channels of product market competition on emission in an unambiguous way, we divide the sample into subsets of plants, so that within each subset we can precisely predict the impact of each channel on emission. To that end, we first examine all the plants that do not have the capacity to use coal. For those plants, the change in fuel mix channel predicts that they will switch from petroleum to gas. As a result, the change in fuel mix will also reduce emission as a byproduct. We then contrast these predictions with the predictions regarding the second group - plants that have the capacity to switch to coal. For the second group, the fuel mix channel predicts an increase in pollution due to the move towards coal, as well the move towards more polluting types of coal. We therefore expect the impact of PMC on emission to be less positive (more negative) among coal plants compared to non-coal operating plants.

To empirically test these predictions, we estimate the amount of pollution as a function of the restructuring dummy. Consistent with our priors, we find a positive and statistically significant effect of restructuring on the amount of emitted toxic chemicals among coal operating plants, and negative and significant – among non-coal operating plants. Next, we test whether the previously established efficiency channels are behind this relation and augment the pollution specification with the vector of efficiency variables, discussed above. We find that after including these variables, the coefficient on the restructuring variable loses its significance and its magnitude declines by 75%-90% compared to the previous result. In addition, we find that among all the efficiency channels, the changes in fuel mix and the capacity factor are the dominant factors in explaining emission.

We also ensure that our results are not driven by omitted variables correlated with both the restructuring and increased efficiency. We perform a parallel trend test and show that the level of input per unit of electricity produced has declined starting at the restructuring year, but not prior to that, in line with the predictions regarding the effect of competition on efficiency. We also show that the average amount of electricity produced by the affected plants has declined starting at the restructuring year, consistent with the increased supply of electric providers due to competition. Finally, we explore differences between Independently Owned Utilities (IOUs) and Municipal Utilities (*Munis*) within states; primarily, the latter were largely exempt from restructuring. Indeed, we find that *Munis* did not increase either their efficiency or their production following the restructuring.

Our finding that the impact of competition on pollution varies depending on the available production technology further alleviates concerns regarding alternative causes for the change in pollution in utilities in restructured states. In particular, if state characteristics were to drive the

results, then the effect on pollution strategy would not vary depending on technology. We also show that within a given state, investor-owned utilities (IOUs), which were more affected by the regulations, had larger changes in their strategy compared with federal or municipality-owned utilities that were not subject to the regulation (Munis). If state characteristics were to drive the results, then change in strategy would have been similar between IOUs and Munis.

The differential effect of competition on pollution across affected plants is also inconsistent with the legal channel. Restructuring legislation requires major changes in rulings, therefore its passage may potentially open the industry to litigations, some of which could be established on the grounds of environmental concerns. To the extent that restructuring exposes utilities to new legal threats, affected utilities may try to mitigate the legal risks by becoming more environmentally friendly.[7] However, our results that plants that rely primarily on coal have actually increased their pollution by decreasing abatement expenses and relying more pollutive coal stand in contrast to the argument that utilities try to mitigate legal risks by becoming more environmentally friendly.

Another potentially instrumental economic channel is the investor channel. If restructuring has attracted more environmentally friendly investor clientele, then that clientele may demand pollution reduction. Again, we note that this channel cannot explain the cross-sectional variations in environmental policy across plants found in our study. Moreover, long-term investors who place the highest value on environmentally friendly policies (Starks et al., 2017), are shown to be attracted to regulated utilities (e.g., Brochet et al., 2012).

Our study contributes to emerging finance research that studies the drivers of corporate environmental policy. Past contributions include the effect of limited liability (Akey and Appel,

[7] In addition, regulators may act favorably towards firms if they observe that they are environmentally friendly. For example, Hong et al. (2019) find that regulators favor socially responsible firms and view them as more reputable.

2020a), legal risk (Ben-David et al., 2020); shareholder preferences (Naaraayanan et al., 2020; Akey and Appel, 2020b; Shive and Forster, 2019); and financial constraints (Bartram et al., 2019; Xu and Kim, 2020; Goetz, 2019). This paper augments the above literature by examining the role of cost-cutting incentives and product market competition on corporate environmental policy. The effect of product market competition on corporate environmental decisions is of particular relevance due to the tendency of competition to motivate cost cutting and increase the focus on profitability, which may be implemented at the expense of environmental protection (Friedman, 1970). We highlight the claim that cost-cutting incentives can bring about lower negative externalities. In our setting, regulated utilities had fewer incentives to adopt new, more cost-efficient production; higher pollution was the byproduct of this inefficiency. We also show a 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.

Our work also belongs to a growing strand of 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; Decaire et al., 2020). Detailed and precise empirical setting is critical for a study of corporate environmental activity, because a change to environmental policy may be attributed to different economic channels. The detailed production-level data allow us to distinguish among those channels. In particular, observing the costs and benefits of different production processes for each plant is crucial for concluding that the observed environmental policies are a by-product of cost-efficient production processes.

Finally, a number of finance papers have recently pointed out 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 2019), labor markets (Benmelech et al., 2018), 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. We thereby offer another channel through which industry consolidation may affect stakeholders.

The rest of the study continues as follows. Section 2 provides a summary of the electric utility industry and its restructuring. Section 3 presents the data and Section 4 reports the results. Section 5 examines the findings in light of the different hypotheses and Section 6 concludes.

2. 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 2.1) and how the electricity generation process affects the environment (Section 2.2). Section 2.3 describes the restructuring process of electric utilities in the US.

2.1 Electric Generation

The focus of our study is steam turbine 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.

The basic process of electricity generation 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.

Plants differ in their modes of operation. Base load power plants usually provide a continuous supply of electricity throughout the year with minimum power generation requirement. These plants are often larger and tend to be cheaper to operate. Peaking power plants are often smaller and run only during peak hours of electricity demand.

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

2.2 Environmental Concerns and Environmental Regulation

The main environmental concern associated with steam generating plants is the hazardous byproducts emitted when burning fossil fuels.[8] A chief byproduct is sulfur dioxide (SO_2), which causes acid rain proven harmful to plants and to animals that live in water. SO_2 also worsens respiratory illnesses and heart diseases in humans. Another hazardous byproduct is nitrogen oxides (NOx), which contribute to ground-level ozone and irritate and damage human lungs. Third, burning fossil fuels emits the poisonous gas carbon monoxide (CO), as well as particulate matter (PM), which results in hazy conditions in cities and scenic areas. Coupled with ozone, PM contributes to asthma and chronic bronchitis, especially in children and the elderly. In addition,

[8] Other environmental concerns include (i) the use of water resources to produce steam, provide cooling, and serve other functions; (ii) discharges of pollution into water bodies, including thermal pollution (water that is hotter than the original temperature of the water body); (iii) generation of solid waste, which may include hazardous waste;(iv) land use for fuel production, power generation, and transmission and distribution lines; and (v) harmful effects on plants, animals, and ecosystems that result from the air, water, waste, and land impacts above.

burning fossil fuels emits small amounts of heavy metals such as mercury, which are hazardous to human and animal health. Finally, electric plants emit large quantities of carbon dioxide (CO_2). While not as toxic as other byproducts, CO_2 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.

To mitigate the environmental effects of burning fuel, electric plants can employ three main strategies. First, they can adopt less polluting fossil fuel: rely on natural gas or less pollutive coal, or pretreat the coal. Second, plants can capture the flue gas during the fuel burning process. Capturing the pollutants can be done in several ways, but 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 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").[9] 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.

2.3 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).

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 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 rate case can be initiated by either the local public utility commission (PUC) or by the utility itself. 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. The PUC will initiate a rate case if it believes rates are in excess of their cost of service or cost of capital. Rate cases are examined by the regulator on a periodic basis, usually every several years.

[9] 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.

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 regulatory process 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.

Numerous studies have shown a positive effect of the restructuring on cost-cutting actions and improved efficiency of utility plants. For example, Fabrizio et al. (2007) show that plants have decreased non-fuel costs after the restructuring, whereas Bushnell and Wolfram (2005) and Davis and Wolfram (2012) show that plants have increased their output-to-input efficiency.

In addition, 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). Davis and Bushnell et al. (2017) conclude that “despite the notable isolated failures of

competition, U.S. electricity markets are now found to be reasonably competitive overall…" (page 2).

3. Data

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

Our main source of information 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.[10]

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 boilers (installation date and primary fuels type), as well as the information on the use of flue-gas desulfurization (FGD) equipment (including its installation date), 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 and is available at monthly frequency (we sum up monthly fuel use by each fuel type within each

[10] 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).

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 additionally contains additional 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[10]

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 at different levels of aggregation, namely plant, state, and grid regions of the country.[11] Because plant production and plant emissions datasets both rely on the same type of plant identifier, namely the Office of Regulatory Information Systems Plant Location (ORISPL), merging the EPA and EIA databases is straightforward.

Although eGRID provides detailed information with respect to plant emissions, it does not cover the pre-restructuring years for most states. Therefore, the concern arises that the resulting time-series is too short to capture emission patterns of utility plants prior to the restructuring to a meaningful degree. To extend the time-series, we supplement the eGRID information with historical information on emissions from a different platform, Air Markets Program Data (AMPD), which is also managed by the EPA.[12] Because SO_2 is one of the principal byproducts of fossil fuel burning and is considered a major threat to human health and to the environment, the US government began gathering SO_2 emissions data as early as the 1980s. 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.[13] The only complete available data 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.

[11] https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid.
[12] https://ampd.epa.gov/ampd/.
[13] 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.

Table 1 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.

3.1 Restructuring

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. As will be described in further detail in section 6.1, our parallel-trends test results confirm that plants began to alter their emissions activity as early as the hearings stage.

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.

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 al., 2007; Sharabaroff et al. 2009). To test the validity of this argument within our sample, in Table 2 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.

The specification in Table 2 Column 1 confirms the conjecture that electricity prices are an important driver of restructuring in a state. To 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 2 Column 2 we also control for the fuel mix. Variations in endowments of fossil reserves across states may be related to a number of state-level economic factors, including the prices of fuel types and electricity, as well as employment in mining, oil refinery, transportation industries, etc. These factors, in turn, may play an additional role in the state's restructuring decision. Empirically, 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 (measured in net MWh). The results indicate that the inclusion of fuel quantities improves the overall explanatory power of the regression, as measured by pseudo R-squared. However, neither 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 2 Columns 3 and 4, we explore the potential role of pollution in a more direct way and include the state-level amount of emissions as another independent variable. Similar to the fuel quantities, we scale the emissions by MWh. 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 emissions levels in a given state.

We do not expand our database beyond 1999 because several events occurred in the early 2000s that complicated the restructuring process in certain states. 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. Other states began debating whether to continue with the restructuring process, and five additional states (Oklahoma, Arkansas, New Mexico, Nevada, and Montana) postponed restructuring. 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.

4. Results

4.1 Empirical framework

In the first set of tests, we establish the existence of each competition-driven efficiency channel. Electricity generation technology dictates the viable range of activities directed at improving efficiency at the plant level. 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 plant operation efficiency 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.

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*. $Restructure_{s,t}$ 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 have an effect on 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") 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 greater detail in Section 2, 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.

In designing our empirical specifications, we assume that the variation in control variables and the technological differences are unlikely to be driven by the restructuring. The Clean Air Act of 1990, which flagged the facilities that would become subject to Phase I of the Acid Rain program, was passed several years prior to the first talks of deregulation. Similarly, we find that most of the variation in the *Scrubber* variable is driven by the years prior to restructuring hearings (unreported for the sake of brevity). Specifically, approximately 84% of the scrubbers in our sample were installed prior to 1993, which is the year the first state, New York, began formal restructuring hearings. Restructuring may have affected certain plants' decisions to install scrubbers. We address this argument in the later part of our analysis.

In a variant of Specification 1, we also control for the overall level of production at the plant level, as measured by net electricity generation in MWh, converted into logs. 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). Including plant fixed-effect absorbs unique production characteristics of the plant 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. We also include time fixed effects to 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.

4.2 Efficiency Channels – Results

4.2.1 Expenditure on 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. A plant can substantially reduce emissions by increased spending on emissions abatement. Specifically, 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. For the given reporting year, EIA requires plants to report all pollution abatement capital expenditures for new structures and/or equipment. We collect this information and examine the effect of restructuring on the level of investment in pollution abatement. The results reported in Table 3 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 3 Column 2 we refine the definition of investment by focusing on scrubbers. 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. 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 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 3 Column 3 we consider abatement costs across all categories of chemicals, including ash, flue gas, and other potentially hazardous chemicals. In Table 3 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 might have been 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 3 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.[14] Since gas produces almost no SO_2 pollution, we expect these plants to spend more on pollution abatement when they use petroleum. We 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.

[14] 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.

4.2.2 Fuel mix

We next examine whether, subsequent to restructuring, plants switched to an environmentally friendly fuel.

To examine whether plants have changed their fuel mix following the restructuring, we first estimate regressions where the dependent variable is the fraction of all the plant's operating boilers (status "OP") that rely on coal, gas, or petroleum 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 4 Panel A. We find the fraction of coal-fired boilers increased on average by 0.7% compared to nonaffected plants (Table 4 Column 1), and the fraction of gas-fired boilers increased on average by 3.4% (Table 4 Column 2). In contrast, the fraction of oil-fired units decreased by 4.3% (Table 4 Column 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 4 Columns 4–6).

Although affected plants may have not changed the overall amount of coal used, they could have switched to less polluting coal types. To analyze this possibility, in Table 4 Panel B we look at the sulfur and ash content of the coal used as measured by the percentage amount of sulfur or ash reported times the amount of coal reported (in tons). We add the value of one before converting each variable into logs. We find that plants switched to coal with higher sulfur content (Column 1), and the results remain similar when we 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 can be released to the atmosphere as particulate matter. 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.

As the next step of the analysis, we need to establish that the switch away from petroleum towards natural gas and coal is consistent with cost-minimizing incentives. To this end, every year we average the price paid by plants in our sample for each fuel category over the period 1985–1999 and plot the resulting average prices in Figure 2. The figure shows that coal is the cheapest fuel throughout our sample period (145 cents/mmBTU), followed by natural gas (262 cents/mmBTU), whereas petroleum, at 404 cents/mmBTU on average, is the most expensive. A switch from petroleum towards coal and natural gas can therefore be the outcome of a higher sensitivity to input prices in particular, and the shift to a less costly production process.

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' incentives to become cost-efficient. We hypothesize that the motive for switching to cheaper fuel will be stronger among those plants that, prior to restructuring, had especially high production costs. The opening of a state to competition would make these plants more vulnerable to losing their market share to out-of-state producers of cheaper electricity, as well as to the potential entry of new incumbents. In response to the threat of entry, existing plants in areas with high operating costs should therefore have greater incentives to reduce production costs by switching to gas from petroleum.

We look at state-level electricity prices to empirically determine which states had especially high production costs prior to restructuring. Absent restructuring, utility rates are established through a rate of return scheme: Electricity prices are set by regulators in a way that allows utilities to recover their return on investment and operating costs. The higher the cost of production, the higher the electricity cost of MWH set by the regulator. We therefore rank all states by electricity prices every year; states with the highest prices receive high ranks, and vice versa. We obtain annual state-level electricity prices from the EIA. We then identify states with notably

high production costs in a year prior to restructuring initiation. For each state, we compare its average electricity price levels a year before restructuring to the distribution of electricity prices in the rest of the states at the same time. The average ranking among states that were subject to restructuring throughout our sample period is 33.5 (where 50 is the highest and 1 is the lowest). This finding is consistent with our Section 2 findings showing that the key motive for restructuring was the high prices of electricity in a given state. For every state *s*, we then define a new time-invariant variable, *High Electricity Price*$_s$, which equals the difference between the state rank and 33.5 whenever the state rank is higher than 33.5 one year before the restructuring, and zero otherwise. The intuition behind the variable construction is as follows: When electricity prices in a given state are above those of other restructured states, plants will have incentives to reduce costs, and the incentives will increase with the deviation of the state's prices from the average in restructured states. However, when electricity prices in a given state are lower than average, we expect that plants operating in this state will keep their production function unchanged rather than increase costs. We interact our proxy of production costs, *High Electricity Price*, with restructuring indicator, and re-estimate the equations of input use. The higher the interaction term, the higher the production costs in a restructured state prior to the initiation of deregulation and the stronger the plants' response through the cost-cutting channel.

Table 5 Column 1 shows that overall fuel costs in plants were reduced in only those restructured states where production costs were high. The coefficient of -0.006 implies that an increase of 10 positions in state ranking relative to the median ranking of 33.5 is associated with a 6% reduction in log fuel costs. This finding confirms the validity of the cost-cutting channel among the restructured plants. Next, in Table 5 Columns 2-4 we examine whether changes in fuel mix were the underlying mechanism. The results show that, among restructured plants, there was an

increase in the fraction of gas-fired boilers and a decrease in the percentage of oil-fired boilers. In both cases the change was statistically pronounced only in those states where production costs were high before the restructuring. The coefficients of 0.008 and −0.009 indicate that an increase in state ranking of 10 positions is associated with an 8% increase in the fraction of boilers operating primarily on gas and a 9% decrease in boilers operating primarily on petroleum. We obtain similar results when we examine the annual physical amount of coal, gas, and petroleum used across plants (Table 5 Columns 5-7). The coefficient of 0.09 for gas use (Table 5 Column 6) indicates that an increase in state ranking of 10 positions is associated with 90% increase in the log amount of gas and the coefficient of −0.047 in Table 5 Column 7 indicates a decrease of 47% for petroleum use. We also find a marginally significant increase in the use of coal after the restructuring (coefficient of 0.011). To summarize, our findings confirm the existence of a cost-cutting channel: Affected plants with higher cost-cutting incentives substituted the cheaper fuel type for the more expensive fuel type.

4.2.3 Efficiency of operations

Finally, we test whether the change in emissions rates may be driven by a more efficient production process. Plants may have improved fuel efficiency by generating the same amount of electricity with a smaller energy input. Plant production efficiency varies with the amount of electricity produced. Plants are often designed to generate base load electricity continuously at relatively high efficiency levels, and then cover peak load intermittently with less efficient units (Warwick, 2002). Higher efficiency can be achieved by avoiding peak load operation, as well as by running a plant continuously. Smaller improvements, such as changes to equipment maintenance practices, may also play a role.

We start the analysis of efficiency by examining whether the heat input, measured in log units of heat (BTU), declined following the restructuring. Table 6 Column 1 demonstrates that, by controlling for the amount of generated electricity, an affected plant reduces its BTU input by approximately 1.2%. This finding implies an increase in electricity generating efficiency following restructuring.

A primary reason for restructuring across states was the inability to meet peak electricity demands (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, and several states initiated third-party power exchanges, in which electricity generators submitted bids to sell electricity. 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 6 Column 2). In Table 6 Column 3 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 (Table 6 Column 3).

To examine if the change in capacity led to the increase in efficiency, we add the capacity factor variable as an additional explanatory variable in Specification 1. After controlling for total production, we find a positive relation between capacity factor and BTU use, which indicates that a higher load is indeed associated with less efficient production. Moreover, once we introduce the capacity factor, the effect of restructuring on efficiency decreases by about 25% (from 1.2% to 0.9%). This result means that the change in production output explains a substantial portion of the increase in efficiency.

Overall, the findings of this subsection are consistent with production efficiency channel: plant production efficiency, as measured by the ratio between electricity output and heat input, increased in restructured states in comparison to plants in non-restructured states. The findings regarding the capacity factor are also consistent with the argument of efficient allocation of resources: competition led to a reduction in the production of local plants with overcapacity in favor of incumbent competing plants.

5. Emissions Policy 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, efficiency channels 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 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 all the efficiency channels 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. 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 therefore 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 – we anticipate that the propensity to switch to coal will be the highest. The input mix channel will then have a negative impact on environmental policy, 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 7. In Table 7 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 improvement in their environmental policy. 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 channel reduces the magnitudes of restructuring coefficients by 75%-90% and eliminates their statistical significance. These findings are consistent with the idea that the previously established efficiency channels are behind the relation between restructuring and emission levels. Second, among all the efficiency channels, 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. 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 policy. Finally, capacity factor also plays an important role, as efficient allocation of production across competing plants has a positive impact on the environment.

6. 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.

6.1 Omitted variables

One concern regarding our results is that changes in plant efficiency may not be related to the restructuring, but to other possible shocks affecting both the competitive landscape and the pollution policy of the electricity generating industry. For example, a push towards newer electricity generation technologies in some states may have initiated both the restructuring process and the efficiency improvement.

To address this concern, we perform two tests. First, 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 $t-3$ to $t+3$ 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 *Muni*s, 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 restructuring (Panel B), further confirming the differential impact of the restructuring on plants of different ownership type.

Second, we test whether the restructuring has impacted efficiency by forcing plants to use less input per unit of output produced. To this end, we estimate total heat input used, as measured by ln(BTU) as a function of total output and other control variables (Panels C and D). We find that while there is no pre-trend, the response of IOU and Munis has actually diverged following the restructuring: while IOUs have become more efficient and reduced the heat input, Munis, if anything, started to use more fuel input.

To further establish the differential impact of the restructuring on IOU versus Muni plants, we re-estimate all of findings after splitting the restructuring indicator variable into Restructured*IOU and Restructured*Muni. The results, presented in the Appendix, indicate that restructuring only affected efficiency incentives and pollution policy of the IOU plants, whereas its impact on Muni plants is mixed and statistically insignificant.

While our setting cannot rule out all alternative explanations, we believe these findings alleviate omitted variables concerns.

6.2 Customer channel

As mentioned in the introduction, customer differentiation channel does not play a significant role in the electric utilities setting. However, a fraction of the states had implemented retail access by the end of our sample period. At the wholesale level, the restructuring allowed all utilities in the state to compete for sales to wholesale distributors. Retail access allowed retail

providers to compete for end users by either buying electricity through the exchange or by buying electricity directly from providers. To the extent that end users prefer providers that rely on less polluting energy, customer differentiation channel could have played a role.

In addressing this question, it is important to note that although some states have given customers the freedom to choose their electricity provider by comparing different utilities, this is not a prevalent practice. Even today, almost 30 years since the beginning of first restructuring initiatives, only 13% of the US customers actively elect to purchase their electricity directly from their choice of energy suppliers.[15]

Although the impact of retail restructuring was even smaller in our sample period, we wish to ensure that a potential impact of customer differentiation channel is not the driver of our results.

To address this concern, we re-estimate our regressions of SO_2 pollution after removing all plant-year observations where retail-level restructuring indicator equals one. This variable, obtained from the Fabrizio et al. (2007) dataset, takes a value of one starting from the year in which a state has implemented retail access, and zero otherwise. If retail access led to the use of less polluting fuels, we should expect the variable to be negative.

The results, reported in Table 8, indicate that retail access does not play a role in our setting. First, it affects only around 1% of the observations in our sample. Second, after excluding these observations, we find that the impact of restructuring on emission remains statistically significant, and the coefficient magnitudes are similar to those obtained using the full sample. This finding indicates that product differentiation is unlikely to be the reason for different patterns in pollution across restructured plants.

[15] https://www.eia.gov/todayinenergy/detail.php?id=37452

6.3 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.

The investor channel can also be manifested through clientele effect, in which some investors prefer firms to be more protective of the environment than others. However, the clientele effect, if present, should generate the opposite pattern for the following reason. Regulated utilities attract long-term, dividend-loving investors (e.g., Brochet et al., 2012), who also tend to focus more heavily on environmental impact (Starks et al., 2017; Nguyen et al., 2020). We should therefore expect a stronger push towards environmentally friendly policies before—rather than after—restructuring. We conclude that the investor channel is unlikely to drive our results.

6.4 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, Chen 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).

6.5 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 et al. (2017) and Koh et al. (2013) 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 7 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. Conclusion

In this paper we examine the impact of efficiency incentives, triggered by opening of markets to competition, on corporate environmental policy by focusing on the effect of electric utility restructuring – one of the most polluting industries in the world, including the U.S. Our empirical strategy takes advantage of a staggered passage of restructuring legislation in the electric utilities industry across the US during the 1990s. We find that plants in restructured states have increased incentives to become more efficient.

We explore possible channels of increased efficiency and find that plants in restructured states have changed their fuel mix and begun to rely more heavily on clean gas as a source of energy. We find that the move to gas was driven by cost-cutting considerations. In addition, operation efficiency has increased, allowing plants to burn less fuel overall. We also find that

despite the decline in pollution, affected plants have reduced abatement-related capital investment, as well as operations and management expenditures on pollution-reduction activities. These changes are also consistent with cost-cutting considerations.

We rule out a number of other potential economic channels for these results, such as the role of customer preferences and product differentiation; investor clientele and activism; managerial entrenchment incentives; and legal motives. We find little evidence in support of any of these channels.

Although the study examines the relation between pollution and cost-cutting incentives in the 1990s, its implications are also relevant today. Sulfur dioxide and nitrogen oxide have decreased substantially since the 1990's, yet electric utilities still remain the number one source of carbon dioxide pollution, responsible for global warming and climate change. Our findings show that cost-cutting incentives and efficient allocation of resources within plants and across plants can mitigate the environmental impact across all types of toxic pollutants.

Our findings that cost-cutting incentives could lead to higher sustainability could be expanded to other industries and production processes. For example, cost-cutting considerations in industries where supply chain structure involve transportation of raw materials and final goods could lead to the establishments of distribution centers which reduce both transportation costs and emission. Similarly, smarter utilization of raw material in the production of final goods would enhance the bottom line while leading to less landfill waste.

Our findings show also the potential benefits of product market competition on the environment. To the extent that product market consolidation in the US has increased in the last two decades, our findings may offer another channel through which industry consolidation affects

the environment. Consequently, we believe the findings of this project would interest both environmental and antitrust regulators.

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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).

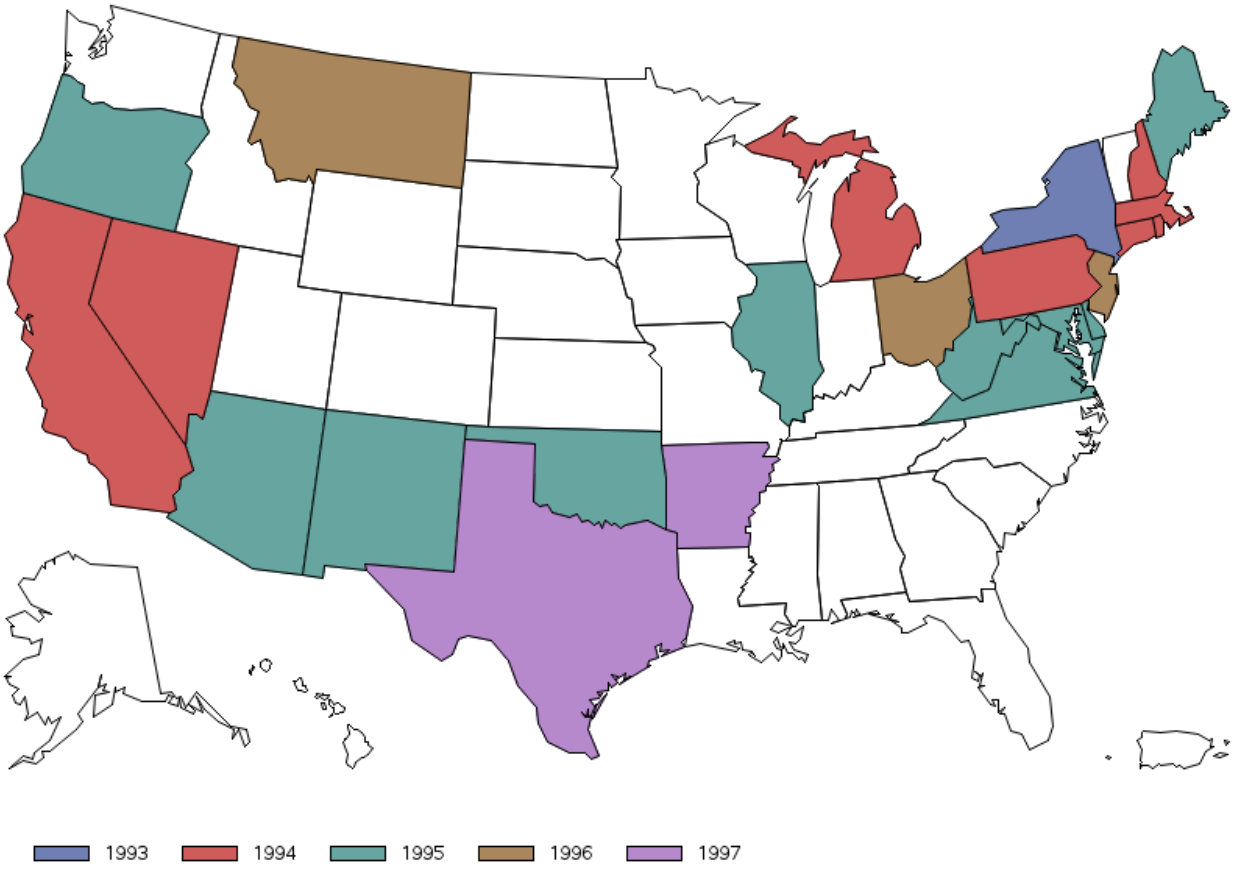


Figure 2:

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.

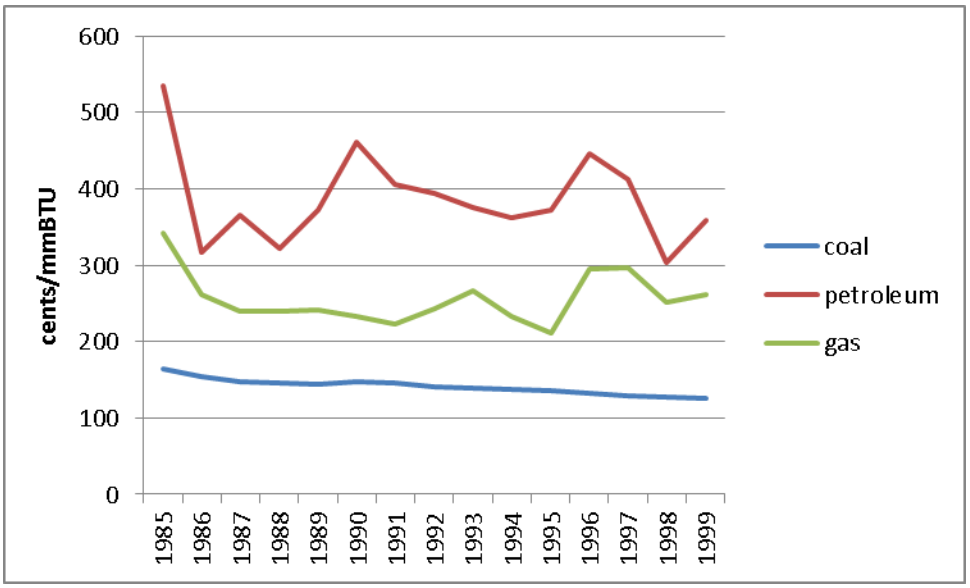
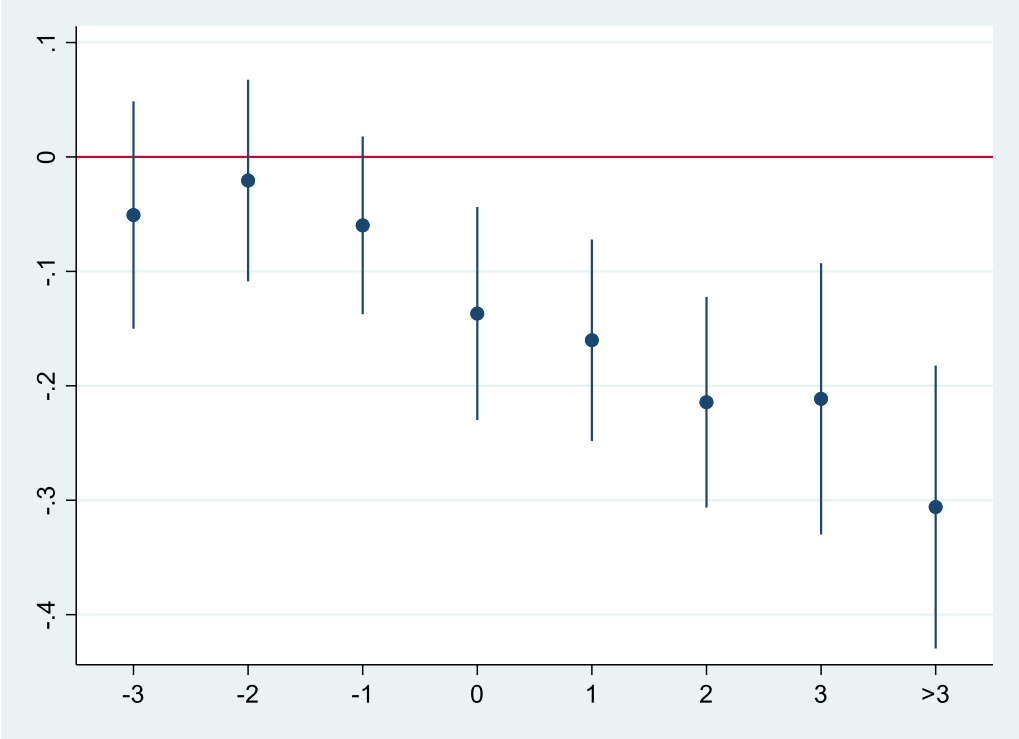


Figure 3:

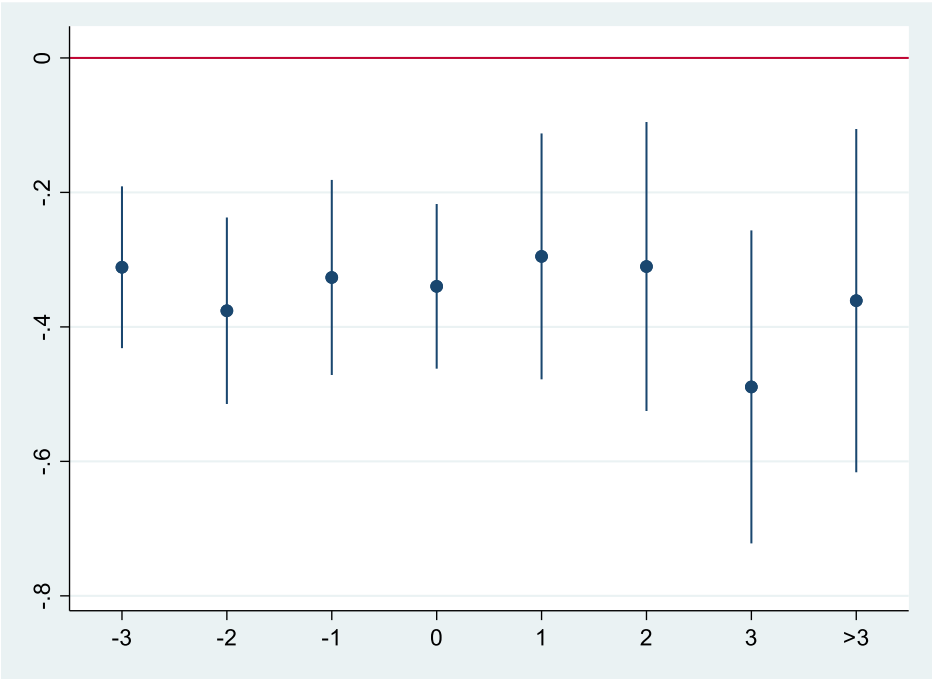
Parallel Trends

This graph reports point estimates and 90% confidence intervals of panel regressions of total output, as measured by natural log of plant-level Net MWh, in Panels A and B; and natural log of plant-level heat energy used to generate electricity (in BTU) as a function of restructuring and other control variables in Panels C and D. The sample consists of all firms in the EPA-EIA- Fabrizio et al. (2007) sample over the following years: 1985-1999. All regressions include also Phase I and Scrubber indicator variables, and regressions of heat energy also include control for natural log of plant-level Net MWh. *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.

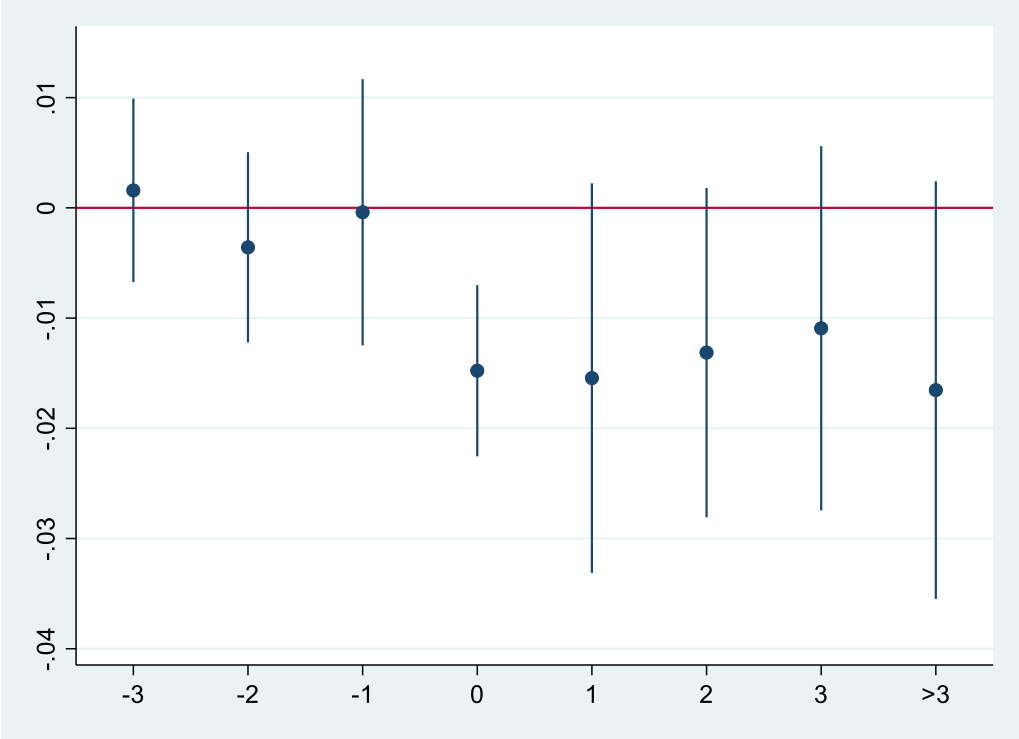
Panel A: Regression of MWh, IOU plants



Panel B: Regression of MWh, *Muni* plants



Panel C: Regression of BTU, IOU plants



Panel D: Regression of BTU, Muni plants

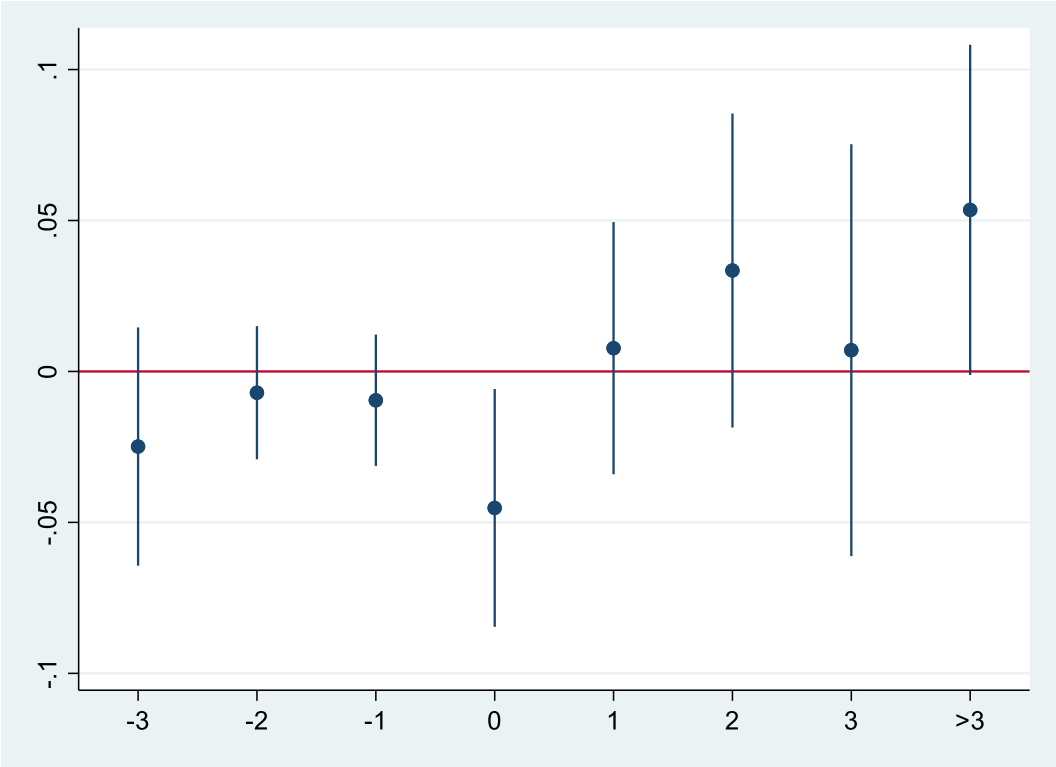


Table 1
Descriptive Statistics

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 1 (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 2
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)
Intercept	-4.684**	-3.041	-10.136***	-5.830
	(2.029)	(7.303)	(3.331)	(7.939)
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 3
Restructuring and 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 1. 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-Operating 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 Operating 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.R2	0.46	0.55	0.50
adj.R2 within	0.02	0.05	0.02

Table 4
Restructuring and Fuel Type

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 consists of all plants in the EIA- Fabrizio et al. (2007) sample over the period of 1985–1999, with the exception of Specifications 2 and 4 of Panel B, which rely on sample that 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 1. In Specifications 4-6 of Panel A and all specifications in Panel B the dependent variable 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: Fuel Mix

	(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: Coal Quality

	(1) ln(Sulf.Coal)	(2) ln(Sulf.Coal)	(3) ln(Ash)	(4) ln(Ash)
Restructured	0.116**	0.142**	0.067	0.058
	(0.044)	(0.050)	(0.046)	(0.040)
ln(Net MWh)	0.285***		0.323***	
	(0.034)		(0.040)	
ln(Coal Quant.)		0.808***		0.941***
		(0.040)		(0.020)
Dummy(Scrubber=1)	0.417***	0.410***	0.137**	0.117***
	(0.097)	(0.087)	(0.052)	(0.039)
Dummy(Phase I=1)	-0.451***	-0.444***	-0.085**	-0.086**
	(0.063)	(0.067)	(0.035)	(0.031)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7788	5169	7788	5169
adj.R^2	0.99	0.94	0.99	0.95
adj.R^2 within	0.13	0.36	0.08	0.44

Table 5
Restructuring, Production Costs, and Fuel Type

This table reports estimates of panel regressions of plant reliance on different fuel types in the production process as a function of restructuring, state-level production costs, and control variables. The sample consists of all plants in the EIA- Fabrizio et al. (2007) sample over the period of 1985–1999. *High Electr. Price* is a proxy for high production costs at a state level and is constructed as described in Section 4.2. Fuel costs are the natural log of the total annual fuel expenses, in $1,000. All other variables are as described in Table 1. In Specifications 5-7 the dependent variable 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.

	(1) ln(Fuel Costs)	(2) %Prim. Coal	(3) %Prim. Gas	(4) %Prim. Pet	(5) ln(Quant. Coal)	(6) ln(Quant. Gas)	(7) ln(Quant. Pet)
Restructured	0.012	0.006	-0.006	-0.001	-0.040	0.153	-0.190
	(0.021)	(0.004)	(0.010)	(0.010)	(0.025)	(0.257)	(0.124)
Restr.*High Electr. Price	-0.006**	0.000	0.008**	-0.009***	0.011*	0.090*	-0.047**
	(0.003)	(0.000)	(0.003)	(0.003)	(0.006)	(0.042)	(0.020)
ln(BTU)	0.849***	0.003	0.008	-0.013	0.366***	0.664***	0.321***
	(0.016)	(0.002)	(0.008)	(0.008)	(0.041)	(0.117)	(0.077)
Scrubber Dummy	0.015	-0.002	-0.009	0.012	0.021	-0.229	-0.109
	(0.032)	(0.005)	(0.009)	(0.008)	(0.044)	(0.495)	(0.150)
Phase I Dummy	-0.061*	0.000	-0.009	0.009	0.015	0.229	0.218*
	(0.029)	(0.006)	(0.007)	(0.006)	(0.027)	(0.239)	(0.114)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7937	7598	7598	7598	7788	7788	7788
adj.R^2	0.98	0.99	0.94	0.88	0.99	0.94	0.86
adj.R^2 within	0.71	0.00	0.02	0.03	0.16	0.02	0.04

Table 6
Restructuring and Production Efficiency

This table reports estimates of panel regressions of various measures of plant-level operation efficiency 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 1. Each dependent variable, except *Capacity Factor*, is converted into natural logs. 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.

	(1) ln(BTU)	(2) Capacity Factor	(3) ln(Net MWh)	(4) ln(BTU)
Restructured	-0.012**	-0.056***	-0.166***	-0.009
	(0.005)	(0.010)	(0.032)	(0.006)
Capacity Factor				0.151***
				(0.044)
ln(Net MWh)	0.914***			0.885***
	(0.008)			(0.015)
Dummy(Scrubber=1)	0.007	0.009	0.007	0.006
	(0.007)	(0.025)	(0.061)	(0.007)
Dummy(Phase I=1)	-0.002	-0.009	-0.053	-0.002
	(0.005)	(0.011)	(0.036)	(0.005)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7940	7940	7940	7940
adj.R^2	0.997	0.853	0.941	0.997
adj.R^2 within	0.947	0.026	0.015	0.948

Table 7
Restructuring and Emissions by Fuel Capacity 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 1. *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.R2	0.92	0.94	0.87	0.93
adj.R2 within	0.35	0.48	0.12	0.52

Table 8
Restructuring, Retail Access and Emissions – excl. Retail

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, excluding cases where the state has implemented retail access (that is, we remove all plant-year observations where *Retail* - an indicator variable that takes on a value of one starting from the year in which a state has implemented retail access - equals one). The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. All other variables are as described in Table 1. *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	0.177*	0.051	-0.727**	-0.075
	(0.079)	(0.035)	(0.215)	(0.154)
ln(Sulfur)		0.552**		
		(0.209)		
ln(Petroleum Quant.)		0.037		0.648***
		(0.030)		(0.046)
ln(Heat rate)		-0.038		-0.073
		(0.392)		(0.238)
Capacity Factor		1.039**		2.115***
		(0.372)		(0.439)
ln(Abate. Expenses)		-0.004		0.024
		(0.008)		(0.021)
ln(Abate. Investment)		-0.001		-0.002
		(0.003)		(0.013)
ln(Net MWh)	0.913***		0.699***	
	(0.073)		(0.144)	
Dummy(Scrubber=1)	-0.832***	-1.064***		
	(0.208)	(0.246)		
Dummy(Phase I=1)	-0.558***	-0.313*	0.252	-0.235
	(0.060)	(0.132)	(0.339)	(0.396)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2290	2288	1077	1072
adj.R2	0.92	0.94	0.87	0.93
adj.R2 within	0.35	0.48	0.12	0.51

Appendix

Table Appendix A-1
Restructuring and 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 1. 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.R2	0.42	0.95	0.76	0.59
adj.R2 within	0.01	0.07	0.07	0.02

Panel B: Coal-Operating Plants

	(1) ln(Abate. CapEx)	(2) Dummy (Scrubber =1)	(3) ln(Abate. Costs, total)	(4) ln(So2 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.R2	0.35	0.94	0.79	0.54
adj.R2 within	0.01	0.06	0.12	0.01

Panel C: Non-Coal-Operating 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.R2	0.46	0.55	0.50
adj.R2 within	0.02	0.06	0.02

Table Appendix A-2
Restructuring and Fuel Type

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 consists of all plants in the EIA- Fabrizio et al. (2007) sample over the period of 1985–1999, with the exception of Specifications 2 and 4 of Panel B, which rely on sample that 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 1. In Specifications 4-6 of Panel A and all specifications in Panel B the dependent variable 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: 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.R2	0.99	0.94	0.88	0.99	0.94	0.86
adj.R2 within	0.00	0.01	0.01	0.16	0.02	0.04

Panel B: 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)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7788	5169	7788	5169
adj.R2	0.99	0.95	0.99	0.96
adj.R2 within	0.16	0.38	0.11	0.52

Table Appendix A-3
Restructuring, Production Costs, and Fuel Type

This table reports estimates of panel regressions of plant reliance on different fuel types in the production process as a function of restructuring, state-level production costs, and control variables. The sample consists of all plants in the EIA- Fabrizio et al. (2007) sample over the period of 1985–1999. *High Electr. Price* is a proxy for high production costs at a state level and is constructed as described in Section 4.2. Since *High Electr. Price*IOU* is a time-invariant variable, it is not included. Fuel costs are the natural log of the total annual fuel expenses, in $1,000. All other variables are as described in Table 1. In Specifications 5-7 the dependent variable 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.

	(1) ln(Fuel Costs)	(2) %Prim. Coal	(3) %Prim. Gas	(4) %Prim. Pet	(5) ln(Quant.Coal)	(6) ln(Quant.Gas)	(7) ln(Quant.Pet)
Restructured*IOU	0.010	0.006	-0.003	-0.002	-0.037	0.200	-0.209
	(0.022)	(0.005)	(0.010)	(0.010)	(0.026)	(0.285)	(0.122)
Restructured*Muni	0.022	0.007*	-0.009	0.002	-0.051	-0.050	-0.013
	(0.043)	(0.003)	(0.011)	(0.009)	(0.043)	(0.192)	(0.263)
Restr.*High Electr. Price*IOU	-0.006*	0.000	0.009***	-0.009***	0.011*	0.101**	-0.040*
	(0.003)	(0.000)	(0.003)	(0.003)	(0.006)	(0.046)	(0.020)
Restr.*High Electr. Price*Muni	-0.003	-0.001	-0.002	-0.003	0.004	-0.024	-0.111
	(0.007)	(0.001)	(0.008)	(0.003)	(0.010)	(0.028)	(0.067)
ln(BTU)	0.850***	0.003	0.007	-0.013	0.365***	0.653***	0.317***
	(0.016)	(0.002)	(0.008)	(0.008)	(0.040)	(0.117)	(0.077)
Scrubber Dummy	0.014	-0.001	-0.007	0.011	0.022	-0.198	-0.101
	(0.031)	(0.005)	(0.010)	(0.008)	(0.044)	(0.496)	(0.152)
Phase I Dummy	-0.059*	0.000	-0.012	0.011	0.012	0.183	0.208*
	(0.029)	(0.006)	(0.007)	(0.006)	(0.027)	(0.239)	(0.112)
Plant-Epoch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7937	7598	7598	7598	7788	7788	7788
adj.R2	0.98	0.99	0.94	0.88	0.99	0.94	0.86
adj.R2 within	0.71	0.00	0.03	0.04	0.16	0.02	0.05

Table Appendix - 4
Restructuring and Production Efficiency

This table reports estimates of panel regressions of various measures of plant-level operation efficiency 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 1. Each dependent variable, except *Capacity Factor*, is converted into natural logs. 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.

	(1) ln(BTU)	(2) Capacity Factor	(3) ln(Net MWh)	(4) ln(BTU)
Restructured*IOU	-0.013**	-0.056***	-0.157***	-0.009*
	(0.005)	(0.011)	(0.032)	(0.005)
Restructured*Muni	-0.008	-0.057***	-0.225***	-0.006
	(0.025)	(0.015)	(0.068)	(0.025)
Capacity Factor				0.151***
				(0.044)
ln(Net MWh)	0.914***			0.885***
	(0.008)			(0.015)
Dummy (Scrubber=1)	0.007	0.009	0.009	0.006
	(0.007)	(0.025)	(0.060)	(0.007)
Dummy(Phase I=1)	-0.001	-0.009	-0.057	-0.002
	(0.005)	(0.011)	(0.036)	(0.005)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7940	7940	7940	7940
adj.R2	0.997	0.853	0.941	0.997
adj.R2 within	0.947	0.026	0.015	0.948

Table Appendix A-5
Restructuring and Emissions by Fuel Capacity 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. All other variables are as described in Table 1. *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.R2	0.92	0.94	0.87	0.93
adj.R2 within	0.35	0.48	0.12	0.52

Table Appendix A-6
Restructuring, Retail Access and Emissions – excl. Retail

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, excluding cases where the state has implemented retail access (that is, we remove all plant-year observations where *Retail* - an indicator variable that takes on a value of one starting from the year in which a state has implemented retail access - equals one). The dependent variable is defined as one plus annual emission level of SO_2 (in ton), all converted into natural logs. All other variables are as described in Table 1. *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	0.183*	0.047	-0.778**	-0.084
	(0.085)	(0.039)	(0.237)	(0.163)
Restructured*Muni	0.133	0.079	-0.458	-0.031
	(0.122)	(0.110)	(0.292)	(0.181)
ln(Sulfur)		0.552**		0.000
		(0.209)		(0.000)
ln(Petroleum Quant.)		0.037		0.648***
		(0.030)		(0.046)
ln(Heat rate)		-0.037		-0.081
		(0.390)		(0.231)
Capacity Factor		1.038**		2.109***
		(0.373)		(0.432)
ln(Abate. Expenses)		-0.005		0.023
		(0.008)		(0.021)
ln(Abate. Investment)		-0.001		-0.002
		(0.002)		(0.013)
ln(Net MWh)	0.912***		0.699***	
	(0.073)		(0.139)	
Dummy(Scrubber=1)	-0.831***	-1.062***	0.000	0.000
	(0.209)	(0.245)	(0.000)	(0.000)
Dummy(Phase I=1)	-0.560***	-0.312*	0.303	-0.229
	(0.060)	(0.131)	(0.393)	(0.427)
Plant-Epoch FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2290	2288	1077	1072
adj.R2	0.92	0.94	0.87	0.93
adj.R2 within	0.35	0.48	0.12	0.51