Short- and Long-Run Impacts of Environmental Regulations on Firm Productivity: Evidence from the U.S. Electricity Sector, 1938-1999

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Abstract

Environmental regulations in the United States have been shown to generate economic inefficiencies in a variety of contexts. However, there is little evidence regarding whether these economic inefficiencies persist in the long-run once firms and technology have had a chance to adapt. Our paper quantifies the short-run versus long-run productive efficiency costs of the National Ambient Air Quality Standards (NAAQS) implemented beginning in 1972 using newly digitized annual data on the vast majority of U.S. fossil fuel fired electric power plants from 1938-1999. Estimating annual, plant-level total factor productivity (TFP) using the latest advances in production function estimation, we first simply document the drastic increase in average TFP from 1938 to the mid-to-late 1960s associated with technological progress. In order to statistically assess to what extent the lack of TFP growth beginning in the early 1970s was due to the Clean Air Act, our paper considers a difference-in-differences framework based on counties moving in and out of attainment with the NAAQS. Within this framework, we find that a plant's TFP drops by 8.4 percent on average when the county where this plant is located moves out of attainment, an effect driven by nonattainment in the NAAQS for particulate matter. This drop in average, plant-level TFP because of stricter environmental regulations in nonattainment counties seems to be persistent; we estimate a similar effect even for plants in counties out of attainment with NAAQS for over 20 years. This suggests that plants are unable to cost-effectively adapt to environmental regulations such as the NAAQS even in the long run.

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1 Introduction

Burning fossil fuels has long been known to emit both global pollutants which contribute to climate change as well as local pollutants which adversely impact the health of local populations.[1] Due to the environmental costs of air pollution from burning fossil fuels, the Clean Air Act (CAA) of 1963, as well as its amendments in 1970, 1977, and 1990, were passed in order to reduce the level of air pollution in the United States. By any conventional benefit-cost metric, the CAA and its amendments were a success; for example, the U.S. Environmental Protection Agency (EPA) estimates that the overall annual average direct benefit of the 1970 Clean Air Act Amendments (CAAA) over the period 1970-1990 is 1.85 trillion dollars (in 2010 USD) compared to an overall annual average direct implementation cost of roughly 43.63 billion dollars (in 2010 USD) (EPA, 1997).

However, there is little evidence pertaining to the *economic costs* of environmental regulations such as the CAA.[2] These costs are likely to be especially high for the electricity generation sector because, according to the Energy Information Administration (EIA), this sector burned roughly 93 percent (36 percent) of the overall amount of coal (natural gas) consumed in the U.S. in 2016. In addition, the electricity industry has been at the center of the debate on air quality regulations since the passage of the 1970 CAAA, making it ideal for assessing the short- and long-term impacts of environmental regulations. While regulations may harm firms' productivity in the short run, Porter (1991) argues that they could trigger innovation, and ultimately make firms more productive in the long run. This paper leverages newly digitized data on the vast majority of fossil fuel fired power plants in the U.S. over the period 1938-1999 to examine the short- and long-run productive efficiency costs of air quality regulations.

This detailed annual, plant-level data, collected by the Federal Energy Regulatory Commission (FERC), includes many different variables such as output (electricity generation in MWh), electricity generating capacity (in MW), average number of employees,

[1]See NRC (2010) for a comprehensive report on the environmental externalities associated with energy use. Chay and Greenstone (2003), Currie and Neidell (2005), Currie and Walker (2011), Currie et al. (2015), Clay, Lewis and Severnini (2016), Schlenker and Walker (2016), and Deschenes, Greenstone and Shapiro (2017), among others, study the health costs associated with local air pollution.

[2]Notable exceptions are Gollop and Roberts (1983) on the costs of the 1970 CAAA sulfur dioxide regulations in 56 private owned utilities over the period 1973-1979, Ryan (2012) on the costs of the 1990 CAAA in the Portland cement industry over the period 1980-1999, and Greenstone, List and Syverson (2012) on the costs of the 1970 CAAA in manufacturing over the period 1972-1993.

fuel consumption (by type, in units of heat energy), fuel prices, and a variety of different production expenses. Building primarily on Fabrizio, Rose and Wolfram (2007) and Ackerberg, Caves and Frazer (2015), we use these data to estimate annual, plant-level total factor productivity (TFP). A higher TFP indicates that a plant can produce more output from a given level of inputs. We first simply show that our estimate of average annual TFP: (1) increases from 1938 to the mid-to-late 1960s, (2) experiences a lack of growth in the 1970s, and (3) is lower for older plants relative to newer plants. Each of these trends is consistent with evidence from both industry sources and previous academic literature such as Gollop and Roberts (1983), Nelson and Wohar (1983), and Joskow (1987), providing supporting evidence that our TFP measure is capturing trends in the productivity of fossil-fuel fired power plants in the U.S.

We next examine whether the National Ambient Air Quality Standards (NAAQS) for different pollutants affect the TFP of fossil fuel fired power plants within a difference-in-differences framework. With the enactment of the 1970 CAAA, the U.S. EPA set up air quality standards for five criteria pollutants: total suspended particles (TSP), which in 1987 became particulate matter (PM), tropospheric ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO). The NAAQS require that the concentration of each of these pollutants stays below some standard, which is built around annual average levels of pollution as well as maximum hourly, 8-hour or daily concentration levels in the year. Each county receives annual pollutant-specific designations based on compliance with the NAAQS. Counties with pollution concentration below the federal standard are designated in attainment, whereas counties with concentration above the threshold are deemed in nonattainment. Emitters in nonattainment counties are subject to greater regulatory scrutiny than emitters in attainment counties.

Using our difference-in-differences framework, we find that the average TFP of plants located in counties that move out of attainment with the NAAQS for any pollutant decreases by 8.4 percent. Our results indicate that most of our estimated impact comes from the NAAQS associated with particulate matter; this is not surprising given that coal-fired power plants emit particularly large quantities of these fine particulates which affect the health of local populations.[3] Identification within a difference-in-differences

[3] Levy, Baxter and Schwartz (2009), Muller (2014), and Clay, Lewis and Severnini (2016) calculate the costs associated with increased mortality from the local air pollution emitted by U.S. power plants. Clay, Lewis and Severnini (2016), in particular, focuses on the sample period 1938-1962, arguing that the emissions of fine particulates from coal-fired power plants during this sample period were especially

framework relies on the parallel trends assumption. Previous studies could not provide evidence supporting this assumption because they lacked data before the passage of the CAA in 1963. This is the first paper to report time trends in total factor productivity (TFP) by county designation status before and after the CAA. In particular, we show that power plants in counties in versus out of attainment with the NAAQS do not exhibit systematically different trends in average annual TFP from 1938 to 1970, prior to the implementation of the NAAQS. This provides suggestive evidence that variation from the NAAQS can be used to causally identify the impact of environmental regulation on a number of economic outcomes.[4]

The average annual fuel costs across power plants for the sub-sample of years 1980-1999 is roughly 11 billion dollars (in 2010 USD); thus, a lower bound on the annual, average cost associated with the NAAQS set forth by the 1970 CAAA implied by our estimated 8.4 percent decline in productivity is roughly 924 million dollars (in 2010 USD). As mentioned above, EPA (1997) estimates that the overall annual average direct benefit of the CAAA from 1970-1990 is 1.85 trillion dollars (in 2010 USD) and the overall annual average direct implementation cost of the CAAA is 43.63 billion dollars (in 2010 USD); though our average annual cost estimate of 924 million dollars clearly does not move the benefit-cost ratio of the CAAA below one, our effect is sizable given that the annual average productivity loss from one sector (electricity generation) is approximately 2 percent of the entire cost of implementing the CAAA estimated by the U.S. EPA.

Finally, it is not ex-ante obvious whether the productivity decreases due to the NAAQS should be transitory versus persistent. As mentioned earlier, Porter (1991) argues that tough standards do not inevitably hinder competitiveness because they may trigger innovation and upgrading, which consequently may enhance productivity growth. Our results indicate that the negative impact of nonattainment with the NAAQS on a plant's TFP in a given year does *not* diminish with the cumulative number of years up to that point that the plant's county was out of attainment. Our estimated effect of nonattainment on TFP is similar in magnitude even for plants located in counties that

severe and, importantly, especially local due to lower average stack heights. The local nature of the emissions of fine particulates make it especially tough for coal-fired power plants to comply with the NAAQS associated with these fine particulates.

[4]Prior to our study, Gollop and Roberts (1983), Henderson (1996), Becker and Henderson (2000), Greenstone (2002), Greenstone, List and Syverson (2012), and Walker (2013), among others, use variation from counties in versus out of attainment with the NAAQS in order to quantify different costs of the CAAA.

have been in nonattainment for more than 20 years. This suggests that adaptation to the stricter environmental regulations implied by nonattainment with the NAAQS may be difficult even in the long run.

Summarizing, this paper makes four contributions to the literature. First, it provides the first estimates of the economic costs of environmental regulations over a long time horizon, allowing the comparison between the short- and long-run effects of the NAAQS on plant productivity. Our findings indicate that plants facing stricter environmental regulations were unable to cost-effectively "catch up" to the productivity levels of other plants even after 20 years of facing this stricter regulation. This runs counter to the intuition that firms and technology will inevitably adapt to existing economic and environmental regulations. However, we caution that adaptation of the sort described in Porter (1991) may occur in other industries/contexts, especially given that the electricity generation industry was undoubtedly the most severely impacted by the air quality standards set forth by the CAAA.

The second contribution is the estimation of the economic costs of environmental regulations in the presence of a baseline period without regulation. By digitizing data on individual power plants since 1938, we provide not only the first estimates of the impact of air quality regulations on TFP in the electricity generation sector, but also the first evidence that TFP trends in the decades before the passage of the CAA of 1963 were similar in counties in and out of attainment with the NAAQS. This strengthens the internal validity of the results of previous studies that we build on: Gollop and Roberts (1983), who analyzed the effects of the 1970 CAAA regulations on productivity growth for a small set of utilities over the period 1973-1979; Greenstone, List and Syverson (2012), who estimated the impact of the 1970 CAAA regulations on TFP in the full manufacturing sector over the period 1972-1993; and Ryan (2012), who assessed the productivity effects of the 1990 CAAA in the Portland cement industry over the period 1980-1999.

The third contribution is that we are among the first to estimate productivity for electric utilities using the methodological innovations made in this space over the last 20 years (e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2007), Ackerberg, Caves and Frazer (2015), and Gandhi, Navarro and Rivers (2017)). An advantage of our data context is that we observe output and inputs in quantities rather than revenue/cost shares. There is a growing literature discussing the issues in estimating total factor productivity using revenues and costs (called TFP-R) rather than quantities (called TFP-Q);[5] for one of many examples, TFP-R will change with changes in market power in input and output markets, whereas TFP-Q would remain the same. That being said, it is encouraging that our estimates of productivity for the full electricity generation sector, based on recent methodologies, is highly correlated to the productivity calculated by Nelson and Wohar (1983), who uses an index-number approach for fifty privately owned utilities over the period 1949-1978 – correlation of 0.88.

The fourth contribution relates to the role of government policy in shaping TFP in the long run. A large literature in the past two decades has documented productivity differences across firms and countries, and investigated the determinants of productivity (see Bloom and Van Reenen (2010), and Syverson (2011), for surveys). While it is assumed that TFP can be influenced by public policy, there is little credible empirical evidence on the magnitude and dynamics of those effects. Here we join Gollop and Roberts (1983), Ryan (2012), and Greenstone, List and Syverson (2012) in assessing the direct TFP impacts of federal air quality regulations, and add that those effects could be persistent. Carlson et al. (2000) and Fabrizio, Rose and Wolfram (2007) also provide invaluable indirect evidence of the effects of federal and state regulatory restructuring on productive efficiency in the electricity sector.

The remainder of the paper is organized as follows. Section 2 presents a background on technological changes in the electricity sector, the evolution of the CAA, and the CAAA attainment designation process and its implications for polluting firms such as electric utilities. Section 3 describes the data sources and summary statistics. Section 4 lays out the empirical strategy, including a conceptual framework that helps interpreting the results. Section 5 reports the findings, and Section 6 concludes.

[5]For example, Foster, Haltiwanger and Syverson (2008) stress that, when industry deflators are used, differences in plant-specific prices show up in TFP-R but not TFP-Q. Hsieh and Klenow (2009) argues that TFP-R is independent from TFP-Q in the case where demand for the final good has constant elasticity (along with the other maintained assumptions underlying their theoretical model). De Loecker (2011) points out that when one does not observe physical output in the estimation of productivity, and does not control for unobserved prices, results may be severely biased.

2 Background

In this section, we discuss technological improvements and productivity growth in steam-electric power plants until the full implementation of air quality regulations, and the details of the CAA and its amendments. They will help understanding the empirical strategy and the interpretation of the results later on.

2.1 Technical Change and Productivity in Power Generation

Several studies of the evolution of the electricity generation industry describe a similar pattern:[6] technical change and total factor productivity (TFP) grew rapidly from the aftermath of World War II until roughly the mid-to-late 1960s, then stagnated by the early 1970s. Joskow (1987) argues that this pattern is consistent with more disaggregated indexes of productivity in the steam generation segment of electricity supply. He points to evidence that the number of Btus of fuel needed to generate a (net) kwh of electricity fell by almost 40 percent from 1925 to 1945, and by an additional 35 percent between 1945 and 1965. From 1965 onwards, however, thermal efficiency stagnated or even deteriorated. Joskow also observes that studies of the costs per unit of generating capacity exhibited similar behavior. Between 1954 and the mid-1960s the real cost per kw of steam electric capacity declined (Wills, 1978). Nevertheless, since the mid-1960s the real cost per unit of generating capacity increased dramatically (Joskow and Rose, 1985).

As pointed out by Gollop and Roberts (1983), identifying the productivity impact of emission regulations in the 1970s is complicated by coincident changes in market conditions, the unprecedented increase in fuel prices, and the dramatic decline in output growth for electric power. They provide evidence that the annual increase in the average price per million Btu of fuel consumed by utilities was less than 0.3 percent between 1958 and 1969, 18 percent from 1969 to 1979, and nearly 30 percent between 1973 and 1976. Because at the time power generation relied mostly on fuel, rising fuel prices may have contributed to the industry's declining rate of technical change, as they find. In addition, they show that kilowatt-hour sales by privately owned utilities increased at average annual rates of 7.6 percent between 1958 and 1969 and 4.6 percent between 1969 and 1979, while

[6] These studies include Gollop and Jorgenson (1980), Gollop and Roberts (1981), Gollop and Roberts (1983), Kendrick (1983), Nelson and Wohar (1983), and Joskow (1987).

falling to 1.8 percent between 1973 and 1976. If there were scale economies in production, then declining output growth may have reduced the contribution of this traditional source of the industry's productivity growth, as found by them, Gollop and Roberts (1981), and Christensen and Greene (1976).

2.2 The Clean Air Act and its Amendments

The Clean Air Act (CAA) of 1963 was the first federal legislation regarding air pollution control. It established a federal research program to study techniques for monitoring and controlling air pollution, but did not mandate reductions in emissions. The 1970 Clean Air Act Amendments (CAAA) marked the federal government's ambitious entry into the business of restricting the emission of pollutants into the air. It required that all states meet National Ambient Air Quality Standards (NAAQS) for certain criteria air pollutants: total suspended particles (TSP) or particulate matter (PM),[7] carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3)[8] (other pollutants, such as lead, have subsequently been added to the list). To do so, states with air quality exceeding the federal guidelines were required to submit a State Implementation Plan (SIP) that detailed their plans to bring violating areas into compliance. Given the amount of confusion, and the inadequate resources to carry-out these plans, many areas of the country had failed to meet the standards by the 1975 deadline.

Due to this lack of progress, Congress passed the 1977 CAAA. The 1977 CAAA stipulated that starting in 1978 every county in the U.S. was to be designated annually as being in-attainment or out-of-attainment (nonattainment) of NAAQS. A county's attainment status was to be determined with respect to each of the criteria air pollutants. If a county is not in attainment of the federal standard with respect to one of these pollutants, the state must submit periodic comprehensive plans that will lead to attainment status in the near future. If standards are not met in due time, states risk losing federal monies that help to fund state-level public goods and services (see, for example, Becker

[7] In 1987 the EPA changed its focus from the regulation of all particulates to the smaller PM_{10}'s, which have an aerodynamic diameter equal to or less than 10 micrometers. In 1997 the PM_{10} regulation was replaced with a $PM_{2.5}$ one.

[8] There are separate standards for NO_2 and O_3. In principle, a county could meet one of these standards, but not the other. However, O_3 is the result of a complicated chemical process that involves NO_2, and the vast majority of counties that were nonattainment for NO_2 were also nonattainment for O_3. As a result, we designated a county nonattainment for O_3 if the EPA labeled it nonattainment for either O_3 or NO_2. All future references to O_3 refer to this combined measure.

and Henderson (2000) and Greenstone (2002)).[9]

Environmental regulations in nonattainment counties are intended to be stringent. Polluting plants entering or expanding in a nonattainment county are subject to a standard of "Lowest Achievable Emission Rate (LAER)" without consideration of cost for all investments. The resulting rules frequently involve compliance with "command and control" style regulations that requires the installation and operation of specified pollution abatement equipment. Further, emissions from new investment must be offset by emissions reductions from an existing source within the same county, and plant expansion or modification leads to the entire plant being subject to more stringent regulations (List, Millimet and McHone, 2004).

Polluting plants locating in attainment areas, on the other hand, face a more lax regulatory standard. These plants are subject to the standard of "Prevention of Significant Deterioration (PSD)." This entails permitting and the installation of the "Best Available Control Technology (BACT)" for new plants that have the potential to emit over 100 tons of a criteria pollutant in a year. The BACT is negotiated on a case-by-case basis and the economic burden on the plant is considered in arriving at a final solution. Given that the installation of BACT in attainment areas is likely to be much less costly than the installation of LAER in nonattainment areas, new polluting plants and expansions of existing ones could face significantly lower pollution control capital construction costs in attainment areas versus nonattainment counties.

Given that SIPs require states to develop plant-specific regulations for every major source of air pollution, existing plants in nonattainment areas also face greater regulatory scrutiny than plants in attainment areas. These plant-specific regulations typically have come in the form of emissions limits. Beyond the necessary abatement investments, inspections and regulatory oversight are more persistent in nonattainment areas. Further, the size of the existing polluter importantly determines the level of regulation (Becker and Henderson, 2000).

Both the states and the EPA are given substantial enforcement powers to ensure that the CAAA's intent is met. For instance, the EPA must approve all state regulation programs in order to limit the variance in regulatory intensity across states. On the com-

[9] While the EPA denoted each county beginning in 1978 as either in or out of attainment for each criteria air pollutant, we followed Greenstone (2002) and compiled the data back to 1972 using air quality data collected via filing a Freedom of Information Act petition.

pliance side, states run their own inspection programs and frequently fine non-compliers. The 1977 legislation also made the plant-specific regulations both federal and state law, which gave the EPA legal standing to impose penalties on states that do not aggressively enforce the regulations and on plants that do not adhere to the regulations. A number of studies document the effectiveness of these regulatory actions at the plant level (Nadeau (1997), Cohen (1998)). Perhaps the most direct evidence that the regulations are enforced successfully is that air pollution concentrations declined more in nonattainment counties than in attainment ones during the 1970s and 1980s (Henderson (1996), Greenstone (2002), Chay and Greenstone (2003), Chay and Greenstone (2005)).

3 Data Description

The analysis in this paper is based on annual plant-level data for the vast majority of fossil fuel fired power plants in the U.S. for the period 1938-1999. The Federal Power Commission (FPC), later renamed Federal Energy Regulatory Commission (FERC), has been collecting data from electric utilities in each year since 1938. With deregulation in the 1990s, utilities facing electricity market mechanisms are under different data requirements, so our sample period ends in 1999.[10] We digitized the data for 1938-1981, and used the data from Fabrizio, Rose and Wolfram (2007) for 1982-1999.[11] Our dataset includes all large fossil fuel steam and combined cycle gas turbine generating plants for which data were reported over the sample period. The data include operating statistics such as size of the plant, total electricity output, fuel usage, number of employees, capacity factor, operating expense, and year built.

Our production function approach assumes each power plant produces one homogeneous output, annual total electricity generation (measured in MWHs). In many ways, electricity is as close to the ideal case study for estimating production functions as one can get; electricity is not storable and the actual electrical energy generated by any plant has the ability to do exactly the same amount of work. That being said, as pointed

[10] Some U.S. states decided to shift the provision of electricity generation from output price regulation to electricity market mechanisms beginning in 1998 ("electricity restructuring"). Some of the variables originally in the FERC Form 1 are not available for plants facing electricity market mechanisms due to the different reporting requirements for these plants as well as the extent to which data collected for these plants is made publicly available. We end our sample period in the year 1999 due to this lack of data associated with state-level electricity restructuring.

[11] Part of the digitization for 1938-1981 was done with resources from the NSF grant SES 1627432.

out by Fabrizio, Rose and Wolfram (2007), generating plants may also provide reliability services (such as spinning reserves, when the plant stands ready to increase output at short notice), voltage support, and frequency control. More broadly, the availability of a plant during different periods of time (such as high electricity demand hours) may itself be an output. The production process varies considerably across these different outputs.

We have information for three variable inputs. The first, *employees*, is a count of full-time equivalent employees at the plant. The second, *fuel*, is the quantity of fuel consumed by type of fuel (tons of coal, barrels of oil, and Mcf of natural gas). We convert fuel into Btus using the reported annual plant-specific Btu content of each fuel to obtain total Btu input at the plant for each year. The third, *nonfuel_expenses*, which will be used only for robustness checks, includes all nonfuel operations and maintenance expenses, such as those for coolants, repairs, maintenance supervision, and engineering. As pointed out by FRW, this variable is less than ideal as a measure of nonfuel materials, both because it reflects expenditures rather than quantities, and because it includes the wage bill for the employees counted in *employees*, although that expense is not separately delineated in our data after 1981. As *nonfuel_expenses* includes payroll costs, both this and *employees* reflect changes in staffing.

The final input is the capital stock of the plant, *capital*, which we measure by plant capacity and vintage. Our data record the plant capacity in megawatts. We combine this with information on unit upgrades and retirements to define plant-epochs. Each plant is assigned a unique identifier. Any time the capacity of the plant is significantly changed, we create a new identifier and associated new plant-epoch specific effect. More specifically, following FRW, plant-epochs consist of plant-years over which plant capacity is relatively constant, i.e., reported capacity changes are less than 40 MW and 15 percent. This allows capital changes to alter the underlying efficiency of the plant.

Table A.1 reports summary statistics for power-plant-level data over 60 years (1938-1999). The average plant in our sample has approximately 235 employees and 1,200MW in nameplate capacity, and generates roughly 6,000MWh of electricity annually. There are about 2,800 plant-epochs in our dataset, and they are located in approximately 700 U.S. counties. Over a third of those counties are out of attainment with the NAAQS, with most of them in nonattainment for particulate matter or ambient ozone.

4 Empirical Strategy

4.1 Productivity Estimation

For a single-output production process, productive efficiency can be assessed by estimating whether a plant is maximizing output given its inputs. In particular, a production function describes the technological process of transforming inputs into an output, ignoring the costs of these inputs; a plant exhibits zero productive inefficiency if it is on the production frontier. We quantify the impact of environmental regulations on productive efficiency by estimating a production function relating inputs to output; we assume this function is the same across plant/years up to a multiplicative scaling factor that varies by plant/year. This scaling factor is termed total factor productivity (TFP); plant/years producing more output for the same level of inputs have a higher total factor productivity (TFP).

In our framework, each power plant i produces electricity generation $Q_{i,t}$, measured in megawatt-hours (MWh) in year t. We consider three inputs to the production of electricity: capital $K_{i,t}$, labor $L_{i,t}$, and fuel $E_{i,t}$. Many studies simply model output $Q_{i,t}$ as a function of inputs using a Cobb-Douglas production function, but Fabrizio, Rose and Wolfram (2007) (hereafter FRW) argue that important institutional characteristics of electricity production strongly point to an alternative specification. In particular, the amount of fuel burned varies in response to real-time dispatching and operational conditions such as realized electricity demand; in contrast, other inputs to a plant's production are determined far in advance of the realization of these real-time conditions. For example, utilities hire labor in advance of these real-time conditions based on expected demand; while these can be adjusted over the medium run, staffing decisions are not tied to short-run fluctuations in output. Capital is typically chosen at the time of a unit's construction (or retirement); large capital changes are relatively infrequent. Thus, managers likely consider capital as fixed when deciding on the level of labor and fuel. This timing assumption, that capital is chosen before labor and fuel, will be important to our estimation strategy. Summarizing, while capital and labor are adjusted based on some forecast over future real-time conditions, fuel is chosen taking capital and labor as fixed in response to the realization of these conditions.

Based on this description of the technology, following FRW, we posit a Leontief production process for power plant i in year t of the following form:

$$Y_{i,t} = min[Q(K_{i,t}, L_{i,t}), G(E_{i,t})]e^{\omega_{i,t}+\epsilon_{i,t}}, \quad (1)$$

We assume that capital, measured by the nameplate generating capacity of the plant, is fixed.[12] Labor decisions are made in advance of production, but after the level and productivity of the plant's capital are observed. This reflects the quasi-fixity of this input over time: staffing decisions are made to ensure that the plant is available when it is dispatched, based on the targeted output. The error term $\omega_{i,t}$ incorporates productivity shocks that we assume are known to the plant manager in advance of scheduling labor inputs, but are not observable to the econometrician.

Building on Atkinson and Halvorsen (1976), Christensen and Greene (1976), Gollop and Roberts (1983), and Carlson et al. (2000), we model the output $Q(.)$ as a translog function of capital and labor.[13] Following FRW and Ackerberg, Caves and Frazer (2015) (hereafter ACF), we assume that $G(.)$ is linear (i.e., $G(E_{i,t}) = aE_{i,t}$). Now, the main idea underlying the Leontief justification is that, under the assumption that $Q(K_{i,t}, L_{i,t}) = G(E_{i,t})$, the right hand side of equation (1) can be written as

$$Y_{i,t} = Q(K_{i,t}, L_{i,t})e^{\omega_{i,t}+\epsilon_{i,t}}, \quad (2)$$

a function that does not depend on intermediate inputs E. The right hand side of equation (2) is a function of only capital, labor, and productivity. Gandhi, Navarro and Rivers (2017) point out that under linearity of $G(.)$, gross output can be used on the left hand side of equation (2) to measure the structural value-added production function. This is in fact a version of what ACF suggest in estimating a structural value-added production function based on an underlying Leontief gross output production function. Using the translog specification for $Q(.)$, taking log of both sides of equation (2), expressing the log

[12]The empirical analysis defines a new plant-epoch, i, whenever there are significant changes in capacity, so that within each plant-epoch, capacity is approximately constant.

[13]Boisvert (1982) points out that the translog specification can be viewed in three ways: "as an exact production function, as a second-order Taylor series approximation to a general, but unknown production function, or as a second-order approximation to a CES production function." (p.6). Regarding the inputs, many different papers have estimated production functions in the U.S. electricity generation context using specifications based only on capital, labor, and fuel, including Barzel (1963), Nerlove (1963), Atkinson and Halvorsen (1976), Christensen and Greene (1976), Gollop and Roberts (1983), Nelson and Wohar (1983), Gollop and Roberts (1985), and Carlson et al. (2000).

of those variables with lowercase letters, and denoting $x_{i,t} \equiv (k_{i,t}, l_{i,t})'$, we can express our production function as:

$$y_{i,t} = \alpha_0 + \sum_r \alpha_r x_{i,t}^r + \sum_r \sum_s \beta_{r,s} x_{i,t}^r x_{i,t}^s + \omega_{i,t} + \epsilon_{i,t}. \tag{3}$$

We estimate this production function using the ACF procedure, which is only a slight adaptation of the Olley and Pakes (1996) (hereafter OP) and Levinsohn and Petrin (2003) (hereafter LP) methodologies, but essentially relies on the same moment conditions. Technically, the main difference between the ACF approach and OP and LP is that it inverts "conditional" rather than "unconditional" input demand functions to control for unobserved productivity. Intuitively, the ACF approach allows labor to have dynamic effects (e.g., hiring or firing costs): $e_{i,t}$ is allowed to be chosen *after* $l_{i,t}$ rather than simultaneously. This is important in our context because, as mentioned above, utilities typically choose capital and labor expenditures in advance, based on expected demand.

The basic ACF procedure requires five assumptions, sharing assumptions 1 and 2 with OL/LP:

Assumption 1 (Information Set): The power plant's information set at t, that is, $I_{i,t}$, includes current and past productivity shocks $[\omega_{i\tau}]_{\tau=0}^{t}$ but does not include future productivity shocks $[\omega_{i\tau}]_{\tau=t+1}^{\infty}$. The transitory shocks $\epsilon_{i,t}$ satisfy $E[\epsilon_{i,t}|I_{i,t}] = 0$.

Assumption 2 (First Order Markov): Productivity shocks evolve according to the distribution

$$p(\omega_{i,t+1}|I_{i,t}) = p(\omega_{i,t+1}|\omega_{i,t}). \tag{4}$$

This distribution is know to firms and stochastically increasing in $\omega_{i,t}$.

Assumptions 1 and 2 imply that we can decompose $\omega_{i,t}$ into its conditional expectation at time $t-1$, and an innovation term, that is,

$$\omega_{i,t} = E[\omega_{i,t}|I_{i,t-1}] + \xi_{i,t} = E[\omega_{i,t}|\omega_{i,t-1}] + \xi_{i,t} = g(\omega_{i,t-1}) + \xi_{i,t}, \tag{5}$$

where, by construction, $E[\xi_{i,t}|I_{i,t-1}] = 0$.

Assumption 3 (Timing of Input Choices): Power plants accumulate capital according to

$$k_{i,t} = \kappa(k_{i,t-1}, i_{i,t-1}), \tag{6}$$

where investment $i_{i,t-1}$ is chosen in period $t-1$. Labor $l_{i,t}$ has potential dynamic implications and is chosen at period t, period $t-1$ or period $t-b$ (with $0 < b < 1$).

Assumption 4 (Scalar Unobservable): Power plants' intermediate (fuel) demand is given by

$$e_{i,t} = \tilde{f}_t(k_{i,t}, l_{i,t}, \omega_{i,t}). \tag{7}$$

Assumption 5 (Strict Monotonicity): $\tilde{f}_t(k_{i,t}, l_{i,t}, \omega_{i,t})$ is strictly increasing in $\omega_{i,t}$.

Given these assumptions, we can follow LP, invert intermediate input demand $\omega_{i,t} = \tilde{f}_t^{-1}(k_{i,t}, l_{i,t}, e_{i,t})$, and substitute into the production function (recall $x_{i,t} \equiv (k_{i,t}, l_{i,t})'$), that is,

$$\begin{aligned} y_{i,t} &= \alpha_0 + \sum_r \alpha_r x_{i,t}^r + \sum_r \sum_s \beta_{r,s} x_{i,t}^r x_{i,t}^s + \tilde{f}_t^{-1}(k_{i,t}, l_{i,t}, e_{i,t}) + \epsilon_{i,t} \\ &= \tilde{\Phi}_t(k_{i,t}, l_{i,t}, e_{i,t}) + \epsilon_{i,t}. \end{aligned}$$

Since we follow LP and treat $\tilde{f}_t^{-1}$ nonparametrically, the first three terms are clearly not identified and are subsumed into $\tilde{\Phi}_t(k_{i,t}, l_{i,t}, e_{i,t}) = \alpha_0 + \sum_r \alpha_r x_{i,t}^r + \sum_r \sum_s \beta_{r,s} x_{i,t}^r x_{i,t}^s + \omega_{i,t}$, resulting in the following first stage moment condition:

$$E[\epsilon_{i,t} | I_{i,t}] = E[y_{i,t} - \tilde{\Phi}_t(k_{i,t}, l_{i,t}, e_{i,t}) | I_{i,t}] = 0. \tag{8}$$

Unlike LP, this moment condition does not permit estimation of any α and β in the first stage. However, it does produce an estimate $\hat{\tilde{\Phi}}_t(k_{i,t}, l_{i,t}, e_{i,t})$ of $\tilde{\Phi}_t(k_{i,t}, l_{i,t}, e_{i,t})$. ACF propose estimating all production function parameters in the second stage using the following second stage conditional moment:

$$E[\epsilon_{i,t} + \xi_{i,t} | I_{i,t-1}] = E[y_{i,t} - \alpha_0 - \sum_r \alpha_r x_{i,t}^r - \sum_r \sum_s \beta_{r,s} x_{i,t}^r x_{i,t}^s$$
$$-g\left(\tilde{\Phi}_{t-1}(k_{i,t-1}, l_{i,t-1}, e_{i,t-1}) - \alpha_0 - \sum_r \alpha_r x_{i,t-1}^r - \sum_r \sum_s \beta_{r,s} x_{i,t-1}^r x_{i,t-1}^s\right) | I_{i,t-1}] = 0,$$

where $\tilde{\Phi}_{t-1}$ is replaced by its estimate from the first stage. As usual, it it easiest to transform conditional moments into unconditional moments for actual estimation (see details in ACF). Once all production function parameters are estimated, we can obtain a measure of productivity by:

$$\hat{\omega}_{i,t} = g\left(\hat{\tilde{\Phi}}_t(k_{i,t}, l_{i,t}, e_{i,t}) - \hat{\alpha}_0 - \sum_r \hat{\alpha}_r x_{i,t}^r - \sum_r \sum_s \hat{\beta}_{r,s} x_{i,t}^r x_{i,t}^s\right). \tag{9}$$

To illustrate, consider a simple model where $\omega_{i,t} = \rho \omega_{i,t-1} + \xi_{i,t}$. In this case, we would have an additional parameter to estimate, ρ, and the productivity measure would be:

$$\hat{\omega}_{i,t} = \hat{\rho}\left(\hat{\tilde{\Phi}}_t(k_{i,t}, l_{i,t}, e_{i,t}) - \hat{\alpha}_0 - \sum_r \hat{\alpha}_r x_{i,t}^r - \sum_r \sum_s \hat{\beta}_{r,s} x_{i,t}^r x_{i,t}^s\right). \tag{10}$$

It is important to mention that these estimates may be subject to selection bias if exit decisions are driven by unobserved productivity shocks. The potential selection issue has been addressed directly in OP, but here we follow FRW and point out that the power plants in our sample are more stable than those studied in many other contexts, suggesting that the selection problem may be somewhat less severe for electric generation. Exit in our sample is relatively rare: adverse productivity shocks are much more likely to result in reduced run time than in plant retirements.[14] Besides, as in FRW, we combine plant capacity with information on unit retirements to define *plant-epochs*. Any time the capacity of the plant is significantly changed, we create a new identifier and associated new plant-epoch specific effect. This allows capital changes to alter the underlying input

[14]To further gauge the significance of potential selection effects, we have compared results for the unbalanced panel we use in the analysis to those for a panel of plants that continues to operate for at least 15 years, where potential selection effects are likely to be most severe. The results from the "semi-balanced" panel are similar to the main results, as shown in Figure 6 and explained in subsection 5.3, suggesting there is little to be gained from a more detailed treatment of potential selection biases.

efficiency of the plant.

4.2 Impact of Clean Air Act on Productivity: Conceptual Framework

In this section we follow Greenstone, List and Syverson (2012) (hereafter GLS) and briefly frame our conceptual view of how environmental regulations might affect a power plant's productivity level and how we would measure such effects. The model motivates the empirical models and provides a lens to interpret the results.

We begin by assuming that a power plant has the translog production function as expressed in equation (3), but with *production-effective* inputs $\tilde{x}_{i,t} \equiv (\tilde{k}_{i,t}, \tilde{l}_{i,t})'$, and a Hicks-neutral technology shifter $a_{i,t}$:

$$y_{i,t} = \alpha_0 + \sum_r \alpha_r \tilde{x}^r_{i,t} + \sum_r \sum_s \beta_{r,s} \tilde{x}^r_{i,t} \tilde{x}^s_{i,t} + a_{i,t} + \epsilon_{i,t}. \tag{11}$$

Production-effective refers to the quantity of each input that actually is used in the production of output rather than the quantity of each input observed at the plant. Production-effective and observed inputs are related to one another; we assume the former is proportional to the latter, with the factor of proportionality allowed to vary between the two inputs. Thus, $\tilde{x} \equiv ln(\tilde{X}) = ln(\Lambda X) = ln(\Lambda) + ln(X) \equiv \lambda + x$, where x's are the observed inputs at the plant and λ's are the factors of proportionality that link observed to production-effective inputs.

As explained in GLS, production-effective inputs captures the notion that plants that fall under more stringent environmental regulations need to employ inputs that are necessary to meet regulatory requirements but that are potentially not useful for producing the plants' commercial output. Indeed, the plant-specific requirements under the Clean Air Act in this period were generally of the "command and control" variety that involved the EPA dictating the installation of particular pollution abatement technologies (rather than imposing emissions limits and allowing plants to achieve them in whatever way they found most efficient).[15] Thus, for example, in order to meet federal air quality

[15] There were exceptions such as the market for transferable sulfur dioxide (SO_2) emission allowances among electric utilities, established by the Title IV of the 1990 Clean Air Act Amendments (CAAA) and studied by Carlson et al. (2000).

standards a power plant may need to install scrubbing or gas reclamation equipment. This equipment is part of the plant's measured capital stock, but in itself is neither necessary nor useful for producing the plant's commercial output – electricity. A labor-input example of the same concept is the hiring of an environmental compliance officer for the plant.

In this framework, the introduction of more stringent regulatory requirements – namely, a nonattainment designation for an emitting power plant's county – can be interpreted as a decrease in λ. When more compliance-related inputs are necessary, there is a larger gap between a power plant's observed and production-effective inputs.[16] The productivity effects of the regulation can be seen by substituting the expressions for production-effective inputs into the production function:

$$y_{i,t} = \alpha_0 + \sum_r \alpha_r x^r_{i,t} + \sum_r \sum_s \beta_{r,s} x^r_{i,t} x^s_{i,t} + \left(\sum_r \alpha_r \lambda^r_{i,t} + \sum_r \sum_s \beta_{r,s} \lambda^r_{i,t} \lambda^s_{i,t} + a_{i,t} \right) + \epsilon_{i,t}. \tag{12}$$

We define $\omega_{i,t} \equiv \sum_r \alpha_r \lambda^r_{i,t} + \sum_r \sum_s \beta_{r,s} \lambda^r_{i,t} \lambda^s_{i,t} + a_{i,t}$, which makes this production function the same as equation (3). The expression for productivity makes obvious the effect of environmental regulation on TFP. Decreases in λ driven by an increased need for compliance-related inputs are inward shifters of the power plant's production function. In other words, the amount of output the plant obtains per unit of observed input – its TFP level – decreases. The greater the amount of compliance-related inputs (the larger the drop in λ), the larger the observed decline in plant TFP.

4.3 Impact of Clean Air Act on Productivity: TFP Trends

We start by estimating the following equation to assess year-by-year changes in TFP:

[16]Another channel through which air quality regulation could affect TFP besides the compliance-related input mechanism discussed here is New Source Review (NSR). Under NSR, if an existing power plant makes "significant" changes to its operations, the entire plant falls under regulations for new plants. TFP may be affected because plants might use suboptimal input mixes in order to avoid NSR. In the conceptual framework, one could interpret λ as measuring the difference between the observed and the optimal input levels.

$$TFP_{i,t} = \sum_{\tau=1939}^{\tau=1999} \alpha_\tau I[t = \tau] + \eta_i + \epsilon_{i,t}. \tag{13}$$

Each observation in this analysis is the natural logarithm of total factor productivity for plant-epoch i in year t, $TFP_{i,t}$. The fixed effects η_i control for all time-invariant determinants of productivity specific to plant-epoch i. The error term $\epsilon_{i,t}$ includes other determinants of productivity. Later on, in subsection 5.2 of the results, we plot the year-by-year coefficients $\alpha_{1939}, \ldots, \alpha_{1999}$ plus the constant. The year-specific points in graphs can be interpreted as mean national patterns of TFP, controlling for plant-epoch time-invariant characteristics.

We also estimate linear TFP trends using the following equation:

$$TFP_{i,t} = \alpha t + \eta_i + \epsilon_{i,t}. \tag{14}$$

The main coefficient of interest, α, represents the mean annual change in productivity, conditional on plant-epoch fixed effects. We also show specifications which interact the trend term t with four indicators related to milestones of the CAAA: $I[t < 1970]$, for the period before the 1970 amendments; $I[1970 \leq t < 1977]$, for the period between the 1970 and 1977 amendments; $I[1977 \leq t < 1990]$, for the period between the 1977 and 1990 amendments; and $I[t \geq 1990]$, for the period after the 1990 amendments. These interactions reveal how TFP trends differ in each period. We emphasize graphs based on equation (13) more than a table based on equation (14) for two reasons: the graphs are more visually transparent, and the nonlinear trends in graphs are crudely approximated with linear trends.[17]

4.4 Impact of Clean Air Act on Productivity: Estimation

We seek to estimate the effect of CAAA nonattainment status on polluting plants' productive efficiencies as embodied in their TFP levels, as described in the conceptual framework. Because a plant's TFP reflects how much output it produces from a given

[17]Although we do not discuss the results from equation (14) in the text, we report the estimates in Table A.2. As we can see in that table, there is a clear break in TFP trends in the period 1977-1990, when the CAAA became more enforceable, relative to the years before 1970, when there were no incentives to reduce emissions.

amount of inputs, our estimates will measure the change in a plant's output due to the nonattainment regulation given a fixed set of inputs. We estimate the following specification:

$$TFP_{i,t} = \sum_{p} \beta_p 1[NonAttain_{p,c,t}] + X_{i,t}\gamma + \eta_i + \theta_{s,t} + \epsilon_{i,t}, \tag{15}$$

where i indexes a plant-epoch, t references a year, p indicates a pollutant, and c and s stand for county and state, respectively.

Again, $TFP_{i,t}$ is the natural logarithm of plant-epoch i's total factor productivity in year t. Importantly, this equation allows for permanent differences in plant-epoch productivity, which are captured with the vector that includes a separate fixed effect for each of the roughly 2,800 plant-epochs in the sample. These plant-specific effects, η_i, may be associated with differences in plant technology type and vintage, ownership (government versus private utilities), and time-invariant state effects. The vector $\theta_{s,t}$ includes state-by-year fixed effects, which control for differential changes in average productivity levels that are common to all plants within a state. They may reflect the efficiency impact of sector-level shifts over time, such as secular technology shocks, macroeconomic fluctuations, or energy price shocks. The matrix $X_{i,t}$ includes other variables that could affect power plants' productivity such as temperature and precipitation.

The indicator functions $I[NonAttain_{p,c,t}]$'s are the core of the regression's explanatory variables. They equal one if the county c in which plant i is located is designated nonattainment for pollutant p in year t. The parameter of interest is the β_p for each pollutant p. They capture the variation in TFP specific to power plants that operate in a county designated nonattainment for a particular pollutant. Because we include the plant-epoch fixed effects, η_i, the β_p for each pollutant p are identified from plant-epochs operating in counties that experience a change in the nonattainment designation for the pollutants they emit.

The estimates are obtained using two approaches. In the first, we pool across the six pollutants (TSP, PM, SO_2, CO, O_3, and NO_2) when defining $I[NonAttain_{c,p,t}]$. In this case, it equals one if the county is in CAAA nonattainment for any one or more of the six pollutants. This specification captures the effect of nonattainment status on TFP and averages it across power plants that face the nonattainment designation for just one or multiple pollutants. The second approach controls separately and simultaneously for each of the "four" pollutants (TSP combined with PM, SO_2, CO, and O_3 combined with NO_2, as explained in the background section), allowing for the estimation of pollutant-specific effects while holding the impacts of others constant. This specification allows for heterogeneity in the impact of the nonattainment designation across pollutants, and is also informative about the impacts on plants of multiple pollutant standards.

A few other estimation details are noteworthy. All versions of Equation (15) are weighted by the power plant's real output. Consequently, the regressions measure average TFP effects on a megawatt-hour-weighted basis, which means that the results can be interpreted as aggregate average effects. Additionally, the tables report standard errors based on clustering at the county level to account for the likely dependence in TFP innovations across plants in the same county, and to allow for arbitrary time-series correlation in TFP shocks within a county.

5 Results

This section describes the empirical results based on our estimates of annual, plant-epoch-level total factor productivity (TFP).[18] As explained before, similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. In the first subsection, we simply describe how the TFP estimates vary over time, with plant characteristics such as vintage (the age of the plant) and primary fuel type, as well as comparing plants in counties in versus out of attainment with the National Ambient Air Quality Standards (NAAQS).

In the second subsection, we document how much of our variation in plant-year level TFP comes from changes in the composition of plant-epochs over time versus within-plant-epoch changes in productivity. We find that the average increase in TFP over the period 1938-1968 comes primarily from the composition of plants (read: newer plants are more efficient than older plants during this sample period). Moreover, the decrease in average TFP associated with being in a county that moves out of compliance with

[18]Although we do not discuss the production function estimates in the text, we report them in Table A.3. In that table, we also compare different specifications with respect to nonfuel materials.

the NAAQS (which corresponds to stricter environmental regulations) is substantially smaller if we focus only on within-plant-epoch changes in productivity.

In the third subsection, we focus on robustness checks, demonstrating that our estimates of TFP are not significantly different if we: (1) include a measure for nonfuel material inputs rather than exclude this measure (our preferred specification), (2) instead consider a "semi-balanced" subsample of plants that we observe in our data for at least 15 years, or (3) focus only on power plants that primarily burn coal rather than all fossil fuel fired plants.

In the last subsection, we report how plants' TFP changes with the more stringent environmental regulation associated with non-compliance with the NAAQS. For example, we find a reduction in average TFP of 8.4 percent for plants located in counties that move out of attainment with the NAAQS for any pollutant. The annual average fuel costs of plants in our sample from 1980-1999 is 11 billion dollars (in 2010 USD); thus, a lower bound on the annual average costs from decreases in productivity due to non-attainment with the NAAQS is roughly 924 million dollars (in 2010 USD).[19] As two points of comparison, EPA (1997) estimates that the overall annual average direct benefit of the 1970 CAAA from 1970-1990 is 1.85 trillion dollars (in 2010 USD) and the overall annual average direct implementation cost is 43.63 billion dollars (in 2010 USD). Although our average cost estimate of 924 million dollars clearly does not move the benefit-cost ratio of the CAAA below one, our effect is sizable given that the annual average productivity loss from one sector (electricity generation) is approximately 2 percent of the overall costs of implementing the CAAA estimated by EPA. Finally, we find that the magnitude of the decrease in average plant-level productivity due to non-attainment with the NAAQS does not diminish with the cumulative number of years the plant's county has been out of attainment. This suggests that U.S. fossil fuel fired power plants were unable to cost-effectively adapt to the stricter CAAA regulations even in the long-run.

5.1 Descriptive Trends in TFP

We first simply plot the annual electricity-generation-weighted average over plant-epochs in our sample of the (log of) total factor productivity (TFP) in Figure 1. The vertical

[19] These annual average cost in terms of productivity loss due to non-attainment with the NAAQS is simply $\$924,065,436 = \$11,000,779,000 \times 0.084$.

green lines correspond to the years 1970, 1977, and 1990: the first set of amendments to the Clean Air Act were passed in 1970 (but implemented by EPA beginning in 1972), the second set of amendments were enacted in 1977, and the final set of amendments to the Clean Air Act were passed in 1990.

We see from Figure 1 that average TFP is steadily increasing from 1938 to roughly 1968, leveling off (perhaps declining for a number of years) until approximately 1990 before increasing slightly again until the end of our sample period in 1999. This is consistent with the trends in the productivity of coal-fired electricity generation plants described in Gollop and Roberts (1983), Nelson and Wohar (1983), Joskow (1987), and Joskow and Schmalensee (1987).[20] Moreover, our estimates of productivity for all fossil fuel fired power plants have a correlation of 0.88 with the productivity calculated by Nelson and Wohar (1983), which uses an index-number approach to estimate the TFP of coal-fired power plants owned by fifty privately owned utilities for the period 1949-1978.[21] Combined, this provides evidence that our TFP estimates are not simply an artifact of our empirical methodology, but rather capture trends in the productivity of U.S. power plants over time.

[Figure 1 about here.]

Figure 2 plots annual electricity-generation-weighted average log TFP separately for plants built in 1938-1959 versus 1960-1979 versus 1980-1999. We see from this figure that plants built in 1938-1959 have a lower average TFP relative to plants built in the later sample periods. This trend in TFP is consistent with the literature (e.g., Gollop and Roberts (1983), Nelson and Wohar (1983), and Joskow (1987)), which documents efficiency gains over time for coal-fired power plants built from the 1930s on to roughly the 1960s with no substantial changes in the production technology for plants built from

[20]Though not the central focus of this paper, one explanation for the increase in average annual plant TFP after 1990 might be changes in the economic regulation facing these plants. A number of U.S. states decided to shift the provision of electricity generation from output price regulation, where a regulator sets the electricity price charged by plants based on their costs to electricity market mechanisms beginning in 1998 (so-called electricity "restructuring"). The framework for this restructuring was set forth by the Energy Policy Act of 1992 (EPACT). Even before EPACT, many states implemented so-called "incentive regulations" that rewarded or punished plants with higher or lower electricity prices based on their performance. Berg and Jeong (1991) and Knittel (2002) shows that incentive programs tied directly to a plant's performance or fuel costs increase their productive efficiency.

[21]See Table A.4 for this and other correlations between alternative measures of TFP estimated from our data.

the 1960s on. This is again reassuring evidence that our measure of TFP is actually capturing plant-level productivity over time in the electricity generation industry.

[Figure 2 about here.]

Figure 3 plots the (log of) generation-weighted TFP averaged over plants for each year-of-sample, separately for plants in counties that have ever been out of attainment with the National Ambient Air Quality Standards (NAAQS) for any pollutant ("Non-Attainment" counties) versus plants in counties that have consistently been in attainment with the NAAQS for all pollutants ("Attainment" counties). Counties out of attainment with the NAAQS face more stringent environmental regulations relative to counties in attainment with the NAAQS. We see from this figure that, prior to the passage of the Clean Air Act Amendments (CAAA) of 1970, the trends in average TFP for plants in attainment versus non-attainment counties are quite similar; this similarity in trends continues up through the implementation of these 1970 CAAA. However, we see that average TFP for plants in attainment counties is consistently higher than average TFP for plants in non-attainment counties after roughly 1981. This difference in average TFP does not become more or less pronounced after the passage of the second set of Clean Air Act Amendments in 1990. Section 5.4 more formally tests how annual plant-level total factor productivity is affected by the NAAQS using a difference-in-differences framework. The similarity in the trends of average TFP for plants located in counties in versus out of attainment with the NAAQS prior to 1970 provides suggestive evidence that our difference-in-differences framework causally identifies the effect of the NAAQS on TFP rather than some unobserved factor that affects both NAAQS compliance status and plant TFP.

[Figure 3 about here.]

5.2 Within versus Across Plant Variation in TFP

Figure 4 plots the annual average of the following variable: plant-epoch-year level total factor productivity (TFP) minus plant-epoch-level average TFP. Similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. The most striking difference between Figures 1 and 4 is that, while annual average TFP is increasing rapidly from 1938 to roughly 1968, there is no such increasing trend in the within-plant residual annual average TFP displayed in Figure 4. From these two figures, it is clear that the increase in average annual TFP from 1938-1968 was driven primarily by the composition of plants: as indicated by Figure 2, newer plants built were simply more productive than older plants.

[Figure 4 about here.]

[Figure 5 about here.]

We are also interested in whether the negative impact of non-attainment with the NAAQS (which corresponds to stricter environmental regulations) on the TFP of plants located in that county is driven primarily by the composition of plants (read: firms are less likely to build new plants or increase capacity at existing plant sites in non-attainment counties) versus within-plant productivity losses (read: existing plants having to comply with stricter environmental regulations become less productive); this decomposition is similar in spirit to Keiser and Shapiro (2017), which studies the consequences of the Clean Water Act. The difference in average TFP after 1970 (especially after 1977, when NAAQS enforceability increased) between plants in attainment and non-attainment counties is much less pronounced in Figure 5, which plots average annual TFP minus plant-epoch average TFP separately for plants located in attainment versus non-attainment counties, relative to Figure 3. This suggests that the composition of plants in attainment versus non-attainment counties shifted significantly in response to the implementation of the NAAQS; firms might have been reluctant to build new plants or increase capacity at existing plant sites in counties that are out of compliance with the NAAQS. Importantly for our difference-in-differences analysis presented below, we see no difference in trends in average TFP net of plant-epoch-level average TFP prior to 1970; any changes in plant TFP after 1970 seem to be occurring due to changes in environmental regulation rather than systematic unobserved differences between attainment and non-attainment counties.

5.3 Robustness Checks/Sensitivity Analyses

This subsection presents evidence that our empirical findings are robust to: (1) including versus excluding nonfuel materials from the production function used to estimate plant-year level TFP, (2) considering a "semi-balanced" panel of plants that we observe in our data for at least 15 years, and (3) considering only coal-fired power plants rather than all fossil fuel fired plants. We do this quite simply by documenting in Figure 6 that the trends in annual average TFP estimated using these different specifications and/or sub-samples are quite similar.[22]

[Figure 6 about here.]

With respect to our first sensitivity analysis, it is important to emphasize that the main results reported in the paper are estimated based on a production function that does not include nonfuel material expenses as an input.[23] This is primarily due to the fact that our measure of nonfuel, nonlabor expenses is only available for the period that we digitized power plant data: 1938-1981. For this period, we check the robustness of our preferred specification by comparing it with TFP estimated using a specification including: (1) nonfuel expenses, and (2) nonfuel, nonlabor expenses. As we can see in Figure A.1, the trends over time for each of these three measures of TFP are quite similar.

Again, our preferred specification does not include nonfuel materials because most datasets, including the one we use for the years 1982-1999, report only an aggregate measure of nonfuel expenses. This measure includes all nonfuel operations and maintenance expenses, such as those for coolants, repairs, maintenance supervision, and engineering. As Fabrizio, Rose and Wolfram (2007) point out, nonfuel expenses is a less than ideal measure of nonfuel materials, both because it reflects expenditures rather than quantities, and because it includes the labor expenses. Given that most of the components of the measure of nonfuel expenses are somewhat associated with reallocation of capital, labor, and fuel away from the generation of the main output, as explained in subsection

[22] Our findings relating these different measures of a plant's TFP to the NAAQS compliance status of the county where this plant is located are also qualitatively similar, and are available upon request.

[23] Again, many different papers have estimated production functions in the U.S. electricity generation context using specifications based only on capital, labor, and fuel, including Barzel (1963), Nerlove (1963), Atkinson and Halvorsen (1976), Christensen and Greene (1976), Gollop and Roberts (1983), Nelson and Wohar (1983), Gollop and Roberts (1985), and Carlson et al. (2000).

4.2, changes in those components may reflect changes in TFP. That is the reason why our preferred specification does not include nonfuel materials expenses.

5.4 Regression Results: TFP and NAAQS Compliance Status

Table 1 presents our difference-in-differences regression results relating a plant-epoch's log of total factor productivity (TFP) in a given year to the NAAQS compliance status of the county in that year. We run the specification described in equation (15), which follows Greenstone, List and Syverson (2012). In particular, the unit of observation for these regressions is a plant-epoch-year, and we cluster standard errors at the county level. Again, similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. We consider county-level attainment in each year associated with the standards for different pollutants. Columns 1 and 3 consider an indicator that is one if the county is in compliance with the standards associated with any of the six pollutants: total suspended particles (TSP), particulate matter (PM), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2). Columns 2 and 4 include separate indicators for county-level compliance for each of "four" different pollutants: TSP combined with PM, SO_2, CO, and O_3 combined with NO_2. Depending on the specification, we include plant-type (coal, oil or gas) by year fixed effects, state-by-year fixed effects, and an indicator for older versus newer plants or plant-epoch fixed effects. As described previously, Figures 3 and 5 provide supporting evidence that there is no difference in trends prior to the passage of the 1970 Clean Air Act Amendments (CAAA) in the average TFP for plants located in counties in versus out of attainment.

[Table 1 about here.]

Focusing on the first two columns of Table 1, which do not include plant-epoch fixed effects, we find within our difference-in-differences framework that, on average, a plant's total factor productivity (TFP) decreases substantially when the county where the plant is located moves from being in compliance with the NAAQS to out of compliance with the NAAQS. For example, the results from Column 1 of this table indicate that a county moving out of compliance with the NAAQS for any pollutant reduces the average TFP of plants located in this county by roughly 21 percent if we include plant-fuel-type-by-year fixed effects, state-by-year fixed effects, and vintage fixed effects. Splitting out by the standards associated with different pollutants in Column 2, we find the strongest estimated impacts for the NAAQS associated with fine particulates (TSP/PM). This is to be expected because: (1) coal-fired power plants emit large quantities of these fine particulates any time coal is burned (e.g., Levy, Baxter and Schwartz (2009), Muller (2014), Clay, Lewis and Severnini (2016)), and (2) due to the relatively short smokestacks prevalent during our historical sample period, the emissions of fine particulates from coal-fired power plants were especially local (Clay, Lewis and Severnini, 2016), making compliance with the NAAQS associated with fine particulates especially difficult.

However, the effect of the NAAQS on TFP is substantially smaller when focusing on the last two columns of Table 1 which include plant-epoch level fixed effects. For instance, the estimate from Column 3 of Table 1 indicates that moving out of compliance with the NAAQS for any pollutant is associated with an 8.4 percent decrease in plants' average total factor productivity. Our findings are almost twice as large as those found in Greenstone, List and Syverson (2012), which considers all U.S. manufacturing plants over the period 1972-1993. This is to be expected because, differently from GLS, our estimate is relative to a baseline of no regulation: we have over 40 years of data before the enforcement of the 1970 CAAA. Additionally, fossil-fuel power plants are large emitters of global and local pollutants even relative to other large, stationary point sources such as manufacturing plants. As with the specification excluding plant-epoch fixed effects, Column 4 indicates that most of our estimated effect of the stricter environmental regulations on TFP comes from nonattainment status associated with the NAAQS for fine particulates.

Based on the results from Table 1, we calculate the annual average plant-level costs of the productivity decreases associated with moving out of compliance with the NAAQS put forth by the Clean Air Act. We do this quite simply by multiplying the plant's annual total fuel expenditures (in dollars) by our estimated effect on TFP of NAAQS noncompliance. The intuition behind this simple calculation is that the plant's average total fuel cost per MWh of electricity generated must be 8.4 percent more when the county where the plant is located moves out of compliance (recall the Leontief production function expressed in equation (1)). Of course, this is a lower bound on the true costs of complying with the more stringent environmental regulations associated with NAAQS noncompliance because we are only considering fuel costs rather than all costs and we are not allowing plants to re-optimize their inputs based on being more versus less productive. Given that the annual average fuel costs of plants in our sample from 1980-1999 is 11 billion dollars (in 2010 USD), a lower bound on the annual average costs from decreases in productivity due to non-attainment with the NAAQS is roughly 924 million dollars (in 2010 USD).[24]

[Table 2 about here.]

Table 2 reports the estimated impacts of nonattainment with the NAAQS associated with any pollutant on plant-epoch TFP separately for whether the cumulative number of years that the county where the plant is located is in nonattainment for less than 10 years, between 11 and 20 years, and greater than 20 years. We see for all of the columns of this table that the negative impact of being out of compliance with the NAAQS for any pollutant on a plant's TFP does not diminish as the county where the plant is located accumulates more years of nonattainment. If anything, the magnitude of the coefficient estimates capturing the negative impact of the NAAQS on TFP increases with the number of years that the county is out of attainment. This provides evidence that the effect of more stringent environmental regulations associated with nonattainment with the NAAQS is persistent; our results suggest that both new and existing fossil fuel fired power plants were unable to cost-effectively adapt, even over a long time horizon, to the CAAA regulations.

6 Conclusion

This study has examined the impact of the passage and implementation of the Clean Air Act of 1963, and its Amendments of 1970, 1977, and 1990, on total factor productivity in the U.S. electricity sector. It has leveraged newly digitized, detailed annual data on steam-electric power plants since 1938 to measure TFP using the latest advances

[24]These annual average cost in terms of productivity loss due to nonattainment with the NAAQS is simply $\$11,000,779,000 \times 0.084 = \$924,065,436$.

in production function estimation. There were three main findings. First, and more descriptively, the average TFP of electric utilities grew from the late 1930s until the late 1960s, then stagnated or even decreased up to the early 1990s, then started increasing again. This pattern is consistent with the technological improvements in steam turbines in the early period, environmental regulations in the middle period, and restructuring in the later period.

Second, power plants in nonattainment counties had similar annual TFP levels than plants in attainment counties until the early 1970s, suggesting no differential pre-trends in TFP for those two types of counties before the passage of the 1970 CAAA. Since the parallel trends assumption seemed to hold in this context, we estimated the causal effect of the CAAA nonattainment county designations on power plants' TFP, and found it to be negative, economically sizable, and statistically significant. Using annual, within-plant-epoch TFP variation for over 60 years, we found out that TFP drops 8.4 percent, on average, when a county is out of attainment for one year in at least one criteria pollutant. This means that regulated plants' output declined by 8.4 percent after holding constant their inputs (i.e., labor, capital, and fuels). This estimated TFP decline highlights a drawback of command-and-control regulations, and should be taken into account in the cost-benefit analysis of the National Ambient Air Quality Standards (NAAQS).

Third, our results indicated that the negative impact of nonattainment with the NAAQS on a plant's TFP in a given year does *not* diminish with the cumulative number of years up to that point that the plant's county was out of attainment. Our estimated effect of nonattainment on TFP was similar in magnitude even for plants located in counties that have been in nonattainment for more than 20 years. This suggests that plants facing stricter environmental regulations were unable to cost-effectively "catch up" to the productivity levels of other plants even after 20 years of facing this stricter regulation. This runs counter to the intuition that firms and technology will inevitably adapt to existing economic and environmental regulations.

There may be other costs of the CAAA regulations that were not explored here. By definition, the impact of CAA regulations on power plant TFP keeps constant the inputs for electricity generation. Notwithstanding, there is some evidence in other contexts that those regulations might induce changes in the levels of inputs per se (e.g., Atkinson and Halvorsen (1976), Greenstone (2002), Gray et al. (2014), Walker (2013)). Moreover, some authors have pointed out that production may shift in time and space in response to environmental regulations (e.g., Henderson (1996), Brunnermeier and Levinson (2004), Kahn and Mansur (2013), Gibson (2017)). These important questions are under investigation, but left for future studies.

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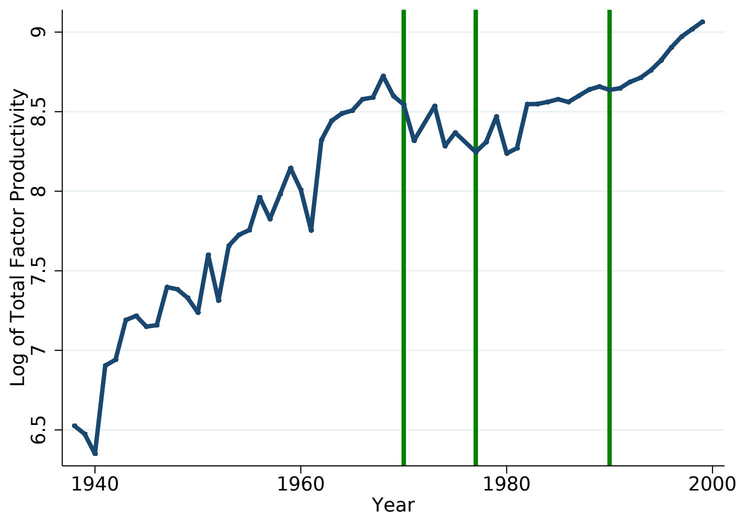
List of Figures

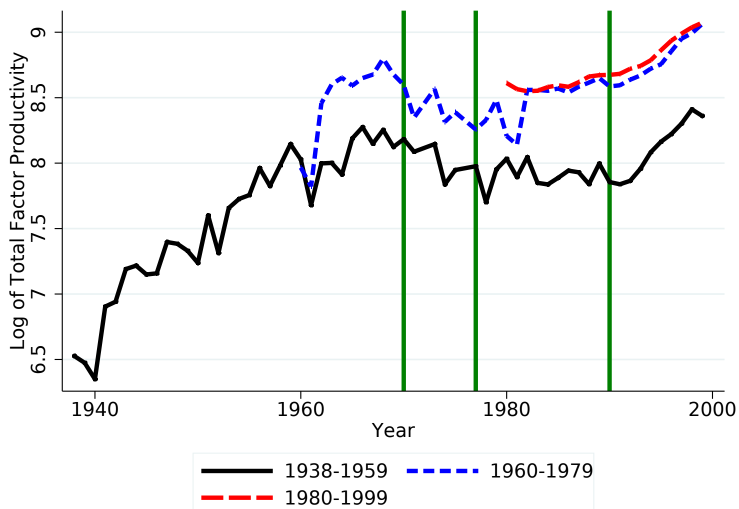
List of Tables

Figure 1: Annual Average Total Factor Productivity – 1938–1999



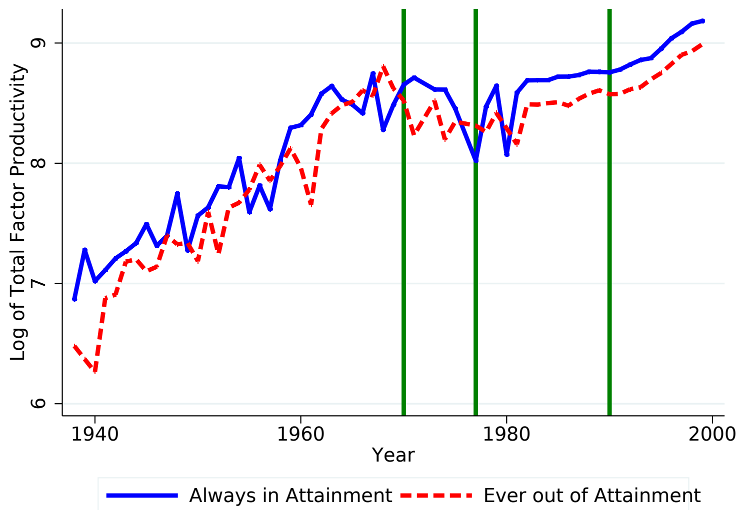
Notes: This figure plots electricity-generation-weighted total factor productivity (TFP) averaged over plants for each year-of-sample. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Subsection 4.1.

Figure 2: Annual Average TFP By Plant Vintage



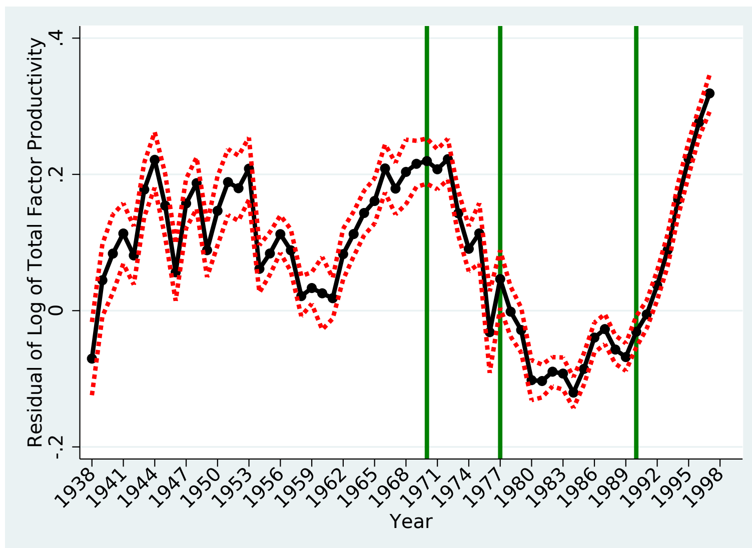
Notes: This figure plots electricity-generation-weighted total factor productivity (TFP) averaged over plants for each year-of-sample, separately for plants commissioned in 1938-1959 versus 1960-1979 versus 1980-1999. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Figure 3: Annual Average TFP By Attainment Status



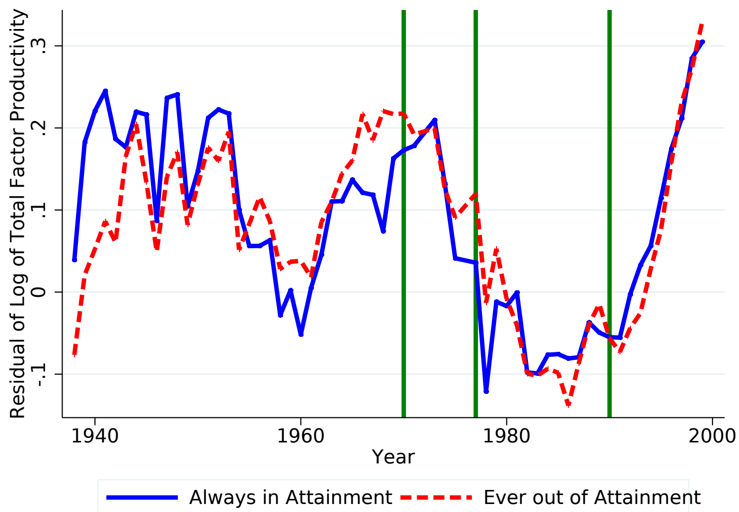
Notes: This figure plots the total factor productivity (TFP) averaged over plants for each year-of-sample, separately for plants in counties that were ever out of attainment with the National Ambient Air Quality Standards (NAAQS) for any pollutant standard during our sample period versus plants in counties that were always in attainment with the National Ambient Air Quality Standards (NAAQS) for all pollutant standards during our sample period. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Figure 4: Annual Residual Average TFP: Within-Plant-Epoch Variation



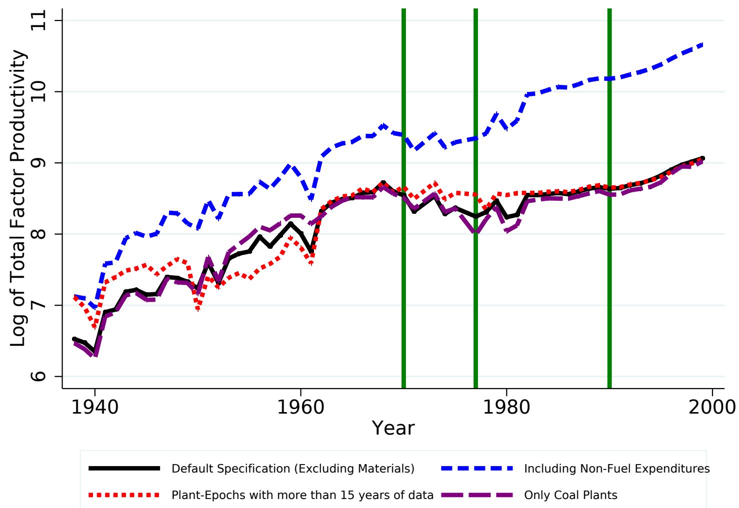
Notes: This figure plots annual average of total factor productivity (TFP) minus plant-epoch level average TFP; similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Figure 5: Annual Residual Average TFP: Within-Plant-Epoch Variation By Attainment Status



Notes: This figure plots annual average of total factor productivity (TFP) minus plant-epoch level average TFP, separately for plants in counties that were ever out of attainment with the National Ambient Air Quality Standards (NAAQS) for any pollutant standard during our sample period versus plants in counties that were always in attainment with the National Ambient Air Quality Standards (NAAQS) for all pollutant standards during our sample period. Similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Figure 6: Annual Average TFP Based on Different Specifications



Notes: This figure plots the annual, generation-weighted average total factor productivity (TFP) over plants, separately for four different specifications used to estimate this TFP. The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970, 1977, and 1990. Our default specification estimates plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1. We estimate two other measures of TFP using the same specification, but based on the sub-sample of plants that: (1) we observe for at least 15 years in our data, and (2) primarily burn coal (rather than all fossil-fuel fired plants). Finally, we construct a plant-year measure of TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), *non-fuel expenditures* (read: nonfuel operations and maintenance expenses, such as those for coolants, repairs, maintenance supervision, and engineering), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Table 1: Difference-in-Differences: Impact of NAAQS Compliance Status on TFP

NAAQS	(1)	(2)	(3)	(4)
Any Pollutant	-0.205***		-0.0838***	
	(0.0546)		(0.0245)	
TSP or PM		-0.221***		-0.0616**
		(0.0542)		(0.0274)
SO_2		0.00856		-0.0190
		(0.0754)		(0.0379)
CO		-0.0780		-0.0301
		(0.0812)		(0.0350)
O_3 or NO_2		-0.0291		-0.0248
		(0.0543)		(0.0267)
Fuel-Type x Year FE	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	No	No
Plant-Epoch FE	No	No	Yes	Yes
N	25,129	25,129	24,675	24,675
R^2	0.369	0.386	0.861	0.861

Notes: This table presents our regression results measuring how each plant-epoch's log of total factor productivity (TFP) in a given year-of-sample changes when the county this plant is located in moves in and out of compliance with the National Ambient Air Quality Standards (NAAQS) associated with different pollutants. We run the specification described in equation (15). We consider county-level attainment in each year associated with the standards for different pollutants. Columns 1 and 3 consider an indicator that is one if the county is in compliance with the standards associated with any of the six pollutants: total suspended particles (TSP), particulate matter (PM), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2). Columns 2 and 4 include separate indicators for county-level compliance for each of "four" different pollutants: TSP combined with PM, SO_2, CO, and O_3 combined with NO_2. Depending on the specification, we include plant-type (coal, oil or gas) by year fixed effects, state-by-year fixed effects, and an indicator for older versus newer plants or plant-epoch fixed effects. Similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. Lastly, the unit of observation for these regressions is a plant-epoch-year, and we cluster standard errors at the county level. *** represents statistically significant at the 1% level, ** statistically significant at the 5% level, and * statistically significant at the 10% level.

Table 2: Difference-in-Differences: Dynamic Impact of NAAQS Noncompliance on TFP

NAAQS for Any Pollutant	(1)	(2)
1(Cumulative Number of Nonattainment Years ≤ 10)	-0.180***	-0.108***
	(0.0584)	(0.0351)
1(Cumulative Number of Nonattainment Years $\in [11, 20]$)	-0.249***	-0.111**
	(0.0725)	(0.0451)
1(Cumulative Number of Nonattainment Years > 20)	-0.550***	-0.157***
	(0.0998)	(0.0527)
Fuel-Type x Year FE	Yes	Yes
State-by-Year FE	Yes	Yes
Vintage FE	Yes	No
Plant-Epoch FE	No	Yes
N	25,129	24,675
R^2	0.378	0.861

Notes: This table reports our estimates measuring how each plant-epoch's log of total factor productivity (TFP) in a given year-of-sample changes when the county this plant is located in moves from in to out of compliance with the National Ambient Air Quality Standards (NAAQS) associated with different pollutants, and remains in non-attainment for a number of years. We adapt the specification described in Equation (15) to estimate separate effects on TFP for plant-epoch-years where the cumulative number of years that the county where the plant is located is in non-attainment is less than 10 years, between 11 and 20 years, and greater than 20 years; we consider non-attainment with the the standards associated with any of the six pollutants: total suspended particles (TSP), particulate matter (PM), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2). Depending on the specification, we include plant-type (coal, oil or gas) by year fixed effects, state-by-year fixed effects, and an indicator for older versus newer plants or plant-epoch fixed effects. Similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. Lastly, the unit of observation for these regressions is a plant-epoch-year, and we cluster standard errors at the county level. *** represents statistically significant at the 1% level, ** statistically significant at the 5% level, and * statistically significant at the 10% level.

List of Appendix Tables

List of Appendix Figures

Table A.1: Summary Statistics: TFP, Production Function, and NAAQS

Variable	Obs.	Mean	Std. Dev.
log(TFP)	25,404	8.68	0.57
Electricity Output (MWh)	27,013	5,919.23	4,595.29
Capacity (MW)	27,013	1,174.77	815.07
Average Number of Employees	25,404	235.50	181.11
Billion of BTUs of Fuel	27,013	18,995.35	54,371.21
1(Out of Attainment with any NAAQS)	27,013	0.353	0.478
1(Out of Attainment with NAAQS: TSP or PM)	27,013	0.184	0.387
1(Out of Attainment with NAAQS: SO_2)	27,013	0.073	0.260
1(Out of Attainment with NAAQS: CO)	27,013	0.091	0.288
1(Out of Attainment with NAAQS: O_3 or NO_2)	27,013	0.261	0.439

Notes: This table presents summary statistics for our difference-in-differences regressions relating NAAQS attainment status and plant-year level TFP (see Table 1 and Table 2). We estimate plant-year level TFP based on a translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.

Table A.2: TFP Trends, 1938–1999

Panel A. Linear Time Trend		
$(Year - 1937)$	-0.014***	
	(0.001)	
Panel B. Time Trends by Period		
(1): $(Year - 1937)\times$ 1[Year<1970]		-0.012***
		(0.002)
(2): $(Year - 1937)\times$ 1[Year>= 1970 & Year<1977]		-0.012***
		(0.002)
(3): $(Year - 1937)\times$ 1[Year>= 1977 & Year<1990]		-0.019***
		(0.001)
(4): $(Year - 1937)\times$ 1[Year>=1990]		-0.014***
		(0.001)
P-value (2) = (1)		0.801
P-value (3) = (1)		0.000
P-value (4) = (1)		0.103
Plant-Epoch FE	Yes	Yes
N	24,968	24,968
R^2	0.773	0.788

Notes: This table presents linear trends of TFP obtained by equation (14), which removes plant-epoch FEs. Column 1 reports results from that exact specification, and column 2 from a variation of that equation where linear time trends are interacted with periods of time related to Clean Air Act Amendments (CAAA) milestones – 1970, 1977, and 1990. Standard errors are clustered at the county level. *** represents statistically significant at the 1% level, ** statistically significant at the 5% level, and * statistically significant at the 10% level.

A Additional Tables and Figures

Table A.3: Production Function Estimates for Different Time Periods, With and Without Materials

	1938 - 1999		**1938 - 1981**		
	(1)	(2)	(3)	(4)	(5)
(L): ln(average employees)	0.838***	0.879***	0.895***	0.751***	0.860***
	(0.002)	(0.014)	(0.002)	(0.002)	(0.013)
(K): ln(capacity)	0.326***	0.650***	0.568***	0.388***	0.404***
	(0.006)	(0.010)	(0.004)	(0.006)	(0.023)
(M1): ln(nonfuel expenses)		-0.379***			0.100***
		(0.007)			(0.016)
(M2): ln(material expenses)				0.188***	
				(0.009)	
L*L	-0.118***	-0.125***	-0.102***	-0.115***	-0.106***
	(0.005)	(0.007)	(0.001)	(0.003)	(0.011)
K*K	-0.00572**	-0.0854***	-0.00973**	-0.0301***	-0.00528
	(0.003)	(0.017)	(0.004)	(0.008)	(0.029)
L*K	0.136***	0.140***	0.0837***	0.118***	0.119***
	(0.002)	(0.007)	(0.000)	(0.007)	(0.023)
M*M		0.0259***		-0.0372***	-0.00634
		(0.005)		(0.003)	(0.019)
M*L		0.0332***		0.0159***	-0.0119
		(0.005)		(0.003)	(0.018)
M*K		0.0464***		0.134***	0.0871***
		(0.008)		(0.007)	(0.010)
N	25028	24990	15607	15109	15569
Post-Estimation Elasticities					
ln(average employees)	0.536	0.677	0.440	0.439	0.434
ln(capacity)	0.257	0.185	0.456	0.042	0.344
ln(nonfuel expenses)		0.202			0.491
ln(material expenses)				0.409	

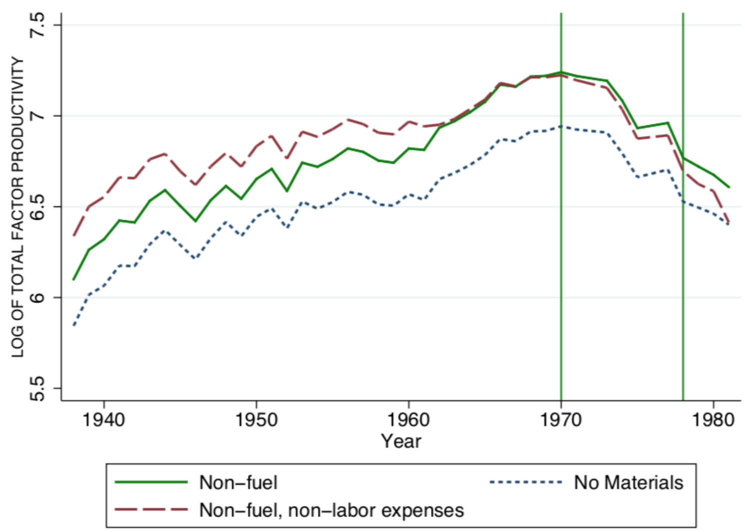
Notes: This table reports the estimated parameters of the translog production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1. Columns 1 and 3 present the estimates from that exact specification, columns 2 and 5 the estimates from the specification including nonfuel materials expenses, and column 4 the estimates from the specification including nonfuel, nonlabor materials expenses. Notice that columns 1 and 2 are estimated for our entire sample period (1938-1999), and columns 3 through 5 for the period that we digitized power plant data (1938-1981). Our preferred specification, which is the basis for the TFP measures used throughout the paper, is presented in column 1. In the bottom panel of the table, elasticities regarding each input are reported. Lastly, the unit of observation for all these analyses is a plant-epoch-year. Similar to Fabrizio, Rose and Wolfram (2007), we define an "epoch" for each plant based on periods of time during which there were no substantial changes in the plant's electricity generating capacity. *** represents statistically significant at the 1% level, ** statistically significant at the 5% level, and * statistically significant at the 10% level.

Table A.4: Correlation Between TFP Estimates from Different Specifications

	Nelson and Wohar (1983)	Translog	Cobb-Doug	Lev-Pet
Nelson and Wohar (1983)	1			
Translog (Our Preferred Specification)	0.877	1		
Cobb-Doug	-0.420	-0.0330	1	
Lev-Pet	-0.452	-0.111	0.948	1

Notes: All TFP estimates are from specifications without nonfuel materials, i.e., we estimate plant-year level TFP based on a production function with capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned). The translog production function is our preferred specification, but we compare our estimates with those from a Cobb-Douglas. Also, we estimate our preferred specification using methodology developed by Ackerberg, Caves and Frazer (2015) (read: estimation procedure described in Section 4.1), but we also compare our results with those obtained by the methodology developed by Levinsohn and Petrin (2003). Nelson and Wohar (1983) correlation is only for years 1949–1978, which is their sample period.

Figure A.1: TFP Comparison Using Different Materials (1938–1981)



Notes: This figure plots electricity-generation-weighted total factor productivity (TFP) averaged over plants for each year-of-sample over 1938–1981, separately for a specification without nonfuel materials ("No Materials"), with nonfuel expenses ("Non-fuel", which is the data also available in Fabrizio, Rose and Wolfram (2007)), and with nonfuel, nonlabor expenses ("Non-fuel, non-labor expenses", which is available only on the data we digitized). The vertical green lines correspond to the years when the Clean Air Act Amendments were enacted: 1970 and 1977. We estimate plant-year level TFP for all those specifications based on a translog production function that also includes capital (read: the plant's capacity), labor (read: average number of employees), and fuel (read: the heat input in mmBTUs from the fuel burned) using the estimation procedure described in Section 4.1.