Clearing the air:
essays on the economics of air pollution

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ABSTRACT

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Exposure to air pollution is a leading cause of premature death worldwide. An increasing part of air pollution results from industrial activity and the production of energy. When unregulated, emissions of air pollutants constitute a market failure as polluters do not bear the costs imposed on society at large. My dissertation develops empirical methods to test the effectiveness and distributional effects of environmental policies designed to address this externality. To do so, I apply econometrics and data science techniques on large datasets from cutting-edge research in environmental science and engineering that I match with microeconomic data. The dissertation makes use of new datasets on air pollution derived from satellite imagery, as well as micro-level data on power plant operations and housing transactions across the United States.

Chapter 1 assembles unit-level data to disentangle the factors that led US power plants to achieve the unprecedented reductions in emissions of the past fifteen years. I calculate the costs incurred by the electricity generation sector and compare these costs to the corresponding health benefits. In hedonic regressions, I use these shocks to emissions to estimate the demand for clean air with micro-level data on housing transactions. Chapter 2 studies the causal impacts and evaluates the distributional effects of stringent emissions markets that were put in place to target power plants emissions of air pollutants in the Eastern US. Chapter 3 uses new satellite imagery to document the inequalities in the exposure to air pollution in American cities and their recent evolutions.

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To Anissa and Noureddine.

Chapter 1

Clearing the Air

The Role of Technology Adoption in the Electricity Generation Sector[1]

Abstract Between 2005 and 2014, the US electricity sector reduced its emissions of local air pollutants by more than half, while maintaining historical levels of electricity generation. This paper seeks to quantitatively uncover the factors that drove these unprecedented decreases in emissions, and to compare the costs incurred by the industry to benefits accrued to health. To that end, I assemble a comprehensive unit-level dataset on power plant operations and costs. In a statistical decomposition of emission reductions at the power plant level, I find that the adoption of capital-intensive abatement technologies accounted for 60% of the achieved reductions, and represented a cumulative investment of $45 billion for power plants. Switching to cleaner fuel and retiring dirty units also each contributed approximately 20%

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of the observed reductions. These emission reductions generated significant health benefits. Using measures of air pollution derived from satellite imagery and estimates from the health economics literature suggests that 19,000 premature infant deaths were avoided during the period considered thanks to the achieved emission reductions. Finally, I use these shocks to emissions to estimate the local demand for clean air. In hedonic regressions that make use of transaction-level information on house prices, I find that the emission reductions caused housing prices to increase close to power plants, thereby appreciating house values by $8 billion.

1.1 Introduction

Air pollution has severe impacts on human health (Schlenker and Walker, 2015; Currie and Walker, 2011; Chay and Greenstone, 2003). In recent years, toxic air has become the primary cause of premature mortality at the global scale, surpassing infectious diseases and tobacco consumption (World Health Organization, 2016).[2] At present, 91% of the global population is exposed to unhealthy levels of air pollution, leading to 4.2 million premature deaths around the world annually. Sulfur dioxide (SO_2) and nitrogen oxides (NO_x) are of particular interest because they affect health both directly and indirectly through the formation of other toxic air pollutants (particulate matter and ground-level ozone). In the 2000s, power plants emitted as much as three-quarters of all SO_2 and one-quarter of all NO_x. When unregulated, emissions from the electricity generation sector constitute a critical market failure, because they cause damages to society that are not accounted for in the costs that power plants face. These emissions are on the rise worldwide, generating dangerous levels of air toxicity.

The United States is one exception to this trend. Between 2005 and 2014, the US electricity generation sector reduced SO_2 emissions by nearly 80%, and NO_x emissions by 60%.

[2] In a recent interview, the director general of the World Health Organization declared that "*The world has turned the corner on tobacco. Now it must do the same for the 'new tobacco'—the toxic air that billions breathe every day. (...) It is a silent public health emergency.*"

These reductions helped achieve an unprecedented abatement of air pollution, particularly in the country's populous eastern states, which had theretofore suffered from elevated levels of air pollution. Understanding the factors that contributed to these reductions is fundamental for reaching international clean air goals, such as the UNs Sustainable Development goal of reducing the number of global deaths from air pollution by two-thirds by 2030.[3]

This paper provides the first quantification of the abatement channels employed at the power plant level to achieve the record reductions in emissions mentioned above. The study also provides the first calculation of the costs incurred by power plants to abate emissions and weighs them against their direct public health benefits and the benefits accrued to housing values.[4] The analysis presented herein assembles and leverages a comprehensive dataset on power plant operations and costs, containing monthly information on unit-level electricity production, fuel input quantities and costs, abatement technology adoption[5] and associated investments, and utility revenues. This unique dataset is augmented with data on air pollutants emissions that are precisely and continuously measured at each fossil fuel power plant throughout the US. Additionally, this research leverages satellite imagery of air pollution and a proprietary micro-level dataset on housing transactions to estimate the benefits for human health and local housing markets. Using these datasets, this paper makes four main contributions. First, this paper quantifies the impacts of the adoption of stringent cap-and-trade markets designed to curb emissions from power plants. Second, the analysis presented herein quantitatively uncovers the mechanisms employed at the power plant level to achieve these emission reductions: this is accomplished in a bottom-up approach that makes use of the observation of abatement technology adoption at the unit level, which also enables the con-

[3]This is the target of the United Nations' Sustainable Development Goal 11.

[4]Benefits could include other impacts on the environment, such as improvements in visibility and reductions in acid rain. Thus, health and housing impacts correspond to an important but lower-bound estimate of the total benefits achieved.

[5]These technologies can be installed to filter local pollutants from gases produced by the combustion of fossil fuels.

struction of the first estimates of the associated costs incurred by power plants. Third, this study provides the first *ex post* quantitative calculation of the impacts of the emission reductions during this period on human health. To that end, a set of novel air pollution datasets derived from three satellite imagery products, which offer spatially continuous coverage of the population's exposure to air pollution at a monthly frequency is compiled: this paper is the first in the literature to use and validate these satellite imagery products. By pairing these measures with commonly used estimates of the health impacts of air pollution, this research performs a fine-resolution calculation of the health benefits resulting from air quality improvements. Fourth, this paper leverages a proprietary dataset containing information on all US housing transactions to estimate the impacts of power plant emission reductions on local housing markets, thereby providing a lower-bound estimate of the demand for clean air.

Multiple factors may have contributed to the aforementioned reductions in power plant emissions. During the period from 2005 to 2014, the electricity generation sector was exposed to three major shocks, namely, (1) to input markets, (2) to the demand for electricity and (3) through the enactment of ambitious environmental regulations. First, the fossil fuel markets were disrupted by the extraction of shale gas, which led to a rapid fall in the price of natural gas, which is by far the cleanest input for fossil fuel power plants.[6] Second, large shocks to the overall economy and weather may have influenced the demand for electricity: the financial crisis followed by the Great Recession and warmer-than-normal winters could have contributed to reductions in the demand for—and thus, the production of—electricity and associated emissions. Third, to address the consequential externalities that emissions represent, the US Environmental Protection Agency (EPA) adopted and implemented a suite of ambitious environmental policies. In 2005, the EPA approved the Clean Air Interstate Rule (CAIR), which introduced cap-and-trade markets to limit SO_2 and NO_x emissions from power plants in twenty-seven states throughout the eastern US. Thereafter, debates escalated

[6]Gas units typically emit negligible levels of SO_2 and much less NO_x than coal units.

over the costs and benefits of environmental policies targeting power plant emissions.[7] In particular, fears over their impacts on coal power plants and upstream industries dominated debates on environmental regulations. To date, no *ex post* assessments of the costs and benefits of these ambitious programs have been provided.

This research procures three sets of results. The first part of the paper demonstrates that most of the achieved emission reductions were driven by the adoption of abatement technology. To that end, this study constructs a micro-level dataset of power plants' operations and costs. To study the abatement mechanisms at the unit level, the analysis statistically decomposes the emission changes at the power plant level. This decomposition builds on an engineering model of the production of emission from the burning of fossil fuels that links those emissions to the physical properties of fuels, the generation of electricity and the adoption of abatement technology. This environmental accounting exercise first recovers power plant-level estimates from a regression of the changes in emissions against the properties of fuel inputs, electricity generation, and abatement technology adoption at the unit level. The exercise then builds region-wide estimates by aggregating the micro-level results based on initial power plant emissions in the eastern US. The analysis finds that over 50% of the decreases in SO_2 emissions under the CAIR between 2005 and 2014 were achieved through the adoption of abatement technology at coal units that operated throughout this period. During the same period, switching to cleaner types of coal or switching from either oil or coal to gas accounted for approximately 20% of the aforementioned reductions. Additionally, approximately one-fifth of the emission reductions were achieved by the retirement of old coal units, which were replaced by cleaner electricity generation units. Certain types of abatement technologies led to a stark reduction of up to 95% of all emissions at the unit level. This paper is the first to document this large wave of technology adoption at coal units throughout the

[7] In discussing the legality of the mercury rules introduced by the Obama-era EPA, Justice Antonin Scalia determined that "It is not rational, never mind 'appropriate,' to impose billions of dollars in economic costs in return for a few dollars in health or environmental benefits"—New York Times.

eastern US that followed the adoption of the CAIR markets in 2005 and intensified during the implementation of the policy: over 80% of the region's coal units that employed SO_2 abatement technologies in 2014 installed them between 2005 and 2014. In addition, this paper constructs estimates of the costs incurred by utilities due to the installation of abatement technology. Using micro-level data on investments at the unit level, this study demonstrates that aggregate costs amounted to $45 billion for the power plants in the CAIR region between 2005 and 2014. Moreover, a calculation of levelized abatement costs reveals that the adoption of abatement technology represented an added $3 per megawatt hour (MWh) of electricity produced at units that installed them—an average of a 2% increase in the costs for electricity generation. These costs represented 3% of the preinstallation yearly revenue of utilities.

Second, to account for the benefits achieved from decreases in NO_x and SO_2 emissions, the analysis presented herein proceeds with a calculation of the health effects. Accordingly, this paper uses and validates novel air quality data derived from satellite imagery,[8] which offer complete and detailed geographic coverage of air pollution throughout the US at a monthly frequency. Using geographic information system methods, this study matches these datasets with the geography of population settlements recovered from the Census and the Center for International Earth Science Information Network. Using estimates produced by health economics studies linking air pollution to infant mortality, this analysis finds that nearly 19,000 premature infant deaths were avoided thanks to the achieved improvements in air quality. Paired with a conservative measure of the statistical value of life, these benefits would amount to approximately $152 billion from 2008 to 2014. However, these preliminary back-of-the-envelope calculations do not account for all the health benefits induced by improvements in the local air quality. First, they capture the reduction in infant mortality only

[8]Local air concentrations of NO_x and SO_2 are recovered from images processed by the Ozone Monitoring Instrument, a satellite launched by NASA in 2004 to take daily footage of pollution around the world. Data on particulate matter concentrations are derived from a reanalysis product that combines inputs from satellites, ground-level monitoring stations and chemistry models. This dataset was produced by Aaron van Donkelaar, Randall Martin, Robert Spurr, and Richard Burnett in van Donkelaar et al. (2015), to whom I am grateful for sharing these monthly frequency data.

between 2008 and 2014 and should therefore be treated as a lower-bound estimate, as they do not consider the long-term positive effects on mortality achieved through permanent reductions in these emissions. Second, these numbers are limited to infant mortality data. Thus, to produce an exhaustive assessment of the benefits of these air quality improvements, the analysis would ideally include estimates of the impacts of pollution on hospitalization, defensive investments, *in utero* effects and adult mortality, to name a few examples. Nonetheless, these lower-bound estimates of the health benefits outweigh the costs incurred by the electricity generation sector.

Third, this paper estimates how residents value local improvements in the air quality around power plants. The causal impact of decreases in emissions on local housing values is estimated using an empirical difference-in-differences strategy. This approach compares the evolution of house values in the immediate proximity of power plants to that of residential units located slightly farther away in response to changes in power plant emissions. In the atmosphere, SO_2 is short lived and does not travel long distances. Accordingly, using satellite imagery measurements of SO_2 concentrations, the analysis demonstrates that power plant emissions translate into high concentrations of pollutants up to 3 miles away from power plants and that the pollutant concentrations decline beyond that radius. As SO_2 has a strong smell and (in high concentrations) leads to irritation of the eyes and respiratory system, local residents would likely notice large changes in the local air pollution observed from space. The results indicate that the decreases in emissions led to a 2% appreciation in local housing values over the period considered. These effects were very concentrated—within a radius of approximately 1 mile around a power plant—and grew stronger for properties closer to the source. In aggregate, these capitalizations amount to a total benefit of $8 billion. Similar results are found when using technology adoption on the right-hand side instead of emissions. Doing so makes it possible to strip away potential cyclical variations in emissions. An ideal experiment would seek to randomly assign various levels of air pollution to housing units while holding all other aspects regarding the areas surrounding plants constant. Hence, to generate variations in exposure to air pollution, papers in the literature have studied the changes in local air pollution levels generated by the opening and closure of dirty plants, which might also cause large changes in local neighborhoods and impact the local noise levels, congestion, and visual architecture, among other things. Therefore, focusing on a balanced panel of plants that primarily reduced emissions by installing abatement technologies better approximates an ideal experiment.

This paper contributes to the literature in four ways. This research constitutes the first study to quantitatively disentangle the channels of abatement mechanisms at the power plant level. Previous studies have qualitatively discussed the implication of declines in cleaner coal prices on abatement costs in earlier periods (Schmalensee and Stavins, 2013; Chan et al., 2012; Stavins, 1998). Recent papers investigated the consequences of the shale gas boom and subsequent decline in gas prices for medium- to long-run switching from coal to gas in US electricity markets (Preonas, 2017; Knittel et al., 2015; Covert et al., 2016). Other papers focused on power plant compliance choices under cap-and-trade markets and how deregulation in electricity markets (Cicala, 2015; Fowlie, 2010) or the roles of geography and access to markets for cleaner inputs (Preonas, 2017) can lead to inefficient outcomes. In contrast, observations of fuel inputs, electricity generation and technology adoption at the unit level disentangles these channels in a systematic manner. Other statistical decompositions of emissions were carried out for the manufacturing sector to disentangle the effects on emissions of the relocation of dirty industries, the adoption of abatement technology and that of changes in inputs and outputs (Shapiro and Walker, 2018).

Second, this paper provides the first *ex post* estimates of the costs incurred by the industry to achieve the unprecedented emission reductions over the last decade. The observations of the actual costs incurred by power plants to reduce emissions allows a direct estimation of those costs, whereas an entire branch of the literature relies on indirect estimations of abatement costs (Fowlie et al., 2018; Meng, 2017; Anderson and Sallee, 2011), in other settings. Costs are important in the context of this paper. Indeed, the stringency of the CAIR was unprecedented and incurred large capital expenditures, as abatement technologies for SO_2 are particularly costly.

Third, this paper provides the first *ex post* calculation of the corresponding health benefits. This part of the analysis builds on seminal papers on the geography of marginal damages (Chan et al., 2015; Fowlie and Muller, 2013; Muller et al., 2011). Compared with those papers, the present analysis provides novel measures of the local exposure to air pollution derived from satellite imagery. Although these data are not without limitations, their coverage improves on measures from monitoring stations that are widely used in the literature, and they promise to reduce the uncertainties in air circulation models derived from atmospheric chemistry models (Grainger et al., 2017; Sullivan, 2016b; Chan et al., 2015).

Fourth, this paper provides the first estimate of how recent declines in power plant emissions impacted local housing markets. Following Rosen's seminal work on hedonic valuation (Rosen, 1974), a large amount of the literature on environmental economics has sought to empirically recover estimates of the demand for local environmental amenities.[9] These papers have focused on changes in water pollution (Keiser and Shapiro, 2018), superfund cleaning (Greenstone and Gallagher, 2008), and toxic plant openings and closures (Currie et al., 2015; Davis, 2010, 2004) in addition to changes in air pollution in response to either an electricity crisis (Sullivan, 2016a) or an economic crisis (Chay and Greenstone, 2005).[10] Here, the analysis seeks to uncover the impacts of changes in emissions from power plants that were active throughout the period from 2005 to 2014 on the surrounding housing markets. Those plants reduced emissions primarily by installing technologies rather than by reducing their power output. The installation of abatement technologies is likely not observable by residents, which means that the recovered effect likely reflects a valuation of the local air quality.

[9]Consult Kahn and Walsh (2015) for a recent review of this literature.

[10]Other papers have used similar empirical strategies to estimate the impacts of crime on real estate, for instance, the impacts of sex offenders moving in to a neighborhood (Linden and Rockoff, 2008).

The remainder of the paper is structured as follows: Section 1.2 provides background information on local air pollution and power plant emissions. Section 1.3 presents the data used in the empirical analysis. Section 1.4 outlines the statistical decomposition of power plant emissions and the calculations of the costs incurred. Section 1.5 documents the large costs incurred by the adoption of abatement technologies. Section 1.6 proposes back-of-the-envelope calculations of their health benefits. Section 1.7 outlines the resulting impacts of emission reductions on local housing markets. Finally, Section 1.8 concludes the paper.

1.2 Local air pollution and power plant emissions

1.2.1 Local air pollution

Local air pollution is a pervasive issue in most countries that costs the world economy more than $5 trillion per year in welfare losses (WHO, 2018), mainly due to the burden it imposes on human health. Children and infants are particularly vulnerable: it is estimated that 600,000 children die prematurely from exposure to air pollution (WHO, 2018). The World Health Organization (WHO) estimates that 91% of the world's population lives in areas with pollution levels detrimental to health. The goal of the WHO is to achieve a two-thirds reduction in global deaths resulting from air pollution by 2030, which would necessitate drastic measures to reduce the emissions of local air pollutants.

The US EPA lists six criteria air pollutants that have particularly severe impacts on health: carbon monoxide (CO), lead, ground-level ozone (O_3), particulate matter ($PM_{2.5}$ and PM_{10}), SO_2, and NO_x.[11] Among them, SO_2 and NO_x are of particular importance: they not only impact health directly but also are involved in chemical reactions responsible for the formation

[11]The effects of these pollutants include infant mortality, respiratory diseases, hospital admissions, and productivity losses. Currie et al. (2014) offers a review of the health economics literature on the impacts of air pollution on various health outcomes.

of ground-level ozone and particulate matter.

Sulfur dioxide can inflame the respiratory system, thereby making it difficult to breathe, and can worsen respiratory diseases. Repeated exposure to SO_2 at high concentrations can cause premature death, particularly among children and the elderly. In addition, it can irritate the eyes, and it is characterized by the distinct and unpleasant odor of rotten eggs. Sulfur dioxide leads to the formation of SO_x, which reacts with other compounds to form tiny particulate matter, notably $PM_{2.5}$.[12] These tiny particles can penetrate deep into the lungs; consequently, they can have severe impacts on respiratory diseases and premature mortality. Sulfur dioxide is short-lived in the atmosphere and thus does not travel far from its point source.[13] However, particulate matter formed through reactions involving SO_2 can travel tens of miles away from emission sources; as a result, SO_2 emissions can have far-reaching impacts through the formation and transport of $PM_{2.5}$.

Nitrogen oxides are mixtures of odorless and transparent gases that are composed of nitrogen and oxygen molecules. Repeated exposure to high levels of NO_x can lead to the irritation of respiratory systems and cause or aggravate respiratory diseases, particularly asthma, leading to hospital admission. Children and the elderly are particularly sensitive to NO_x exposure. Nitrogen oxides are also responsible for the formation of particulate matter and ground-level ozone, particularly in hot temperatures, which have severe impacts on health.

Throughout most of the world, air pollution has exhibited an upward trend, reflecting the relentless growth of industrial and fossil fuel energy production and consumption. One notable exception has been the US, where local air pollution has been significantly reduced over the past 30 years, particularly since 2005: between 2004 and 2014, the air concentrations

[12] Those particles have diameters smaller than 2.5 micrometers, making them 25 times thinner than the average human hair.

[13] See Figure A.16, which plots the concentration of SO_2 against the distance from coal power plants.

of SO_2, NO_x and $PM_{2.5}$ dropped by more than 75%, approximately 40% and approximately 25%, respectively, relative to their 2004 levels (see Figure A.18 and Figure A.19). The eastern parts of the US were particularly affected by this unprecedented abatement of air pollution, as can be observed from the state-of-the-art satellite measurements of NO_x, SO_2 and $PM_{2.5}$ concentrations shown in Figure 1.4.

How were these unprecedented air quality improvements achieved in the eastern US? Understanding the mechanisms that led to the abatement of air pollution in the US could be essential in helping the WHO achieve its goal of a two-thirds reduction in air pollution-related premature deaths worldwide. In 2005, fossil fuel power plants emitted over 75% of all SO_2 and 25% of all NO_x emissions in the US[14] Accordingly, these unprecedented improvements in air quality were achieved through significant reductions in power plant emissions.

1.2.2 Emissions from the electricity generation sector

This section describes how power plants emit both NO_x and SO_2 and how they can limit these externalities by either switching to cleaner inputs or installing and operating abatement technologies.

Emissions as externalities

Figure A.3 describes the electricity generation process at the coal unit level. This process consists of burning coal in the *boiler*, a large chamber bounded by walls lined with steel tubes. Fuel combustion generates heat that is transmitted to high-pressure demineralized water that fills the steel tubes. The high-pressure steam released by the boiler (at temperatures exceeding 550°C) drives a turbine in the *turbo generator*. The metallic *generator* rotates within a magnetic field, which produces alternating current by induction following Faraday's law.

[14]Other sources of SO_2 include heavy industries and volcanoes, and other sources of NO_x include transportation and heavy industries.

The generated current leaves the generator, after which it is adapted within the *transformer* and then transmitted over high-voltage *transmission lines*.

The burning of fossil fuels in the boiler generates incombustible materials (ash and particulate matter), toxic gases (NO_x and SO_2), greenhouse gases (carbon dioxide) and water vapor. These byproducts are released into the air through the *stack*: a large chimney connected to the boiler. These emissions constitute the main externality of generating electricity through the combustion of fossil fuels. However, the amounts of NO_x and SO_2 released into the atmosphere can be limited by either switching to cleaner fuels (see section 1.2.2) or installing and operating capital-intensive technologies that can filter out pollutants at the stack level (see section 1.2.2).

Fossil fuel power plants are composed of several electricity generation units that can use coal-specific, oil-specific or gas-specific boilers. Figure A.2 maps out fossil fuel power plants according to the type of boiler: certain power plants have only gas-specific boilers, whereas others have only coal-specific boilers. Nonetheless, some power plants contain oil-specific, gas-specific and coal-specific boilers and can therefore decide to generate electricity using some or all units.

Fossil fuels: inputs

In 2005, 70% of all generated electricity was produced by fossil fuel power plants.[15] These power plants are composed of electricity generation units that burn one of three main types of fossil fuel, namely, coal, gas, and oil, in their boilers, and different types of fuel cannot be interchanged within a boiler. Different varieties of coal, gas and oil are available, and the quality of each variety can be defined by three measures: the heat content (in MMBtu per unit of mass) in addition to the ash content and sulfur content (in percentage of mass). The heat content represents the amount of energy that can be extracted from the burning of

[15]Coal accounted for 50% of the total electricity generation, while gas accounted for 20%.

a unit of mass of the fuel in a boiler, whereas the ash and sulfur contents correspond to the quantities of ash and SO_2, respectively, that can be formed from the burning of one unit of mass of fuel.[16]

Coal is a type of sedimentary rock dominated by combustible organic material that originated as plants that were deposited in swampy environments, covered by other sediments and ultimately subjected to high pressures and temperatures for up to 350 million years. Four categories of coals are used for electricity production: anthracite, bituminous coal, sub-bituminous coal and lignite. Most power plants use either bituminous or sub-bituminous coals. Bituminous coals, which are predominantly found in the Appalachian Basin, have high heat contents,[17] and they have historically constituted the dominant source of coal used for electricity generation: in 2000, 60% of electricity generated from coal power plants originated from bituminous coal. In contrast, sub-bituminous coals from the Powder River Basin were rarely used before the 1970s due to their low heat content (18 MMBtu per ton on average compared with 24 MMBtu per ton for bituminous coals) in addition to their high extraction and transport costs at that time.[18] In the 1990s, these trends changed as a result of the implementation of the Acid Rain Program, a cap-and-trade market targeting SO_2 emissions from fossil fuel power plants (Goulder, 2013; Schmalensee and Stavins, 2013). The sulfur content of sub-bituminous coals is 3.5 times lower than that of bituminous coals (0.063 tons of sulfur per MMBtu of heat content compared with 0.018 tons per MMBtu for bituminous coals). However, the extraction and transport costs of sub-bituminous coals remained high prior to the 1970s, at which time the rail system became deregulated, making it cheaper to transport sub-bituminous coals from the Powder River Basin across the US, and thus, extraction

[16]Table A.1 describes the heat input, ash and sulfur contents and costs of the coal, gas and oil used in fossil fuel power plants in the US.

[17]Give number and refer to table in the appendix

[18]In 1990, sub-bituminous coals accounted for less than 20% of all electricity generated from coal.

became profitable.

As a consequence, coal power plants reduced their SO_2 emissions primarily by switching to cleaner sub-bituminous coals, and they managed to comply with the price regulations of the Acid Rain Program at costs ten times lower than what had been anticipated. Aided by an unrelated but simultaneous shock to fuel input markets that allowed power plants to switch to cleaner coals, SO_2 emissions dropped during the implementation of the Acid Rain Program. However, not all coal power plants could switch to cleaner coals: some power plants were locked into long-term contracts with bituminous coal mines, while others lacked access to sub-bituminous coal sources because they were too remote from railroads and rivers that could transport these coals (Preonas, 2017). Thus, under the Acid Rain Program, it remained cheaper for many coal power plants in the eastern US to purchase extra emissions permits under the SO_2 market instituted by the Acid Rain Program than to reduce emissions; consequently, the local air pollution emitted from these plants remained an issue in the densely populated eastern US (Chan et al., 2015).

Oil-fired[19] electricity generation units provide small amounts of the electricity capacity and net electricity generation in the US. Oil units, which are often paired with gas or coal units that are used as a base for electricity generation, can be used during peak hours when electricity prices are high. Indeed, oil units are fast and cheap to both start and stop. However, oil is up to 8 times more expensive than coal (Figure B.5). Moreover, the combustion of oil releases larger amounts of both SO_2 and NO_x than does the combustion of either gas or coal.

Gas refers to hydrocarbons composed mostly of methane, ethane and propane.[20] Gas deposits occur naturally and are often mixed with crude oil reservoirs. Prior to recent technological advances in its extraction and transport, gas was an oil exploration byproduct and had to be

[19] I use oil and petroleum interchangeably throughout the paper.

[20] I use gas and natural gas interchangeably throughout the paper.

burned off at oil exploration sites (flaring). Improvements in three-dimensional computerized geophysical exploration, refining methods, horizontal drilling in the 1980s, vertical drilling in the 1990s, and hydraulic fracturing in the 2000s[21] permitted the extraction and transport of unprecedented amounts of gas throughout the US. The shale gas boom of the 2000s and 2010s led to a sharp decrease in the price of natural gas relative to coal, affecting the electricity supply curve merit order,[22] that is, electricity production became progressively cheaper with gas than that with coal. Figure B.5 displays the evolution of the price ratio of a unit of the heat content contained in gas and oil to a unit of the heat content contained in coal. As a consequence, a large number of new gas power plants were built in the 2000s (Davis, 2010). Since the burning of gas in gas boilers releases almost no SO_2 and approximately 25% less CO_2 per unit of the heat content, these newly constructed gas power plants and the subsequent retirement of older coal units contributed to the abatement of pollution within the electricity generation sector in the US (Knittel et al., 2015).

The vast majority of the coal power plants operating during the 2000s throughout the eastern US were still young; in addition, a majority of those plants were composed of coal units only, and thus, switching from coal units to gas units as a mechanism to reduce emissions was impossible. Furthermore, it was not possible to switch to cleaner coals as a mechanism to reduce emissions because these plants were either locked into long-term contracts with bituminous coal mines or too remote to access sub-bituminous coals. In other words, switching to cleaner fuel inputs is a low-cost solution to reduce emissions that has not always been available to all power plants. Nonetheless, another option to reduce emissions from coal boilers resides in the installation of capital-intensive abatement technologies.

[21] This technique forces a mixture of pressurized water, sand and various chemicals into wells drilled horizontally through shale deposits.

[22] The merit order of coal, oil and gas units within a power plant reflects the order of their short-run marginal costs of electricity production.

Abatement technologies

Abatement technologies can be installed at the stack level to limit emissions from the burning of fossil fuels.

For SO_2, two main types of control equipment exist for coal units: wet flue gas desulfurization (FGD) technologies[23] and dry FGD technologies.[24] In wet FGD systems, SO_2 is filtered out of the polluted gas stream through contact with a liquid sorbent either by forcing the gas into a pool of the liquid (in JB systems) or by spraying the sorbent (in SP systems). In dry systems, SO_2 is removed by putting the gas into contact with a semi-dry sorbent through use of a spray dryer.

Most importantly, dry FGD systems cannot be used in boilers that burn high-sulfur-content coals, as their efficiency drops dramatically with the SO_2 concentration in the emitted gas. As a result, dry FGD systems are an option only for coal plants that can burn low-sulfur sub-bituminous coals. For those units that do not have access to low-sulfur-content coals, the only option available to reduce the emissions of SO_2 is wet FGD, which can remove up to 98% of SO_2 from the gases flowing out of boilers.[25]

Two main types of abatement technologies exist for NO_x:[26] selective catalytic reduction

[23] In the dataset used in the analysis and described in section 1.3, three technologies fall into this category: jet bubbling reactor (JB) scrubbers, tray-type (TR) scrubbers, and spray-type (SP) scrubbers. These technologies differ with regard to the chemical used to dissolve and capture gaseous SO_2.

[24] Four technological sub-categories are observed for dry FGD technologies in the dataset: venturi-type (VE) scrubbers, circulating dry (CD) scrubbers, spray dryer-type, semi-dry (SD) FGD, and dry sorbent injection-type (DSI) scrubbers.

[25] Cicala (2015) shows that privately owned plants in deregulated markets during the early 2000s were more likely to switch to cleaner coals, which constituted a less costly option than investments in abatement technologies, to reduce SO_2 emissions. Under the more stringent regulations of the late 2000s that compose the focus of our analysis, power plants had to install abatement technologies to reach new caps.

[26] Here, I list *post-combustion* technologies that remove NO_x from the gases produced by combustion. However, other techniques, including the regulation of the flame characteristics, such as the temperature and fuel-air

(SCR) technologies and selective non-catalytic reduction (SNCR) technologies. For SNCR technologies, ammonia vapor is injected into the gases exiting the boiler to react with NO_x, producing acids and water. SCR operates similarly but achieves higher rates of filtering by using a catalyst bed composed of various metals; as a consequence, SCR systems are more costly than SNCR technologies.

Compared with the technologies utilized to remove SO_2, NO_x removal systems are much less capital intensive (the capital costs for NO_x systems are up to fifty times lower than those for SO_2 removal technologies). Most importantly, NO_x technologies run on electricity and hence can be switched on and off. This means that plants equipped with such systems can decide not to operate them and continue to emit NO_x. As a consequence, most power plants in the eastern US installed NO_x abatement technologies and operated them in the summer months to comply with the NO_x Budgeting Program[27], which imposed a cap-and-trade market on summertime emissions. These same power plants would switch their abatement technologies off during unregulated winter months to avoid operational costs. This is an important feature of these technologies, and it will be discussed in greater detail Chapter 2 of this dissertation.

1.3 Data

1.3.1 Data sources

1. Power plant emissions. The EPA installed monitors on every boiler in the country to precisely measure their emissions of SO_2, NO_x and CO_2 at an hourly frequency. I collected

mixing characteristics, exist to limit NO_x emissions during combustion.

[27] See Chapter 2.

these SO_2 and NO_x emissions data from the EPA's Air Markets Program Database,[28] which contains observations at the electricity generating unit level. The majority of emissions are monitored using a continuous emissions monitoring system at the stack level, implying that these data are of particularly high quality.

2. Power plant operations and costs. The US Energy Information Administration (EIA) collects a large amount of information on the operations and costs of power plants. Accordingly, I assembled and constructed a detailed dataset at the monthly frequency and plant level by pulling data from a variety of surveys conducted by the EIA. The database I assembled includes information acquired monthly on power plants' generation capacities according to the type of fuel, their electricity generation (both the net generation and the gross load), quantity and quality, their costs of fuel inputs, and their adoption of abatement technologies. I augmented this dataset with information on yearly revenues accrued from electricity generation at the utility level.

Data regarding power plants' technical characteristics, including the generator capacity according to the type of fuel, the initial operation dates and planned retirement dates of the boiler and generator, and the plant coordinates were retrieved from the EIA. Information on the boiler type and design, the generator type, design and capacity, the stack design and height, and the power plant addresses was retrieved from Forms 767 between 2001 and 2005 and Forms EIA860 from 2006 onward. These forms contain information on all operable, proposed and retired units within every fossil fuel power plant with a nameplate capacity exceeding 50 MW. These datasets also contain information on the first day of operation and the planned retirement date (year-month) for every electricity generation unit.

Data were also obtained on the fuel delivered to every power plant at a monthly frequency containing information regarding the type of fuel (gas, oil, or coal), the type of coal (either

[28] See appendices for a complete description of the data sources used and how to access the publicly available datasets.

bituminous or sub-bituminous), the fuel heat content, the fuel sulfur content, the fuel cost and the quantity of fuel delivered. These data were retrieved from EIA Forms 423 and 923.[29] As fuel costs were not available for deregulated, privately owned plants, I also assembled data on fuel prices from the EIA at a monthly frequency and at the state level. I complemented these data on fuel costs at the power plant level with data on yearly and state-average fuel prices faced by the electricity generation sector obtained from EIA State Energy Data System (SEDS) forms.

Data on the net electricity generation at the generation unit level within each fossil fuel power plant were further collected at a monthly frequency. These data contain information on the quantity of electricity produced (in MWh) according to the type, quantity and quality of fuel input.[30]

Data on the adoption of abatement technologies and setup costs for NO_x and SO_2 for each boiler within every power plant in the US were gathered from the EIA. In particular, the EIA reports information with a monthly frequency on the installation of different technologies used to reduce the emissions of NO_x and SO_2 and the corresponding costs incurred by power plants. Furthermore, information on the abatement technology type, manufacturer, installation date (month-year) and installation costs were retrieved from yearly EIA publications, namely, Form 767 from 2001 to 2005 and from Form 860 from 2006 onward.

Finally, information regarding the owner and operator of each power plant in addition to the electricity market regulations was retrieved from Form EIA860. Utilities' electricity generation revenues were retrieved from EIA Forms 861 and 861S, which are collected annually from both utilities and independent producers of electricity.

[29] Every year, the EIA uses these forms to collect data on the fuel quality (heat content in addition to sulfur and ash contents), fuel costs for utility-owned plants, and fuel origin (coal mines). EIA Forms F906, E423, and F423 were used from 2002 to 2007, and pages 3 and 5 of Form F-923 were used from 2008 to 2015.

[30] These data are collected by the EIA and published yearly on page 1 of Form F-923 from 2008 onward.

3. Air quality data. Air quality data were derived both from observations at ground-level monitoring stations installed across the country and from novel satellite imagery. The EPA has installed monitoring stations in population centers across the US. These monitoring stations measure the concentrations of six criteria air pollutants: NO_x, SO_2, carbon monoxide, lead, mercury and particulate matter. These stations precisely measure those pollutants at a high frequency; however, their geographic coverage is limited. Measurements of NO_x and SO_2 were derived from satellite imagery acquired by NASA's Ozone Monitoring Instrument, which produces daily measurements of NO_2 and SO_2 air columns over the US and reports them with a resolution of 0.25 by 0.25 degrees. I aggregated these daily measurements at a monthly frequency and at the block group level. I also validated these measurements by estimating the correlations among the pollutant concentrations derived from both satellite measurements and monitoring measurements in counties that possess monitors. Finally, I used processed $PM_{2.5}$ concentration data with a 0.05 by 0.05 degree resolution from (van Donkelaar et al., 2015).

4. Housing data. Housing data were derived from Corelogic.[31] This dataset contains micro-level data on most housing transactions in the US. In particular, I used the dollar amounts of sales of residential units that the dataset collected from 2000 to 2016. I used the transaction date, dollar amount and location (latitude, longitude) of all units sold in the US during the period of study.

5. Other datasets. I used data from the 2000 and 2010 Censuses and the American Community Surveys of 2009, 2010, 2011, 2012, 2013, 2014 and 2015. These datasets contain information on the population age, race, income, and education at the block group level. They also contain information on the built environment at the block group level: number of housing

[31] Columbia Business School's Milstein Center for Real Estate graciously made these data available to me.

units and gross rent.[32]

Measurements of local temperatures were derived from ground-level monitoring stations and aggregated at a daily frequency on a 2.5 km by 2.5 km grid across the contiguous US[33] I subsequently calculated measurements of extreme heat and cold using commonly used degree-day methods and aggregated them at the monthly frequency on every grid cell in the contiguous US.

1.3.2 Merging datasets

I used data on the locations of power plants (longitude, latitude) to merge all of the geographic datasets. Specifically, I constructed circles of various radii around every power plant and intersected other datasets using Geographic Information System methods coded in Python. For gridded datasets (such as the PRISM and satellite data), I averaged the measurements of the intersections between the circles and grid cells based on area weights. For shapefiles containing information on the population (from the Census), I constructed circles with measurements by weighting shape measurements with the population of the intersection. For point-level data with coordinates (notably for housing transactions), I calculated the distances between power plants and other point locations and aggregated the information in different circle radii. Finally, I merged the data on power plant emissions, operations and costs using the power plants' unique identifiers provided by the EIA.

[32] I downloaded data from the National Historical Geographic Information System website. The data produced by the Census were assembled at the block group level by Steven Manson, Jonathan Schroeder, David Van Riper, and Steven Ruggles in the Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System: Version 12.0 Minneapolis: University of Minnesota. `http://doi.org/10.18128/D050.V12.0`. More information and descriptive statistics are available in the online appendix.

[33] Wolfram Schlenker graciously shared the Parameter-elevation Relationships on Independent Slopes Model (PRISM) data with me.

1.4 Statistical decomposition of power plant emissions

1.4.1 Abatement strategy

To reduce emissions, power plants are given three distinct options for boilers that continue to operate: switch to cleaner inputs, reduce the output—electricity generation—or install capital-intensive abatement technologies.

At the boiler level, those choices are separable. As discussed in section 1.2.2, lower-cost abatement technologies (dry scrubbers) can be used with low-sulfur coals only, while high-cost wet scrubbers function only with the burning of high-sulfur coals. Those technical characteristics imply that power plants will either invest in capital-intensive scrubbers or switch to cleaner sub-bituminous fuels to reduce emissions.[34] In a regression discontinuity-like graph, Figure 1.1 plots the monthly average boiler emissions before and after the installation of abatement technologies.[35] These findings show that the adoption of abatement technologies has immediate and long-lasting effects on boiler emissions: up to 98% of emissions are filtered following the adoption of these technologies.

If changes in the input quantity and quality are systematically correlated with the timing of technology adoption, it will be difficult to separate their effects on emissions. It is therefore useful to reproduce regression discontinuity-like graphs that plot measurements of the electricity production and fuel pollution intensity against the timing of technology adoption. In particular, emissions of carbon dioxide are correlated with the type and amount of coal burned in the boiler.[36] Hence, Figure A.11 plots the evolution of boiler-level variables that can impact emissions of SO_2 against the timing of technology adoption, demonstrating the

[34] A boiler is designed specifically for one type of fuel: it can function with any sort of coal but cannot burn gas. Switching fuels from coal to gas would lead to the more intensive use of gas-specific units in coal power plants that are equipped with both coal-specific and gas-specific units.

[35] Figure A.10 reproduces these graphs according to the type of abatement technology.

[36] These emissions are not filtered out of the output gases by scrubbers because carbon dioxide does not dissolve easily and is thus difficult to capture. For these chemical reasons, abatement technologies for NO_x and SO_2 do not affect carbon dioxide emissions.

lack of significant changes in carbon dioxide emissions—and hence the type and quantity of coal burned—that would be correlated with the installation of emission controls.

1.4.2 Empirical approach

A power plant j is composed of several boilers i. The emissions $e_{i,t}$ from boiler i in month t can be reduced by decreasing the amount of electricity produced, switching to cleaner fuels to produce the same amount of electricity, or installing capital-intensive abatement technologies to filter out pollutants from its air outflows. As discussed above, the emissions of boiler i in month t can be decomposed into an extensive margin—the generated electricity—$Y_{i,t}$, an intensive margin that captures the intensity of emissions from the fuel inputs $\pi_{i,t}$, and a technology channel $\theta_{i,t}$. The emissions $e_{i,t}$ could thus be written as follows:

$$e_{i,t} = Y_{i,t}^{\alpha} \pi_{i,t}^{\beta} \theta_{i,t}^{\gamma}, \tag{1.1}$$

where $Y_{i,t}$ is the generated electricity for boiler i in month t (in MWh), $\pi_{i,t}$ is the emissions intensity of the fuel inputs (in the sulfur content per MWh) for boiler i in month t, and $\theta_{i,t}$ represents the abatement technologies installed on boiler i in month t.[37]

1.4.3 Estimation

To decompose the emission reduction channels at the power plant level, I estimate three power boiler-level parameters, namely, α_i, β_i, and γ_i, in regressions that are run for every

[37] The emissions intensity of the fuel inputs used to produce electricity with boiler i is derived as follows:

$$\pi_{i,t} = f_i^{-1} \times s_{i,t} \times h_{i,t}^{-1},$$

where $s_{i,t}$ is the pollutant content of the fuel inputs (in percentage of mass), and $h_{i,t}$ is the quality of fuel inputs measured in the heat content of the fuel (in MMBtu per unit mass). The conversion factor f_i captures the efficiency of the electricity generation unit at transforming the primary energy contained within the fuel inputs (in MMBtu) into electricity (in MWh): it represents the amount of electricity that can be produced per unit of heat generated through the burning of the fuel (in MWh per MMBtu). Hence, f_i depends on the design of boiler i and the associated generators and gives an indication of its efficiency.

boiler that was operable continuously from 2005 to 2014:[38]

$$log(e_{i,t}) = \gamma_i \theta_{i,t} + \beta_i log(\pi_{i,t}) + \alpha_i log(Y_{i,t}) + \epsilon_{i,t}, \tag{1.2}$$

where $e_{i,t}$ represents the emissions of boiler i in month t, $\theta_{i,t}$ is a dummy variable equal to one on all dates after the month t of the installation of an abatement technology and a unit i, $\pi_{i,t}$ is the pollution intensity of the fuel burned in boiler i in month t, $Y_{i,t}$ is the electricity generated by unit i, and $\epsilon_{i,t}$ is the idiosyncratic error term.

These regressions enable the recovery of estimates of the share of the reductions in emissions achieved through technology adoption ($\hat{\gamma_i}$), fuel switching ($\hat{\beta_i}$), and output reduction ($\hat{\alpha_i}$) at the boiler level for a balanced panel of power plants between 2005 and 2014. Estimates of these parameters are recovered for each of the 1,483 fossil fuel boilers continuously operating in the CAIR region from 2005 to 2014.

1.4.4 Findings

Technology adoption

As mentioned above, boilers running on high-sulfur bituminous coal can use only capital-intensive wet scrubbers. Of the 432 boilers running on bituminous coal in 2005, 175 installed an abatement technology. On average, the installation of a wet scrubber led to a 91% reduction in SO_2 emissions from bituminous coal boilers. Of the 143 boilers running on low-sulfur sub-bituminous coals, only 35 installed low-cost abatement technologies, which led to an average reduction of 15% in emissions from those boilers.

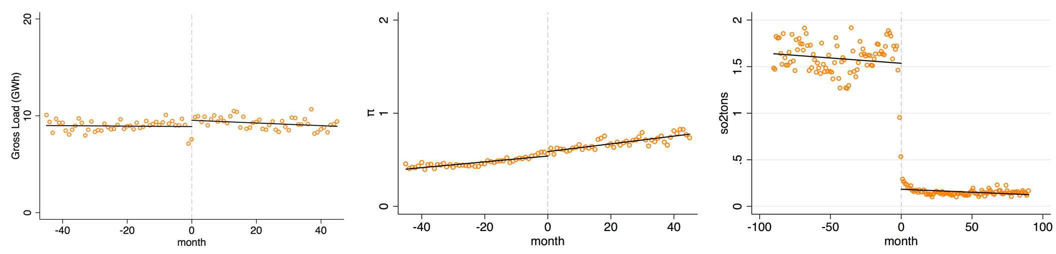
Figure 1.3 displays the timing of the adoption of abatement technologies at the boilers in the CAIR region. Most NO_x abatement technologies were installed at the beginning of the NO_x Budgeting Program implementation period between 2003 and 2005. In addition, a significant wave of adoption of SO_2 abatement technologies followed the announcement

[38]The assumption here is that the adoption of abatement technologies, the switch to cleaner fuels and the decision to decrease electricity production are separable, as discussed above.

of the CAIR; as a result, more than 85% of all SO_2 abatement technologies were installed between 2005 and 2012.

Figure 1.1: Impacts of technology adoption on gross load, fuel sulfur intensity and emissions

(a) Gross load Y **(b)** sulfur intensity of coal (π) **(c)** Emissions e



Notes: The figure displays the average impact of technology adoption on monthly gross load (a), coal sulfur intensity (b) and emissions of SO_2 (c) across coal boilers. Averages include all boilers in the Western region, at which technology was installed between 2005 and 2014. One boiler typically receives a unique retrofit: only one technology (if any) is installed by boiler. The panels depict the impact of spray type scrubbers systems adoption on SO_2 emissions, a leading abatement technology for SO_2.

Fuel switching

Within a coal boiler, it is possible only to switch to different types of coal.[39] In regression 1.2, the impact of switching from high-sulfur coal to low-sulfur coal at the unit level is captured by $\hat{\beta}_i$. Of the 237 bituminous coal boilers operating in 2005 for which abatement technologies were not installed, 58 switched to low-sulfur sub-bituminous coal, which achieved an average reduction of 54% in emissions.

Reduction in output

For bituminous boilers that did not switch to cleaner coal and did not install abatement technologies, reductions in emissions were achieved through a reduction in the electricity output, which was made possible only for coal boilers in plants that operated both coal and gas units. In the CAIR region, 87 such plants operated during the period of analysis (see Figure A.2). As gas prices plunged, gas units became cheaper to operate than coal units in those plants.

[39] Only 14 coal boilers were retrofitted to switch to gas.

Hence, power plants used their gas units more intensively to compensate for the diminished electricity production from coal units. Figure A.6 shows that reductions in the output from coal units at those plants were compensated by an increase in electricity generation from gas units.

This alternative could be regarded both as a reduction in output and as a switch from coal to gas across units within the same plants. As the burning of gas does not emit SO_2, the switch from coal units to gas units at those plants led to reductions in emissions. Similar switching was observed between oil units and gas units.

Retirement

Between 2005 and 2014, 204 coal boilers and 43 oil boilers were retired, accounting for 17.2% of the total reduction in SO_2 emissions. The vast majority of these boilers were not equipped with any abatement technologies. The average age of retirement of these boilers was 60 years, which was the typical retirement age for such boilers. In the same period, 130 new boilers came into operation across the CAIR region; all of these new boilers burned gas, which emits almost no SO_2.[40] Figure A.7 plots the monthly number of coal and gas units that were retired during the period of study.

Aggregation at the industry level

To recover the industry-level relative importance of these emission reduction channels, the analysis proceeds with the following aggregation:

$$\mathcal{A} = \sum_{i \in CAIR} \upsilon_i \hat{\alpha}_i$$

$$\mathcal{B} = \sum_{i \in CAIR} \upsilon_i \hat{\beta}_i$$

[40]Fifty gas boilers were also retired in the period considered.

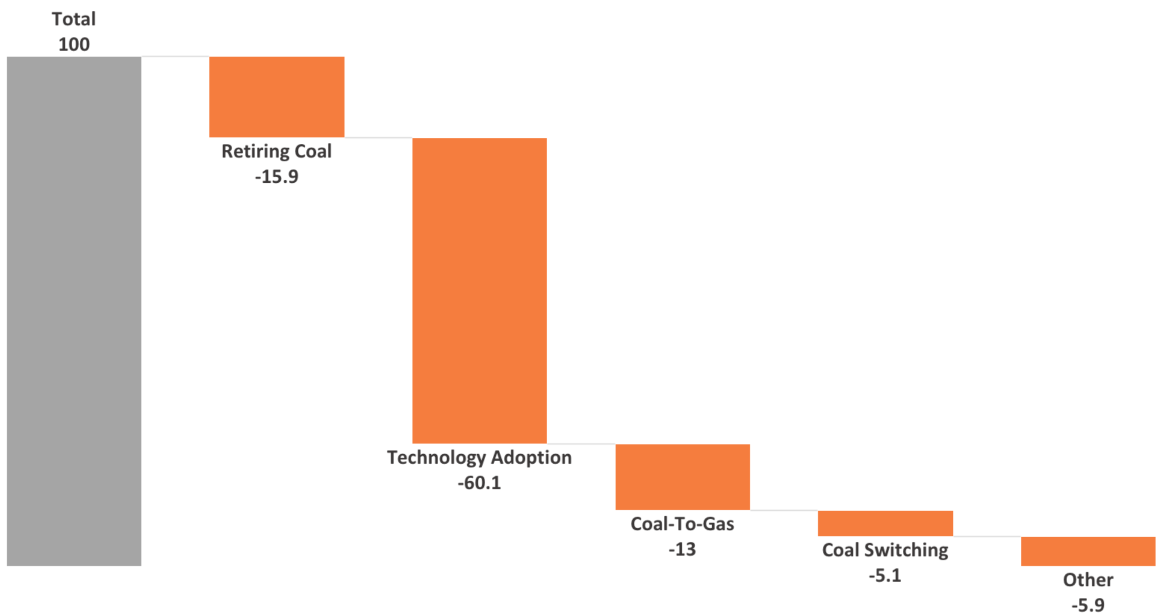
$$\mathcal{C} = \sum_{i \in CAIR} \upsilon_i \hat{\gamma}_i,$$

where υ_i is the share of emissions that boiler i accounted for in 2005 relative to the total emissions of power plants throughout the CAIR region in the same year.

This statistical decomposition is informative of the mechanisms employed for a balanced panel, to which this analysis adds the contribution from the retirement of coal units. Figure 1.2 summarizes the results obtained at the industry level in the CAIR region. In aggregate, 60% of the total reduction in SO_2 emissions in the CAIR region was achieved through the adoption of abatement technologies at units that continuously operated throughout the period. The retirement of older coal units accounted for approximately 16% of the achieved emissions reductions, whereas switching from coal-based to gas-based electricity production in power plants that operated both coal and gas units accounted for 13%, and switching from high- to low-sulfur coals accounted for only 5% of the observed decline.

Figure 1.2: Statistical decomposition of SO_2 emission reductions at coal power plants

(a) SO_2



Notes: The figure summarizes the contribution of coal unit retirement, technology adoption, coal-to-gas switching and bituminous-to-sub-bituminous coals switching at coal power plants in the CAIR region. Plants included in this analysis were operable in 2004. Between 2004 and 2014, the retirement of coal units accounted for 15.9% of total SO_2 emission reductions. Figures for technology adoption are recovered from the statistical decomposition conducted at the plant level, in a balanced panel of plants as described in section 1.4.2. Figures assigned to coal-to-gas switching and switching to cleaner coals combine estimates on output and fuel pollution intensity.

1.5 Abatement Costs

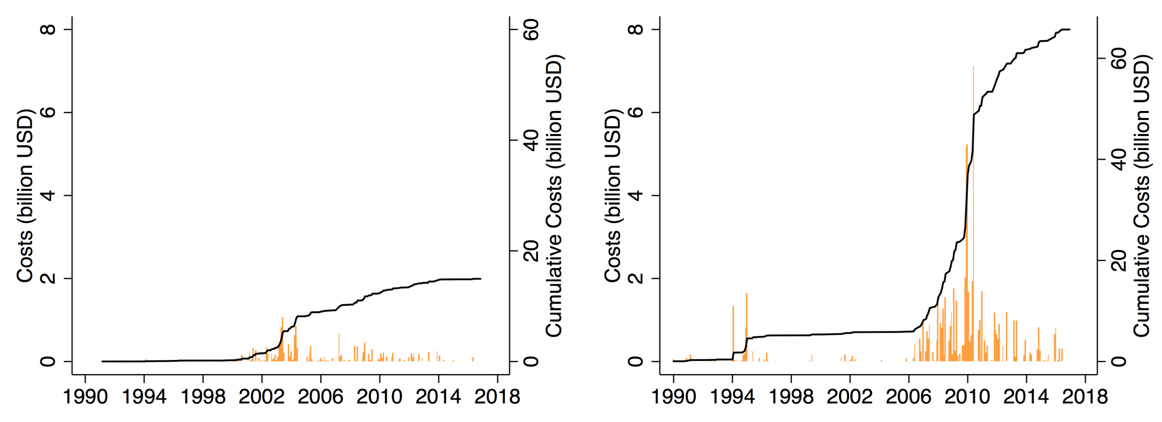
Retrofitting coal units is a capital-intensive process. Figure A.8 displays the average costs of installation for all types of abatement technologies. Wet scrubbers that can be installed on bituminous coal boilers are expensive pieces of equipment whose installation can cost up to $250 million for a large boiler.[41] Next, the levelized costs of these technology adoptions are calculated. The date on which the technology was installed and each unit's proposed retirement date are known for all boilers. This enables the calculation of an annualized installation cost. Reported in the amount of electricity generated, the adoption of abatement

[41]The low variance in reported costs from plants owned and operated by different utilities lends confidence that reports do not inflate costs. A cross-validation of the costs incurred for a couple of abatement technology designs confirms that the costs reported in EIA surveys are consistent.

technology represents an additional \$3 dollar per MWh of electricity produced at units for which such technologies were installed—an average increase of 2% in the costs for electricity generation.[42] These investments represented a sizable 3% of utilities' annual revenues.

Figure 1.3: Timing of technology adoption and cumulative costs—Eastern US

(a) NO_x **(b)** SO_2



Notes: The figure displays the timing and costs of technology adoption for NO_x (left) and SO_2 (right) for plants in the CAIR region. Technology adoption occured during the NO_x Budgetting Program for NO_x, yet power plants could switch off abatement technologie during unregulated month in the winter. The introduction of the annual market for NO_x emissions led power plants to keep technologies switched on throughout the year, hence leading to the sharp decrease of emissions in the winter. For SO_2, most of the technology adoption occured after the adoption of the CAIR, and during its preparation and its implementation phases. Costs of SO_2 technologies are an order of magnitude more expensive, which may rationalize why power plants did not install such technologies under less stringent preceeding regulations.

The aggregate costs across all power plants operating in the CAIR region amounted to \$45 billion between 2005 and 2014. This exceeded the *ex ante* EPA cost prediction by an order of magnitude. These costs should be compared with the *ex post* calculation of abatement costs under the Acid Rain Program, the flagship cap-and-trade market for SO_2 emissions implemented in the 1990s and early 2000s across the US. The EPA calculated that the aggregate costs required to achieve reductions under this program amounted to \$3 billion. This is not surprising because the Acid Rain Program was much less stringent: it imposed a cap three times higher than that imposed in the CAIR. Moreover, reductions in emissions at plants in the western US were achieved by switching to cleaner coals, while plants in the east bought

[42]These costs include only the fixed installation cost. Since scrubbers need large amounts of electricity to operate, they also incur operating costs that are not accounted for in these calculations.

emission permits on the market and continued to emit (Chan et al., 2015). As illustrated in Figure 1.3, almost no abatement technology was installed at power plants in the region prior to the adoption of the CAIR.

The high costs incurred during the adoption of abatement technologies in response to some of the most stringent environmental policies ever implemented should be compared with the benefits of those policies. To date, no *ex post* cost-benefit analyses of these policies have been reported. Accordingly, the rest of this paper estimates the health impacts of the air quality improvements achieved across the US due to these emission reductions as well as the demand for local air quality in the vicinity of power plants.

1.6 Health Benefits

The EPA is required by law to produce *ex ante* projections of the costs and benefits associated with its rules. How do *ex ante* projections compare with *ex post* health benefits? In this section, I provide the first *ex post* calculations of the health benefits realized through air quality improvements.

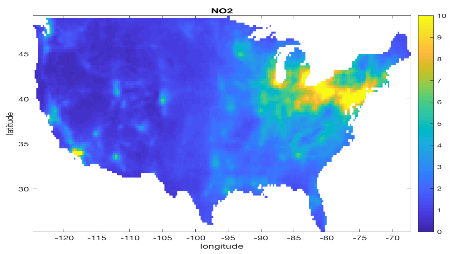
The goal of the CAIR was to limit emissions that contributed to local air pollution in neighboring states through the transport of particulate matter. Interestingly, the results from back-of-the-envelope calculations show that the health impacts of reductions in SO_2 emissions were indeed greater locally.

1.6.1 Air quality improvements

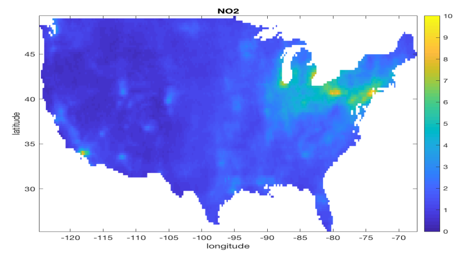
The EPA projected that most of the benefits achieved through the CAIR would be captured in improvements to human health, that is, through avoiding 17,000 premature deaths, 22,000 non-fatal heart attacks, 12,300 hospital admissions, 1.7 million lost work days, and 500,000 lost school days (EPA, 2005). According to the EPA, more than 90% of these health benefits would be captured by avoiding the occurrence of 17,000 premature deaths. To the best of my knowledge, here, I provide the first *ex post* estimates of the health benefits achieved through the air quality improvements resulting from the CAIR.

Figure 1.4: The geography of local air pollution improvements

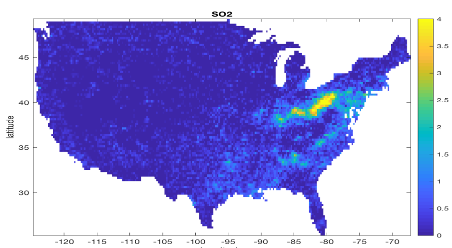
(a) 2004 - NO_2



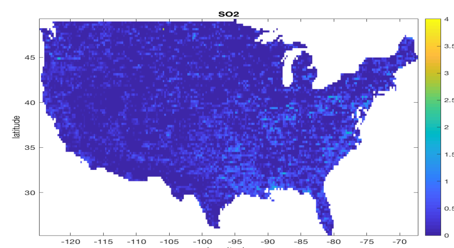
(b) 2013 - NO_2



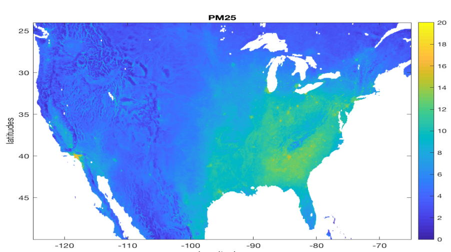
(c) 2004 - SO_2



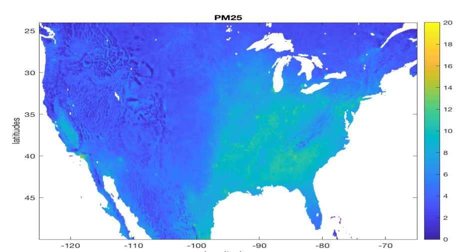
(d) 2013 - SO_2



(e) 2004 - $PM_{2.5}$



(f) 2011 - $PM_{2.5}$



Notes: NO_x and SO_2 measures are retrieved from images collected by NASA's Ozone Monitoring Instrument. Data on daily concentrations were accessed through NASA portals and averaged at the monthly and yearly frequency. Panel (a) (resp. b) displays monthly frequency averages of NO_2 concentrations in 2004 (resp. 2013). $PM_{2.5}$ concentrations are derived from a reanalysis product developed by van Donkelaar et al. (2015) that blends satellite imagery, atmospheric chemistry circulation models and ground-level measurements. The authors made the data available to me at the monthly frequency. Panel (e) (resp. d) presents yearly averages of $PM_{2.5}$ concentrations in 2004 (resp. 2011).

To do so, I use satellite imagery of NO_x, SO_2 and $PM_{2.5}$ air concentrations to augment commonly used air quality data derived from ground-level monitoring stations. This is the first paper in the economics literature to use and validate such datasets (see section A.2.5

for the results of the validation exercise). The main advantage of air quality measurements derived from satellite imagery is that they cover the entire contiguous US; consequently, an investigation of the population exposure is possible. In contrast, most analyses employ air quality measurements derived from ground-level monitoring stations that are sparsely distributed in space (see FigureA.17) and do not provide complete measurements of the exposure of the US population to local air pollution.[43]

1.6.2 Health impacts

To associate the air quality improvements measured through satellite imagery with the corresponding health outcomes, I employ estimates from the health economics literature. I focus on infant mortality, which has been found to be the primary source of mortality resulting from air pollution. This obviously does not capture all of the health impacts, since air pollution has been shown to have significant consequences for morbidity, medical expenses, and adult mortality, among others. However, this back-of-the-envelope exercise is useful insomuch that it provides the first *ex post* comparison of the costs and benefits of the CAIR. Given the large costs incurred by the electricity generation sector, it is important to establish whether the achieved emission reductions translated into net benefits to society.

The results from this exercise, which matches air pollution data with the population, are summarized in Table 1.1. Using information on natality and infant mortality at the cell level, this analysis first determines the exposure of the population to air pollution. Back-of-the-envelope impacts on infant mortality are produced by using estimates of the impacts of SO_2, NO_x and $PM_{2.5}$ on infant mortality. The estimates used for this calculation are retrieved from the papers summarized in Table A.3.

I find that decreases in the concentrations of SO_2, NO_x and $PM_{2.5}$ resulted in 18,976

[43] Other studies use dispersion models that build on air circulation models based on atmospheric sciences to simulate the responses of local air pollution to changes in power plant emissions (Chan et al., 2015). Although these studies provide complete geographic coverage of air pollution, they do not measure local air pollution directly, and thus, the uncertainties regarding local exposure remain high.

fewer premature infant deaths between 2008 and 2014. These lower-bound calculations of health costs are in the same range as those projected by the EPA in its analysis of the CAIR. Interestingly, most of the deaths were avoided as a result of lower exposure to SO_2 pollution in the vicinity of power plants. This exercise presents several limitations. In particular, it is not clear whether estimates from the literature can be used in any setting (external validity).

In future work, I plan to use shocks to emissions introduced by the adoption of abatement technologies to estimate the impacts of SO_2 pollution on various health outcomes. This unique setting would likely improve the current literature because it provides a shock to emissions only, which would help identify a causal impact of pollution on health.

Table 1.1: Health benefits from reductions in air pollution

	SO_2	NO_x	$PM_{2.5}$
% drop	80	37	19
% drop (pop weighted)	62	37	20
Mortality			
Avoided Deaths	13,312	3,976	1,688
Dollar Value (Billion USD)	106.4	31.8	13.5

Notes: This table summarizes results from the back-of-the-envelope evaluation of emission reduction benefits accrued to health. This uses spatially continuous measures of concentrations in SO_2, NO_x and $PM_{2.5}$ recovered from satellite imagery and matched with population. Using information on natality and infant mortality at the cell level, and estimates of the impacts of these pollutants on infant mortality, the exercise produces the results above.

How were improvements in the air quality valued by local residents? The next section investigates the impacts of emission reductions on local housing markets in the vicinity of power plants.

1.7 Demand for clean air: impacts on local housing markets

The goal of this section is to investigate the causal impact of the large declines in emissions from power plants on local housing markets.

1.7.1 Local pollution

The demand for local environmental amenities can be recovered through a hedonic estimation of the impacts of changes in the environment on real estate. Estimating these effects in the case of air pollution presents several challenges. First, most local air pollutants are not observable by residents, who may not respond to invisible changes in the local air quality. Second, many pollutants travel long distances, thereby complicating the definitions of treated and control areas for an empirical investigation. Third, sharp changes in the local air pollution are rare, difficult to observe and often confounded with other changes in economic activity. Recent papers have focused on the opening and closure of dirty plants, which cause sharp changes in local air pollution, along with multiple changes in the local economy and architecture. Thus, isolating the effects of pollution on local outcomes is difficult.

An ideal experiment would seek to randomly assign various levels of air pollution to houses while holding all other aspects constant. The analysis presented herein offers a unique setting. By observing a balanced panel of plants that drastically reduced their emissions through the adoption of abatement technologies, the setting can better approach that of an ideal experiment. In particular, technology adoption is unlikely to be directly observed by residents, but it nevertheless leads to sharp and quasi-instant decreases in power plant emissions.

How local is sulfur dioxide pollution? An investigation of satellite imagery of pollutant concentrations in the US reveals that most SO_2 emitted from power plants lies within three miles of the point source (Figure A.16). At the high concentrations observed in these areas, SO_2 is highly noticeable: it leads to significant irritation of the lungs and eyes and has the distinct odor of rotten eggs.

1.7.2 Empirical strategy

Local impacts of emission reductions

The empirical strategy employed herein will exploit the differential impacts of changes in power plant emissions on the immediate vicinity of each power plant relative to locations slightly farther away. Within a difference-in-differences setting, I estimate the impacts of changes in emissions on local outcomes by comparing the evolution of outcomes close to the power plant to that of outcomes slightly farther away. In practice, I estimate the following:[44]

$$\begin{aligned} y_{j,t,d} = \beta_0 &+ \beta_1 e_{j,t} \\ &+ \beta_2 e_{j,t} \times near_{j,d} \\ &+ \beta_3 near_{j,d} \\ &+ f(\mathbf{X}_{j,t}) \\ &+ c_j + \lambda_t + \epsilon_{j,t}, \end{aligned} \tag{1.3}$$

where $y_{j,t,d}$ is the natural logarithm of the mean house value in month t within a circle of radius d around power plant j, $e_{j,t}$ is the natural logarithm of SO_2 emissions from power plant j in month t, and $near_{j,d}$ is a dummy variable indicating whether the observation lies within a circle of radius d centered on plant j that controls for time-invariant characteristics of the treated areas. I estimate these models using data containing observations within a circle of radius d around plant j and contained in donuts with a radius from d to $d + 0.3$ miles that serve as the control group. No theoretical framework is available to define the immediate vicinity of a power plant. Therefore, I estimate equation 1.3 using distances varying from 0.3

[44]Similar procedures are used in Currie et al. (2015); Davis (2010). These papers estimate the impacts of the opening and closure of dirty plants (toxic plants or gas power plants) on local housing markets. Plant openings and closures may lead to numerous changes in local neighborhoods that would be correlated with emissions, including changes in the landscape, traffic congestion and noise from the plant's operation. By using changes in emissions driven by technology adoption at power plants that continue operating, the current setting permits a cleaner identification of the effects of changes in local pollution on local housing markets.

to 12.5 miles from power plants.[45]

Identification assumption. The identification relies on the parallel trends assumption: in the absence of decreased emissions at the power plant level, the evolution of housing values for residential units close to the power plant will be similar to the evolution of those for residential units slightly farther away.

1.7.3 Results

Table 1.2 displays the estimation results of the difference-in-differences specification modeled in equation 1.3. Each column corresponds to a regression in which the treatment group corresponds to a circle with radius d centered on a power plant. The regressions are run separately for various values of d.

Emission reductions have a small but significant positive effect on local housing values. A 10% decrease in SO_2 emissions leads to a 0.3% increase in the prices of houses located within 0.3 miles of a power plant. This effect decays with distance and is significant up to 1.2 miles away from a plant. For higher values of d, the effect is null and non-significant.

In addition, an 80% reduction in SO_2 emissions leads to a 2.4% appreciation in house values within 0.3 miles of power plants. Given the mean value of housing units in the treated groups, this corresponds to an appreciation of $1,500 per house. Since there are 6,000 units on average within this distance of power plants (ACS, 2009) and there are 375 coal power plants in the sample, the total housing appreciation that resulted from the reductions in emissions amounts to $3.4 billion.

[45]Figure A.15 displays the treated and control areas.

Table 1.2: Impact of SO_2 emissions on local housing markets

	0.3	0.6	0.9	1.2	1.5	1.8	2.1	2.4	2.7
emissions × near	-0.0260***	-0.0112***	-0.0050	-0.0034	-0.0040	-0.0049**	-0.0048***	-0.0042**	-0.0030
	(0.0080)	(0.0038)	(0.0030)	(0.0028)	(0.0025)	(0.0020)	(0.0017)	(0.0019)	(0.0019)
Observations	5164	7056	8035	8558	8871	9124	9320	9452	9563
Number of Facilities	375	393	411	416	417	420	422	422	425
Number of Years	15	15	15	15	15	15	15	15	15
Number of States	25	25	25	25	25	25	25	25	25
Mean Sale Amount (in 2005)	199248	191346	187002	180850	178029	177668	179218	176460	175727

Notes: The table displays results from ten separate regressions. The estimated parameter of interest is β_2 in equation 1.3. It captures the difference in the evolution of housing prices at housing units located in the immediate vicinity of a plant and exposed to its pollution and housing units located slightly further away. Each column corresponds to a regression in which the treatment group is composed of housing units located within distance d of a power plant, and the control group includes all housing units located in an adjacent ring within d and $d + 0.3$miles of a power plant. Distances d are given in miles on the header of each column. All regressions include power plant fixed effects, state-specific time trends, as well as time-varying controls of local demographics recovered from block-group level data from the ACS and summarized over circles of interest.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.8 Conclusion

This paper quantitatively investigates factors that led to the unprecedented reductions in air pollutants emissions from the electricity generation sector in the eastern US between 2005 and 2014. Using a micro-level dataset on the operations and costs of power plants compiled from various sources, the study proceeds to a statistical decomposition of the emissions at the plant level. The results reveal that investments in capital-intensive abatement technologies accounted for over 50% of the emission reductions achieved during that period, and followed the adoption of some of the most stringent emissions markets to date. Particularly high numbers of these retrofits were performed on coal units that were still far from retirement age and could not switch to cleaner coal. Through calculations using micro-level data on plant expenditures, the analysis finds that the costs incurred due to the adoption of these capital-intensive emission controls amounted to an unprecedented $45 billion between 2005 and 2014, corresponding to a few percentage points of utilities' revenues.

This paper then compares those costs with the benefits accrued to human health. Using continuous measures of local air pollution derived from satellite imagery, a calculation reveals that 19,000 premature infant deaths were avoided during the period considered thanks to the achieved emission reductions. Using a conservative statistical value of life, saving these lives amounted to health benefits of \$152 billion. Although these health impacts constitute a crude lower-bound estimate of the obtained benefits, they outweigh the costs incurred by the industry. Finally, this paper estimates the demand for clean air around power plants using hedonic methods. The sharp decreases in emissions following the adoption of abatement technologies provides a unique setting with which to estimate the impacts of air pollution on local housing markets. Using micro-level data on housing transactions matched to power plants, this paper concludes that emission reductions caused local housing markets to appreciate by \$8 billion.

This paper opens several avenues for future research. First, estimating the direct impacts of air pollution on health would be useful for informing the benefit calculations of this study. The sharp decreases in emissions documented in this paper constitute a unique setting with which to identify the impacts of air pollution on local health outcomes. Indeed, the adoption of abatement technologies at the plant level led to sharp decreases in emissions that were likely uncorrelated with other changes in the local economy. Second, the large costs incurred by power plants due to the adoption of abatement technologies are an interesting topic to investigate further. In deregulated electricity markets where prices reflect the equilibrium between the local supply and demand for electricity, the adoption of capital-intensive abatement technologies could impact mark-ups. Hence, it will be useful to study the effects that these large investments had on the local competition for electricity generation, as only dirty coal units had to install abatement technologies. Finally, more formal work could be conducted on the impacts of air pollution on housing markets. This paper offers estimates of the demand for clean air as captured by changes in local housing values resulting from sharp decreases in power plant emissions that are likely invisible to residents. It would be useful to investigate how the responses of local housing markets differ with the amount of information available on the local air quality.

More broadly, future research could focus on the urban economics of power generation as it relates to local disamenities such as air pollution. Understanding how history, regulations, recent electricity market deregulations and changes in electricity production and distribution technologies are shaping local plant profits and their location choices represents a fruitful area of research.

Chapter 2

The Environmental and Distributional Consequences of Emissions Markets

Evidence from the Clean Air Interstate Rule[1]

with Elisabeth T. Isaksen

Abstract Who benefits from emissions markets? We investigate this question by examining cap-and-trade programs to mitigate SO_2 and NO_x from US power plants. Using double and triple differences, we find that these programs lowered emissions on average, but reductions were smaller at plants located in disadvantaged communities. Emissions reductions in these areas were primarily due to shutdowns of dirty units, while plants in higher income neighborhoods lowered emission intensity. Policy-induced emissions reductions capitalized into home values and led to sorting of poorer households out of cleaned areas. Our findings suggest that benefits from emissions markets are unevenly distributed across socioeconomic groups.

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2.1 Introduction

Over the past three decades, environmental policies have played a significant role in reducing air pollution in the United States (Auffhammer et al., 2009; Shapiro and Walker, 2018). Health benefits associated with air quality improvements are substantial (Currie and Neidell, 2005; Schlenker and Walker, 2015; Deschênes et al., 2017). However, whether these benefits are evenly distributed across socioeconomic groups is still subject to disagreements (Fowlie et al., 2012; Bento, 2013; Grainger and Ruangmas, 2017; Hsiang et al., 2019). Such debates have been particularly pronounced on cap-and-trade markets, which are commonly used to regulate emissions of air pollutants in the United States.[2] Under a cap-and-trade system, locations of emissions reductions are determined by firms' decisions to reduce emissions or buy allowances to comply with the policy. As non-uniformly mixed air pollutants, like sulfur dioxide (SO_2) and nitrogen oxides (NO_x), have local impacts, the benefits of emissions reductions are linked to plants' locations. By letting firms trade emissions rights, skeptics fear that disadvantaged communities will experience smaller reductions in local air pollution. This could be the case if marginal abatement costs are systematically higher for plants located in low-income neighborhoods, or if local pressure to reduce emissions is stronger in more affluent communities.

The main goal of this paper is to investigate the distributional profile of emissions reductions induced by cap-and-trade programs. Concretely, we want to test if plants' compliance mechanisms and emissions reductions vary with the socioeconomic characteristics of their surrounding neighborhood, and if lower emissions affect home values and neighborhoods'

[2] Under a cap-and-trade system, the legislator decides on a cap on aggregate emissions and initial allocations of pollution rights, and allows emitters to trade allowances on a market. The core idea of the policy is to exploit heterogeneity in marginal abatement costs across firms. Trading will enable polluters with low marginal abatement costs to reduce emissions beyond their allocated pollution rights, and sell unused permits to emitters with higher marginal costs of abatement, for which it is cost-effective to buy additional allowances to offset emissions (Coase, 1960). While a cap-and-trade system with a single market price will (in theory) equalize the marginal abatement costs across firms, hence ensuring cost-efficient reductions, it may not yield an efficient outcome if the marginal damage of pollution varies across locations (Fowlie and Muller, 2013).

composition. We examine these issues in light of the Clean Air Interstate Rule. The Rule instituted three cap-and-trade programs targeting fossil fuel-fired power plants in 27 US states: an annual program for SO_2 emissions, an annual program for NO_x emissions, and a summertime program for NO_x emissions. The programs were adopted in 2005 and operative from 2008 to 2014.

We start by examining the average effect of the Clean Air Interstate Rule on SO_2 and NO_x emissions. To identify the causal effects of the Rule, we employ a difference-in-differences (DiD) approach, where we compare changes in emissions for plants targeted by the Rule to plants not covered. Causal interpretation relies on the assumption of parallel trends in the absence of treatment - an assumption we carefully discuss in the analysis. For NO_x emissions, we exploit the fact that the annual program should only affect wintertime emissions.[3] This allows us to estimate a triple difference (DiDiD), which relies on weaker assumptions than a traditional DiD.

Second, we examine how policy-induced emission changes vary with neighborhoods' socioeconomic characteristics.[4] Did wealthier neighborhoods experience more substantial reductions in emissions under the cap-and-trade programs? If so, what mechanisms could lead to such a result? In particular, are there systematic patterns as to *how* plants achieve emissions reductions (e.g., by installing technology, switching to cleaner fuels or by scaling down production)? To explore these issues, we pair data on emissions, plant characteristics, and air pollution from the US Environmental Protection Agency with socioeconomic, neighborhood-level data from the US Census, and data on fuel delivery from the US Energy Information Administration.

[3] As the summertime cap-and-trade program under the Clean Interstate Rule replaced the former NO_x Budget Trading Program, the new annual NO_x program should only have an effect on wintertime emissions.

[4] Throughout the paper, a neighborhood corresponds to the area within a 1-mile radius circle of a power plant. We also conduct robustness checks with 0.5, 2 and 3-mile radii circles. Within these distances, power plants can be visible, which implies that residents might more easily detect changes to a plant's emissions. The pungent smell of sulfur dioxide will also primarily affect households near the plant. Furthermore, previous studies find that power plant openings affect house values and rents only within a 4-mile radius (Davis, 2010), while toxic plant openings affect house values only within a 0.5-mile radius (Currie et al., 2015).

Lastly, we use the policy as a quasi-natural experiment to estimate the impacts of emissions reductions on property values and neighborhood composition. This contributes to our understanding of distributional effects in two ways. First, if pollution reductions are capitalized into home values, the Rule will generate economic gains locally. The size of these gains will depend on the magnitude of emissions reductions, the responsiveness of house values to lower emissions, and the rate of home-ownership. Second, higher house prices might, in turn, lead to a sorting of poorer households out of cleaned areas, hence influencing who ultimately enjoys cleaner air. To examine these effects, we exploit that gas power plants experienced no significant reductions in emissions under the Rule. By comparing neighborhoods surrounding gas plants to neighborhoods surrounding coal or oil power plants before and after the policy implementation, and controlling for state-specific time trends, we estimate a reduced form effect of the Rule on house values and demographics. Furthermore, we estimate a direct effect of emissions on the same outcome variables by using $coal \times post$ as an instrument for changes in SO_2 and NO_x emissions. To our knowledge, this is one of only a few studies to empirically estimate the distribution of benefits under cap-and-trade programs, and to investigate mechanisms leading to such patterns.

Why would emissions reductions under a cap-and-trade system differ across neighborhoods? One potential explanation is that plants located in more impoverished neighborhoods might have higher marginal abatement costs relative to those located in wealthier neighborhoods. Under cap-and-trade markets, plants are free to choose which compliance mechanism to adopt: they can lower production, invest in capital-intensive abatement technology, switch to cleaner fuels, or buy allowances. Plants with higher marginal costs of abatement may find it cheaper to buy emissions permits, resulting in small or no reductions in emissions.[5] Characteristics of their immediate neighborhood could also influence the compliance mechanisms that plants choose. Households living near power plants are likely to favor emissions reduc-

[5]While plants' marginal cost of abatement cannot be observed directly, we use a variety of technical characteristics of power plants to proxy for them in the analysis.

tions over permits, in particular if reductions can be achieved without lowering electricity production. As environmental awareness and vocal opposition tend to be more widespread in affluent communities , a plant's choice of compliance mechanism might hence be influenced by the type of residents living in nearby areas.[6] A stronger community push-back could, in this way, serve as an added cost to buying permits.

Results from the empirical analysis suggest that the cap-and-trade programs implemented under the Clean Air Interstate Rule led to significant reductions in SO_2 and NO_x emissions. On average, emissions from operative coal power plants covered by the Rule decreased by 22–29% over the period, compared to the control group. We find that policy-induced reductions of SO_2 emissions were significantly smaller for power plants located in neighborhoods with an initial high share of low-income, poorly educated and minority households. Estimates of emissions reductions range from 0% for destitute neighborhoods to over 60% for the top-income neighborhoods. There is a similar but weaker pattern for NO_x emissions.

After investigating compliance mechanisms, we find that more substantial emissions reductions in high-income areas were primarily achieved through lowering emission intensity rather than making cuts to production.[7] The lower intensity was partly achieved by adopting capital-intensive abatement technology, like scrubbers, and not by switching to cleaner fuels. In an extended analysis, we expand the sample by including power plants that opened up or shut down during the treatment period. Using a linear probability model, we find that plants located in low-income neighborhoods are more likely to shut down in response to the policy. If we bring these plants into the main analysis, by imputing zeros after shutdown, the systematic pattern of lower emissions reductions in low-income neighborhoods persists but is weaker. This suggests that plants located in low-income and high-income neighborhoods

[6] A positive correlation between environmental awareness and income could have several explanations. If environmental quality is a normal good, the willingness to pay for clean air will increase with income. Furthermore, income is typically positively correlated with educational attainment, and better-educated individuals might be better informed about environmental risks. In the analysis, we examine heterogeneous effects along both the income and education dimension.

[7] Emission intensity is defined as emissions in ton per GWh electricity produced by the plant.

are complying with the policy in different ways; plants located in deprived areas either do not reduce emissions or decide to shut down, while plants located in high-income neighborhoods lower their emissions intensity. While both compliance choices reduce emissions, the latter is less likely to be accompanied by job losses, and hence could be more attractive to residents.

What can explain this observed heterogeneity in emissions reductions? In particular, why would low-income neighborhoods experience smaller reductions? Controlling for initial plant characteristics such as average electricity production, age of the plant, emissions intensity, technology stock, and fuel type (coal or oil) have minor effects on the heterogeneity of the estimates.[8] This suggests that observable, pre-existing differences in plant characteristics do not fully explain the different pattern of emissions reductions.

Lastly, we examine how the socioeconomic composition and housing market of power plants' neighborhoods evolve in response to the CAIR. We find that areas around coal and oil power plants, which experienced substantial emissions reductions under the CAIR, also experienced an increase in home values, median income, and college attainment, as well as a decrease in the poverty rate. The demographic change and rise in home values are more substantial in high-income neighborhoods than in low-income neighborhoods. For the top-income neighborhoods, home values increased by 4-5%, while there was no significant effect for the most impoverished neighborhoods. This implies that the policy translated into economic benefits through the housing market and that these benefits were unequally distributed across low- and high-income neighborhoods. The higher home values point to taste-based sorting as an explanation for the demographic changes. Lastly, by using the higher treatment intensity for coal plants (compared to gas plants) as an instrument for plant-level emission changes, we find that a 1% decrease in SO_2 emissions led to a 0.07% increase in home val-

[8]We control for plant characteristics by including interaction terms between the policy variable and the level of the plant characteristics prior to policy implementation. To see if the heterogeneous effects reflect cross-regional variation, we also run six separate regressions where we restrict the sample to different geographical regions. The regressions reveal a clear pattern of heterogeneous effects in the North-East, East, and South-East, with a more significant treatment effect for high-income neighborhoods. The average treatment effects for the Mid-West and Texas are small and insignificant, with no apparent heterogeneous pattern.

ues.[9] Overall, our findings suggest that environmental and economic benefits induced by the Clean Air Interstate Rule were unevenly distributed across socioeconomic groups.

There exist few empirical studies on how emissions reductions under cap-and-trade programs are distributed across neighborhoods. An exception is Fowlie et al. (2012). Looking at the Southern California's NO_x Trading Program (RECLAIM), which targeted NO_x emissions from manufacturing industries, the authors find no systematic pattern in emissions reductions along with the socioeconomic characteristics of firms' neighborhoods. Grainger and Ruangmas (2017) revisit the study by Fowlie et al. (2012) using a dispersion model to determine affected areas, and find that higher income areas experienced more substantial reductions in NO_x concentration under the policy.[10] The distributional profile of emissions markets is hence disputed, and one goal of this paper is to resolve some of this ambiguity. We do so by improving on the existing literature in several ways. First, we study a policy that comprised half of the US states and two different pollutants. The larger geographical scope may leave more room for heterogeneity in emissions reductions while examining both NO_x and SO_2 reveals a stronger heterogeneous pattern for SO_2 emissions.[11] Second, focusing on power plants rather than manufacturing industries enhances comparability between the treatment and control group.[12] In particular, we avoid problems of industry-specific shocks confounding the treatment. For NO_x, we also show that a DiDiD strategy renders similar results as the DiD, strengthening the credibility of our result. Third, and importantly, we expand on the previous literature in several ways. By examining compliance choices of plants, and

[9]The instrumental variable estimate for NO_x emissions is of a similar magnitude (0.06%).

[10]Although more distant, our study is also related to Ringquist (2011). Examining the Acid Rain Program, he finds that plants in neighborhoods with a high share of Blacks and Hispanics were less likely to buy additional SO_2 allowances, while plants in poorly educated neighborhoods were more likely to buy additional allowances. While he compares emissions relative to an assigned cap, we look at the development in SO_2 and NO_x emissions for a treatment group compared to a control group.

[11]We discuss potential explanations for this differential effect, including the role of smell externalities and overlapping regulations.

[12]This is corroborated by the estimated parallel trend in NO_x and SO_2 emissions for the two groups prior to the policy implementation. Focusing on the power sector also allows us to compare detailed plant characteristics between the treatment and control group.

how these vary across neighborhoods, we generate novel insights on how plants respond to market-based policies. In contrast to previous studies, we also account for shutdown as a compliance mechanism. Overlooking this option will give an incomplete picture of the effects of cap-and-trade markets on emissions. Furthermore, we empirically explore potential explanations for *why* emissions reductions might be larger in higher income neighborhoods. Lastly, we show that the heterogeneous pattern of emissions reductions manifest itself in changing house values and demographics.

Our paper also contributes to the broader empirical literature on the distribution of environmental benefits.[13] Recent studies look at emission changes caused by stricter air quality standards (Grainger, 2012; Bento et al., 2015), shutdown and opening of plants (Currie et al., 2015), and an electricity crisis (Sullivan, 2016b). Emission changes in these settings might differ from those induced by a market-based policy. In particular, Bento et al. (2015) find that stricter air quality standards led US policymakers to target emissions sources in the dirtiest areas, which tended to benefit low-income households as these disproportionately reside in these areas. Mechanisms under cap-and-trade are likely to be different.[14] Furthermore, our identification strategy avoids some of the problems associated with commonly used methods in the air pollution literature, such as using bordering areas as controls in a geographic DiD design, and using interpolations of pollution monitor data.[15] As pointed out by Sullivan (2016b), sharp changes in pollution dispersion can lead to contamination of the control group, as well as inaccurate measures of pollution exposure. We mitigate such problems

[13] See Bento (2013) and Hsiang et al. (2019) for recent literature reviews.

[14] Grainger (2012) examine the effects of lower air pollution induced by stricter air quality standards on housing values and rents. He finds that while the pass-through to rents is incomplete, landowners still capture much of the value of the air quality regulations. Currie et al. (2015) investigate the effects of toxic emissions from industrial plants in the US on housing values and birth weight. While the authors find some evidence of a larger decline in house prices in lower-income communities, they find no strong heterogeneous pattern in the estimated health effects. Sullivan (2016b) uses data from a pollution dispersion model to examine changes in rents and neighborhood demographics caused by the California Electricity Crisis of 2000 and finds that higher-income households gained the most.

[15] See e.g., Currie and Walker (2011) and Currie et al. (2015).

by (i) using plant-level emissions and focusing on the immediate vicinity of plants, and (ii) comparing outcomes around coal power plants to those around gas power plants.[16] Lastly, by exploiting emissions reductions caused by lower emissions intensities at operative plants rather than those caused by shutdowns, we mitigate problems of air quality improvements being confounded by labor market effects and changes to visual amenities.[17]

The rest of the paper is structured as follows. Section 2.2 presents a simple model for plants' decision to abate or buy allowances. Section 2.3 introduces the policy. Section 2.4 describes the data used in the analyis. Section 2.5 establishes the causal link of the markets on emissions. Section 2.6 presents results on the distribution of emission reductions across neighborhoods. Section 2.7 investigates the sorting of households in response to emission reductions. Section 2.8 concludes.

2.2 Conceptual framework

We present a simple modeling framework to guide the empirical analysis and discussion. The model defines compliance choices available to plants and identifies factors that can lead to heterogeneous reductions in emissions across low- and high-income neighborhoods.

[16]By using an IV-DID design, we also mitigate potential attenuation bias caused by measurement error in exposure to pollution.

[17]Our study also relates to the literature on cap-and-trade and local marginal damages (Muller and Mendelsohn, 2009; Chan et al., 2015). Studies in this literature typically rely on structural models; by contrast, we use a reduced-form approach. We also focus on the distributional profile of emissions reductions, while the mentioned studies focus on the spatial variation in reductions and consequences for efficiency. Two recent working papers on cap-and-trade and health outcomes are also relevant to our paper. Barreca et al. (2017) exploit changes in long-term exposure induced by the Acid Rain Program, and compare changes in mortality over time in counties near regulated plants (within 100 miles) to changes in mortality in similar counties far from the plants. **?** looks at changes in $PM_{2.5}$ induced by the CAIR and effects on county-level infant mortality rates. In contrast to these studies, we look at spatially refined effects on home values and demographics, and how these effects vary across neighborhoods.

2.2.1 A simple model of a cap-and-trade market

Assume that power plants operate in perfectly competitive input and output markets. Assume further that plants' emissions are regulated under a cap-and-trade program and that each power plant chooses the compliance mechanism that minimizes the present value of costs.[18] Following Stavins (1995), we let u_{it} denote a power plant's unconstrained (or status quo) emissions, $q_{it} \geq 0$ denote a plant's abatement, and A_i denote initial allowances allocated to plant i.[19] To remain in compliance with the policy, a plant must hold enough allowances to offset its own emissions, $u_{it} - q_{it}$. Assume that allowances are tradable and that plants take the market-clearing allowance price, p_t, as given. A plant can then remain in compliance by (i) lowering emissions (i.e., increase q_{it}), (ii) buying additional allowances, (iii) or shutting down.

To reduce emissions (i.e., increase abatement q_{it}), plant i can lower its electricity production, or lower the emissions content of the electricity production by installing abatement technology, or by switching to cleaner inputs. Assume that a plant's cost of abating at time t, c_{it}, depends on both the level of abatement, q_{it}, and its operating characteristics, θ_i: $c_{it}(q_{it}, \theta_i)$.[20] θ_i can be interpreted as a vector of technical characteristics.[21]

Lastly, assume that power plants may face non-technical, location-specific costs that are not captured by $c_{it}(q_{it}, \theta_i)$. Such costs could take the form of community pressure exerted on power plants to lower their emissions, either directly or through local political channels.

[18] By assuming perfect competition, plants will be price takers and minimizing costs will be equivalent to maximizing profits.

[19] We assume that allowances are distributed gratis at the beginning of the program.

[20] We assume that the cost function is continuous and twice differentiable, where partial derivatives with respect to q satisfy $c'_q > 0$ and $c''_q > 0$.

[21] For simplicity, we disregard subscript t in the model. Note, however, that a plant might influence θ_i by, e.g., installing new technology or switching fuel, which would change the profile of the abatement cost function for any given level of abatement. Additionally, installing technology or switching to cleaner input have a fixed cost at the time of the upgrade (e.g., the cost of buying the scrubbers or the cost of searching and switching to other input sellers), as well as a variable cost (e.g., cost of operations in the case of scrubbers and of buying cleaner fuel). For simplicity, we consider that θ_i incorporates the fixed costs and the present value of future variable costs.

Suppose that such costs depend on both the emission level of the plant, $u_{it} - q_{it}$, and the demographic characteristics of neighborhood l, X_{il}: $s_{il}(u_{it} - q_{it}, X_{il})$.

A plant's cost minimization problem can then be expressed as:

$$C_i = \min_{\{q_{it}\},\theta_i} \quad \sum_{t=0}^{T_{ir}} \frac{1}{(1+r)^t}\Big(c_{it}(q_{it},\theta_i) + p_t(u_{it} - q_{it} - A_i) + s_{il}(u_{it} - q_{it}, X_{il})\Big) \qquad (2.1)$$

where r is the discount rate, T_{ir} is the retirement date of plant i, and $(u_{it} - q_{it} - A_i)$ is the quantity of allowances traded. For a given period t, retirement date, T_{ir}, and plant characteristics, θ_i, the problem yields the following first-order condition:

$$c_i'(q_{it},\theta_i) = p + s_{il}'(u_{it} - q_{it}, X_{il}), \qquad (2.2)$$

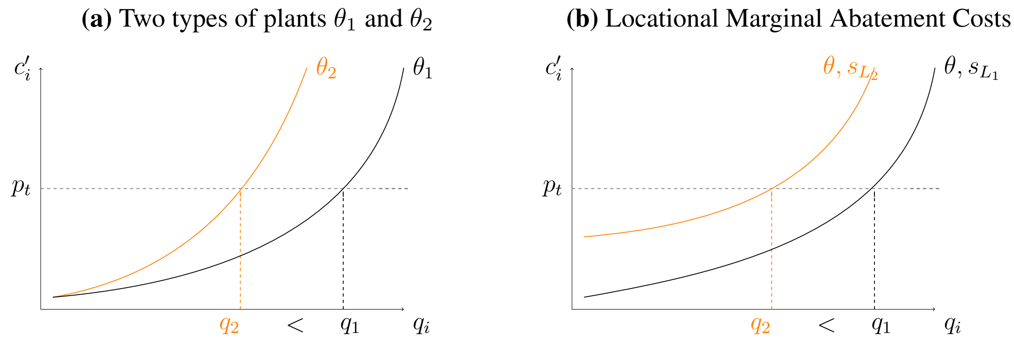
where s_{il}' is the neighborhood-specific marginal cost. If a plant's marginal abatement cost in period t is less than the sum of the allowance price and the neighborhood-specific marginal cost, $c_i' < p + s_{il}'$, the plant will choose to reduce own emissions over buying allowances, and vice versa. s_{il}' could then be interpreted as an additional, plant-specific cost to buying allowances.

2.2.2 Factors that could lead to uneven reductions across neighborhoods

Equation 2.2 identifies two primary factors that can lead to uneven reductions in emissions across neighborhoods: the technical marginal abatement cost, $c_i'(q_{it},\theta_i)$, and the neighborhood-specific marginal cost, $s_{il}'(u_{it} - q_{it}, X_{il})$.

Technical abatement costs: If $c_i'(q_{it},\theta_i)$ is systematically higher for plants located in lower-income neighborhoods, it will lead to less abatement at these plants. This case is illustrated in

Figure 2.1: Technical and locational marginal costs of abatement



Notes: In both panels, the marginal cost of abatement (c_i') is drawn against abatement quantities (q_i). Figure (a) illustrates the market equilibrium in the case of two different plants of types θ_1 and θ_2. In equilibrium, the price of permits (p_t) equates the marginal costs of both plants. Plant θ_2, which displays a steeper marginal cost curve, achieves a smaller abatement $q_{2,t}$ than plant θ_1. Figure (b) displays the equilibrium in the case of two identical plants of type θ located in neighborhoods L_1 and L_2, which are subject to different locational costs on emissions (s_{L1} and s_{L2}). The plant located in the neighborhood with the most stringent constraint (s_{L1}) on emissions abate more than the identical plant located in a less stringent location (s_{L2}).

panel (a) in Figure 2.1.[22] As the geographic distribution of socioeconomic groups is not random, we might expect systematic differences in both plant characteristics and initial emission levels across neighborhoods. In particular, previous studies have found that disadvantaged groups tend to scatter around dirtier emissions sources (Hanlon, 2014). If dirtier plants are, e.g., older and harder to retrofit, such historical sorting might lead to less abatement at plants in lower income areas.[23]

Neighborhood-specific costs: If the location-specific marginal cost of emissions, s_{il}', is larger for power plants in more affluent neighborhoods, it would lead to a larger abatement in these areas. This case is illustrated in panel (b) in Figure 2.1. As discussed in Section 2.6, community push-back and reputation costs might be more substantial for power plants located in wealthier, more educated neighborhoods as residents may be more aware of environmental risks, as well as better equipped to put pressure on plants.

[22]Differences in $c_i'(q_{it}, \theta_i)$ could be due to differences in initial abatement levels and/or differences in plant characteristics, θ_i, such as age, size, fuel mix, and installed abatement technologies.

[23]Note that the opposite could also be true: plants with high initial emissions levels and old technology might have a larger potential for emissions reductions.

Other costs and constraints: Beyond the costs describe above, there might be other types of constraints and costs that vary with the socioeconomic profile of neighborhoods, and that influence the compliance mechanism of plants. First, if plants in low-income neighborhoods face binding financial constraints, this might make it harder to make significant upfront investments in abatement technology (Levine et al., 2018). Second, previous studies have found that deregulated plants are less likely to invest in capital-intensive SO_2 abatement technologies compared to publicly-owned plants (Fowlie, 2010; Cicala, 2015). If ownership correlate with income, it might lead to systematically different emissions reductions.[24]

2.3 The Clean Air Interstate Rule

In March 2005, the US Environmental Protection Agency (EPA) adopted the Clean Air Interstate Rule (CAIR) to reduce emissions of SO_2 and NO_x from power plants in 27 US states and the District of Columbia. The CAIR introduced three separate interstate cap-and-trade markets targeting fossil fuel power plants: a SO_2 annual trading program, a NO_x annual trading program, and a NO_x ozone season trading program imposing a cap on summertime emissions of NO_x.[25] Figure A.1 gives an overview of the states and power plants covered by the new cap-and-trade programs.

2.3.1 The SO_2 annual trading program

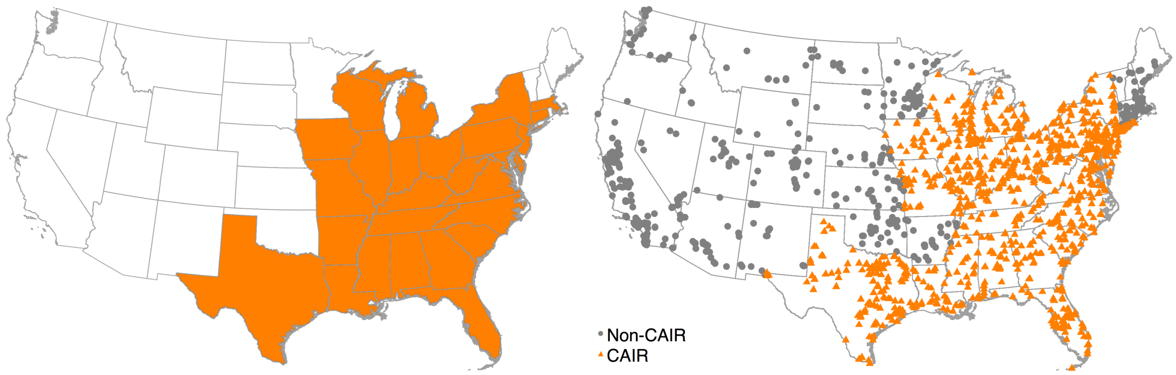
Sulfur dioxide (SO_2) contributes to poor ambient air quality and is one of the six criteria pollutants regulated by the EPA. SO_2 has a pungent smell similar to rotten eggs and irritates nose and lungs. It is also a precursor for the formation of particulate matter, which can lead to increased respiratory symptoms, irregular heartbeats, and premature mortality (EPA,

[24]There might also be differences in access to skilled labor to install and operate the technology.

[25]The programs were meant to complement an existing federal policy regulating emissions from power plants (the Acid Rain Program), and replace and expand a former regional program (the NO_x Budget Trading Program). See Figure B.1 for more details.

Figure 2.2: States and facilities targeted by the CAIR

(a) States **(b)** Facilities



Notes: The figure displays states (left map) and power plants (right map) that are part of the CAIR. Orange triangles represent facilities that are part of the annual cap-and-trade programs for SO_2 and NO_x introduced by the CAIR.

2013). Fossil fuel-fired power plants are the primary source of SO_2 emissions in the US (EPA, 2005), and emissions from these plants are covered by the Acid Rain Program - a federal cap-and-trade program established in the 1990s. In the early 2000s, the EPA intended to lower the cap for the Acid Rain Program but failed to secure Congress' approval. Without such approval, the EPA could not act at the federal level.[26] Instead, the EPA used the Clean Air Act's "good neighbor" provision[27] and created an additional annual cap-and-trade market to lower emissions from 24 eastern states and the District of Columbia, where pollution was most severe. The SO_2 market was one of three programs implemented under the Clean Air Interstate Rule and imposed a cap intended to reduce emissions by 70% from 2003 levels. The program operated from 2009 to 2014, with 2009 as a training year.[28]

The initial allocation of SO_2 allowances under the CAIR was calculated with a close link to the Acid Rain Program. Each CAIR state was allocated a CAIR SO_2 budget by taking the sum of the Acid Rain Program allowances initially assigned to that state, adding any

[26]In 2002, the Bush administration proposed the Clear Skies Act to tighten the SO_2 cap of the Acid Rain Program, but then abandoned the project in 2005 (Schmalensee and Stavins, 2013).

[27]The "good neighbor" provision requires the EPA and states to address interstate transport of air pollution which affects states' air quality downwind of emissions sources.

[28]During the training year, units were required to monitor and report their emissions but were not required to hold allowances for compliance.

additional special reserve allowances specified under the CAIR, and dividing this total by 2. Essentially, the new rule required a two-to-one exchange of Acid Rain Program SO_2 allowances to CAIR SO_2 allowances (EPA, 2013). Facilities covered by the CAIR were only allowed to buy permits from other CAIR facilities in complying with the stricter regulation. To encourage early reductions, the EPA allowed power plants to use Acid Rain Program permits of vintage years preceding 2010 with a one-to-one ratio to comply with the CAIR.[29] This phased approach created strong incentives for early reductions in SO_2 emissions, as banked allowances of the pre-2010 vintage were expected to have a higher market value than 2010-2014 vintage allowances. This was reflected by the unprecedented spike in the price of ARP allowances, in 2005, at the adoption of the CAIR (see Figure A.12). Given the stringency of the CAIR, plants expected future spikes in the price of SO_2 allowances and sought to bank allowances from the ARP and sell them under the CAIR. The large spike in the price of SO_2 allowances created an incentive for early reductions in emissions as soon as the CAIR was adopted in 2005.[30]

2.3.2 The NO_x annual and seasonal trading programs

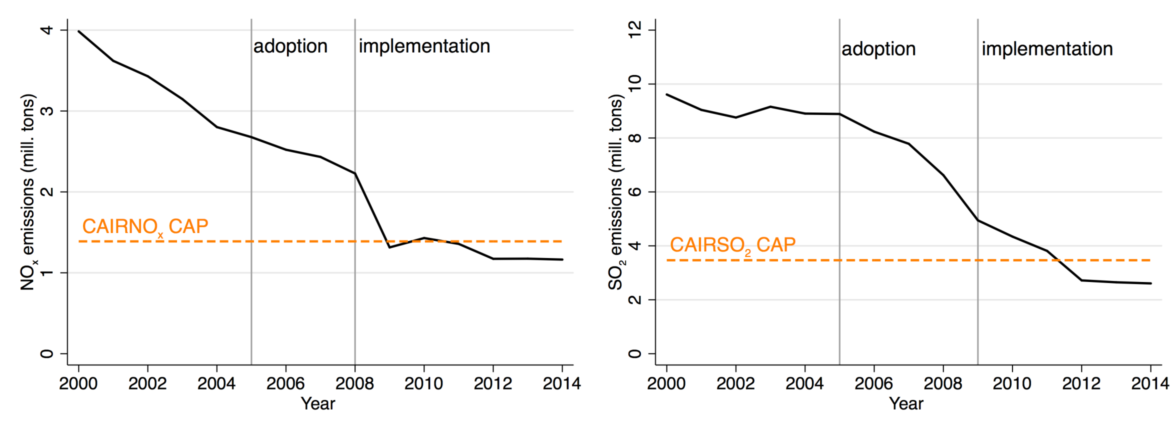
Nitrogen oxides (NO_x) are odorless and colorless gases that have significant impacts on air quality and human health. NO_x is a precursor for ground-level ozone (O_3) and particulate matter (mainly PM_{10}), which have adverse impacts on health. As a consequence, NO_x is a criteria pollutant for the EPA. From 2003 to 2009, the NO_x Budget Trading Program (NBP) applied a summertime (May-September) cap-and-trade program for NO_x emissions from fossil fuel-fired power plants in 20 North-eastern states. The Clean Air Interstate Rule replaced

[29]The vintage year of an allowance indicates the earliest year for which it can be used to comply with the emission cap. An allowance of the vintage year 2010 can be used to comply with the 2010 cap on emissions or banked and used to comply with caps in a later year.

[30]Prior to implementation, the EPA projected that plants covered by the CAIR would significantly reduce SO_2 emissions in the years before 2010 (Fraas and Richardson, 2010). This would allow power plants to carry unused allowances from the Acid Rain Program into the CAIR SO_2 cap-and-trade program.

Figure 2.3: Total SO_2 and NO_x power plant emissions and CAIR caps

(a) NO_x emissions (annual) **(b)** SO_2 emissions



Notes: Graphs show total emissions of SO_2 and NO_x from power plants targeted by the CAIR (solid black lines), as well as aggregate emission caps (brown dashed lines). Vertical lines indicate the year the CAIR policy was adopted (2005), and implemented (2008 for NO_x, 2009 for SO_2).

and expanded this former program by introducing two new cap-and-trade markets. The first market replaced the old summertime market and expanded its geographic scope from 20 to 25 states. The second market instituted a cap on annual emissions of NO_x in 25 states. Initial allowances of NO_x under the new programs were allocated to each state based on the heat input of the state's power plants in 2005.[31] While the SO_2 market under the CAIR came on top of a federal cap-and-trade market, the two emissions markets for NO_x came on top of a federal rate-based policy.[32]

Figure 2.3 depicts aggregate SO_2 and NO_x emissions from CAIR units between 2000 and 2014, as well as overall emissions caps. While NO_x emissions were below the cap by 2009, SO_2 emissions were below the cap by 2012.[33]

[31] Specifically, each state's budget was calculated by summing the heat input of each source, adjusted by a fuel factor. The adjusted heat input was calculated by taking the average heat input multiplied by a fuel adjustment factor, where the factors for coal, gas, and oil were the following: coal:1.0, gas:0.4, oil:0.6.

[32] The Acid Rain Program imposed boiler-specific NO_x emissions rates uniformly across the country, with penalties to power plants exceeding the rates. See Appendix B.1 for more details.

[33] The use of banked Acid Rain Program allowances from the pre-2010 period made it possible for SO_2 emissions under the CAIR to exceed the caps set in the years 2010-2014. For NO_x, the total emissions in the period 2009-2014 could not exceed the overall cap for the period.

2.3.3 Legal challenges and replacement policy

As is common for EPA rules, the CAIR was challenged in court as soon as it was adopted. States and industry representatives challenged the EPA on the grounds that it did not have the authority to regulate interstate matters. This created uncertainties regarding the implementation of the CAIR. In 2008, the Supreme Court vacated the CAIR, ruling that only Congress could impose interstate emission markets in which power plants from different states could trade. Most importantly, however, the Supreme Court did not question the stringency of the policy and did not prohibit its implementation. Instead, it allowed the EPA to implement the CAIR and mandated that it revise the policy, the goal of which was to replace the interstate trading scheme with state-specific policies that would achieve the same cap. In these markets, power plants would only be allowed to trade allowances with plants within the same state.

In 2011, the EPA announced the set of policies that would replace the CAIR from 2014 onward: the Cross-State Air Pollution Rule. This new rule imposed state-specific cap-and-trade markets for summertime NO_x emissions, annual NO_x emissions and annual SO_2 emissions. More importantly, the stringency of these rules was unchanged from the CAIR. If anything, it became more apparent to the industry that emissions would become more costly. Accordingly, the prices in the newly created markets rose.

2.4 Data

2.4.1 Data sources

Emissions data: We collected monthly data on SO_2 and NO_x emissions from the EPA's Air Markets Program Database.[34] The database contains observations at the electricity-generating unit level for facilities that are part of major emissions trading programs, like the Acid Rain program, the NO_x Budget Trading program, or the CAIR. The majority of

[34] See Appendix B.2 for a complete description of data sources used.

emissions are monitored using a continuous emissions monitoring system at the stack outlet: this implies that the data is of particularly high quality. From the same database, we also collect unit-specific data on electricity generation, fuel input types, technology adoption, startup and shutdown dates, and location coordinates.[35]

Demographics data: Demographic variables come from the 2009 and 2014 American Community Survey (ACS). The survey datasets are available as 5-year averages (2005-2009 and 2010-2014) at the block group level[36] and include different measures of income, education, population, and race. Based on the Survey data, we constructed different variables that capture the distribution of households' income level (median income, the share of households below the poverty line, the share of households with income above $100 000), the education level, as well as a measure of share of black and Hispanic residents. To obtain demographics for areas surrounding power plants, we constructed circles of differing radii (0.5, 1, 2, and 3 miles) around each power plant. For each circle, we identified the block groups that intersect with the circle. We then calculated population-weighted averages of each demographic variable, using intersections between block groups and the circle to compute weights.[37]

Other variables: We assembled a dataset of monthly coal and gas deliveries to fossil-fueled power plants in the US from the Energy Information Agency (EIA). The data contains information on the energy source, the quantity of fuel delivered, Btu content, sulfur content

[35]We use emissions data from power plants because the CAIR regulated *emissions*. As the dispersion of emissions depends on prevailing winds and topology, locations that experience emissions reductions do not necessarily fully correspond to locations that benefit from policy-induced *air pollution* reductions. To fully evaluate which populations experienced improved air quality as a result of plant-level emission reductions, a more geographically-refined measure of local air pollution would be needed.

[36]A block group is the smallest unit for which data is available and typically contains between 600 to 3000 people. There are around 200 000 block groups in the US

[37]The procedure is illustrated in Appendix Figure B.6. A similar procedure has been used in recent papers (Fowlie et al., 2012; Currie et al., 2015).

and ash content.[38] We use measures of heat derived from daily measures of minimum and maximum temperatures on a 2.5 by 2.5 mile grid.[39] Temperature data are aggregated at the plant level using spatial averages on a 100-km radius around each power plant. We also collected data on time-varying state-level real GDP from the EIA. To capture ambient air quality in the area surrounding the power plant, we collected monitor-level pollution readings of SO_2, NO_x and O_3 from the EPA. Information on non-attainment counties for criteria pollutants and all National Ambient Air Quality Standards are derived from the EPA.[40]

2.4.2 Descriptive statistics

Sample adjustments We restrict the main sample to power plants that had at least one coal unit in 2005 and that operated throughout the time period 2003-2014. We focus on non-gas plants due to the very low NO_x and SO_2 intensity for gas units. Balancing the sample ensures that the composition of the treatment and control group does not change over time. The balanced sample contains both gas and non-gas units, consists of 2,551 electricity generating units (EGUs) located at 938 facilities in 48 states (see Table B.1).

Descriptives Table B.1 presents summary statistics for selected plant characteristics.[41] From the table, we observe that average SO_2 emissions are higher for CAIR units than non-CAIR

[38]Note that the data from EIA only covers power plants with a generating capacity of 50 or more megawatts. We used information from the forms E243 and F243 from 2002 to 2007, and form EIA-923 for the years 2007 to 2015.

[39]The daily temperature datasets is drawn from Wolfram Schlenker's interpollation of the PRISM data, an extensive database of US monitoring stations for weather data.

[40]These were provided to us by Nick Muller. To construct a measure of air quality in the areas surrounding the power plants, we calculated a distance-weighted average of monitoring readings. We limited the number of monitoring stations to those located within a 100-kilometer radius of the power plant. The weights were constructed by taking the square of the inverse distance between the power plant and the monitoring station. Note that the distance between a power plant and the closest monitoring station can vary substantially. This implies that pollution readings might give very inaccurate measures of the ambient air quality for the 1-mile radius circle around each power plant.

[41]Plant-level emissions, gross load and heat input are found by taking the sum of all units within the facility. Plant-level fuel shares and technology stock are found by averaging over units within a facility. See Appendix B.2 for summary statistics of all plant characteristics.

units, while NO_x emissions are very similar across the two groups.[42] CAIR facilities are on average 2.4 years older than non-CAIR facilities. They also have a somewhat lower level of SO_2-specific technologies installed but a lager stock of NO_x-specific technologies. Gross load, heat input and fuel mix are not significantly different across the two groups.

Table 2.1: CAIR plants and permit trading

	CAIRNO$_x$	CAIROS	CAIRSO$_2$
Number of Facilities	929	925	966
Number of Facilities with at least one coal unit	449	458	457
Number of coal units (2005)	968	1,010	961
Number of gas units (2005)	1,598	1,470	1,681
Number of oil units (2005)	356	456	372
Average number of units per facility	4	4	4
Total cap (mill. tons)	1.54	0.63	4.57
Total cap allocated to facilities (mill. tons)	1.39	0.56	3.60
Total cap allocated to facilities with at least one coal unit (mill. tons)	1.23	0.48	3.36
Total cap allocated to facilities with no coal unit (mill. tons)	0.16	0.08	0.24
Correlation initial allocation x population density	-0.04	-0.03	-0.04
Correlation initial allocation x median income	-0.06	-0.09	-0.05
Average number of transactions per year	4,054	4,570	.
Average quantity of emissions exchanged per year	29.21	25.67	.
Average quantity of emissions realocated per year	0.86	0.38	.

Notes: The table gives summary statistics on cap-and-trade markets implemented under the Clean Air Interstate Rule: the annual NO_x (CAIRNO$_x$) and SO_2 (CAIRSO$_2$) markets and the summertime NO_x market (CAIROS). Data come from EPA's Air Markets Program Data.

2.5 Effects of the CAIR markets on emissions

2.5.1 Estimation strategy

Difference-in-Differences (DiD) To identify a causal effect of the CAIR, we exploit both a time break in the regulation and spatial variation in targeted facilities. Our main specification

[42]Figure B.4 shows density functions for SO_2 and NO_x emissions. While the distribution in levels show more treated units in the upper parts of the distribution, the log versions show a better overlap between CAIR and non-CAIR units. We address the skewed distribution in one of the robustness checks by trimming the sample in both ends of the distribution, see Appendix B.3.

is a difference-in-differences (DiD) estimator, with which we can compare the development in emissions of treated facilities to a control group, before and after treatment. When $CAIR_{j,t}$ is a dummy that indicates if facility j is affected by the treatment at time t, the DiD estimator is written as:

$$y_{j,t} = \beta_1 CAIR_{j,t} + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_t + \epsilon_{j,t}, \tag{2.3}$$

where j is facility, t is time, $y_{j,t}$ is facility-level emissions, $\mathbf{X}_{j,t}$ is a vector of observable covariates, c_j are facility-specific fixed effects, λ_t are time dummies (month$\times$year) and $\epsilon_{j,t}$ is the idiosyncratic error term.[43] The main identifying assumption is that, in the absence of treatment, the treatment and control groups would have followed parallel trends in the outcome variable. If the error term is correlated with time-varying omitted variables,[44] the DiD fails to give consistent estimates.

While we cannot directly test the common trend assumption, similar pre-treatment trends give an indication that this assumption holds. In Section 2.5.3, we investigate the parallel trends assumption by including leads and lags dummies for the time of treatment. Specifically, we interact the treatment variable ($CAIR_{j,t}$) with time dummies, where we use the year before the first treatment year as the reference. The lead dummies include the years before the treatment while the lag dummies include the treatment years. If we denote M as the number of leads and K as the number of lags, we can estimate the unfolding of the treatment with the following regression:

$$y_{j,t} = \sum_{m=0}^{M} \beta_{-m} CAIR_{j,t-m} + \sum_{k=1}^{K} \beta_{+k} CAIR_{j,t+k} + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_t + \epsilon_{j,t}, \tag{2.4}$$

where lead m captures potential deviations in the pre-treatment m years before treatment, and lag k captures the effect of the policy k years after the start of the treatment. The estimated

[43]Note that the interpretation of the DiD estimate differs across the two pollutants. For SO_2, the CAIR imposed a cap that was twice as stringent as for the control group. Additionally, CAIR units also faced the constraint that they were only allowed to buy permits from other facilities covered by the rule. The treatment effect hence reflects the difference in stringency between the regional and the national cap-and-trade system. For NO_x, the CAIR added a cap-and-trade system to an already established national rate-based policy, and the treatment effect hence reflects any added stringency.

[44]That is, if $E[\epsilon_{j,t}|c_j, \mathbf{X}_{j,1}, ..., \mathbf{X}_{j,T}] \neq 0$

coefficient for leads dummies (β_{-m}) should show no effect of treatment under the parallel trends assumption, while the coefficients for the lags dummies (β_{+k}) capture how treatment effects unfold over time.

Identification in the DiD set-up relies on an assumption of no spillovers from the treatment to the control group. In the case of SO_2, the two-to-one exchange of Acid Rain Program SO_2 allowances to CAIR SO_2 allowances implied a mechanical link between the treatment and control group.[45] The treatment estimate hence reflects the effect of CAIR units facing an allowance price twice that of the control group. The DiD strategy might therefore either understate or overstate the overall gains of the policy on SO_2 emissions, as it does not account for such spillovers. For NO_x, there is no shared pool of allowances for the treatment and control group, and the DiD estimate can be interpreted as the effect of a cap-and-trade market added to an already established command-and-control regime.[46]

Even though the pre-treatment trends are parallel, it could still be the case that the treatment and control groups were exposed to different shocks in the treatment period - something that would violate the identification assumption.[47] Regions implementing CAIR might have experienced different trends in factors influencing power plant's emissions of NO_x and SO_2, for instance via inputs markets or electricity markets. In order to account for potential unobserved effects, we run robustness checks that include time-varying covariates ($\mathbf{X}_{j,t}$).[48]

[45]Emissions reductions induced by the CAIR could hence have a direct effect on the SO_2 allowance price in the control group. According to Goulder (2013), the more stringent requirements for emissions reductions for CAIR units led to a drop in the demand for SO_2 allowances in the national cap-and-trade market. This, in turn, resulted in a decline in allowances prices on the Acid Rain Program market. Various court actions related to the CAIR also introduced uncertainty, which affected the allowances prices.

[46]Other potential spillovers from the treatment to the control groups could include: changes in the fuel prices as the CAIR may lead to changes in input mix or the relocation of electricity production to non-CAIR states. These mechanisms could potentially materialize for both NO_x and SO_2. We test for such potential leakage in the robustness checks.

[47]While the DiD approach will net out any general trends that are common to the control and treatment groups, it does not take care of differential group-specific trends.

[48]Specifically, we include a proxy for economic activity and weather controls. We could potentially include the price of natural gas. By including local natural gas prices, we need to be aware of the fact that the natural gas price may be endogenous. If power plants constitute a large buyer of natural gas, the policy itself could affect

Difference-in-Difference-in-Differences (DiDiD) Even though we include time-varying observables, we might still worry about omitted time-varying variables that affect the treatment and control groups differently. One way of mitigating this problem is to use a difference-in-difference-in-differences (DiDiD) specification. The DiDiD requires that the treatment group be divided into two subgroups, where only one is treated. The main advantage of the DiDiD over the DiD is its ability to difference out trends that affect the CAIR and non-CAIR units differently.

Here, we exploit the fact that a majority of treated units were already subject to a cap-and-trade for summertime NO_x emissions under the NO_x Budget Trading Program between 2003 and 2009. When the CAIR was formally implemented in 2009, former NO_x Budget Trading Program units were carried over to the summertime CAIR market for NO_x emissions. This implies that the annual cap-and-trade program for NO_x introduced under the CAIR only represented a regulatory break for the winter months (October to April). Hence, for units previously regulated under the NO_x Budget Trading Program, the CAIR should only have an effect on wintertime emissions.

If $CAIR_{j,t}$ is a dummy variable indicating if facility j is affected by the treatment in time t, $post_t$ indicates the treatment period and $winter_t$ indicates the winter months, the DiDiD estimator can be written as:

$$\begin{aligned} y_{j,t} &= \alpha_1 CAIR_{j,t} + \beta_1 CAIR_{j,t} \times winter_t \\ &\quad + \alpha_2 post_t \times winter_t + \gamma' \mathbf{X}_{j,t} + c_j + c_j \times winter_t + \lambda_t + \epsilon_{j,t}, \end{aligned} \tag{2.5}$$

where β_1 is the DiDiD estimate. If the CAIR only affected emissions in the winter months, we should find $\alpha_1 \approx 0$ and $\beta_1 \neq 0$.[49] In order for the DiDiD to give a consistent estimate, we must assume that there were no shocks during the treatment period that only affected

the price - making it a bad control. We could also include state-specific linear time trends. In this case, the DiD would be interpreted as the deviation from a linear time trend for the treatment group minus the deviation from a linear time trend for the control group. A potential problem with this approach is that the time trends might absorb large parts of the treatment effect.

[49] As with the DiD estimate, we specify a version with leads and lags. If we denote m as the number of leads

wintertime emissions for the treated units. Furthermore, we must assume that there are no spillovers from winter to summer months as a consequence of the policy.[50]

2.5.2 Findings

Table 2.2 presents the estimated average treatment effects using equations 2.3 and 2.5. In estimating an average treatment effect, we restrict the sample to the years 2004-2005 (pre-period) and 2009-2014 (post-period). From the first column, we see that SO_2 emissions were reduced by an average of 286 tons relative to non-CAIR units, conditional on facility and month$\times$year fixed effects. This corresponds to a reduction of 22% relative to a counterfactual. For NO_x, the reduction is 25% for the DiD estimate and 20% for the DiDiD estimate. The average treatment effects are robust to the inclusion of time-varying variables controlling for weather, economic activity, fuel costs and changes in the attainment status of power plants' counties. In addition, we present a battery of robustness checks in Appendix B.3.

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and k as the number of lags, we can estimate the unfolding of the treatment as

$$\begin{aligned} y_{j,t} = &\sum_{m=0}^{M} \alpha_{-m} CAIR_{j,t-m} + \sum_{k=1}^{K} \alpha_{+k} CAIR_{j,t+k} + \sum_{m=0}^{M} \beta_{-m} CAIR_{j,t-m} \times winter_t + \\ &\sum_{k=1}^{K} \beta_{+k} CAIR_{j,t+k} \times winter_t + \alpha_2 post_t \times winter_t + \gamma' \mathbf{X}_{j,t} + c_j + c_j \times winter_t + \lambda_t + \epsilon_{j,t}. \end{aligned} \tag{2.6}$$

[50] We regard it as unlikely that units will re-optimize and move parts of their electricity production from winter months to summer months.

Table 2.2: Treatment effects of the CAIR markets on NO_x and SO_2 emissions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - log SO_2 (DiD)						
CAIR x post$_t$	-0.24**	-0.15**	-0.15**	-0.13*	-0.21**	-0.22**
	(0.11)	(0.07)	(0.07)	(0.07)	(0.08)	(0.10)
Panel B - SO_2 (DiD)						
CAIR x post$_t$	-286.25***	-263.96***	-261.34***	-223.33***	-239.53***	-247.33***
	(72.99)	(60.24)	(59.92)	(54.56)	(53.83)	(62.09)
Panel C - log NO_x (DiD)						
CAIR x post$_t$	-0.29**	-0.24*	-0.25*	-0.27**	-0.31***	-0.30**
	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)
Panel D - NO_x (DiD)						
CAIR x post$_t$	-133.60***	-153.80***	-149.15***	-124.63***	-111.70***	-102.99***
	(45.23)	(34.07)	(34.34)	(32.21)	(31.63)	(37.60)
Panel E - log NO_x (DiDiD)						
CAIR x post$_t$	-0.38*	-0.30	-0.30	-0.32	-0.40*	-0.36*
	(0.21)	(0.22)	(0.22)	(0.22)	(0.20)	(0.20)
CAIR x post$_t$ x winter	-0.22***	-0.22***	-0.22***	-0.21***	-0.21***	-0.22***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Panel F - NO_x (DiDiD)						
CAIR x post$_t$	-50.74	-63.20	-62.69	-16.51	-30.58	-16.49
	(63.64)	(63.87)	(64.04)	(60.58)	(58.21)	(56.23)
CAIR x post$_t$ x winter	-132.78***	-132.71***	-132.71***	-133.12***	-132.24***	-132.82***
	(28.31)	(28.32)	(28.32)	(28.57)	(28.69)	(28.30)
Facility FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Temperatures				X	X	
GDP			X	X	X	
Fuel Costs		X	X	X		
NAAQS dummies				X	X	X

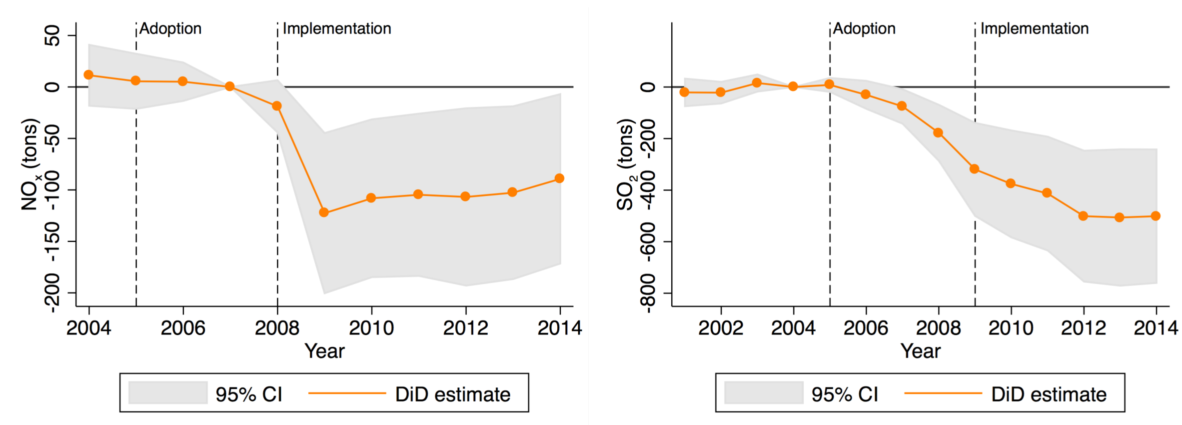
Notes: This table reports regression coefficients from 36 separate regressions, 6 per panel. Panels A, B, C, and D present results from a difference-in-differences specification comparing the evolution of emissions at power plants targeted by the Clean Air Interstate Rule to power plants in the control group. The dependent variable is power plant SO_2 emissions in panel A (natural logarithm), and panel B (absolute value), and NO_x emissions in panel C (natural logarithm) and panel D (absolute value). In panels C and D, only wintertime emissions of NO_x are included. Panels E and F report results from the triple differences that compares the evolution of power plant emissions in the winter compared to the summer in the treated area compared to the control group after implementation of the annual market for NO_x. The annual market for NO_x introduced by the CAIR was only a break in policy in the winter months as the CAIR continued an existing cap-and-trade market for NO_x emiisons in the summer. The dependent variable is the natural logarithm of NO_x emissions (panel E) and the absolute value of NO_x emissions (panel F). Emissions are measured continuously and summarized at the monthly frequency and the power plant level. All regressions include facility fixed effects, and year fixed effects. Columns (4) and (5) include non-linear controls for minimum and maximum temperature, and measures of extreme heat and cold recovered at the monthly frequency and power plant level (see appendix for details). Columns (4), (5) and (6) include year and state level controls for GPD. Columns (2), (3), and (4) include monthly-frequency and state-level measures of fuel costs. These include gas prices, coal prices, and a ratio of gas-to-coal prices. Finally, columns 4 to 6 include controls for county attainment status to the National Air Ambient Quality Standards. Those are pollutant-specific, county-level and yearly-frequency dummies, that are equal to 1 for counties in non-attainment. Standard errors are clustered at the state-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.3 Parallel trends assumption

We visually investigate the parallel trends assumptions underlying the DiD and DiDiD estimations. Figure 2.4 displays the coefficients $\hat{\beta}_{-t}$ and $\hat{\beta}_t$ estimated from equation 2.4 (DiD) or equation 2.6 (DiDiD). The figure reveals a fairly stable development of SO_2 emissions for the treatment group until the end of 2005, when emissions start to decrease. For both NO_x and SO_2, pre-trends are not statistically different for the treatment and control groups.

Figure 2.4: Effects of the CAIR on coal power plant emissions of SO_2 and NO_x

(a) NO_x (DiD) **(b)** SO_2 (DiD)



Notes: Figures plot the coefficients $\hat{\beta}_{-t}$ and $\hat{\beta}_t$ estimated from equation 2.4 (DiD) or equation 2.6 (DiDiD). The dependent variable $y_{j,t}$ is emissions in absolute value. The connected lines depict the estimated yearly treatment effects, while the gray areas are 95% confidence intervals. In panel (a) the coefficient for year 2005 is normalized to 0, while in panel (b) the coefficient for year 2007 is normalized to 0. Standard errors are clustered at the state level in all regressions. The sample is balanced over the period 2003-2014 and restricted to coal power plants. Only winter months are included in the DiD estimation for NO_x.

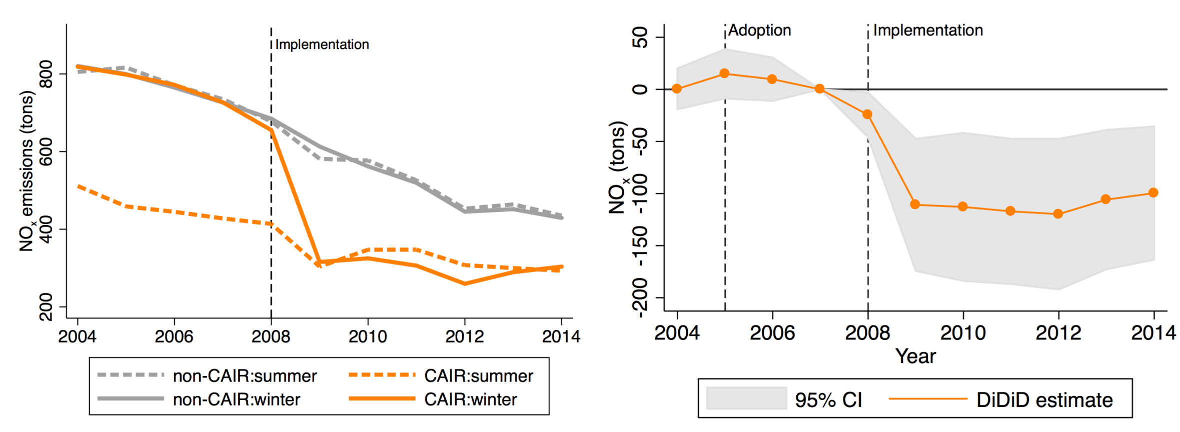
The effects of the CAIR on the NO_x emissions of targetted power plants was sharp and immediate. Figure B.3 displays the average daily NO_x emissions across coal power plants in the CAIR region. It shows that during the NO_x Budgeting Program, power plants abated emissions in the summer only, from May 1st to September 30th. They used abatement technologies that could be switched on and off. On September 30th, plants switched abatement technologies off and NO_x emissions were not controlled outside of the NO_x Budgeting Program market period. This changed with the implementation of the annual market for NO_x

emissions, which the CAIR introduced. As depicted in Figure B.3, plants continued to abate NO_x emissions in newly regulated months under the CAIR.

Figure 2.5 panel (a) shows the trends for winter and summer separately, and reveals very similar developments prior to the policy in the treated and control plants for both seasons. While the trends appear to be parallel for NO_x, shocks could have occurred in the post period that confound the policy. By employing a triple differences, we circumvent this problem by looking at the difference between winter and summer months, pre and post, for the treatment and the control groups.[51]

Figure 2.5: Effects of the CAIR on coal power plant emissions of NO_x—winter

(a) NO_x Trends (winter & summer) **(b)** NO_x (DiDiD)



Notes: The left panel plots the raw data. It depicts average NO_x emissions from coal power plants in the CAIR region in orange and in the control group in grey. Dashed lines represent summer emissions (from May 1st to September 30th) and solid lines represent winter emissions (from October 1st to April 30th). The right panel shows results from the triple-differences specification, where the treatment effect is interacted with year dummies. From 2004 to 2008, NO_x emissions in the summer were regulated under the NO_x Budgeting Program (NBP) for CAIR power plants. The NBP imposed a cap on NO_x emissions in the summer only. Plants installed abatement technologies that could be switched on and off. Most importantly, plants switched abatement technologies off during unregulated winter months between 2004 and 2008 and did not abate NO_x emissions in the winter. In 2008, the CAIR continued the summer cap from the NBP and imposed an annual cap on NO_x emissions. The annual market was thus a break in policy for winter emissions only.

[51] As some CAIR units were not covered by the former NO_x Budget Trading Program, it is expected to see a small drop also for the summer months.

2.6 Heterogeneous effects of the CAIR markets on emissions

Having established a large and robust treatment effect, we move to the second part of the analysis. In this part, we investigate whether emission changes induced by the CAIR vary systematically with socioeconomic characteristics of the neighborhoods surrounding each power plant.

2.6.1 Empirical strategy

Our main empirical specification allows for the treatment effect to vary with demographic variables in a linear way:

$$y_{j,t} = \beta_1 CAIR_{j,t} + \beta_2 CAIR_{j,t} \times Demo_j + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_t + \epsilon_{j,t}, \tag{2.7}$$

where $y_{j,t}$ is facility-level emissions, and $Demo_j$ is a facility-specific, time-invariant variable measuring a socioeconomic characteristic of the surrounding neighborhood prior to policy implementation. The net treatment effect is given by $\beta_1 + \beta_2 \times Demo_j$. For the DiDiD strategy, we estimate the following equation:

$$\begin{aligned} y_{j,t} = {} & \alpha_1 CAIR_{j,t} + \beta_1 CAIR_{j,t} \times winter_t + \beta_2 CAIR_{j,t} \times winter_t \times Demo_j \\ & + \alpha_2 post_t \times winter_t + \gamma' \mathbf{X}_{j,t} + c_j + c_j \times winter_t + \lambda_t + \epsilon_{j,t}, \end{aligned} \tag{2.8}$$

where the net treatment effect is given by $\beta_1 + \beta_2 \times winter_t \times Demo_j$.[52]

[52]In a robustness check, we also allow for the treatment effect to vary in a non-linear way with the socioeconomic characteristics by constructing k different bins:

$$y_{j,t} = \sum_{k=1}^{n} \beta_k (CAIR_{j,t} \times Demo_{j,k}) + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_t + \epsilon_{j,t}, \tag{2.9}$$

where β_k captures the treatment effect for bin k.

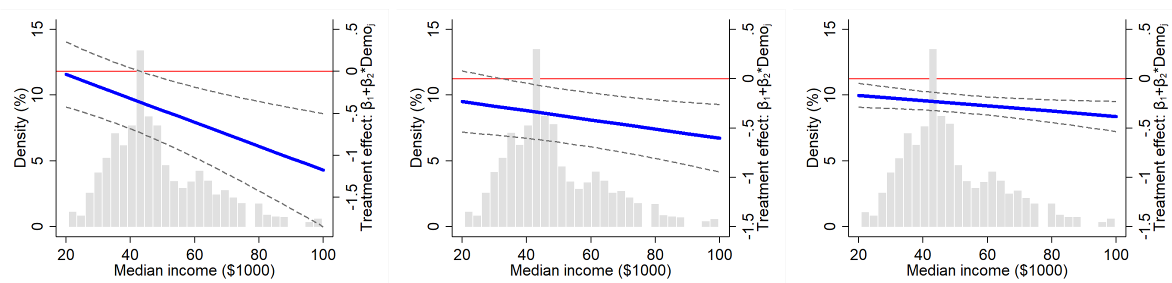
2.6.2 Results

Household income

To test whether CAIR-induced emission reductions vary with income, we interact the treatment variable ($CAIR_{j,t}$) with the median income of neighborhoods. The estimated heterogeneous effects for SO_2 and NO_x, using both the DiD and DiDiD specifications, are presented in Figure 2.6. Values of the income variable are indicated on the x-axis. The left y-axis indicates the density for different values of the income variable, while the right y-axis indicates the net treatment effect for different values of the income variable.

Figure 2.6: Heterogeneous treatment effects, by median income

(a) log SO_2 **(b)** log NO_x **(c)** log NO_x (DiDiD)



Notes: The solid blue lines in all figures are the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$ estimated from equation 2.7 (DiD) or equation 2.8 (DiDiD). The dependent variable $y_{j,t}$ is log SO_2 emissions (panel a) or log NO_x emissions (panels b and c). The horizontal axis indicates median income as $Demo_j$, where a histogram of the variable is shown in the background. The left y-axis reports the density of $Demo_j$ in percent, while the right y-axis reports the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the state level in all regressions. The sample is balanced over the period 2003-2014, restricted to non-gas units and to the years 2004-2005 (pre period) and 2009-2014 (post period). Median income is from the 2005-2009 American Community Survey (ACS), and is constructed for 1 mile radius circles around the power plants.

Looking at SO_2, there is a clear downward sloping curve for the net treatment effect (see Figure 2.6a). This means that CAIR-induced reductions in emissions were relatively smaller for plants located in neighborhoods with a low median income, and relatively higher for plants located in neighborhoods with a high median income. The net treatment effect varies between 0 for the poorest neighborhoods and up to a 60% reduction for the very richest neighborhoods. For NO_x, we see a similar but weaker pattern (see Figures 2.6b and 2.6c).

Using both a DiD and DiDiD specification, the slope of the interaction term is about 1/3 of the slope for SO_2.

Other measures of wealth and demographics

Results for each measure of the demographics are presented in Table 2.3. Overall, the heterogeneity in emission reductions persist across measures for wealth and demographics: for median income, income per capita, $\%$ of black people living in the neighborhood, $\%$ of university educated people living in the neighborhood, or median gross rent.

To test whether the heterogeneity in the CAIR's treatment effect uncovers differences between states, or between plants neighborhoods within the same state, we use different measures of the distributions in demographic variables: $demo_j$ can hence be taken as the absolute value of the demographic variable (e.g.: median income in 1,000 of USD), or the percentile of the neighborhood's demographics across all US plants, across CAIR's plants or within each CAIR state. Emissions reductions were also stronger in high density neighborhoods. These patterns reveal heterogeneity within states, and do not seem to reflect a geographic devide between states in the CAIR region, as shown by the negative coefficients displayed in columns 2, 3, and 4.

Table 2.3: Heterogeneous treatment effects of the CAIR markets on SO_2 emissions (in log)

	(1) Absolute Value	(2) Across Plants	(3) Across CAIR	(4) Within States
Median Income	-0.000013	-0.0042	-0.0058	-0.0047
	(0.000006)	(0.003163)	(0.003867)	(0.003396)
Income per Capita	-0.000047	-0.0069	-0.0098	-0.0096
	(0.000018)	(0.003951)	(0.005189)	(0.004546)
% Black Population	0.640723	0.0028	0.0030	0.0033
	(0.438332)	(0.003166)	(0.003482)	(0.003701)
% University Educated	-1.300033	-0.0056	-0.0076	-0.0095
	(0.860295)	(0.004063)	(0.005249)	(0.004419)
Population Density	-0.000476	-0.0133	-0.0201	-0.0145
	(0.000259)	(0.005005)	(0.007029)	(0.005040)
Median Gross Rent	-0.001464	-0.0066	-0.0088	-0.0054
	(0.000782)	(0.004174)	(0.005185)	(0.003180)

Notes: The table presents results of the estimations of coefficient β_2 in equation 2.7, for 24 separate regressions, 4 per demographic variable. The dependent variable is the logarithm of SO_2 emissions as measured at the monthly frequency and power plant level. In column (1), $demo_j$ is the absolute value of the given demographic variable. $demo_j$ is the percentile of plants'neighborhoods in the demographic distribution across all US plants neighborhoods (column (2)), across CAIR based power plants neighborhoods (column (3)), or across CAIR power plants located within the same state (column (4)).

2.6.3 Compliance mechanisms of power plants

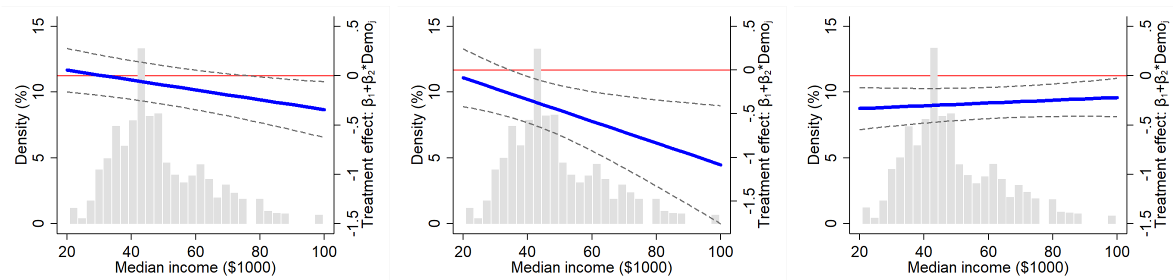
Here, we examine how power plant owners are choosing to comply with CAIR, and if their choice systematically differs with socioeconomic characteristics of the plant's surrounding neighborhood. In particular, we investigate three potential compliance mechanisms: lower electricity production, lower emissions intensity (by installing abatement technologies or switching to cleaner fuels) and shutting down. To test if power plants' compliance choices correlate with neighborhoods' socioeconomic characteristics, we estimate equation 2.7 using electricity generation and emissions intensity of SO_2 and NO_x as outcome variables.

Lower electricity production

Figure 2.7a shows the estimated heterogeneous treatment effect when using gross load as an outcome variable in equation 2.7. The estimation reveals that, on average, the Rule had minor effects on electricity production. We see no effects in low-income neighborhoods, while high-income neighborhoods experienced a small decline in production.

Figure 2.7: Heterogeneous treatment effects on compliance choice, by median income

(a) log gross load (GWh) **(b)** log SO_2 intensity (ton/Gwh) **(c)** log NO_x intensity (ton/Gwh)



Notes: The solid blue lines in all figures are the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$ estimated from equation 2.7 (DiD). The dependent variable $y_{j,t}$ is log electricity production (panel a), log SO_2 intensity (panel b) or log NO_x emissions (panel c). The horizontal axis indicates different values of the demographic variable $Demo_j$, where a histogram of the variable is shown in the background. The left y-axis reports the density of $Demo_j$ in percent, while the right y-axis reports the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the state level in all regressions. The sample is balanced over the period 2003-2014, includes only non-gas units and is restricted to the years 2004-2005 (pre period) and 2009-2014 (post period). Demographic variables are from the 2005-2009 American Community Survey (ACS). Median income is measured in $1000, and is based on inflation adjusted values. The demographic variable is constructed for 1 mile radii circles around the power plants.

Lower emissions intensity

We find that the CAIR led to a reduction in power plants' emissions intensity for SO_2 and NO_x (see Figures 2.7b and 2.7c). While NO_x intensities were reduced evenly across power plants located in different socioeconomics neighborhoods, there were small or no reductions in the intensity of SO_2 emissions for power plants located in low-income neighborhoods. For power plants located in high-income neighborhoods, we observe large and significant reductions in SO_2 emissions intensity. Reductions in emissions intensity could be caused by plants installing abatement technology or switching to cleaner fuels.

Technology adoption: To test for heterogeneous adoption of abatement technologies across neighborhoods of different socioeconomic composition, we estimate equation 2.7 using a measure of technology adoption as the outcome variable. The two main technologies used to reduce emission intensity are flue-gas desulfurization (FGD) for SO_2 and Selective Catalytic or Non-Catalytic Reduction (SCR or SNCR) technologies for NO_x. Figure B.10 shows the results when interacting the policy variable with the share of households living below the poverty line. The estimation reveals that plants located where poor populations are more concentrated were less likely to adopt sulfur abatement technologies as a response to CAIR, while NO_x technologies were evenly adopted across neighborhoods.[53]

Fuel switching: Given the technical constraints of boilers, switching from coal to gas at the plant level is rare.[54] The lower emissions intensity must therefore be achieved by switching to cleaner coal, installing technology, or both. Using detailed data on ash and sulfur content of coal delivered to power plants, we estimate average and heterogeneous impacts of the CAIR on the quality of coal purchased. We find that, on average, power plants targeted by the CAIR did not switch to higher quality coals. This suggests that reductions in emissions intensity were achieved through technology adoptions rather then switching to cleaner fuels.

2.6.4 Discussion

Why are SO_2 reductions smaller in poorer neighborhoods? Why would emissions trading induce less abatement at plants located in low-income areas? Guided by the framework in Section 2.2, we discuss potential explanations for the heterogeneous reductions observed

[53]Note that many power plants had already installed NO_x abatement technologies under the former NO_x Budget Trading Program, which they only used during summer months. When the CAIR expanded the NO_x Budget Trading Program to the winter months, it was easy for units to use the already installed technologies in winter months as well. When interacting the policy variable with the median income instead of the poverty rate, wee see a positive and even treatment effect across income groups. This implies that the lower probability of installing SO_2 technologies was only present in the very bottom of the income distribution.

[54]We estimate the probability of switching to gas as a primary input to be around 2%.

in the context of the CAIR.

Plant characteristics: If the marginal abatement cost, $c_i'(q_{it}, \theta_i)$, is systematically higher for power plants located in low-income areas relative to higher income areas, this might explain the observed pattern of emissions reductions. A plant's operating characteristics, θ_i, can be either observed (X_i) or unobserved (u_{it}). In our case, X_i contains information on age, fuel inputs, gross loads, and the technology stock. Comparing the mean of these characteristics for plants located in low- and high income areas, we find small differences across the two groups (see Table B.7).[55] Next, we include plant characteristics as controls when estimating equation 2.7, and find that the heterogeneous treatment effect remains intact (see Table B.15). These results suggest that pre-policy, observable plant characteristics cannot explain the larger treatment effect observed in higher income neighborhoods.[56]

Neighborhood characteristics: Finally, power plants located in lower and higher income neighborhoods could face differences in community pressure or local reputation costs, $s_{il}(u_{it} - q_{it}, X_{il})$. In our setting, it is difficult to establish such sources of causation between neighborhood income and power plants' emissions reductions. However, focusing on areas experiencing repeated problems with air pollution (non-attainment counties), the heterogeneous effect is strong and significant, while for attainment counties we do not see any systematic pattern in emissions reductions. This suggests that uneven reductions are taking place in areas where the marginal damage of pollution is high. In these counties, populations

[55]The only significant difference between the two groups is the share of coal versus oil used as primary input.

[56]Note that there might be unobserved technical characteristics, u_{it}, that vary systematically between power plants located in lower and higher income areas. One example is the boiler's model and constructor, which could limit available options for low-cost abatement technologies. Potential differences in boiler characteristics could be due to differences in financial constraints: installing new technology is capital intensive, and plants in poorer areas might face a binding financial constraint. Beyond technical plant characteristics, there might be systematic differences in non-technical costs. In particular, plants located in low and high-income neighborhoods could face differences in unobserved input costs, such as labor costs.

are more likely to be aware of risks associated with air pollution, and the heterogeneous effect may hence stem from differences in local opposition.

Why is the heterogeneous pattern stronger for SO_2?

The stronger heterogeneous pattern for SO_2 compared to NO_x could have different explanations. First, while SO_2 has a strong odor which causes a substantial negative externality in nearby areas, NO_x is odorless and seemingly undetectable by local observers. This could imply that the neighborhood-specific cost, s_{il}, is larger for SO_2.[57]

2.7 Effects of emissions reductions on neighborhood characteristics

In Section 2.6, we showed that the CAIR induced larger emissions reductions in wealthier neighborhoods. Here, we expand on this analysis by (i) testing whether the heterogeneous pattern of emissions reductions is reflected in changing house values and demographics (Section 2.7.2), and (ii) estimating effects of emission changes on home values and neighborhood demographics (Section 2.7.3).

2.7.1 Empirical strategy

Heterogeneous effects of the CAIR on house values and neighborhood composition To see if emissions reductions induced by the CAIR also affected neighborhood composition, we use home values and neighborhood characteristics as outcome variables. In addition to the two differences used in equation 2.7 (CAIR vs. non-CAIR, pre vs. post), we also exploit the fact that the treatment intensity is larger for coal plants than gas plants. In fact, gas power

[57] Additionally, coal power plants are the single largest source of SO_2 emissions, while they only contribute to about 20% of total NO_x emissions in the US This could make residents scrutinize coal plants' emissions of SO_2 to a larger extent than NO_x, also influencing s_{il}.

plants experienced close to zero emissions reductions under the CAIR.[58] Including both gas and coal plants in the sample allows us to estimate the following triple difference:

$$ln\ y_{j,t} = \alpha_1 CAIR_{j,t} + \beta_1 CAIR_{j,t} \times coal_j + \alpha_2 post_t \times coal_j + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_{s,t} + \epsilon_{j,t}, \quad (2.10)$$

where $ln\ y_{j,t}$ is the natural logarithm of a socioeconomic characteristic of the neighborhood surrounding the power plant, β_1 indicates the DiDiD estimate and $\lambda_{s,t}$ stands for state-specific time dummies. By including the latter, the DiDiD estimate reflects the difference in development in socioeconomic characteristics for coal and gas plants within the same CAIR state, compared to the difference between coal and gas plants within non-CAIR states. The vector $\mathbf{X}_{j,t}$ includes an interaction term between $post_t$ and the log of the pre-policy level of the demographic variable. To see how the DiDiD estimate varies with income, we estimate the following regression:

$$\begin{aligned} ln\ y_{j,t} = {} & \alpha_1 CAIR_{j,t} + \beta_1 CAIR_{j,t} \times coal_j + \beta_2 CAIR_{j,t} \times coal_j \times Demo_j \\ & + \alpha_2 post_t \times coal_j + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_{t,s} + \epsilon_{j,t}, \end{aligned} \quad (2.11)$$

where $Demo_j$ is a facility-specific, time-invariant variable capturing a neighborhood characteristic prior to policy implementation.

Effects of emissions reductions on house values and sorting Lastly, we exploit the CAIR as a quasi-natural experiment to estimate the effects of power plants' emissions reductions on home values and neighborhood demographics. The empirical strategy is similar to the one described in Section 2.7.1, but restricts the sample to CAIR states only. Using the restricted sample, we can exploit $coal_j \times post_t$ as an instrument for changes in SO_2 or NO_x emissions. The reduced form, first stage and second stage then take the following forms:

Reduced form: $$ln\ y_{j,t} = \alpha_1 coal_j \times post_t + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_{t,s} + \epsilon_{j,t} \quad (2.12)$$

[58] The insignificant effect for gas power plants can be explained by natural gas generating much lower levels of SO_2 and NO_x emissions.

First stage:
$$emissions_{j,t} = \alpha_1 coal_j \times post_t + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_{t,s} + \epsilon_{j,t} \tag{2.13}$$
Second stage:
$$ln\ y_{j,t} = \beta_1 \widehat{emissions}_{j,t} + \gamma' \mathbf{X}_{j,t} + c_j + \lambda_{t,s} + u_{j,t}, \tag{2.14}$$

where $ln\ \ y_{j,t}$ is the natural logarithm of a socioeconomic characteristic of the neighborhood surrounding the power plant, $coal_j \times post_t$ is the excluded instrument and $\lambda_{t,s}$ are state-specific year dummies. By including state-specific year dummies, the coefficient α_1 in equation 2.13 captures differences in the development in emissions for coal and gas plants located within the same state. The IV-DiD estimate β_1 in equation 2.14 captures the effect of changes in facility-level emissions on neighborhood characteristics. The vector $\mathbf{X}_{j,t}$ includes an interaction term between $post_t$ and log of the pre-policy level of the demographic variable.

2.7.2 Results

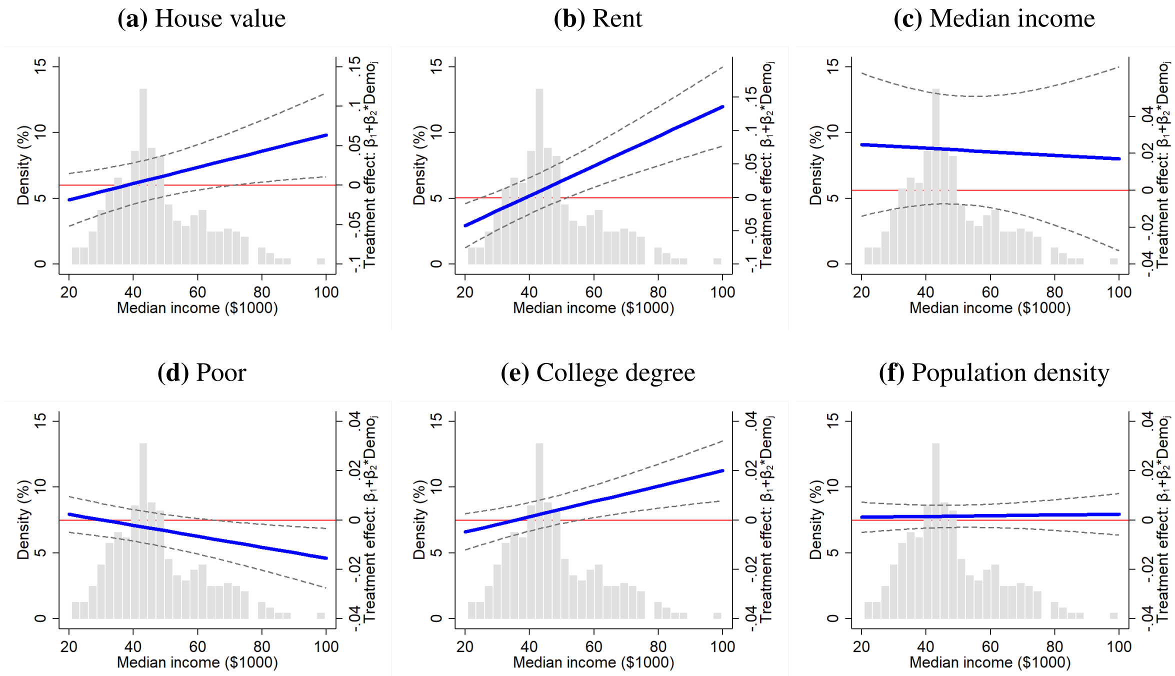
Heterogeneous effects of the CAIR on house values and neighborhood demographics

Did the CAIR effect house values and neighborhood demographics? Figure 2.8 plots treatment effects ($\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$) estimated from equation 2.11 where neighborhoods demographics are used as outcome variables.

From the figure, we observe that high-income neighborhoods located around coal power plants in CAIR states experienced an increase in home values and rents, compared to similar neighborhoods in the control group. The result suggests that neighborhoods experiencing large emissions reductions under the CAIR also experienced economic benefits via higher home valuation. While rents also increased, the share of home-owners is large in high-income neighborhoods.[59] Further, we see that higher income neighborhoods experienced a decline in the share of poor residents and an increase in residents holding a college degree. Since population density is not affected, this suggests that the environmental benefits induced by

[59] In our sample, the home-ownership rate in neighborhoods with a median income below the 25th percentile is 70%, while the home-ownership rate in neighborhoods with a median income above the 75th percentile is 86% (see Table B.9 in the Appendix).

Figure 2.8: Effects of CAIR on neighborhood characteristics.



Notes: The solid blue lines are net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$ estimated from equation 2.11. The dependent variable $y_{j,t}$ is log of the demographic variable indicated by the sub-figure heading. Data is from the 2005-2009 and 2010-2014 American Community Survey (ACS). Horizontal axis indicates different values of the demographic variable $Demo_j$ from the 2005-2009 ACS, where a histogram of the variable is shown in the background (and restricted to coal CAIR plants). The left y-axis reports the density of $Demo_j$ in percent, while the right y-axis reports the net treatment effect. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the state level in all regressions. All demographics are constructed for 1 mile radius circles around the power plants.

the CAIR led to a sorting of poorer households out of cleaned areas while college-educated households sorted into those areas.

2.7.3 Sorting

Here, we exploit the CAIR as a quasi-natural experiment to estimate effects of emission changes on home values and neighborhood demographics.[60] Table 2.4, panel (a) displays re-

[60] As explained in Section 2.7.1, our empirical strategy is to limit the sample to CAIR units only and compare the neighborhoods around coal and oil plants (treatment group) to those around gas plants (control group) before and after policy implementation. While both types of plants are covered by the CAIR, only the coal power plants experienced notable reductions in emissions, as gas unit do not emit SO_2. Furthermore, before the implementation of the CAIR, neighborhoods around coal and gas plants within CAIR states shared similar characteristics, see Appendix Table B.8. By including state-specific time dummies, as well as facility fixed effects, we compare the facility-level changes over time for gas and non-gas facilities within the same state.

sults from the reduced form estimation (equation 2.12). Results suggest that neighborhoods surrounding coal- or oil-fired plants experienced an increase in home values, median income, and share of college-educated residents, and a decline in the share of households below the poverty line. The estimated effects on population density and rents are not statistically different from zero.

Panel B in Table 2.4 shows the estimated effects when instrumenting for facility-level SO_2 emissions, both in levels and logs. Looking at column 1, we observe that reductions in plant-level SO_2 emissions increase home values in plant neighborhood. In particular, the log-log estimation coefficient suggests that a 1% reduction in SO_2 emissions leads to a 0.07% increase in home values.[61] The F-statistics on the excluded instrument (77.62 and 40.99) reveals a strong first stage. The rest of the columns show results when using other demographics as outcome variables. Overall, the coefficients reveal that reductions in SO_2 emissions result in a decline in the share of poor and an increase in the share of college-educated people. The coefficients on population density and rent are not statistically different from zero.

Panel C in Table 2.4 shows the effects of NO_x emissions on plants neighborhoods demographics and home values. All coefficients for NO_x share the same sign and same order of magnitude as for SO_2. The coefficients, however, are more precisely estimated for NO_x, which is likely due to a stronger first stage.

Time-varying shocks at the state level are hence absorbed by the state-specific time dummies, and what is left is the variation within a state.

[61] Using the log-level estimation coefficient (-0.0351) suggests that a 1000-tons reduction in SO_2 emissions leads to a 3.51% increase in home values. Combining these estimates with the heterogeneous emissions reductions found in Section 2.6.2, the richest neighborhoods experienced around a 4% increase in home values (60% $\times$ 0.07%). The average effect was a 2.6% increase in home values (37% $\times$ 0.07%).

Table 2.4: Effect of the CAIR markets on house values and neighborhood demographics

	House value	Rent	Median Income	% Below Poverty	% College Educated	Population Density
Panel A: Reduced form						
Coal*post	0.0518***	0.00453	0.0473**	-0.0113*	0.0101**	-0.00117
	(0.0180)	(0.0248)	(0.0186)	(0.00659)	(0.00415)	(0.00301)
Panel B: IV estimates (SO_2)						
SO2 (1000 tons)	-0.0351**	-0.00298	-0.0324**	0.00783*	-0.00689**	0.000819
	(0.0139)	(0.0162)	(0.0145)	(0.00454)	(0.00328)	(0.00207)
log SO2	-0.0691**	-0.00586	-0.0659*	0.0159	-0.0136*	0.00161
	(0.0320)	(0.0319)	(0.0369)	(0.0109)	(0.00766)	(0.00423)
Panel C: IV estimates (NO_x)						
NOx (1000 tons)	-0.0850***	-0.00734	-0.0779**	0.0187	-0.0166**	0.00196
	(0.0286)	(0.0398)	(0.0346)	(0.0115)	(0.00793)	(0.00501)
log NOx	-0.0582**	-0.00499	-0.0539*	0.0130	-0.0112*	0.00132
	(0.0215)	(0.0271)	(0.0283)	(0.00897)	(0.00587)	(0.00345)
Obs	1308	1236	1304	1296	1308	1300
Number of facilities	654	618	652	648	654	650
Clusters (state)	24	24	24	24	24	24
Mean dep.var (pre)	11.70	6.583	3.873	0.130	0.222	0.177
Mean SO2 (1000 tons) (pre)	0.977	0.987	0.971	0.981	0.973	0.983
Mean NOx (1000 tons) (pre)	0.391	0.393	0.390	0.393	0.390	0.393
F-stat (excl. instr.): SO2	77.62	82.30	74.78	72.46	74.55	77.95
F-stat (excl. instr.): log SO2	40.99	40.51	37.27	38.48	43.37	40.79
F-stat (excl. instr.): NOx	201.6	198.2	193.6	189.6	196.2	195.5
F-stat (excl. instr.): log NOx	66.69	69.67	63.20	61.92	72.35	68.35

Notes: Panel A reports the coefficient $\hat{\alpha}_1$ estimated from equation 2.12. Panel B and C reports the coefficient $\hat{\beta}_1$ estimated from equation 2.14. The dependent variable $y_{j,t}$ is indicated by the column heading and is the log of a demographic variable from the 2005-2009 and 2010-2014 American Community Survey (ACS). All regressions include interaction terms between $post_t$ and log of the demographic variable. Standard errors clustered at the state level in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.8 Conclusion

This paper examines how environmental benefits from cap-and-trade systems are distributed across different population groups, and to what degree these benefits are translated into economic gains via the housing market. We investigate these questions in the context of three large cap-and-trade systems targeting air pollution from US power plants. When studying *how* power plants reduced emissions, we find that facilities located in higher income areas lowered emission intensities by installing expensive abatement technologies, while plants located in poorer areas shut down dirtier units. Further, we find that policy-induced emissions reductions led to an increase in home values in power plants' neighborhoods. Since homeowners tend to be wealthier, these policy-induced effects on real estate disproportionately benefited higher income households. What is more, the increase in house values coincided with a demographic sorting, where poorer households initially living near power plants that reduced their emissions were replaced by higher income households. Overall, our findings suggest that the environmental and economic benefits were unevenly distributed across socioeconomic groups.

Chapter 3

Air Pollution and American Cities

Is there environmental gentrification?[1]

Abstract I match granular information on air pollution derived from satellite imagery with precise demographic data from the census to document the evolution and heterogeneity of the exposure to particulate matter—a harmful set of air pollutants, in the United States between 2000 and 2016. I find vast inequities in exposure to air pollution both across and within American cities. Neighborhoods with a higher share of low-income inhabitants face an average concentration of particulate matter 8% higher than the US mean, and almost 15% higher than wealthiest neighborhoods within the same city. These heterogeneities are more pronounced along with the racial composition of neighborhoods: black populations in the US are disproportionately more exposed to high levels of air pollution. These distributions did not change across time despite the unprecedented drops in air pollution across the US. I hypothesize that changes in local air pollution capitalize into housing values, leading to the sorting of poorer households out of clean areas. I test this hypothesis with housing transaction level data and find that a 1% drop in the local concentration of particulate matter leads to a 0.5 to 0.8% increase in house prices and that these effects are stronger in locations where

[1] I am deeply indebted to Donald Davis, Arlene Fiore, Geoffrey Heal and Wolfram Schlenker for their advise. For sharing reanalysis data on particulate matter pollution in the US, I am grateful to Aaron van Donkelaar, Randall Martin, Robert Spurr, and Richard Burnett. For allowing me to use their clusters and for sharing micro-level data on housing transactions from CoreLogic, I am thankful to Christopher Mayer and the Milstein Center for Real Estate at Columbia Business School. For sharing data on attainment status of counties in the US, I thank Nicholas Muller. All remaining errors are mine.

information on air pollution is publicly available.

3.1 Introduction

Since the industrial revolution, urbanization has been linked to the rise of air pollution, representing a significant disamenity of city life, and endangering populations' health and life expectancy (Hanlon and Tian, 2015; Hanlon, 2014). The focus has recently been put on understanding the relations between increasing levels of air pollution and the advent of sprawling cities in the developing world (Kahn and Walsh, 2015). Less is known on the impact of declining levels of air pollution on the development of neighborhoods and cities, and on the evolution of inequalities in the exposure to air pollution across populations both between and within cities.

In the past twenty years, air pollution in the US has dramatically dropped, offering a unique historical experiment to study the impacts of air pollution improvements on cities. At the same time, spatial inequalities have risen, with the concentration of highly skilled workers and industries in a few city centers. The changes in the spatial distribution of wealth has led to the rebirth of cities and neighborhoods often associated with gentrification (Couture et al., 2019).[2] How have inequalities in exposure to air pollution been impacted by local changes in air pollution? How are recent improvements in the environment linked to the ever-increasing spatial concentration in wealth? Is there environmental gentrification? A necessary first step is to document the evolution in the exposure to air pollution, its distribution across populations, and its impacts on house values. This chapter leverages satellite imagery of air pollution, reports from EPA's ground-level monitoring stations, demographic information provided by the Census at the block group level and a proprietary micro-level dataset on housing transactions to document inequalities in the exposure to air pollution and establish a

[2] In this paper, I use gentrification as the process of improving a neighborhood that is accompanied with the influx of middle-class or higher income households and is often associated with the sorting of poorer households out of this neighborhood.

link between air pollution and house prices. The paper makes three main contributions. First, this chapter documents vast and persistent inequalities to the exposure to air pollution: both across and within cities, lower-income households are disproportionately exposed to higher levels of air pollutants. Although inequalities have tended to decrease over the studied period, they seem to persist. Second, to understand these patterns, the analysis proposes to estimate the impact of changes in air pollution on real estate prices. Higher home prices in cleaned areas could lead to the sorting of poorer households out of cleaner areas. In doing so, the analysis provides a measure of the marginal willingness to pay for air quality by estimating a hedonic model with block-group level data. On the whole, however, local air pollutants are hard to observe directly, and it is not apparent how inhabitants could react to changes in air pollution that cannot be perceived by a naked eye. Lastly, the paper provides an estimate of the impact of air pollution monitoring on house values, by pairing measures obtained through the parsimonious network of monitors installed by the EPA and the geographically continuous measure of air pollution provided by satellite products. This allows the analysis to provide a lower bound estimate of the value of air pollution monitoring by focusing on the additional impact to air pollution variations that monitoring reports can have on local housing values.

In a first step, I document inequalities in the exposure to air pollution across the US population. This is made possible by matching precise data on demographics with new datasets that offer a geographically continuous measure of air pollution with an unprecedented spatial granularity.[3] By matching time-varying block group level data from the Census to high-resolution air pollution imagery, I describe the evolution of the distribution in the exposure to air pollution, within cities, and across cities. I find that overall, populations living in the most deprived areas of the US experience exposure to particulate matter pollution 10% higher than the average American, and that populations living in blocks with the highest share of

[3]The pollution data was developed by van Donkelaar et al. (2019) and contains annual data on the concentration of eight major air pollutants on 1km by 1km grid cells.

black inhabitants experience exposure to particulate matter 20% higher than average. These patterns reflect inequalities between cities and between neighborhoods within the same city: on average, poorest neighborhoods present particulate matter concentrations 8% higher than the city's average, and 15% higher than the wealthiest neighborhoods. Between 2000 and 2016, I document that the average exposure to key human-made air pollutants has dramatically dropped: by 75% for ammonium, 65% for sulfate, close to 30% for particulate matter, and up to 50% for nitrate. These large drops materialized across cities, reducing between cities inequalities in the exposure to air pollution. Inequalities between neighborhoods were unchanged on average, although some cities (e.g., New York) managed to reduce the gaps between their poorest and wealthiest neighborhoods. Why do these vast inequalities in the exposure to air pollution persist? This is precisely the question that the second part of the paper investigates. I conduct hedonic regressions to indirectly recover the average household's marginal willingness to pay for clean air. Using house prices derived from transaction level data that I match to satellite imagery of air pollution at the block group level, I find that a 1% drop in the concentration of particulate matter is associated with an appreciation in house values ranging from 0.5% to 0.6% across specifications.[4] One unobserved variable that could lead to both changes in house values and air pollution could be changed in the location of dirty plants or other pollution sources (e.g.: roads): house prices may respond to the local changes in industrial activity that would also drive changes in local air pollution. In that sense, the hedonic estimates may overestimate the impact of changes in air pollution on house values. Pollutants like particulate matter can travel long distances from their source, and since air pollution impacts health, residents may notice changes in air pollution through changes in their overall health, even far from pollution sources. However, at the concentrations level experienced in the US, fine particulate matter might not be observable by a naked eye, and some may argue that it is not clear how residents could value changes in air pollution

[4] These estimates may suffer from endogeneity. The analysis could be refined in the future, using instruments to air pollution.

that they cannot observe directly. In the last part of the paper, I investigate how information on air pollution impacts changes in house values. I use measures of air pollution derived from ground level monitoring stations installed by the EPA as the primary source of information on air pollution at the county level. Because this network of monitors is sparse, many counties do not have any ground-level monitors. Hence, in an additional hedonic regression that links satellite imagery of air pollution to county-level changes in house values, I estimate the additional effect that information on air pollution has on house values by interacting changes in air pollution described by satellites with changes in air pollution described by monitors in counties that have monitors. This allows me to estimate the impact that information on air pollution has on housing values. I find in counties with monitors, the impact of changes in air pollution on real estate is more substantial than in counties that do not have monitors. This suggests that households pay attention to readings from monitoring stations.

This paper contributes to two lines of research. First, it is the first paper to document the recent evolution of the exposure to air pollution in the US, and of its distribution across households. Using air pollution data derived from satellite imagery allows a granular description of populations exposed to air pollution, both across cities and within cities at the neighborhood level. Other studies on the inequality to air pollution focused on data derived from monitoring stations or emission sources or proposed a static description (Hsiang et al., 2019; Clark et al., 2014). To my knowledge, this is the first paper to offer a complete description of spatial inequalities in the exposure to air pollution and their evolution across time. The description takes into account changes in local air pollution and in the composition of local populations across time. In doing so, the analysis attempts to link the literature on environmental amenities with the growing literature on the sorting of households along the skill and income distribution (Davis and Dingel, 2019; Couture and Handbury, 2017).

Second, the paper contributes to the sizeable empirical hedonics literature, which links changes in amenities to changes in housing values (Rosen, 1974; Albouy and Stuart, 2014; **?**). Papers focus on changes in air pollution brought about by the opening or closure of dirty plants (Currie et al., 2015; Banzhaf and Walsh, 2008; Davis, 2010), which can often be associated with changes in amenities of a neighborhood other than air pollution, such as changes in traffic congestions, employment, or noise level. Other papers study the impact of air pollution on house values in Los Angeles (Sullivan, 2016b). With county-level data only (Chay and Greenstone, 2005), previous studies had to assume that the US constituted a unique housing market and that households were optimizing across the US to choose a location to live in. Combining data on house values and pollution at the block group level allows this paper to estimate the impact of changes in air pollution on real estate prices by comparing block groups within the same city. Finally, most variations in air pollution used in the literature are drawn from observable changes (opening of dirty plants) or measured pollution levels that can be publicly available. This study intends to disentangle the impact of air pollution (measured by satellites) from the impact of information on air pollution (from monitoring stations) and aims to contribute to the literature on the value of information on environmental hazards (Davis, 2004).

The remainder of the chapter is structured as follows: Section 3.2 describes datasets used in this chapter. Section 3.3 documents the heterogeneity in exposure to air pollution and its evolution across time. Section 3.4 outlines the impact of changes in air pollution on housing prices. Section 3.5 estimates a lower bound of the value of information on air pollution. Section 3.6 concludes the paper.

3.2 Data and descriptive statistics

3.2.1 Data sources

This paper uses detailed satellite-derived data on air pollution, transaction-level real estate data, and block group level demographic data. Here, I present the datasets I obtained and matched and provide descriptive statistics.

1. Air pollution — I obtained data on air pollution from three primary sources: reanalysis data derived from satellite imagery products were developed by van Donkelaar et al. (2019), readings from monitoring stations installed by the Environmental Protection Agency across the US, and National Ambient Air Quality Standards status for all counties and standards.[5] Summary statistics for all three sources are provided in Table 3.1.

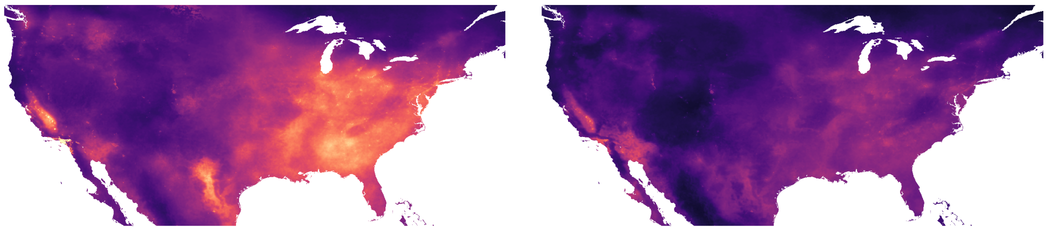
van Donkelaar et al. (2019) statistically combines information from satellites, chemical transportation models, and monitoring readings to provide the most detailed data on air pollution to date. The data covers North America and contains information on the concentration of eight major air pollutants at 0.01^o by 0.01^o grid cells (roughly 1km^2): particulate matter ($PM_{2.5}$), sulfate (SO_4^2), nitrate (NO_3), ammonium (NH_4^+), organic matter (OM), mineral dust and sea salt. Those pollutants constitute the bulk of fine particulate matter known to affect health. Some of these particles stem from industrial activity, or car emissions ($PM_{2.5}$, SO_4^2, NO_3, NH_4^+ and organic matter) while others are formed naturally close to the coasts (sea salt) or in desertic areas (dust). The files report yearly averages of each air pollutant at the grid cell level from 2000 to 2016 across North America.

Monitoring stations readings are provided by the Environmental Protection Agency's Air Quality System. I obtained data for five air pollutants deemed dangerous to health by the Agency and included in its list for criteria air pollutants: nitrogen oxides, ground-level ozone, particulate matter (10), particulate matter (2.5) and sulfur dioxide. I obtained data on daily measures of the air quality index associated with each of these pollutants. These data were averaged at the yearly frequency from 2001 to 2015 at the monitoring station level. I then took county-level simple averages. Because monitors are expensive to install and operate, the coverage is scarce (e.g., 417 monitors are installed throughout the US to measure nitrogen oxides concentrations). Based on these geographically limited data, I estimated county-level

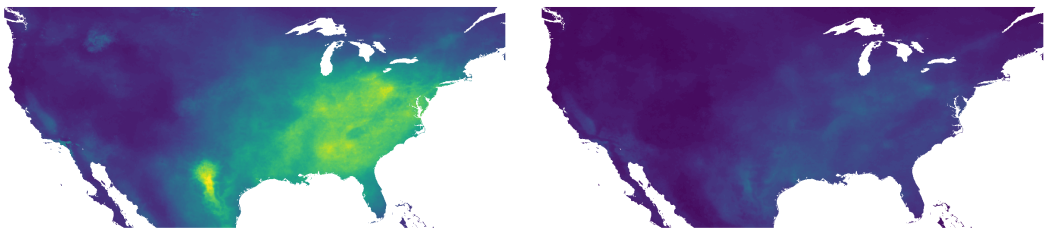
[5] A version of this dataset was provided to me by Nicholas Muller.

Figure 3.1: The geography of local air pollution improvements

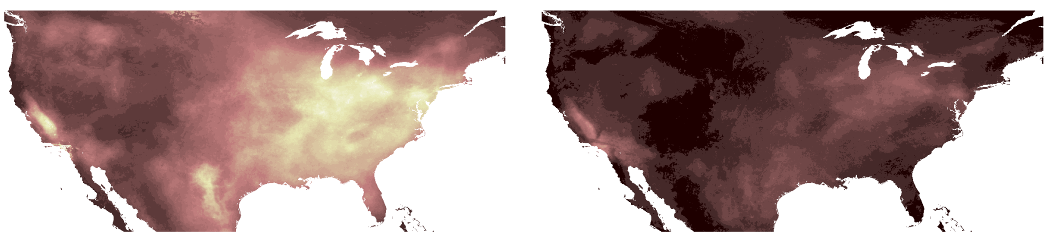
(a) Particulate Matter



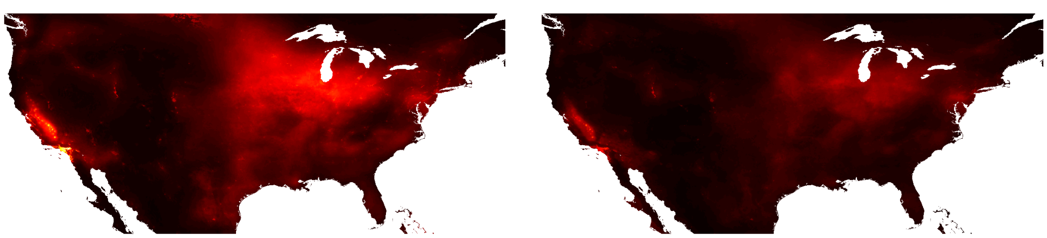
(b) Sulfate



(c) Ammonium



(d) Nitrate



Notes: The maps display air concentrations of major air pollutants produced by industrial activity. The left panels represent yearly average air concentrations in the year 2000, and the right panels represent yearly average air concentrations for year 2016. For each pollutant, scales for left and right panels are identical. Geographic resolution is of 0.01 by 0.01 degrees (approximately 1km by 1km).

averages by taking the simple average of monitor readings in counties that have at least a station.

Finally, the EPA releases annual data on the attainment status of every county in the

US. Attainment status is decided by comparing the readings of monitoring stations to some threshold defined individually for every pollutant on a list of six criteria pollutants: carbon oxides, lead, nitrogen oxides, ozone, particulate matter, and sulfur dioxide. Individual ceilings are determined by the national ambient air quality standards introduced by the clean air act and revised in 1971, 1978, 1979, 1987, 2006, 2008, and 2010. Enforcement of these thresholds was often delayed. I use annual data on the attainment status of every county in the US from 2000 to 2014.

Table 3.1: Descriptive statistics: air pollution data

	Frequency	Years	N	Mean in 2010	SD in 2010
Satellite Imagery					
Black Carbon	yearly	2000-2016	8,219,192	0.9	0.4
Ammonium	yearly	2000-2016	8,219,192	0.9	0.4
Nitrate	yearly	2000-2016	8,219,192	1.2	0.8
Organic Matter	yearly	2000-2016	8,219,192	3.3	1.3
Particulate Matter	yearly	2000-2016	8,219,192	9.6	2.3
Sulfate	yearly	2000-2016	8,219,192	2.0	0.8
Dust	yearly	2000-2016	8,219,192	0.7	0.3
Sea Salt	yearly	2000-2016	8,219,192	0.3	0.4
Monitoring Stations					
Nitrogen Oxides	yearly	2001-2015	417	17.9	9.3
Ozone	yearly	2001-2015	1,280	37.8	6.4
Particulate Matter (10)	yearly	2001-2015	853	19.5	10.3
Particulate Matter	yearly	2001-2015	1,333	34.4	11.5
Sulfure Dioxide	yearly	2001-2015	469	9.6	12.7
NAAQS Status					
CO (1971)	yearly	2000-2014	3,109	0.00	0.00
Lead (1978)	yearly	2000-2014	3,109	0.06	2.54
Lead (2008)	yearly	2000-2014	3,109	0.55	7.38
Nitrogen Oxides (1971)	yearly	2000-2014	3,109	0.00	0.00
Ozone (1979)	yearly	2000-2014	3,109	6.98	25.48
Ozone (1997)	yearly	2000-2014	3,109	7.94	27.05
Ozone (2008)	yearly	2000-2014	3,109	0.00	0.00
Particulate Matter (10) (1987)	yearly	2000-2014	3,109	1.19	10.85
Particulate Matter (2.5) (1997)	yearly	2000-2014	3,109	6.69	24.99
Particulate Matter (2.5) (2006)	yearly	2000-2014	3,109	3.83	19.19
Sulfure Oxides (1971)	yearly	2000-2014	3,109	0.23	4.74
Sulfure Oxides (2010)	yearly	2000-2014	3,109	0.00	0.00

Notes: The table displays summary statistics for data on pollution used in this analysis.

2. Housing transactions — Data on the price of a house is disclosed whenever a house is sold. This information is gathered in a deed record attached to the house being sold. These documents are made public in most states due to information disclosure act. CoreLogic has gathered information on all US housing transactions between 2000 and 2016. I use transaction-level data on housing prices for all types of residential units. The data includes information on the location (longitude and latitude), price and date of the housing transaction. About 5.5 million transactions per year are included in the dataset. I matched every house in the dataset the centroid of its closest block groups, using the shapes of block groups as defined by the census of 2010. I then constructed annual averages of the price of houses sold at the block group level. This also allowed me to match every house with its Core-Based Statistical Areas (CBSA).

Table 3.2: Descriptive statistics: housing transactions data

	Observations/Year	Years	Mean in 2010	SD in 2010
All Transactions	5,990,574	2000-2016	252,037	.
By block group	27	2000-2016	252,037	1,565,526
By county	3,336	2000-2016	167,338	175,315
By CBSA	6,266	2000-2016	173,302	163,276

Notes: The table displays summary statistics on housing transactions used in the analysis.

3. Demographics — I assembled information on population demographics at the block group level from the 2000 and 2010 census and every annual American Community Surveys between 2009 and 2016.[6] To compare demographics across years, I merged all datasets at the block group level as defined by the census of 2010. A block group contains 1,500 inhabitants on average and has an average area of 3.9 km^2 across the US with a standard deviation of 57 square kilometers.[7] Table 3.3 gives descriptive statistics of the main variables used in

[6]Data were downloaded from the National Historical GIS platform developed by the University of Minnesota.

[7]Block groups in densely populated cities are smaller, and can be as small as 0.0004 km^2.

this study: total population, population density, percentage of households with no university degree, percentage of white households, percentage of black households, median household income, per capita income, percentage of population living under the poverty line, number of housing units, median value, median gross rent and percentage of homeowners.

4. Additional datasets — Other datasets were used as control variables. In particular, I used temperature data derived from the PRISM network of stations in the contiguous United States.[8]

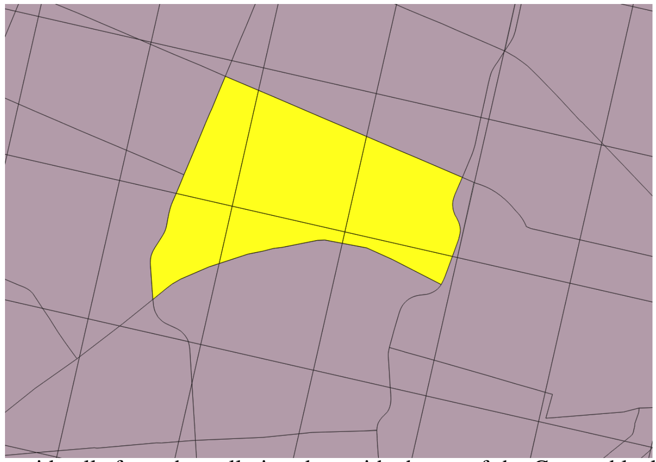
3.2.2 Merging datasets

All datasets are first brought to the block group level of the 2010 census. For gridded variables, such as satellite measures of air pollution and temperature, grids are overlayed with block group shapes, and block group averages are performed using the intersection area between the block group and the grid cells as a weight. Before 2010, the census used a different definition for block groups. I used the crosswalk between block groups of census 2000 to census 2010, available on IMPUMS NHGIS's website.[9]

[8] Temperature data is available on a 2.5 by 2.5-mile grid for the contiguous United States, based on a spatial interpolation procedure conducted by Wolfram Schlenker and available to download on his website.

[9] website: `data2.nhgis.org`

Figure 3.2: Aggregation of gridded data to census block groups



Notes: The figure overlays grid cells from the pollution data with shapes of the Census block groups. The yellow area corresponds to a census block group. The block group measure of air pollution is the weighted average of the values at each grid cell that intersects with the block group. Weights (ω_j) correspond to the percentage of the block group area intersecting with the grid cell.
$\text{polCensus}_{i,t} = \Sigma_j \, \omega_j \, \text{polGrid}_{j,t}$

Housing transactions are recorded at the address level. I assigned each house in the dataset to its closest group, using longitude and latitude to estimate the distance between block group centroids and houses. I then calculated the means of housing transaction prices at the block group level and on an annual frequency.

To calculate county-level measures of air pollution based on measurements from EPA's monitoring stations, I took the simple average of measures from stations within each county.

3.2.3 Descriptive statistics

Block-group level — Census variables are available for about 215,000 block groups in the contiguous US (see Table 3.3). Information was retrieved at the block group level on demographics (total population, % of white and black people living in the block group, and education levels), on income (median income, per capita income and % of people living below the poverty line), and housing (number of housing units, median value, median gross rent and % of homeowners).

Table 3.3: Descriptive statistics: block group level demographics

	N	2000	2009	2010	2011	2012	2013	2014	2015	2016
Total Population	216,331	1,641	1,354	1,396	1,408	1,419	1,430	1,442	1,453	1,463
% No University Degree	215,187	49	47	45	45	40	40	39	39	38
% White	215,256	76	73	73	73	73	73	73	72	72
% Black	215,256	13	14	13	13	13	13	13	13	13
Median Household Income	214,662	45,516	55,135	56,321	57,350	57,499	57,568	58,155	59,105	60,698
Per Capita Income	215,154	21,645	26,801	27,372	27,915	28,032	28,123	28,519	28,887	29,759
% Under Poverty	214,917	13	15	15	15	16	16	17	16	16
Number of Housing Units	216,331	675	571	597	602	605	607	610	613	616
Median Value (Dollars)	209,396	134,494	237,449	235,946	230,248	222,471	216,513	215,913	225,584	233,387
Median Gross Rent (Dollars)	186,824	639	870	906	937	957	950	967	997	1,020
% of home owners	214,865	67	67	67	66	66	65	65	64	64

Notes: The table displays mean values for key variables from the census, collected at the block group level. Data for 2000 comes from the US Census of 2000. In 2009, the Census bureau drew new block group shapes. Data from the 2000 Census were aggregated at the block group level of the census 2010 block group shapes using a crosswalk file developped by IMPUMS NHGIS. Data for years above 2009 come from the annual American Community Serveys developped by the Census Bureau. All census data at the block group level were collected from IMPUMS NHGIS (website: `data2.nhgis.org`).

Figure C.2 displays the evolution of population-weighted exposure to each air pollutant between 2000 and 2016. Of particular interest, pollutants stemming from industrial and transportation activities have sharply declined. Between 2000 and 2016, the average exposures to $PM_{2.5}$ and nitrate were reduced by close to 50%, exposure to sulfate was reduced by 60%, and exposure to ammonium was reduced by 80%.[10]

CBSA level — A core-based statistical area (CBSA) is defined as a US geographic area centered by an urban core of at least 10,000 people. All residents of a CBSA can commute to the urban center daily, which means that a CBSA can be thought of as constituting unique local labor and housing markets. In 2010, there were 934 CBSAs in the contiguous US Table3.4 provides descriptive statistics for census and pollution variables. Column (2) displays the cross-CBSAs mean for key variables in the 2010 census and population-weighted pollution exposures in 2010. Coefficient of variation is the standard deviation of a variable, normalized by the mean and gives information on the spread of the variable in the sample. Column (3)

[10] Exposure to black carbon and organic matter dropped by about 20 % in the same time frame, while variations in exposure to mineral dust was unchanged. Exposure to sea salt seems to have dropped, yet this may be an artifact of the data or caused by natural phenomena.

displays coefficients of variation based on the sample of 934 CBSAs. Column (4) displays the mean across the 934 CBSAs of the coefficients of variation calculated with block group level data for each CBSA. It gives information on the average within-CBSA spread in key demographic and pollution variables.

Table 3.4: Descriptive statistics: CBSA level demographics and pollution

	(1) N	(2) Cross-City Mean	(3) Cross-City Standard Deviation	(4) Within-City Standard Deviation
Total Population	934	410,494	1,491,045	626
% No University Degree	934	50	10	15
% White	934	81	14	15
% Black	934	9	13	11
Median Household Income	934	47,403	9,815	16,953
Per Capita Income	934	22,787	4,465	8,420
% Under Poverty	934	16	6	13
Number of Housing Units	934	165,572	605,490	257
Median Value (Dollars)	934	150,631	85,535	60,170
Median Gross Rent (Dollars)	934	717	175	207
% of Home Owners	934	70	6	20
Particulate Matter (μ g/m^3)	934	8.9	2.4	0.42
Sulfate (μ g/m^3)	934	1.9	0.8	0.06
Ammonium (μ g/m^3)	934	0.8	0.4	0.05
Nitrate (μ g/m^3)	934	1.0	0.7	0.11
Black Carbon (μ g/m^3)	934	0.7	0.3	0.08
Organic Matter (μ g/m^3)	934	2.9	0.9	0.39
Mineral Dust (μ g/m^3)	934	0.7	0.3	0.05
Sea Salt (μ g/m^3)	934	0.2	0.3	0.04

Notes: The table displays mean values for key variables from the census, collected at the block group level and aggregated at the CBSA level.

3.3 Heterogeneity in the exposure to air pollution

By matching census data to the geographically continuous measures of air pollution offered by the reanalysis data on air pollution, the previous part described the vast heterogeneity in exposure to air pollution across and within cities. Who gets exposed the most to air pollution? Have the distributional profiles of exposure to air pollution evolved in the past twenty years? These are the two questions this part will address.

Table 3.5 exhibits cross-sectional correlations between $PM_{2.5}$ concentrations and key demographic variables for every year for which census data is available.[11] This allows to observe the evolution in the correlation between pollution and demographics, accounting for both changes in air pollution and changes in the demographics of each location.

Across the country, $PM_{2.5}$ pollution seems to consistently by higher for black populations: block groups with a higher proportion of black people are likely to be more polluted, with a correlation across the country of 0.18 in 2016. Similarly, white populations live in locations that are less exposed to $PM_{2.5}$ pollution. These are the two most salient features of the correlation between air pollution and key demographics when looking at the entire contiguous US It would seem at first sight that there is no clear pattern linking air pollution and income at the US level. However, looking at the relationship between income and pollution in a non-linear way reveals that the poorest block groups in the US are exposed to $PM_{2.5}$ concentrations that are 10% higher than the average. At the same time, the higher percentiles in the country's income distribution are exposed to slightly more pollution than average, likely because wealthier block groups are disproportionately located in cities, where air pollution is a more salient issue than in less densely populated areas.

Are disparities in exposure to air pollution, revealing a divide between regions, cities, or within cities? The second panel in Table 3.5 displays correlation between CBSA-level pollution and demographics. It reveals that there is a negative correlation between income and pollution at the city level, meaning that poorer cities tend to be relatively more polluted than

[11] See appendix for similar tables for all other air pollutants. Particulate matter is correlated with black carbon (0.7), sulfate (0.7) and ammonium (0.86). Table C.1 displays spatial correlations between air pollutants.

Table 3.5: Correlations between pollution and key demographic variables ($PM_{2.5}$)

	2000	2009	2010	2011	2012	2013	2014	2015	2016
Average Concentration (μ g/m ^{3})	12.6	9.7	9.6	9.8	9.0	8.8	8.8	8.4	7.7
Cross Country									
Population Density	0.12	0.14	0.12	0.18	0.16	0.16	0.13	0.18	0.14
Median Income	0.00	0.02	-0.06	-0.01	-0.03	0.01	-0.00	0.02	-0.01
Income per capita	-0.00	-0.01	-0.06	-0.03	-0.05	-0.02	-0.03	-0.01	-0.04
% Under Poverty	0.12	0.06	0.10	0.10	0.11	0.09	0.10	0.10	0.11
% Black	0.25	0.14	0.23	0.19	0.19	0.10	0.15	0.17	0.18
% White	-0.32	-0.28	-0.24	-0.30	-0.28	-0.25	-0.27	-0.30	-0.30
% No University Degree	0.11	0.06	0.12	0.10	0.11	0.08	0.10	0.08	0.10
Median House Value	0.06	0.18	-0.02	0.11	0.06	0.12	0.10	0.13	0.11
Median Gross Rent	0.08	0.17	0.01	0.13	0.11	0.16	0.15	0.18	0.17
Cross Cities									
Population Density	0.06	0.14	-0.01	0.06	0.08	0.18	0.11	0.18	0.11
Median Income	-0.01	-0.01	-0.15	-0.15	-0.13	-0.02	-0.09	-0.05	-0.13
Income per capita	-0.00	-0.07	-0.18	-0.20	-0.18	-0.13	-0.16	-0.12	-0.21
% Under Poverty	0.10	0.06	0.17	0.21	0.17	0.09	0.15	0.14	0.21
% Black	0.46	0.28	0.37	0.36	0.33	0.17	0.32	0.28	0.38
% White	-0.24	-0.14	-0.15	-0.24	-0.18	-0.10	-0.19	-0.18	-0.28
% No University Degree	0.38	0.29	0.38	0.41	0.37	0.31	0.34	0.31	0.37
Median House Value	-0.12	-0.09	-0.27	-0.23	-0.24	-0.13	-0.22	-0.15	-0.20
Median Gross Rent	-0.08	-0.00	-0.17	-0.09	-0.10	-0.01	-0.08	-0.01	-0.06
Within City									
Population Density	0.23	0.30	0.32	0.33	0.34	0.33	0.31	0.31	0.31
Median Income	-0.22	-0.21	-0.22	-0.21	-0.21	-0.20	-0.19	-0.18	-0.19
Income per capita	-0.14	-0.14	-0.15	-0.14	-0.14	-0.13	-0.13	-0.13	-0.13
% Under Poverty	0.25	0.21	0.22	0.22	0.22	0.22	0.20	0.20	0.20
% Black	0.25	0.21	0.21	0.20	0.22	0.21	0.21	0.19	0.21
% White	-0.30	-0.26	-0.26	-0.26	-0.26	-0.25	-0.25	-0.24	-0.25
% No University Degree	0.13	0.11	0.12	0.11	0.10	0.10	0.09	0.09	0.09
Median House Value	-0.16	-0.12	-0.13	-0.12	-0.12	-0.12	-0.14	-0.11	-0.12
Median Gross Rent	-0.06	-0.08	-0.09	-0.09	-0.08	-0.08	-0.07	-0.07	-0.07

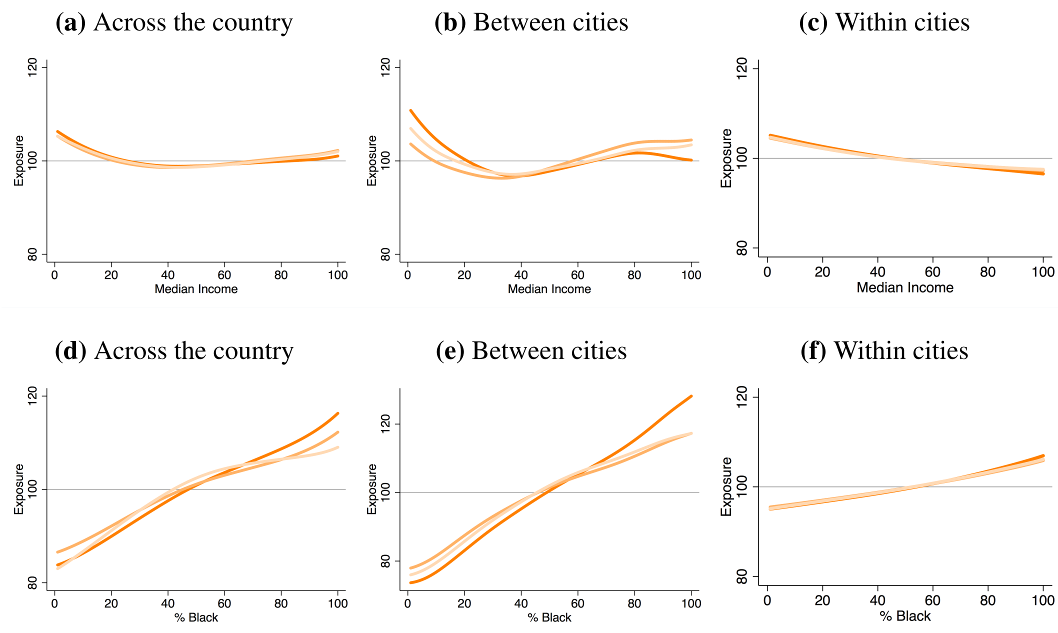
Notes: The table displays correlations between exposure to $PM_{2.5}$ pollution and key demographic variables. Correlations are computed for each year for which demographic variables are reported by the US Census (or American Community Survey) and allow for comparison across years, taking into account both changes in air pollution and changes in the demographic composition of each location. Cross country correlations are computed at the block group level for all blocks in the contiguous US. Cross cities correlations are calculated based on population-weighted averages of air pollution and demographics aggregated at the CBSA level for 944 CBSAs. Within city correlations are computed at the block group level for each of the 944 CBSAs. The table reports population-weighted averages across cities of correlations computed within each city.

richer cities. This demographic divide between cities is also exhibited by the positive correlation between education levels (% of people with no university education) and pollution: cities that attract talents tend to be less polluted. Finally, the racial differences in exposure to air pollution seem to be stronger across cities than on average across the country: cities with higher shares of black inhabitants are more polluted than cities with a higher share of the white population.

The third panel in Table 3.5 describes correlations between pollution and demographics at the city level: it compares block groups within each CBSA in the US and presents mean correlations across all CBSAs. This reveals that within a given CBSA, more impoverished neighborhoods tend to be more polluted (correlation of -0.19 between median income and $PM_{2.5}$ in 2016). The same disparities in exposure to air pollution exist between neighborhoods along the lines of racial composition and house values. On average, the relations between air pollution and demographics seem to hold across years.

Figure 3.3 depict the distribution of exposures to $PM_{2.5}$ pollution across income and racial groups, across the country, between cities, and within cities. When looking at the distribution across income groups, the distributions reveal non-linearities that correlations cannot picture. In particular, it seems that block groups in the lowest percentiles of the US income distribution are exposed to levels of $PM_{2.5}$ pollution that are 10% higher than the national averages. This pattern persists over time as distributions seem identical in 2000, 2008 and 2010. Distributions across cities also reveal that cities in the lowest percentiles of the income distribution across CBSAs are on average 10% more polluted than the average CBSA. This pattern becomes weaker with time, suggesting that differences across cities have tamed with time. At the city level, however, unequal exposure to $PM_{2.5}$ seem to persist with time: blocks in the poorest percentile in the city-level income distribution remain almost 20% more polluted than blocks in the highest percentiles. Differences across races seem to be even more pronounced: blocks with the highest proportions of black populations are exposed to $PM_{2.5}$ concentrations on average 18% higher than the US mean, while blocks that have the lowest share of black populations are exposed to concentrations that are 18% lower than the mean. This pattern comes both from disparities across cities and within cities (panel e and f). These differences seem to become less severe across time, mainly due to changes in the cross-city heterogeneity.

Figure 3.3: Distribution of exposures to particulate matter pollution



Notes: The figures display the distribution of exposures to $PM_{2.5}$ along the income distribution (panels a,b and c) or along the racial composition of the population (panels d, e and f). Each line corresponds to a year of data: the darker brown line represent the distributions of exposure to $PM_{2.5}$ in year 2000, the orange lines correspond to year 2008, and the lighter orange lines correspond to year 2016. The grey horizontal line correspond to the average population weighted concentration of $PM_{2.5}$. All other lines are drawn relative to the year's average population weighted concentration of $PM_{2.5}$. Each line represent the exposures to $PM_{2.5}$ predicted a locally weighted regressions of population-weighted $PM_{2.5}$ concentrations against median income (panels a,b and c) or against the percentage of black population (panels d, e and f). Panels (a) and (d) are derived from regressions conducted at the block group level for all blocks in the contiguous US Panels (b) and (e) result from regressions conducted at the CBSA level, in which population weighted $PM_{2.5}$ concentrations and census variables are aggregated at the CBSA level. Panels (c) and (d) represent cross-CBSA averages of regressions conducted at the block-group level within each of the 944 CBSAs. All x-axis variables picture the percentile of income group (resp. % of black population) of the block group across the US (panels a and d), CBSAs among the 944 CBSAs (panels b and e) and block groups within each city (panels c and f). Demographic variables come from the 2000 Census.

Table 3.6 describes the mean $PM_{2.5}$ exposure in the 21 CBSAs with the largest population in the U.S in 2000 and 2016 (and Fresno, CA, which was the CBSA with the highest $PM_{2.5}$ concentration in 2000). It also outlines their ranking across all 934 cities in terms of exposure to air pollution and the correlations between block group median income and $PM_{2.5}$ concentrations within each CBSA in 2000 and 2016. Importantly, all cities in the sample experienced large drops in exposure to $PM_{2.5}$ between 2000 and 2016. In most CBSAs, there exist a negative correlation between $PM_{2.5}$ concentrations and median income at the block group level, which seems to persist between 2000 and 2016. In some cities, however, inequalities in exposure seem to have diminished (e.g., New York).

Table 3.6: Whithin city inequality in the exposure to air pollution

	$PM_{2.5}$ Concentration		Rank		Pollution x Income	
City	2000	2016	2000	2016	2000	2016
Fresno, CA	20.6	13.2	1	2	0.01	-0.12
New York City, NY	14.2	7.6	171	341	-0.44	-0.13
Los Angeles, CA	19.3	12.1	2	4	-0.36	-0.23
Chicago, IL	14.6	8.8	116	51	-0.47	-0.28
Miami, FL	9.9	7.2	628	461	-0.19	-0.09
Atlanta, GA	17.3	9.6	7	17	-0.04	-0.07
Dallas, TX	11.9	8.2	433	175	-0.11	-0.11
Washington, DC	13.9	7.9	240	277	-0.29	-0.24
Houston, TX	11.7	8.2	459	188	-0.17	-0.11
Philadelphia, PA	14.0	8.7	214	65	-0.54	-0.43
Phoenix, AZ	10.0	8.0	621	247	-0.23	-0.30
San Francisco, CA	11.3	7.5	496	379	-0.30	-0.31
Riverside, CA	15.3	10.8	62	10	-0.01	-0.02
Detroit, MI	13.4	8.7	295	69	-0.39	-0.44
Boston, MA	10.3	6.0	588	674	-0.17	-0.16
Tempa, FL	12.2	7.9	412	279	0.22	0.06
Minneapolis, WI	10.3	6.7	583	564	-0.24	-0.20
San Diego, CA	14.2	10.5	179	11	-0.23	-0.07
Seattle, WA	9.7	5.0	653	798	-0.31	-0.37
Saint Louis, IL	13.9	8.4	229	112	-0.28	-0.25
Las Vegas, NV	9.3	7.9	684	288	-0.04	-0.14
Baltimore, MD	14.2	8.3	173	151	-0.55	-0.42

Notes: For each of the 21 most populous CBSAs in the U.S, the table displays $PM_{2.5}$ average concentration (in μg/m^3), rank of the CBSA among the 934 US CBSAs in terms of $PM_{2.5}$ average concentration, and block-group level correlations between $PM_{2.5}$ concentration and median income within each CBSAs. For each CBSA, the table displays figures for years 2000 and 2016. $PM_{2.5}$ concentrations correspond to a population weighted average of block group level concentrations within the CBSA. Census data are from the 2000 Census for year 2000 and the 2012-2016 American Community Survey for year 2016. The first row of the table corresponds to Fresno, the most polluted CBSA in 2000.

3.4 The impact of air pollution on house values

Why do we observe persistent inequalities in exposure to air pollution both across and within cities? If residents value changes in air pollution, reducing air pollution could lead to an increase in local house values that would lead to the sorting of poorer households out of cleaned areas. This part investigates links between changes in air pollution and house prices.

3.4.1 Empirical strategy

The following fixed effect model is used to estimate the impact of changes in the concentration of air pollution on housing values:

$$\pi_{i,t} = \alpha + \beta pol_{i,t} + X_{i,t} + \alpha_i + \epsilon_{i,t}, \tag{3.1}$$

where $\pi_{i,t}$ is the logarithm of the average house value in block group i and year t, $pol_{i,t}$ is the logarithm of the average concentration of particulate matter in block group i and year t, and α_i represents block group fixed effects and control for time-invariant block group omitted variables, and $\epsilon_{i,t}$ is the idiosyncratic error term. $X_{i,t}$ contains time-varying controls and includes block-group level temperature measures at the annual frequency (average temperature, number of heating degree days, number of cooling degree days), dummy variables for county-level attainment status to the National Ambient Air Quality Standards (I include separate dummies for each of the criteria pollutants and standards), time-varying block group level demographic characteristics (population density, percentage of black population, median income, percentage of households living below the poverty line). In further specifications, I include changes in the concentration of all pollutants in the **?** dataset as controls.

β is the parameter of interest and captures the relationship between changes in pollution levels and the average house value at the block group level. In further specifications, I include fixed effects at the block group level to absorb the block-group permanent effects (time-invariant block group specifics). Year fixed effects are added to control for time-varying unobserved variables that would affect pollution and house prices on a yearly frequency (e.g., the financial crisis). I also include CBSA level time trends to control for unobserved variables that would vary linearly with time at the CBSA level.

Identification relies on the assumption that there are no unobserved shocks to pollution levels that would covary with unobserved shocks to housing prices, an assumption I discuss further in section 3.4.3. Formally, the error term $\epsilon_{i,t}$ is assumed to be uncorrelated with the explanatory variables, or $E(\epsilon_{i,t}|\alpha_i, pol_{i,t}, X_{i,t}) = 0$

3.4.2 Results

Table C.3 summarizes results from block group-level data regressions using block group averages of house prices on the left side and satellite imagery of air pollution on the right side in log-log specifications. Estimates for β are consistently negative, meaning that an increase in local air pollution would lead to a decrease in house prices. When adding block group fixed effects to remove the effects of time-invariant block group characteristics on house values (column 1), or CBSA-specific time trends to control for temporal variations in pollution level (in column 2), results seem to indicate that a percent increase in $PM_{2.5}$ concentration at the block level leads to a decrease in mean house values ranging from 0.53 to 0.6 percents.

However, controlling for both time-invariant block group characteristics and year-specific shocks to air pollution yields non-significant estimates. Column 4 reports result from a regression that includes both block-group level fixed effects and year fixed effects: the coefficient remains negative but is no longer significant. This result suggests that a one-percent increase in $PM_{2.5}$ concentration leads to 0.024 percent decline in mean house value. Including city-specific time trends and block-group fixed effects yields a non-significant elasticity of 0.014 (column 5). The fact that these estimates are non-significant may reveal that there is not enough variation in the data to allow to control for both time fixed effects and block group fixed effects.

Columns 5 to 8 report results from regressions where block group fixed effects are included. Instead of controlling for all temporal shocks to air pollution using time fixed effects, I include here time-varying controls at the block group level. Even more significant impacts are found when controlling for temperature variables that can affect pollution levels (columns 6 to 8): a one percent increase in $PM_{2.5}$ concentration would lead to a drop in house values ranging from 0.57 to 0.87 percents. These effects may seem sizeable, but are comparable to effects found in regressions at the county level conducted by Chay and Greenstone (2005).[12]

Table 3.7: Treatment effect of $PM_{2.5}$ concentration on real estate prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
House Prices	-0.539***	-0.527***	-0.600***	-0.024	0.014	-0.866***	-0.866***	-0.568***
	(0.092)	(0.181)	(0.109)	(0.125)	(0.051)	(0.094)	(0.094)	(0.078)
N	2,180,337	2,179,912	2,179,370	2,179,370	2,178,944	2,169,549	2,169,549	1,884,171
Adjusted R^2	0.00	0.43	0.62	0.65	0.71	0.63	0.63	0.64
Number of Units	150,590	150,589	149,623	149,623	149,622	149,281	149,281	146,973
Number of Clusters	47	47	47	47	47	47	47	47
Block Group FE			X	X	X	X	X	X
Year FE				X				
CBSA Trends		X			X			
Temperatures Data						X	X	X
Demographics							X	X
NAAQS dummies								X

Notes: This table reports regression coefficients from 9 separate regressions. Estimates for coefficient β from equation 3.1 are reported. Each column represents a regression with different sets of controls. The dependent variable and the main explanatory variables, as well as demographic and temperatures controls are at the block group - year level. Data on attainment status to the NAAQS are at the county-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[12] In this seminal paper, the authors find an elasticity of housing values to changes in total suspended particles ranging from -0.20 to -0.35.

3.4.3 Discussion

By using satellite imagery products that offer a geographically continuous measure of air pollution, and statistics derived from the observation of all housing transactions in the US, the above analysis unveils the negative correlation between air pollution and housing prices with unprecedented geographic details. In using block group level aggregates offers enough power to disentangle the effects of pollution on housing values within and across cities, something that county-level data used in the literature did not allow (Chay and Greenstone, 2005).

However, one caveat in this part of the analysis resides in the causal interpretation of coefficient estimates on the impact of air pollution on house prices. In particular, identification may suffer from the omitted variable bias: another factor could impact both local air pollution and local housing prices. Multiple papers have established the impact of the opening or shutting down of dirty plants on both local air pollution and housing prices (Davis, 2010; Currie et al., 2015), and similar impacts could be driven by changes in congestions, or the opening or shutting down of new roads. House values could thus be responding to changes in the local environment that could be correlated with changes in air pollution at the block group level. Indeed, an extensive epidemiology literature hypothesizes that households do not respond to changes in air pollution because they are assumed not to realize variations in air pollution. To some degree, fine particulates are invisible and odor-free, and information on air pollution may not be available to households locally.

The next part of the paper aims to uncover the impact of information about local air pollution on changes in housing values.

3.5 Does information on air pollution matter?

What is the role of information disclosure about air pollution on real estate prices?

3.5.1 Information disparities

One way to recover an estimate of the value of air pollution measurement is to identify the effects of air pollution reports on housing values.[13] To estimate the impact that information on air pollution has on housing prices, the ideal experiment would randomly assign information on air pollution to a treatment group and compare the evolution of house values in this group to a control group that would be comparable in all other aspects (including pollution levels). This would enable to obtain the causal impact of information about air pollution on house values by comparing the evolution of house prices in the treatment group to the evolution of prices of houses facing the same level of air pollution, but having no information about air pollution.

To approximate this ideal experiment, I rely on the parsimony of monitors in the United States. The assumption is that households can only have information on air pollution through the measurements of EPA monitoring stations and that in the absence of monitors at the county level, no information on air pollution is available. A subsequent assumption is that information on air pollution at a specific county cannot be used for other nearby counties. Satellite imagery of air pollution offers complete information on air pollution at every county of the contiguous US, allowing to disentangle levels of air pollution from information diffusion about air pollution. We can, in principle, compare the evolution of house prices in response to air pollution variations in counties that have monitors to counties that do not have any monitors.

EPA monitors are placed in counties with any levels of pollution. Figure C.3(a) shows the number of counties that have monitors for $PM_{2.5}$ in each quartile of the distribution of air pollution as measured by satellite. Surprisingly enough, the EPA placed monitors in counties that have relatively low mean $PM_{2.5}$ concentrations as measured by satellites. Importantly,

[13]This would underestimate the value of air pollution reports, which has been proved to lead to adaptation behavior of inhabitants to protect against the adverse health effects of pollution (Zivin and Neidell, 2009). Reports on air pollution also have great value for scientific research or for the enforcement of laws and standards such as the NAAQS.

there are EPA monitors in counties across the distribution of counties according to their mean $PM_{2.5}$ concentrations. Table 3.8 compares counties that have EPA monitors to counties that do not have any monitors for $PM_{2.5}$ along with key demographic and pollution variables. Stations are installed in counties that are more densely populated (e.g., counties in cities), slightly more affluent, with more educated and more diverse populations. However, differences along these lines and pollution are not very large, which will allow comparing the evolution of housing values in response to air pollution in counties that have monitors and in counties that do not.

Table 3.8: Differences in means for key variables across counties with or without $PM_{2.5}$ monitoring stations

	With Station		Without Station		Difference	
	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)
Population Density	3.11	(0.16)	0.54	(0.02)	2.57	(0.16)
Median Income	28,335.0	(239.1)	26,742.4	(104.1)	1,592.6	(260.8)
Income per capita	13,805.3	(113.2)	13,338.5	(50.6)	466.8	(124.0)
% Under Poverty	7.99	(0.08)	9.16	(0.05)	-1.16	(0.09)
% Black	4.59	(0.09)	4.72	(0.06)	-0.13	(0.11)
% White	34.76	(0.39)	44.22	(0.22)	-9.46	(0.45)
% No University Degree	17.64	(0.22)	25.07	(0.14)	-7.43	(0.26)
Particulate Mater	9.26	(0.03)	8.85	(0.01)	0.40	(0.03)
Ammonium	0.88	(0.01)	0.84	(0.00)	0.04	(0.01)
Black Carbon	0.73	(0.00)	0.66	(0.00)	0.07	(0.00)
Nitrate	1.01	(0.01)	0.88	(0.00)	0.13	(0.01)
Organic Matter	3.25	(0.01)	2.81	(0.01)	0.44	(0.01)
Sulfate	2.19	(0.01)	2.27	(0.01)	-0.08	(0.01)
Sea Salt	0.31	(0.00)	0.21	(0.00)	0.09	(0.00)
Dust	0.60	(0.00)	0.60	(0.00)	0.00	(0.00)
Number of Stations	2626		502			
Number of Counties	776		2328			

Notes: The tables displays means and standard errors for key demographic and pollution variables. It compares means across counties that have at least one monitoring station $PM_{2.5}$ with counties with no such stations. Pollution data are drown from year 2005, while demographic data are derived from ACS 2009.

3.5.2 Empirical strategy

The goal of this analysis is to estimate the added impact that reports on air pollution have on house prices on top of the effects of air pollution variations on housing values. To do so, I estimate the following panel-data model:

$$\pi_{i,t} = \alpha + \beta_1 pol_{i,t} + \beta_2 pol_{i,t} \times \delta_{i,t} \times AQI_{i,t} + X_{i,t} + \alpha_i + \epsilon_{i,t}, \tag{3.2}$$

in which for county i and year t, $\pi_{i,t}$ is the logarithm of the county-average house price, $pol_{i,t}$ is the logarithm of the population-weighted average of $PM_{2.5}$ satellite concentrations at the county level, $\delta_{i,t}$ is a dummy variable equal to one for counties that have at least one $PM_{2.5}$ monitoring station in year t, $AQI_{i,t}$ is the logarithm of the county-wide average of Air Quality Index for $PM_{2.5}$ reported by all monitors in the county, $X_{i,t}$ is a set of time-varying controls, α_i are county fixed effects, and $\epsilon_{i,t}$ the idiosyncratic error term.

β_2 is the coefficient of interest and measures the additional effect that variations in monitors measures of $PM_{2.5}$ pollution has on housing values. If households pay attention to county-level pollution reports from the EPA, β_2 should be negative.

3.5.3 Results

Table 3.9 summarizes results from the estimation of model 3.2. As in the previous section, β_1 is negative and reveals that a one percent increase in $PM_{2.5}$ leads to a decrease in an average decrease in house values ranging from -0.56 to -0.75 percent. All specifications reveal that β_2 is negative, suggesting that reports from monitoring stations have an additional negative impact on house values ranging from 0.04 to 0.07 percent. This seems to be robust to the inclusion of county fixed effects and state-specific time trends, as well as the inclusion of time-varying controls.

These results suggest that measures of air pollution delivered by EPA's monitoring stations do have an impact on house values. As particulate matter pollution is hardly visible at a low level, this suggests that information about air pollution does matter. It is likely that other aspects of a county or neighborhood could reveal information about air pollution: the location of dirty plants or roads would likely have a greater impact on local populations' knowledge about air pollution, something we can control for in this setting.

Table 3.9: Interacting $PM_{2.5}$ concentrations with ground-level measures

	(1)	(2)	(3)	(4)	(5)	(6)
Reading Interaction						
log $PM_{2.5}$	-0.215	-0.753***	-0.607**	-0.607**	-0.607**	-0.563**
	(0.242)	(0.267)	(0.243)	(0.243)	(0.243)	(0.251)
log $PM_{2.5}$ x Monitor x log AQI	-0.147***	-0.115***	-0.069*	-0.069*	-0.069*	-0.036
	(0.037)	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)
N	9,016	9,016	9,016	9,016	9,016	8,355
Adjusted R^2	0.00	0.07	0.07	0.07	0.07	0.07
Number of Clusters	48	48	48	48	48	48
County FE		X	X	X	X	X
State Trends					X	X
Temperatures Data			X	X	X	X
Demographics				X	X	X
NAAQS dummies						X

Notes: This table reports regression coefficients from 6 separate regressions. The dependent variable is the log of the county-average sale prices from corelogic. The independent variables includes measures of $PM_{2.5}$ concentrations derived from satellite imagery (in logs). The term log $PM_{2.5}$ x Monitor x log AQI interact satellite imagery data on $PM_{2.5}$ concentration with ground-level measurements from monitors (log AQI) at counties that have at least one monitor (Monitor is a dummy equal to one for counties that have at least one monitor for $PM_{2.5}$ in year t).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6 Conclusion

Is there environmental gentrification? This paper documents the vast inequalities that exist and persist concerning exposure to air pollution. These inequalities materialize between cities and between neighborhoods within the same city: poorer households are more likely to live in neighborhoods that experience higher levels of air pollution. I find that changes in local air pollution are inversely associated with house values, and formulate and test a hypothesis: house values respond to the local cleaning of the air. This mechanism could explain in part why spatial inequalities with regards to air pollution persist with time.

The description of the heterogeneity in the exposure to air pollution and its evolution across time proposed in this paper constitutes the first step in our understanding of the spatial inequalities to environmental hazards such as air pollution.

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Appendix A

Appendix to Chapter 1

A.1 Additional data descriptives

A.1.1 Data sources

From 2002 to 2007: EIA-423 Survey form EIA-423 collect monthly non-utility fuel receipts and fuel quality files on plants with a fossil-fueled nameplate generating capacity of 50 or more megawatts. We use forms from 2002 to 2007 to collect monthly-frequency data on type of fuels

Form E-243 for non-utility plants: Detailed data are provided on monthly deliveries of fossil fuels to nonutility generating facilities are included at the specific energy source, quantity of fuel delivered, the Btu content, sulfur content, ash content, coal mine state and county (or country) of origin, coal mine type (surface/underground), as well as the supplier of the fuel. Fuel cost data collected on this survey is not be made available to the public because it is protected.

Form F-243 for utility plants: Survey form FERC-423 collected monthly utility fuel receipts and fuel quality data prior to 2008. Data files include information on type of fuel purchase, fuel cost, fuel type, fuel origin, fuel quantity and fuel quality.

From 2007 to 2015: EIA-923 The Form EIA-923, Power Plant Operations Report, is used to collect plant-level data on generation, fuel consumption, stocks, and fuel heat content from utility and non-utility power plants and for combined heat and power plants, beginning with the monthly 2008 data and annual 2007 data collections. Page 5 contains information on fuel receipts and costs at the plant level and monthly frequency.

A.1.2 Descriptives

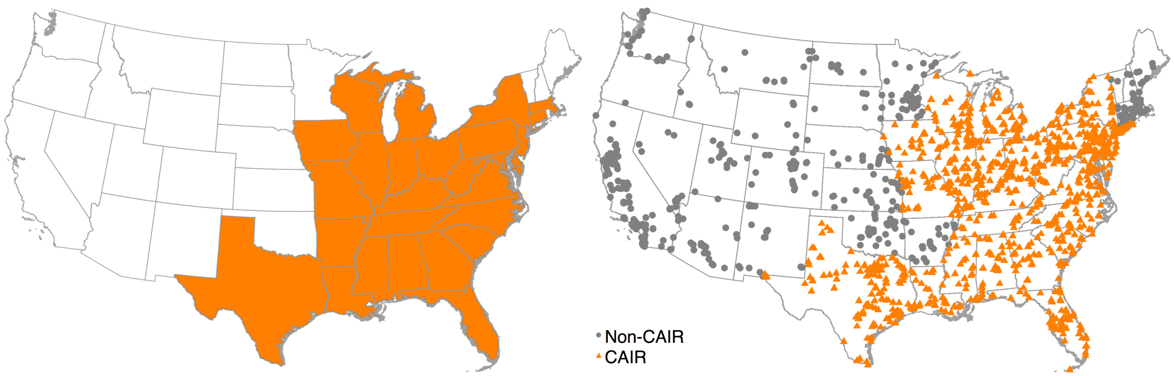
Table A.1: Summary statistics on fuels received in 2005

	Count	Mean	SD	Min	Max	Sum
Quantity of Gas (Mcf)	1,406	4,544,498	(9,693,613)	0	102,608,626	6389564554
Quantity of Oil (Barrels)	1,406	53,602	(389,820)	0	7,310,855	75,364,814
Quantity of Coal (tons)	1,406	702,985	(1,705,916)	0	14,464,625	988,396,341
Quantity of Bituminous Coal (tons)	1,406	305,374	(964,938)	0	8,657,200	429,356,184
Quantity of Sub-Bituminous Coal (tons)	1,406	319,265	(1,227,900)	0	13,617,400	448,885,971
Quantity of Other Coal (tons)	1,406	78,346	(619,485)	0	12,897,227	110,154,186
Cost of Gas (USD/Mcf)	306	902	(485)	104	7,933	276,123
Cost of Oil (USD/Barrel)	19	352	(574)	43	1,807	6,689
Cost of Coal (USD/Ton)	313	166	(61)	46	439	52,087
Cost of Bituminuous Coal (USD/Ton)	215	202	(59)	81	439	43,451
Cost of Sub-Bituminuous Coal (USD/Ton)	155	128	(45)	46	345	19,891
Cost of Other Coal (USD/Ton)	22	131	(49)	62	203	2,889
Ash Content of Gas (percent weight)	472	0	(0)	0	0	0
Ash Content of Oil (percent weight)	213	0	(0)	0	2	27
Ash Content of Coal (percent weight)	474	10	(6)	1	51	4,594
Ash Content of Bituminuous Coal (percent weight)	335	10	(3)	5	29	3,386
Ash Content of Sub-Bituminuous Coal (percent weight)	204	6	(3)	1	29	1,197
Ash Content of Other Coal (percent weight)	60	19	(13)	7	51	1,127
Sulfur Content of Gas (percent weight)	478	0	(0)	0	0	0
Sulfur Content of Oil (percent weight)	250	1	(2)	0	6	240
Sulfur Content of Coal (percent weight)	474	1	(1)	0	4	525
Sulfur Content of Bituminuous Coal (percent weight)	335	1	(1)	0	4	493
Sulfur Content of Sub-Bituminuous Coal (percent weight)	204	0	(0)	0	2	71
Sulfur Content of Other Coal (percent weight)	60	1	(1)	0	4	86
Heat content in Gas (MMBtu/Mcf)	912	1	(0)	1	1	934
Heat content in Oil (MMBtu/Barrel)	281	8	(7)	4	29	2,348
Heat content in Coal (MMBtu/ton)	474	22	(4)	10	27	10,195
Heat content in Bituminous Coal (MMBtu/ton)	335	24	(2)	19	27	8,088
Heat content in Sub-Bituminous Coal (MMBtu/ton)	204	18	(1)	16	22	3,628
Heat content in Other Coal (MMBtu/ton)	60	18	(6)	10	27	1,079

Notes: Table shows statistics of characteristics of fuel received by power plants for the year 2005. Unit-level fuel shares and technology stock are averaged over facility to arrive at facility-level data. All facility-level data is then collapsed by year. Quantity refers to quantity received at the monthly level by facility, summed up across month in 2005 at the facility level. Costs, sulfur, ash and heat content are averages of monthly values meaned across month in 2005 at the facility level.

Figure A.1: States and facilities targeted by the CAIR

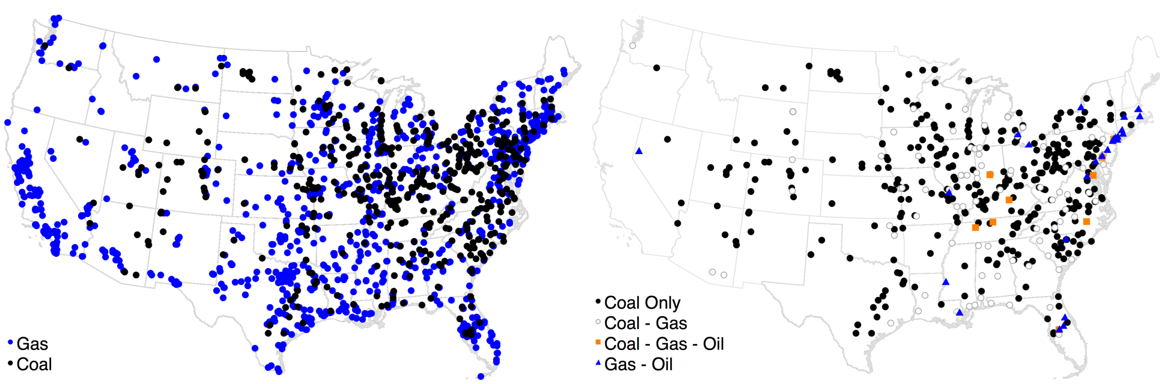
(a) States **(b)** Facilities



Notes: The figure displays states (left map) and power plants (right map) that are part of the CAIR. Orange triangles represent facilities that are part of the annual cap-and-trade programs for SO_2 and NO_x introduced by the CAIR.

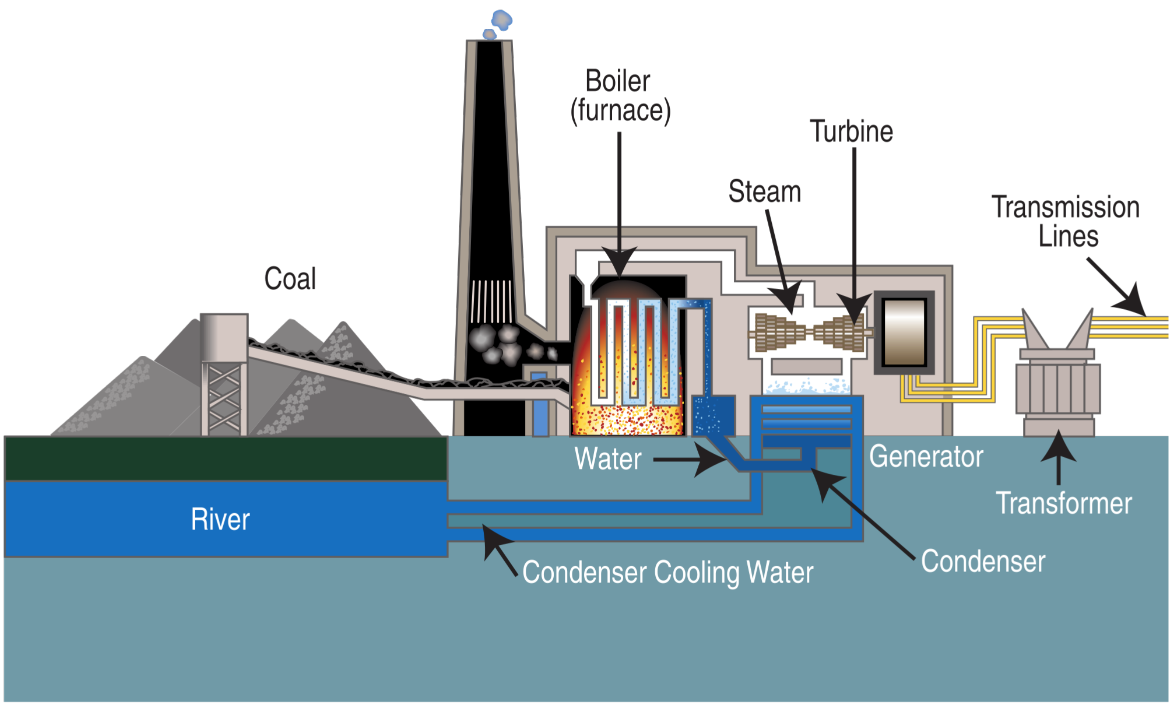
Figure A.2: Composition of fossil fuel power plants

(a) Gas plants vs other fuels **(b)** Composition of coal/oil plants



Notes: fossil fuel power plants are composed of several fuel-specific units — four units per power plant on average. Panel (a) plots the location of gas-only power plants (in blue) and power plants that have at least one unit burning coal or oil. Panel (b) plots the location of these latter units and distinguishes power plants that only have coal units (black), that have both coal and gas units (white), that have coal, gas and oil units (orange) or gas and oil units (blue).

Figure A.3: Coal unit within a power plant

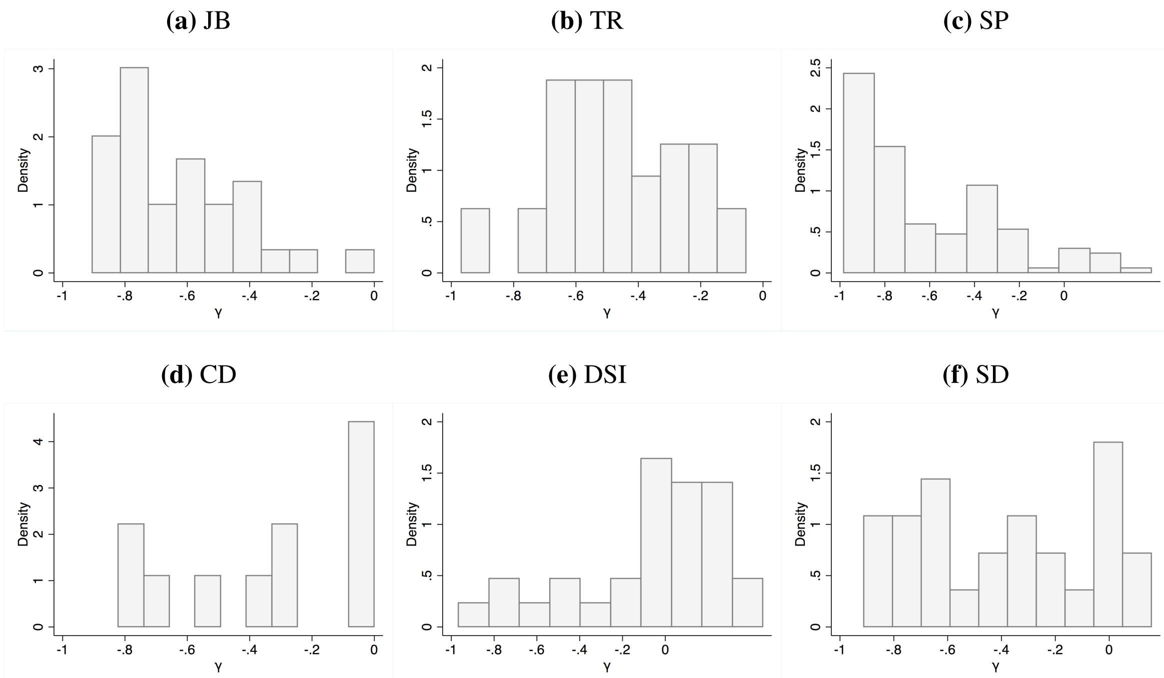


Notes: This scheme describes the functioning of a coal unit within a fossil-fuel power plant. Coals are transported from deposits to the *boiler* in which they are burnt to produce heat. The heat generated boils pressurized water that transforms into vapor and liquid water in the *condenser*. The steam is released to lead a *turbine* that rotates a *generator* in a magnetic fields to produce alternative current by induction following Faraday's law. Electricity is then adapted in the *transformer* to be released in the *transmission lines*. The process of burning fuel in the boiler generates incombustible material (ashes, particulate matters), toxic gases (CO_2, NO_x, SO_2) and water vapor. These by-products are released in the cheminee, also called *stack* and constitute the main externality of power generation from fossil fuel burning.

A.2 Supporting material

A.2.1 Statistical decomposition

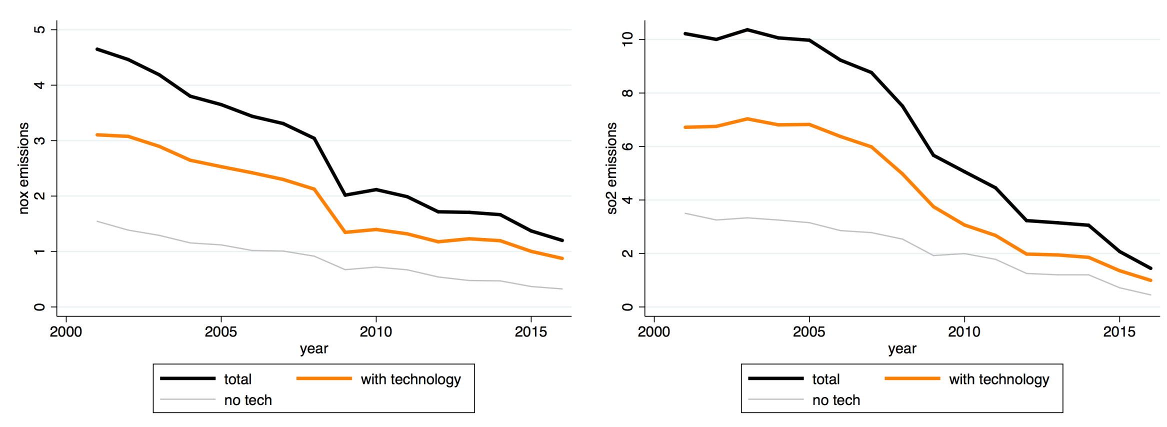
Figure A.4: Distribution of the impact of technology adoption on SO_2 emissions



Notes: The figure displays the distribution of the estimates of γ from boiler-level regressions. I plot here the exponential of γ minus one, which gives the percentage impacts of technology adoption on SO_2 emissions. The top row displays the impact of wet flue gas desulfurization technologies: jet bubbling reactor scrubbers (JB), tray type scrubbers (TR), spray type scrubbers (SP). The bottom row displays the impact of dry flue gas desulfurization technologies: circulating dry scrubber (CD), dry sorbent injection type (DSI) and spray dryer type, semi-dry flue gas desulfurization (SD).

Figure A.5: Emission reductions at coal boilers with and with no abatement technology

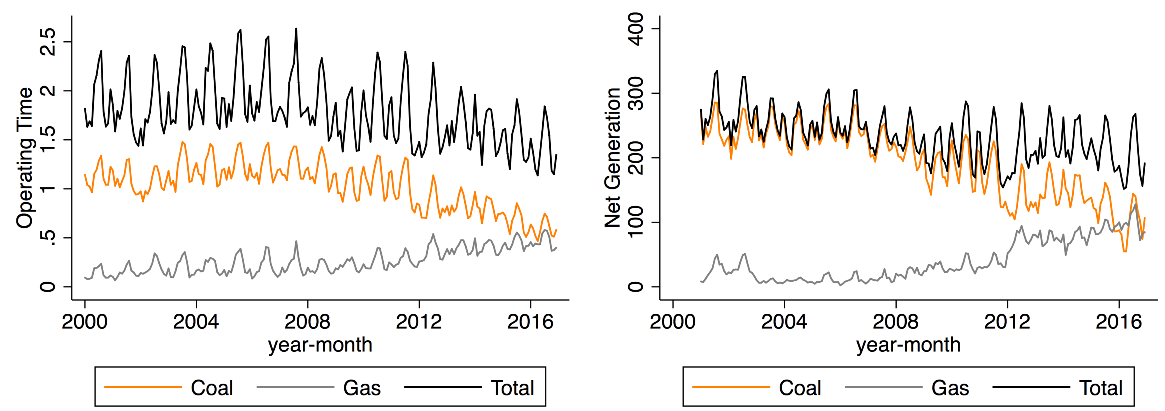
(a) NO_x **(b)** SO_2



Notes: The figure displays the total emissions of NO_x (left) and SO_2 (right) from coal boilers that install abatement technology between 2004 and 2014 and boilers with no new installation.

Figure A.6: Switching from coal to gas units for electricity generation

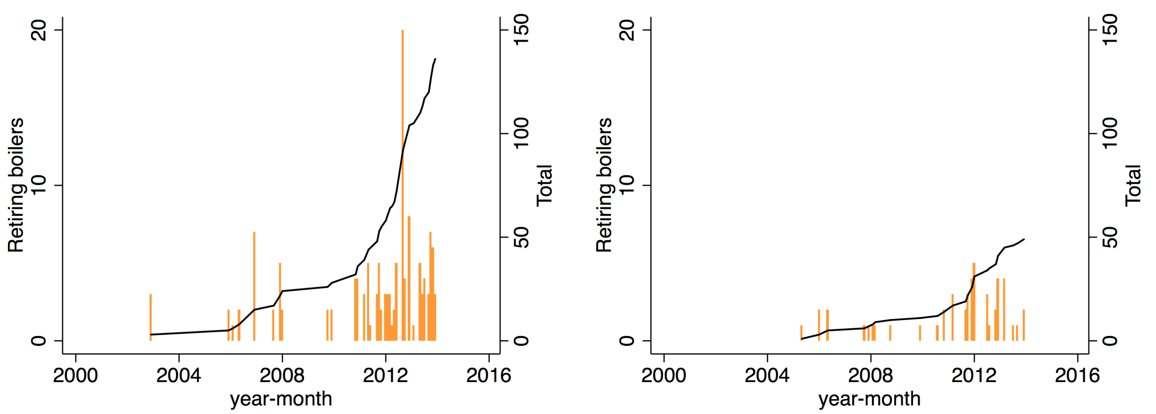
(a) Operating Time **(b)** Net Generation



Notes: Figure (a) depicts the evolution of the monthly number of hours that coal and gas units operated at plants in the CAIR region that were composed of both coal-specific and gas-specific boilers. These include a balanced panel of units that did not shut down. For the same plants, figure (b) describes the evolution of net generation at coal and gas units within the same plants. Both panels show that gas units were used more intensively at plants that had both coal and gas units. Total electricity production at these plants was unchanged during the period of study.

Figure A.7: Retirement of coal and gas units

(a) Retiring Coal Boilers **(b)** Retiring Gas Boilers



Notes: The figure displays the timing and number of coal (left) and gas (right) units shut-downs in the CAIR region. Most shut downs happened after emissions had dropped to the level of the CAIR cap. In 2012, the EPA's Mercury rule was signed and is thought to have pushed dirtiest units out of operation, although no paper in the literature investigates the question. In our sample, most units that shut down had been operating for more than 60 years and had hence reached retirement age.

Table A.2: Technology adoption

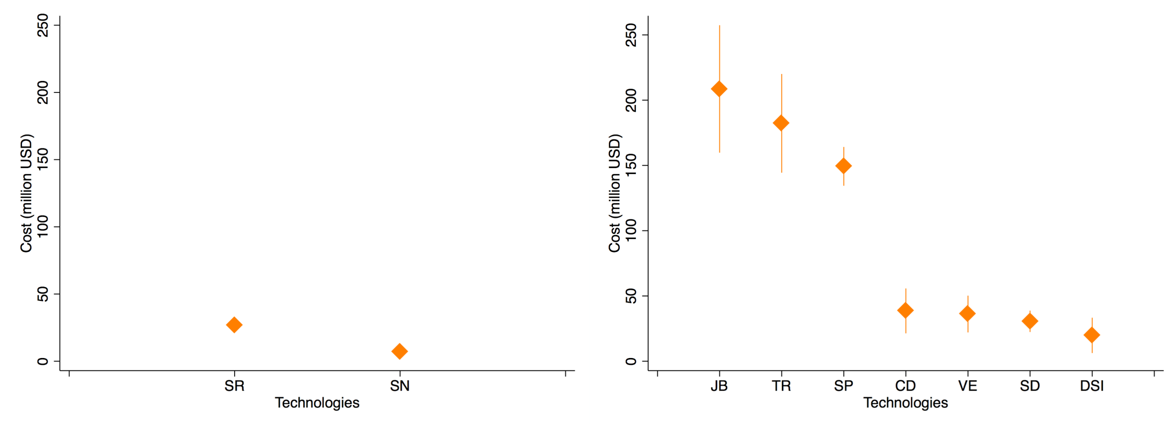
	SO_2 emissions (mill. tons) 2002	2014	Drop	Share of drop (%)	Number of boilers
Total	9.90	2.86	7.04	100.0	1483
Bituminous Boilers	5.86	1.62	4.24	60.2	412
Bituminous Boilers—installed tech	3.83	0.34	3.49	49.6	175
Bituminous Boilers—did not install tech	2.03	1.28	0.75	10.7	237
Sub-Bituminous Boilers	1.22	0.62	0.60	8.5	143
Sub-Bituminous Boilers—installed tech	0.49	0.07	0.42	6.0	35
Sub-Bituminous Boilers—did not install tech	0.73	0.55	0.18	2.6	108
Bituminous to Sub-Bituminous switchers	0.57	0.21	0.36	5.1	58
Bituminous to Sub-Bituminous switchers—installed tech	0.19	0.01	0.18	2.6	14
Bituminous to Sub-Bituminous switchers—did not install tech	0.37	0.20	0.17	2.4	44
Other Coals Boilers	0.35	0.26	0.09	1.3	20
Other Coals Boilers—installed tech	.	.	.	.	.
Other Coals Boilers—did not install tech	0.35	0.26	0.09	1.3	20
Retiring Coal Boilers	1.21	0.00	1.21	17.2	204
Retiring Coal Boilers—installed tech	0.09	0.00	0.09	1.3	6
Retiring Coal Boilers—did not install tech	1.12	0.00	1.12	15.9	198
Oil Boilers	0.09	0.00	0.09	1.3	21
Oil Boilers—installed tech	.	.	.	.	.
Oil Boilers—did not install tech	0.09	0.00	0.09	1.3	21
Retiring Oil Boilers	0.07	0.00	0.07	1.0	43
Retiring Oil Boilers—installed tech	.	.	.	.	.
Retiring Oil Boilers—did not install tech	0.07	0.00	0.07	1.0	43
Switch coal-to-gas Boilers	0.06	0.00	0.06	0.9	14
Switch coal-to-gas Boilers—installed tech	0.01	0.00	0.01	0.1	2
Switch coal-to-gas Boilers—did not install tech	0.05	0.00	0.05	0.7	12
Switch oil-to-gas Boilers	0.06	0.00	0.06	0.9	14
Switch oil-to-gas Boilers—installed tech	0.01	0.00	0.01	0.1	2
Switch oil-to-gas Boilers—did not install tech	0.05	0.00	0.05	0.7	12
Gas Boilers	0.05	0.00	0.05	0.7	134
Gas Boilers—installed tech	.	.	.	.	.
Gas Boilers—no tech	0.05	0.00	0.05	0.7	134
Sub-Bituminous to Bituminous switchers	0.06	0.02	0.04	0.6	8
Sub-Bituminous to Bituminous switchers—installed tech	0.06	0.02	0.04	0.6	8
Sub-Bituminous to Bituminous switchers—did not install tech	.	.	.	.	.
New Boilers	0.00	0.04	-0.04	-0.6	130
New Boilers—installed tech	0.00	0.04	-0.04	-0.6	26
New Boilers—did not install tech	0.00	0.00	0.00	0.0	104

Notes: The table gives summary statistics on technology adoption and type of boilers operating between 2005 and 2014

A.2.2 Abatement technology

Figure A.8: Average costs incurred to power plants for abatement technology installation

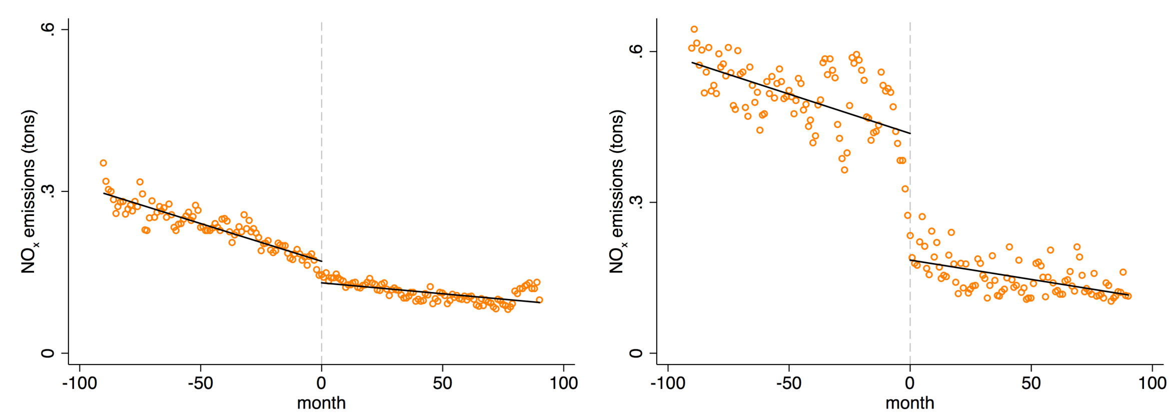
(a) NO_x **(b)** SO_2



Notes: The figure displays fixed costs reported by power plants for installing each type of abatement technology for NO_x emissions (left) and SO_2 emissions (right). Costs are averaged across power plants. Vertical bars display standard deviations.

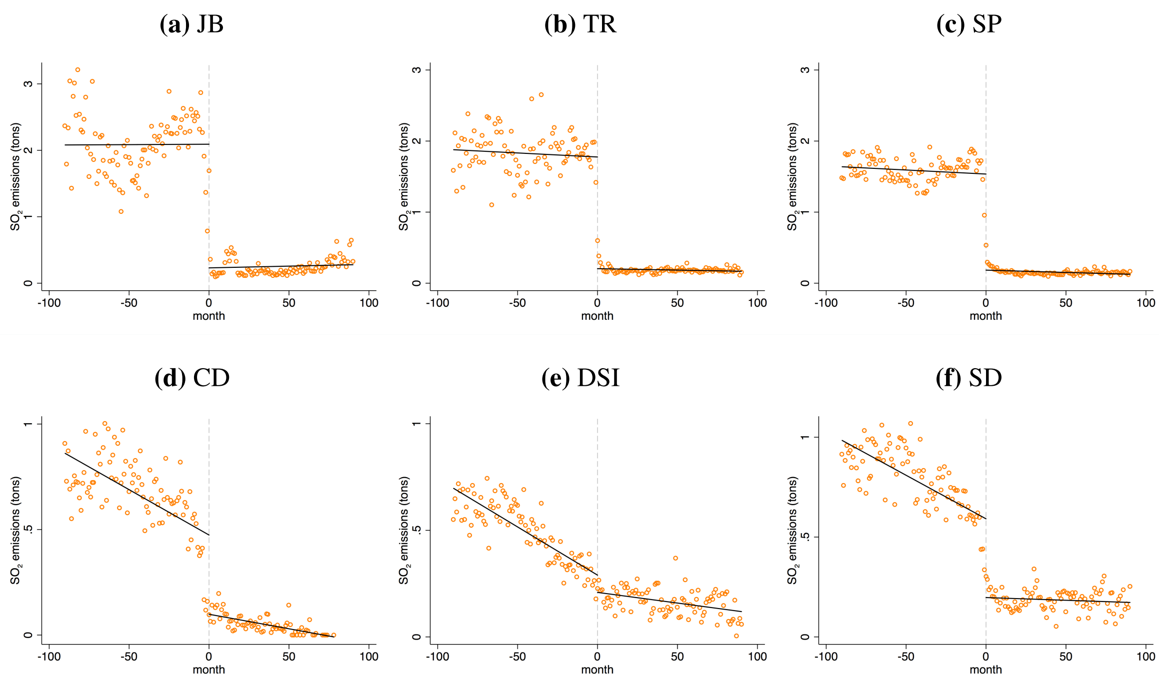
Figure A.9: Impacts of NO_x abatement technology adoption on NO_x emissions

(a) SNCR **(b)** SCR



Notes: The figure displays the average impact of technology adoption on monthly emissions of NO_x across all boilers. Averages include all boilers in the CAIR region, at which technology was installed between 2005 and 2014. One boiler typically receives a unique retrofit: only one technology (if any) is installed by boiler. Impacts are displayed for selective non-catalytic reduction systems (left) and selective catalytic reduction systems (right).

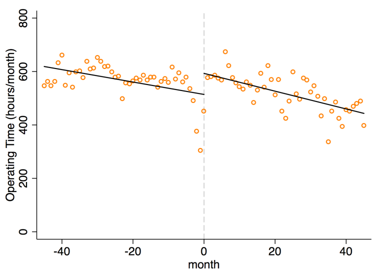
Figure A.10: Impacts of SO_2 abatement technology adoption on SO_2 emissions



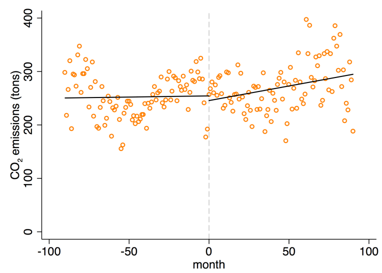
Notes: The figure displays the average impact of technology adoption on monthly emissions of SO_2 across coal boilers. Averages include all boilers in the CAIR region, at which technology was installed between 2005 and 2014. One boiler typically receives a unique retrofit: only one technology (if any) is installed by boiler. The top row displays the impact of wet flue gas desulfurization technologies: jet bubbling reactor scrubbers (JB), tray type scrubbers (TR), spray type scrubbers (SP). The bottom row displays the impact of dry flue gas desulfurization technologies: circulating dry scrubber (CD), dry sorbent injection type (DSI) and spray dryer type, semi-dry flue gas desulfurization (SD).

Figure A.11: Evolution of key operation variables of coal units with technology adoption

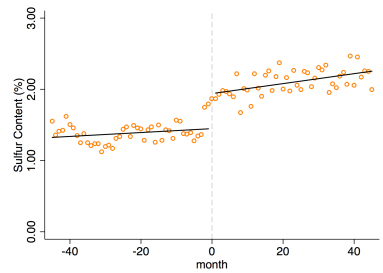
(a) Operating time



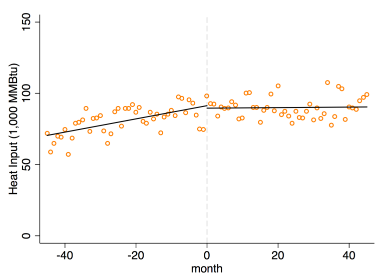
(b) CO_2 emissions



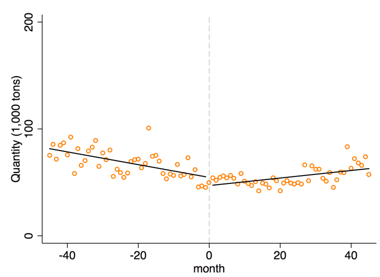
(c) Sulfur content of coals



(d) Heat content of coals



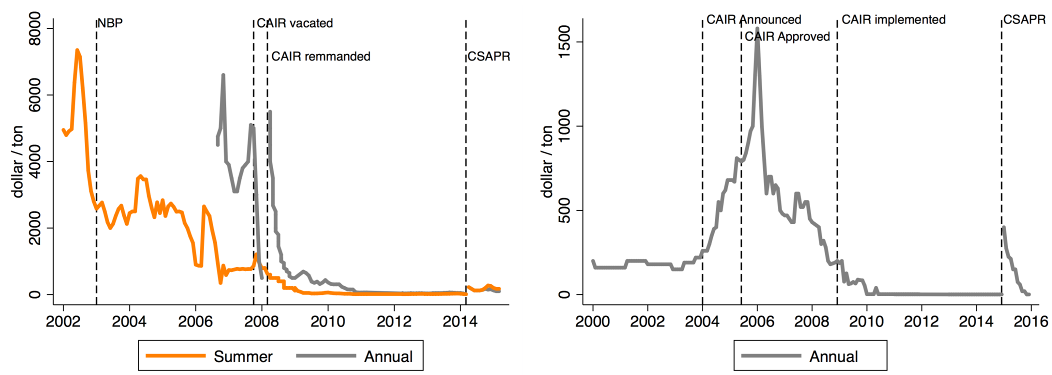
(e) Quantity of coal



Notes: The figure displays the average impact of technology adoption across coal boilers on key operating variables at the monthly frequency: operating time, CO_2 emissions, Sulfur content of coals, heat content of coals and quantity of coal. Averages include all boilers in the Western region, at which technology was installed between 2005 and 2014. The figure displays the impact of wet flue gas desulfurization technologies: jet bubbling reactor scrubbers (JB). Technology adoption does not seem to be correlated with changes in operating time of coal boilers, or other key variables that could impact emissions of SO_2.

Figure A.12: Emissions markets prices

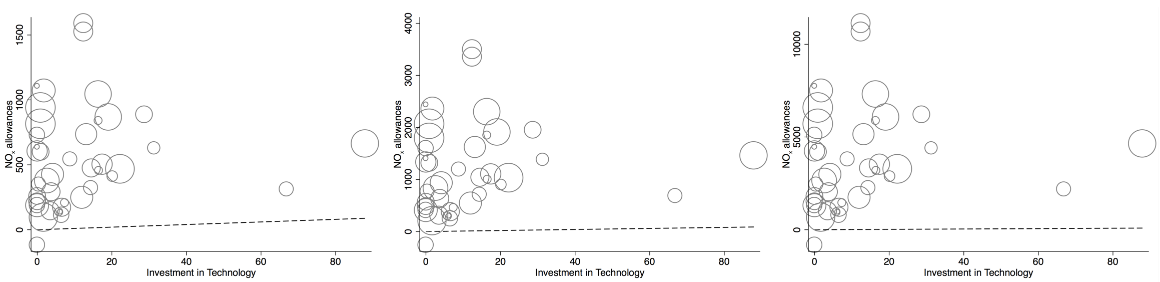
(a) NO_x prices **(b)** SO_2 prices



Notes: The left panel displays allowance prices for NO_x emissions under the NO_x Budgeting Program (from 2003 to 2008), the CAIR (from 2008 to 2014), and the CSAPR which replaced the CAIR in 2014. The orange line represent prices on the summer markets, and the grey line represent prices in the annual markets. Prices are from the spot markets during implementation of each policy and from forward markets for months preceeding implementation. The right panel displays prices for SO_2 allowances on the Acid Rain Program (ARP), the CAIR market and the CSAPR markets. Under the ARP, prices were stable for about 10 years prior to 2004. In 2004, when the EPA announced it was working on the CAIR, prices started to rise. In 2005, when the CAIR was published and approved, allowance prices on the ARP skyrocketted. Under the CAIR, the cap for SO_2 emissions was divided by two. The spike in prices in the ARP maket can in part be explaine by the fact that the CAIR allowed plants to bank their ARP allowances and use them during the CAIR implementation, and that one ARP allowance would be worth two allowances on the CAIR (Schmalensee and Stavins, 2013). This was meant to be an incentive for early emission reductions. Demand for allowances on the ARP thus grew in 2005, in response to the CAIR approval, and before the CAIR was implemented. Only a few companies keep track of spot and forward prices on US NO_x and SO_2 emissions markets. I collected manually information on allowance prices for NO_x and SO_2 markets from annual reports published by the EPA and from Resources for the Future working papers. The data that are displayed in these documents were acquired from CantorCO2e Market Price Index, BGC Environmental Brokerage Services Market Price Index, Bloomberg, and SNL Financial.

Figure A.13: NO_x: Present value of permit purchases v. Investment in abatement technology

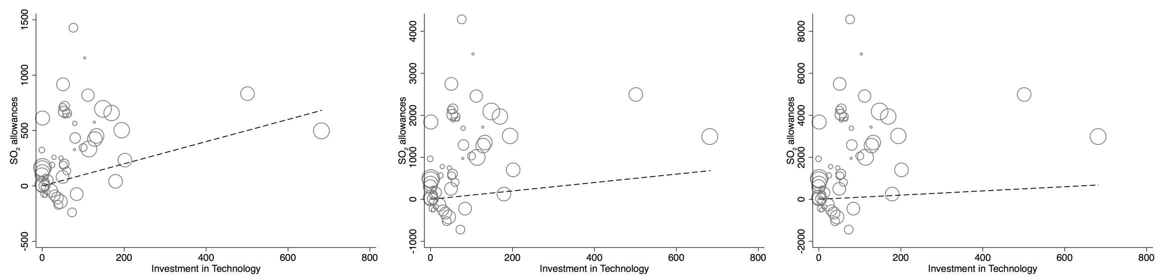
(a) Low price expectations **(b)** Medium price expectations **(c)** High price expectations



Notes: The figure compares the present value of the costs of purchasing permits on the NO_x market to the investments in abatement technologies at the plant level. Each circle corresponds to a power plant in the CAIR and NBP region. The size of each circle corresponds to the number of years of operations left at the date of installation of an abatement technology. The number of years left is calculated using the facility planned retirement date as described in EIA form 860. For each power plant, the present value the purchases of permits is calculated in three steps. First, initial allowances are recovered from the EPA Clean Air Market database, and compared with "unabated" emissions at the plant level. Second, the excess yearly emissions recovered is multiplied with the "expected" price of allowances, derived from observed allowance prices (see Figure A.12): panel (a) uses a low expected price, corresponding to the lowest price observed during the NBP market years ($1,000 per ton), panel (b) uses a medium expected price ($2,200 per ton) and panel (c) a high expected price corresponding to the peak price ($7,000 per ton). Finally, future streams of permit costs are actualized at 2003 year values. The black doted line represent the break-even points at which the cost of technology would be equal to the present value of expected permits costs. In all scenarii, power plants faced a higher costs of buying extra permits compared to the investment realized in technologies. Technology adoption was the least-cost option to comply with the NBP.

Figure A.14: SO_2: Present value of permit purchases v. Investment in abatement technology

(a) Low price expectations **(b)** Medium price expectations **(c)** High price expectations



Notes: The figure compares the present value of the costs of purchasing permits on the NO_x market to the investments in abatement technologies at the plant level. Each circle corresponds to a power plant in the CAIR and NBP region. The size of each circle corresponds to the number of years of operations left at the date of installation of an abatement technology. The number of years left is calculated using the facility planned retirement date as described in EIA form 860. For each power plant, the present value the purchases of permits is calculated in three steps. First, initial allowances are recovered from the EPA Clean Air Market database, and compared with “unabated” emissions at the plant level. Second, the excess yearly emissions recovered is multiplied with the “expected” price of allowances, derived from observed allowance prices (see Figure A.12): panel (a) uses a low expected price, corresponding to the historical SO_2 price observed during the ARP market years ($220 per ton), panel (b) uses a medium expected price ($500 per ton) and panel (c) a high expected price corresponding to the 2006 peak price ($1,500 per ton). Finally, future streams of permit costs are actualized at 2005 year values. The black doted line represent the break-even points at which the cost of technology would be equal to the present value of expected permits costs. In all scenarii, power plants faced a higher costs of buying extra permits compared to the investment realized in technologies. Technology adoption was the least-cost option for a large part of power plants targeted by the CAIR, under the asumption that plant managers expected prices to remain at least as high as they had been under the Acid Rain Program, a market that operated a cap 3 times less stringent. However, under any expectation skims, some power plants invested in technologies that were more expensive than the present value of not abating. This leads support to two hypotheses: (1) power plants over invested in abatement technologies to insure themselves against large policy uncertainties, (2) some plants installed technologies in response to other policies that are unobserved in the analysis and may have been implemented at the state, or municipality level.

A.2.3 Health benefits

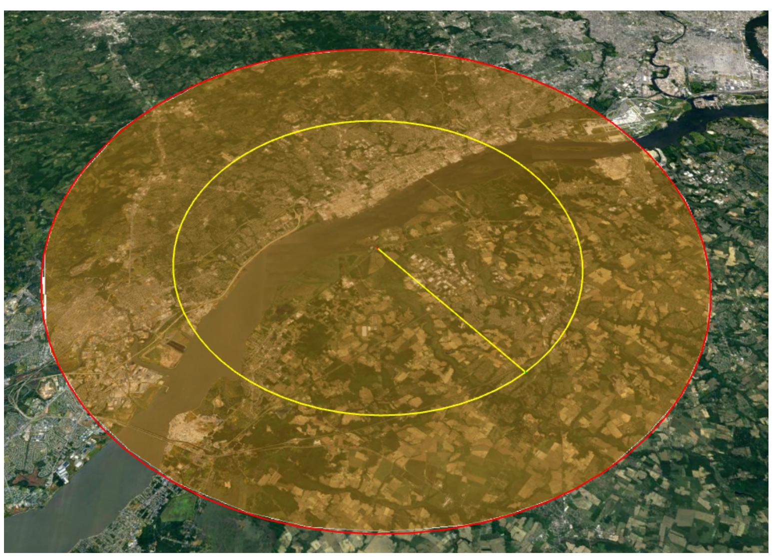
Table A.3: Literature review: effects of SO_2 and NO_x pollution on health outcomes

Paper	Pollutant	Health Impact	% drop of pollutant	% drop of health issue
?	SO_2	Birth Weight	1 μg	5 g
		Gestation duration	1 μg	0.18-day
Luechinger (2014)	SO_2	Infant Mortality	1 %	0.13 %
?	NO_x, O_3	Mortality	10%	0.04%
		death/100,000 population		
?	NO_2	Prematurity	6.8%	10.8 %
	NO_2	Low birth weight	6.8%	11.8 %
Chay and Greenstone (2003)	TFP	Infant Mortality	1%	0.5%
	(PM_{10}, $PM_{2.5}$)			
Knittel et al. (2016)	PM_{10}	Infant Mortality	1 unit	18 fewer infant mortality/100,000

Notes: This table summarizes results from a selection of health economics studies linking local air pollutants to health outcomes — mainly, infant mortality. These estimates are used to calculate the back-of-the-envelope health effects reported above.

A.2.4 Hedonics

Figure A.15: Impact on housing: treatment and control groups



Notes: The picture illustrates the empirical strategy of the housing estimations. The circles center on a coal power plant. The treated area corresponds to housing units in the yellow circle. The control group is composed of housing units in the ring contained in between the yellow and red circles.

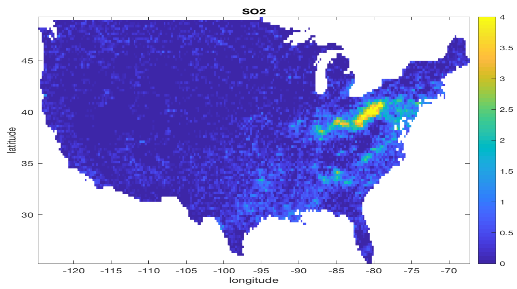
Table A.4: Air pollution around coal power plants

	SO_2	NO_x	$PM_{2.5}$	% of U.S. Area
Disk of ray 1 miles	3	2	2	0
Disk of ray 2 miles	10	7	5	1
Disk of ray 3 miles	18	14	10	1
Disk of ray 5 miles	37	30	22	3
Disk of ray 10 miles	72	63	50	10
Disk of ray 20 miles	94	86	77	29
Disk of ray 50 miles	99	97	95	69
Disk of ray 100 miles	100	99	99	92

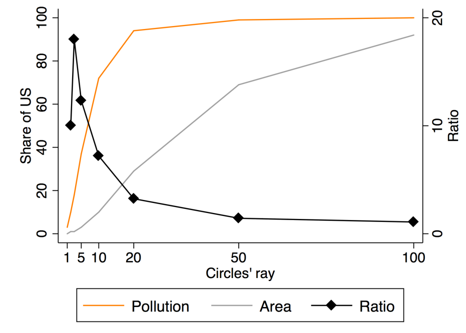
Notes: The table displays the total amount of pollution that is contained within circles of varying distances from coal power plants (column 1 to 3). Numbers correspond to the percentage of pollution that is detected from satellites and lies within circles of varying distances from power plants as compared with the total pollution detected from space across the US. The last column displays the percentage of the US surface that those circles represent.

Figure A.16: Air pollution concentration around coal power plants

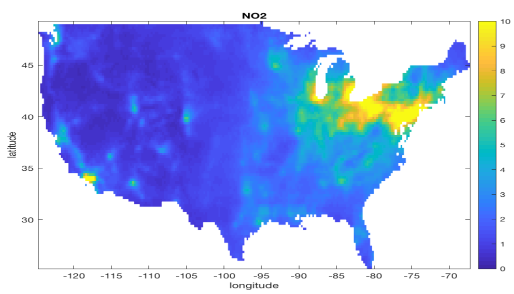
(a) SO_2



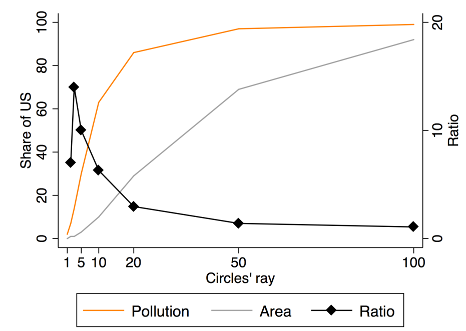
(b) Ratio Pollution/Area



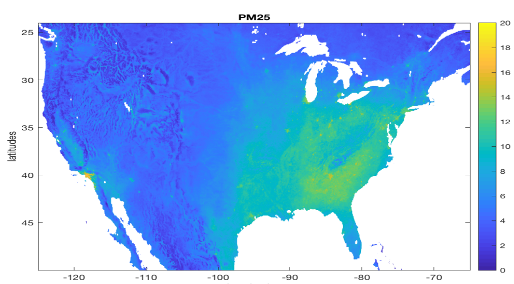
(c) NO_x



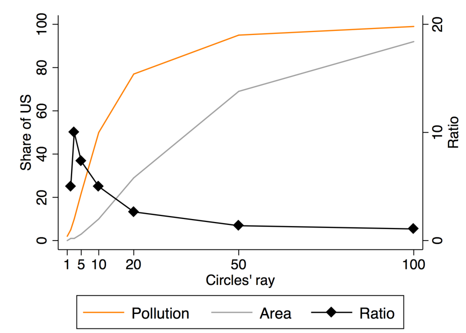
(d) Ratio Pollution/Area



(e) $PM_{2.5}$



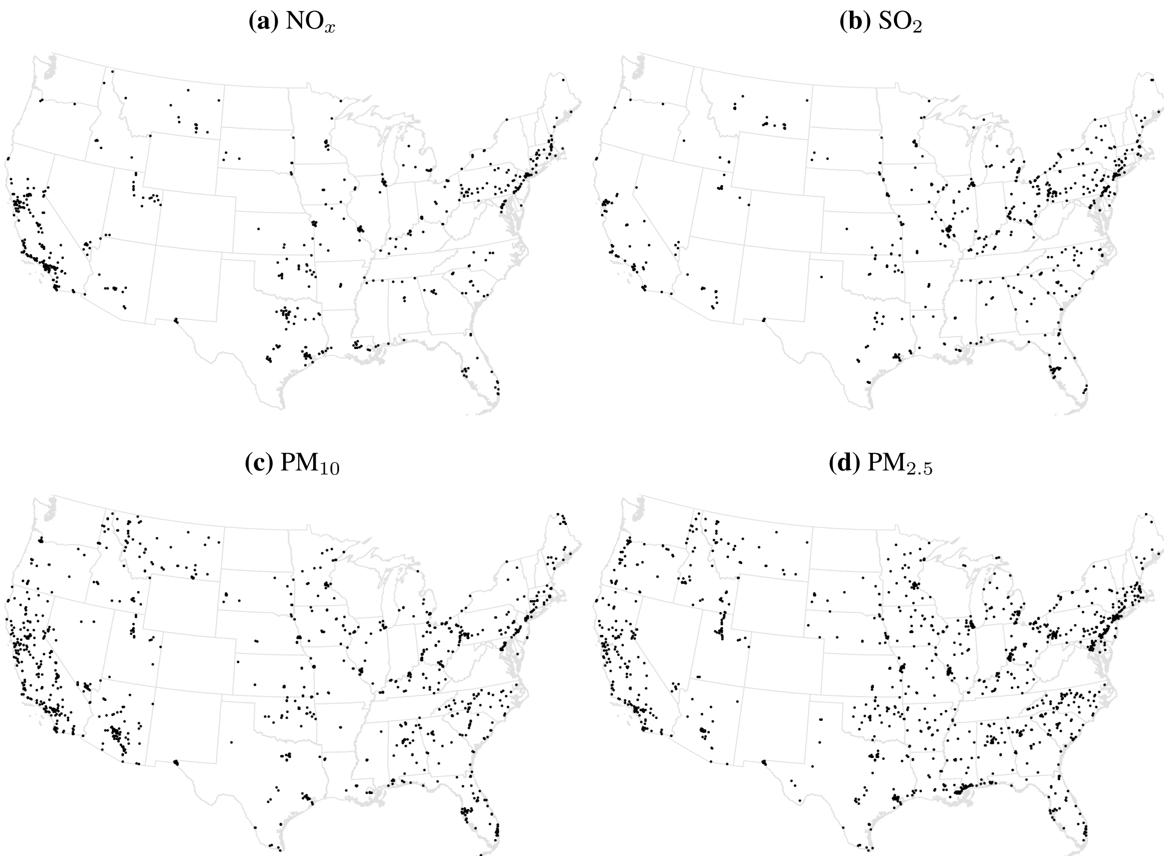
(f) Ratio Pollution/Area



Notes: These figures represent the concentration of pollutants around all coal power plants in the US. The left column depicts air concentrations of SO_2, NO_x and $PM_{2.5}$ in 2004. The right graphs plot the total amount of pollution that is contained within circles of varying distances from coal power plants. The black lines represent the ratio of total air pollution on total surface of these circles. It shows that pollution from SO_2 is concentrated within 3 miles of coal power plants. For NO_x and $PM_{2.5}$, pollution is more diffused. Although concentration of these two pollutants is higher in the vicinity of power plants, levels of pollution away from plants is high. For NO_x, this is because coal power plants only account for a quarter of total emissions. Other sources include cars, hence NO_x concentrations are high in city centers. In the case of $PM_{2.5}$, SO_2 transforms into compounds that can travel dozens of miles and become $PM_{.2.5}$ far away from power plants.

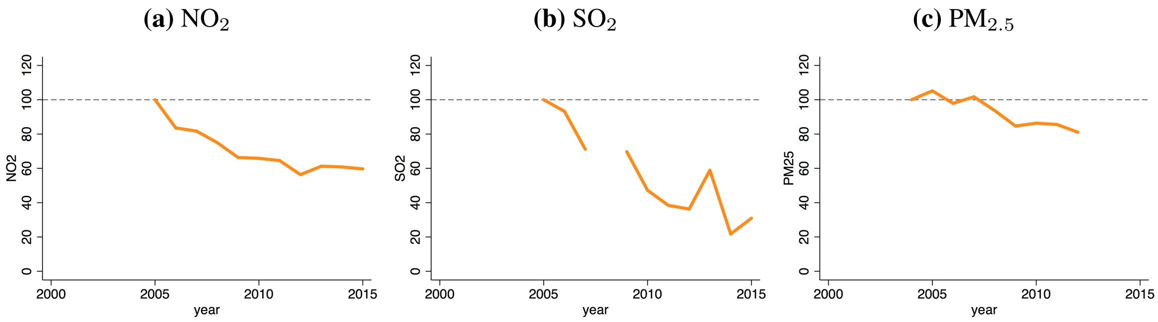
A.2.5 Validation of satellites' air pollution data

Figure A.17: Ground-level monitoring stations



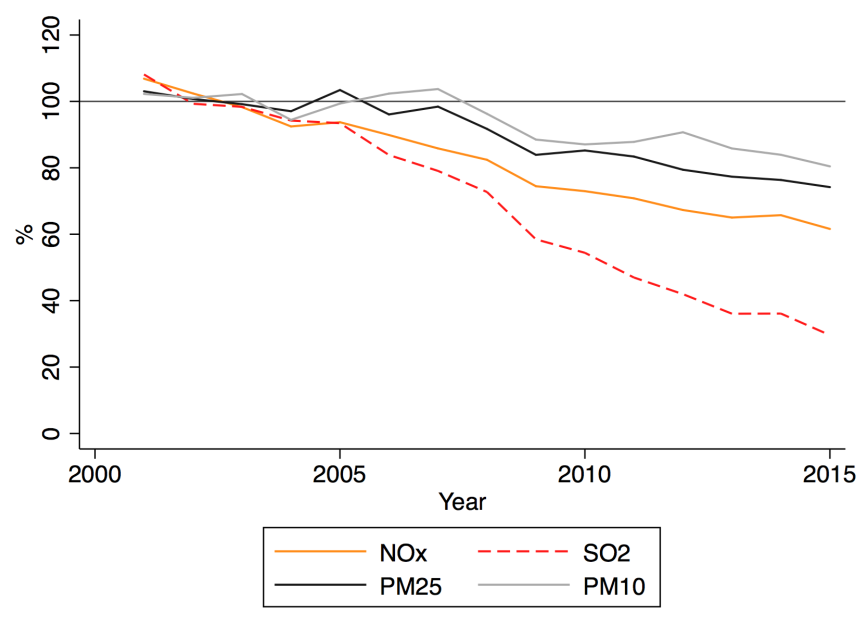
Notes: The maps display the location of ground-level monitoring stations installed by the EPA to continuously collect information on local concentrations of NO_2, SO_2, $PM_{2.5}$, and PM_{10}.

Figure A.18: Evolution of concentration of major pollutants—Satellites



Notes: The graphs display changes in local air concentrations of NO_2, SO_2 and $PM_{2.5}$. Values are recovered from satellite imagery derived from the Ozone Monitoring Instrument and from van Donkelaar et al. (2015). Measures are weighted by population using Census and CIESIN geographic information on population in the US. Values from 2004 are normalized to 100.

Figure A.19: Evolution of concentration of major pollutants—Monitors



Notes: The graph displays changes in local air concentrations of NO_2, SO_2, $PM_{2.5}$, and PM_{10}. Values are recovered from information collected by ground-level monitoring stations installed by the EPA.

Table A.5: Correlation between monitoring stations and satellite measures—SO_2 and NO_2

Year	Correlation	Number of County	Year	Correlation	Number of County
2005	0.70	253	2005	0.64	326
2006	0.70	252	2006	0.60	326
2007	0.68	252	2007	0.54	327
2008	0.69	247	2008	0.55	312
2009	0.67	240	2009	0.36	300
2010	0.65	242	2010	0.27	298
2011	0.65	232	2011	0.31	293
2012	0.62	236	2012	0.23	303
2013	0.58	243	2013	0.11	311
2014	0.61	255	2014	-0.02	312
2015	0.64	250	2015	0.06	315
Overall	0.68	2702	Overall	0.52	3423

Notes: The left table displays correlation between monthly measures of NO_x concentrations from ground-level stations and measures derived from satellite imagery obtained from NASA's Ozone Monitoring Instrument. All measures are aggregated at the monthly frequency and county level. Correlations are estimated for every year. The right table displays correlation between monthly measures of SO_2 concentrations from ground-level stations and measures derived from satellite imagery obtained from NASA's Ozone Monitoring Instrument. All measures are aggregated at the monthly frequency and county level. Correlations are estimated for every year. Initial years display high correlation between satellite data and monitoring stations. As air concentrations of SO_2 dropped after 2008, they were less precisely measured from space. Low concentrations of SO_2 are difficult to detect from space.

Table A.6: Correlation between monitoring stations and satellite measures—PM

Year	Correlation (2.5)	Number of County (2.5)	Correlation (10)	Number of County (10)
2004	0.84	641	0.28	481
2005	0.82	638	0.35	466
2006	0.82	603	0.24	442
2007	0.82	595	0.31	416
2008	0.79	585	0.15	395
2009	0.77	589	0.13	384
2010	0.80	594	0.29	378
2011	0.78	548	0.17	371
2012	0.70	552	0.16	369
Overall	0.82	5345	0.27	3702

Notes: The table displays correlation between monthly measures of $PM_{2.5}$ concentrations derived from the reanalysis product provided by van Donkelaar et al. (2015) and ground-level measures of $PM_{2.5}$ and PM_{10}. All measures are aggregated at the monthly frequency and county level. Correlations are estimated for every year. Not suprisingly, the reanalysis data for $PM_{2.5}$ correlates well with ground-level measures of the pollutant. It is interesting to observe that correlation with PM_{10}, a visible pollutant similar to smog is low. The invisibility of $PM_{2.5}$ makes it one of the most dangerous pollutants as it often goes unoticed.

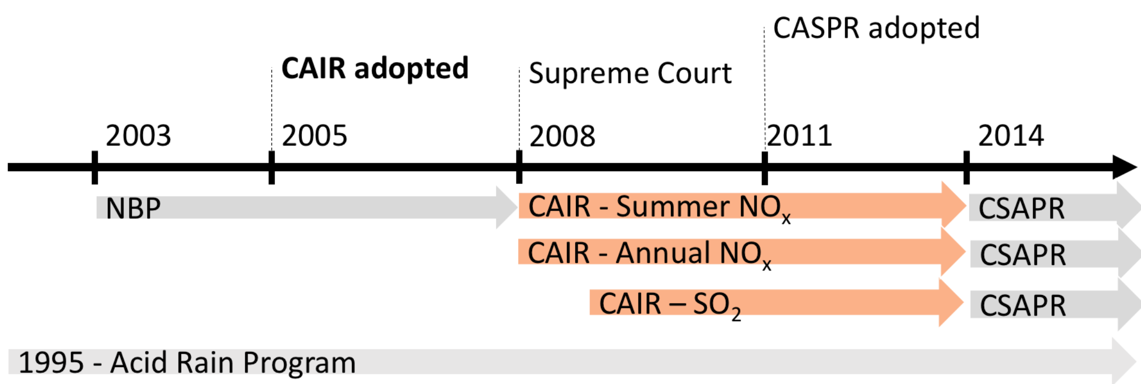
Appendix B

Appendix to Chapter 2

B.1 Policies targeting SO_2 and NO_x

Figure B.1 describes the timeline of the CAIR and preceeding and overlapping regulations towards power plant emissions of SO_2 and NO_x.

Figure B.1: Regulations timeline: cap-and-trade markets in the eastern US states



Notes: The EPA implemented the NO_x Budgeting Program (NBP) from 2003 to 2008 in eastern US states. This consisted in a cap-and-trade market targeting power plant emissions of NO_x in summer months. In 2005, the EPA adopted the Clean Air Interstate Rule (CAIR) that would implemented three cap-and-trade markets from 2008 on. The NBP would be continued under the summertime CAIR market for NO_x emissions. In addition, the CAIR implemented an annual market for NO_x emissions, to force power plants to reduce emissions in winter months also. In addition, the CAIR introduced an annual cap-and-trade market to limit annual emissions of SO_2 from the same power plants in the eastern US. The CAIR SO_2 market came to complement the existing federal market for SO_2 emissions implemented under the Acid Rain Program since 1995. After several legal actions challenging the adoption of the CAIR for its stringency, the Supreme Court decided to vacate the CAIR in 2008. It invoked one reason unrelated to the CAIR stringency: the EPA did not have the authority to implement inter-state trading systems and should revise the CAIR to implement as stringent caps at the state level. Until the EPA came up with a new policy, the CAIR was allowed to be run. In 2014, the Cross State Air Pollution Rule (CSAPR) implemented 27 state-specific cap and trade systems for NO_x and SO_2.

The National Ambient Air Quality Standards In order to mitigate the negative health effects of air pollution, the 1970 revision of the Clean Air Act[1] imposed upper-limit concentrations for six criteria air pollutants. These upper limits are known as the National Ambient Air Quality Standards (NAAQS).[2] The criteria pollutants include SO_2 and NO_x, as well as

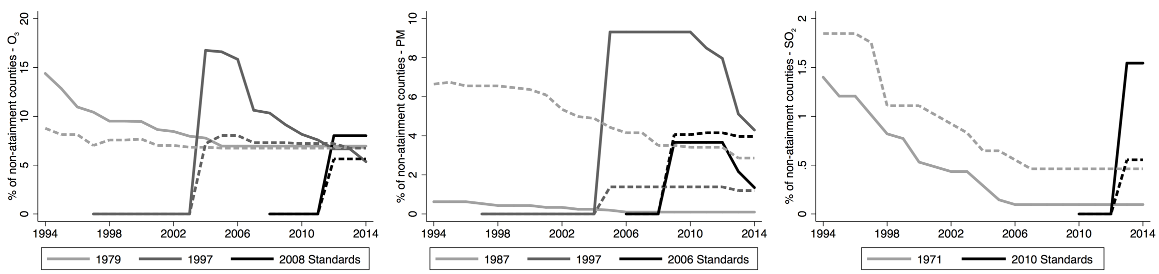
[1]The Clean Air Act is the law that defines the responsibilities of the EPA for addressing air pollution.

[2]The NAAQS do not directly regulate emissions of air pollutants, but aim to limit *concentrations* of air pollutants. The ambient air quality is measured by a network of monitoring stations across the US

particulate matter ($PM_{2.5}$ and PM_{10}) and ozone.[3] Counties that violate the upper-limit are designated as ”non-attainment” areas. The EPA requires states with non-attainment counties to form a State Implementation Plan to bring all counties to attainment by targeting emissions.[4]

Figure B.2: Percentage of counties in violations of the NAAQS

(a) O_3 **(b)** PM **(c)** SO_2



Notes: The figure displays the percentage of counties in the CAIR region (plain lines) and the non-CAIR region (dashed lines) for O_3 (a), PM (b) and SO_2 (c). The figures show the evolution of the proportion of counties considered in non-attainment of the NAAQS. The NAAQS were revised in 1979, 1997 and 2008 for O_3, 1987, 1997, and 2006 for PM, and 1971 and 2010 for SO_2. The 2006 and 2010 revisions led to more drastic standards for both PM and SO_2. In doing so, the EPA hoped to add another layer of legislation on air quality, which contributed to signaling that SO_2 emissions were going to be controlled more stringently than ever before. Importantly, shocks to NAAQS were as important in the treated and control areas, and mostly happened at a later stage of the CAIR, once emissions had already been reduced. We thank Nicholas Z. Muller for graciously sharing data on county attainment status for all US counties and criteria pollutants, at a yearly frequency.

The Acid Rain Program To counter air pollution at the federal level, the EPA developed the Acid Rain Program. The program was established under Title IV of the 1990 Clean Air Act Amendments, and was primarily formed to reduce acid rain. The Acid Rain Program introduced a federal cap-and-trade program on SO_2 emissions, and a rate-based policy on NO_x emissions, both on large fossil-fueled power plants.[5] The EPA is responsible for setting the federal cap, which must be approved by Congress. Initial allowances were grand-fathered

[3]The other two are carbon monoxide and lead.

[4]Failing to comply with the regulation would trigger EPA sanctions on the state. The EPA can for instance withhold federal grant money or ban the construction of potential new emission sources.

[5]The policy was unfolded in two phases. Phase I ran from 1995 to 1999 and affected the largest coal-burning units in 21 eastern and Midwestern states. Phase II began in 2000 and expanded the program to include smaller units fired by coal, oil and gas.

by the EPA to power plants. Plants are then allowed to purchase allowances if they fail to keep their emissions below their allocated level, or to sell or bank excess allowances if they manage to reduce their emissions beyond the allocated allowances.[6]

Contrary to the regulations on SO_2, the Acid Rain Program implemented a rate-based policy on NO_x emissions. The policy imposed boiler-specific NO_x emissions rates uniformly across the country, with penalties to power plants exceeding the rates. However, the rates were thought to be too lenient, particularly during summer months, when NO_x is an important precursor to ground-level ozone. Further, there was a growing concern over prevailing winds transporting NO_x from the industrial Midwest to the Northeast, contributing to ozone non-attainment status in eastern US states. In response to these concerns, 13 northeastern states introduced the NO_x Budgeting Program in 2003.[7]

The NO_x Budget Trading Program The NO_x Budgeting Program established a cap-and-trade program for summertime emissions (May to September) of NO_x from fossil-fueled power plants.[8] It operated from 2003 to 2008 and covered a total of 20 states by the end of the program period. Under the program, emissions allowances were grand-fathered to power plants. The allocated allowances were fully tradable, meaning that plants were free to buy and sell permits in the market to comply with the policy. At the end of September each year, affected units had to surrender one allowance for each ton of NO_x emitted. Previous studies have found that the NO_x Budgeting Program was efficient in reducing NO_x emissions (Fowlie

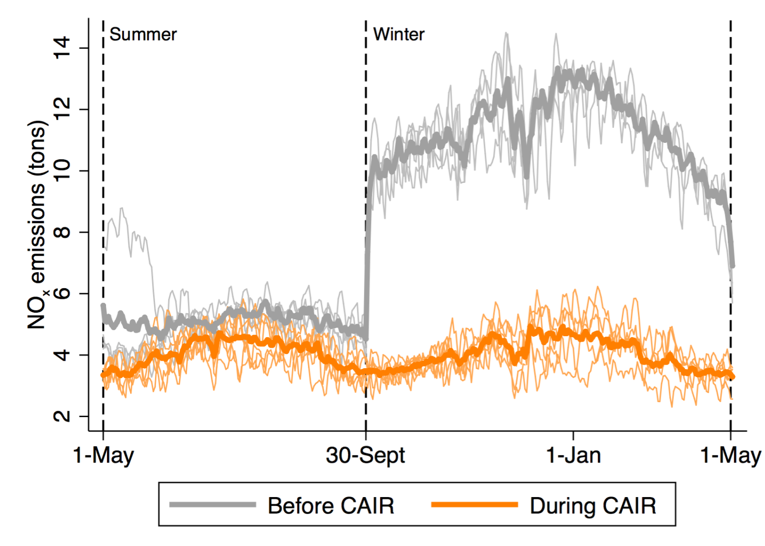
[6]Between 1990 and 2004, emissions of SO_2 from power plants involved in the program declined by 36%, while electricity generation by coal power plants increased by 25 % (Schmalensee and Stavins, 2013). However, *ex-post* studies have found the Acid Rain Program to displace SO_2 pollution from West to East (Chan et al., 2015). As the marginal damages of air pollution are generally higher in the east, partly due to higher population density, this displacement likely increased the overall damages of local pollution.

[7]An earlier, less stringent version of the program operated from 1999-2002: the so-called Ozone Transport Commission (OTC) NOx Budget Program. This earlier program covered in total 12 North-eastern states.

[8]The seasonal program also included a few, large industrial units that were carried over to the CAIR summertime market for NO_x.

and Muller, 2013), and generated substantial health benefits (Deschênes et al., 2017).[9]

Figure B.3: NO_x emissions in summer and winter days



Notes: The figure displays daily NO_x emissions from coal electricity generation units in the CAIR region against days of the year. Thin lines represent daily emissions averaged across coal EGUs, each line representing a year of emissions from these units. Thick lines represent the daily averages across years. Grey lines correspond to years preceeding the implementation of the CAIR NO_x annual market. During those years (2003 to 2008), summertime emissions where regulated under the NO_x Budgeting Program, which imposed a cap on NO_x emissions between May 1st and September 30th every year. Between 2003 and 2008, winter time emissions were not regulated. On September 30th every year, power plants switched off their abatement technologies for NOx. Orange lines correspond to years at which the CAIR markets operated: from 2009 to 2014. The CAIR continued the Summertime market for NO_x emissions and introduced an annual market. Under the CAIR, wintertime emissions were also regulated, which led power plants to keep their abatement technologies on all year long.

[9]See Burtraw and Szambelan (2009) for more details on the different US emissions trading programs.

B.2 Additional data descriptives

Power plants

Table B.1: Summary of plant characteristics, by CAIR and non-CAIR

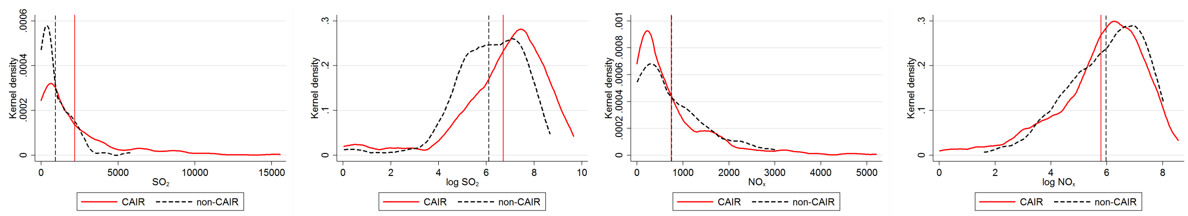
	CAIR		non-CAIR		Difference	
	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)
SO_2 emissions (tons)	12,023.3	(991.1)	3,795.2	(527.0)	8,228.1	
NO_x emissions (tons)	3,579.7	(245.1)	3,243.5	(408.6)	336.2	(476.5)
CO_2 emissions (1000 tons)	2,344.0	(146.7)	1,835.1	(201.3)	508.9	(249.0)
log(SO_2+1)	4.80	(0.17)	3.69	(0.23)	1.11	(0.29)
log(NO_x+1)	5.92	(0.10)	5.31	(0.17)	0.61	(0.20)
log(CO_2+1)	5.96	(0.10)	5.71	(0.14)	0.24	(0.17)
Average heat input (1000 MMBtu)	2,261.2	(130.4)	1,814.7	(178.8)	446.4	(221.3)
SO_2/Heat input (tons/MMBtu)	0.24	(0.02)	0.10	(0.01)	0.14	(0.02)
NO_x/Heat input (tons/MMBtu)	0.10	(0.00)	0.09	(0.01)	0.01	(0.01)
CO_2/Heat input (tons/MMBtu)	71.76	(1.50)	66.93	(1.08)	4.83	(1.85)
Gross Load (GWh)	2,726.4	(164.2)	2,163.7	(209.5)	562.7	(266.2)
Operating time (hours per month)	955.6	(38.0)	784.3	(43.4)	171.3	(57.6)
SO_2 rate (tons/GWh)	3.47	(0.97)	1.15	(0.14)	2.32	(0.98)
NO_x rate (tons/GWh)	2.56	(1.35)	1.47	(0.39)	1.08	(1.40)
CO_2 rate (1000 tons/GWh)	2.38	(1.45)	0.85	(0.05)	1.53	(1.46)
Average number of units per facility	2.76	(0.08)	2.13	(0.08)	0.64	(0.12)
Average number of coal units	0.87	(0.05)	0.55	(0.06)	0.31	(0.08)
Average number of gas units	1.66	(0.08)	1.50	(0.10)	0.16	(0.13)
Average age of units (years)	22.56	(0.64)	21.23	(0.97)	1.33	(1.16)
Age of oldest unit (years)	24.70	(0.70)	23.59	(1.07)	1.11	(1.28)
SO_2 controls (total number)	0.28	(0.03)	0.29	(0.05)	-0.01	(0.05)
NO_x controls (total number)	3.30	(0.12)	2.54	(0.15)	0.76	(0.20)
PM controls (total number)	1.06	(0.06)	0.69	(0.07)	0.37	(0.10)
Hg controls (total number)	0.02	(0.01)	0.02	(0.01)	0.00	(0.01)
Number of Units	1938		613			
Number of Facilities	665		273			
Number of States	24		24			

Notes: Table shows the means and standard deviations of plant characteristics for the year 2005, by CAIR and non-CAIR facilities. The two last columns show the difference in means and the standard errors from a t-test on the equality of means. The sample is balanced over the period 2003-2014 and is restricted to power plants that have at least one coal unit, see Section 2.4.2.

Emissions

Figure B.4: Densities for SO_2 and NO_x emissions, by CAIR and non-CAIR. 2005

(a) SO_2 **(b)** log SO2 **(c)** NO_x **(d)** log NOx



Notes: Figures show the kernel densities for SO_2 and NO_x emissions (curves) and the mean (vertical lines) for the treatment and the control group. Balanced panel (2003-2014). Only non-gas units. The monthly unit observations are summarized within a facility, then averaged over the year. The density for NO_x emissions is based on wintertime emissions.

Fuels

Table B.2: Quantity of fuels received, by CAIR and non-CAIR

	CAIR		non-CAIR		Difference	
	Mean	(sd)	Mean	(sd)	Mean	(se)
Quantity of Gas (Mcf)	4,433,589	(9,889,399)	5,004,791	(8,836,919)	-571,201	(610,219)
Quantity of Oil (Barrels)	52,097	(364,258)	59,848	(482,380)	-7,751	(31,136)
Quantity of Coal (tons)	662,057	(1,633,672)	872,840	(1,972,055)	-210,783	(128,845)
Quantity of Bituminous Coal (tons)	340,745	(998,724)	158,581	(794,718)	182,164	(56,514)***
Quantity of Sub-Bituminous Coal (tons)	245,538	(1,073,343)	625,244	(1,696,141)	-379,706	(107,494)***
Quantity of Other Coal (tons)	75,775	(604,661)	89,016	(678,639)	-13,241	(44,830)

Notes: Table shows the means and standard deviations of plant characteristics for the year 2005, by CAIR and non-CAIR facilities. Unit-level fuel shares and technology stock are averaged over facility to arrive at facility-level data. All facility-level data is then collapsed by year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Costs of fuels received, by CAIR and non-CAIR

	CAIR		non-CAIR		Difference	
	Mean	(sd)	Mean	(sd)	Mean	(se)
Cost of Gas (USD/Mcf)	938.61	(557.03)	803.35	(139.43)	135.26	(40.28)***
Cost of Oil (USD/Barrel)	384.57	(600.16)	75.64	(46.23)	308.93	(149.19)*
Cost of Coal (USD/Ton)	181.68	(57.30)	118.81	(46.75)	62.86	(6.53)***
Cost of Bituminuous Coal (USD/Ton)	207.05	(56.17)	156.32	(62.00)	50.73	(14.12)***
Cost of Sub-Bituminuous Coal (USD/Ton)	136.19	(44.55)	116.54	(44.16)	19.65	(7.27)***
Cost of Other Coal (USD/Ton)	164.39	(34.29)	83.51	(15.29)	80.88	(10.79)***

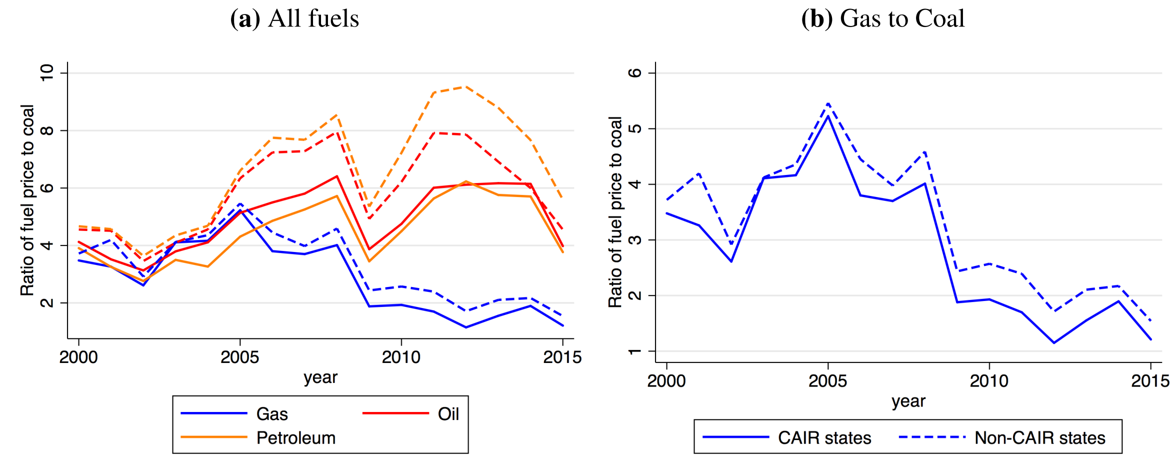
Notes: Table shows the means and standard deviations of plant characteristics for the year 2005, by CAIR and non-CAIR facilities. Unit-level fuel shares and technology stock are averaged over facility to arrive at facility-level data. All facility-level data is then collapsed by year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Quality of fuels received, by CAIR and non-CAIR

	CAIR		non-CAIR		Difference	
	Mean	(sd)	Mean	(sd)	Mean	(se)
Ash Content of Gas (percent weight)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Ash Content of Oil (percent weight)	0.14	(0.33)	0.06	(0.11)	0.08	(0.03)**
Ash Content of Coal (percent weight)	10.10	(6.45)	7.71	(3.95)	2.40	(0.55)***
Ash Content of Bituminuous Coal (percent weight)	10.04	(2.87)	11.08	(3.52)	-1.04	(0.77)
Ash Content of Sub-Bituminuous Coal (percent weight)	5.42	(2.37)	6.79	(3.87)	-1.37	(0.51)***
Ash Content of Other Coal (percent weight)	20.44	(13.44)	9.38	(1.33)	11.06	(1.93)***
Sulfur Content of Gas (percent weight)	0.00	(0.01)	0.00	(0.00)	0.00	(0.00)
Sulfur Content of Oil (percent weight)	0.98	(1.68)	0.76	(1.51)	0.23	(0.33)
Sulfur Content of Coal (percent weight)	1.24	(0.89)	0.49	(0.25)	0.75	(0.05)***
Sulfur Content of Bituminous Coal (percent weight)	1.52	(0.88)	0.77	(0.69)	0.75	(0.16)***
Sulfur Content of Sub-Bituminous Coal (percent weight)	0.32	(0.18)	0.41	(0.18)	-0.08	(0.03)***
Sulfur Content of Other Coal (percent weight)	1.56	(0.92)	0.67	(0.18)	0.89	(0.14)***
Heat content in Gas (MMBtu/Mcf)	1.02	(0.04)	1.02	(0.03)	0.00	(0.00)
Heat content in Oil (MMBtu/Barrel)	8.42	(6.93)	7.68	(6.24)	0.74	(1.32)
Heat content in Coal (MMBtu/ton)	22.13	(3.61)	18.48	(2.74)	3.65	(0.35)***
Heat content in Bituminous Coal (MMBtu/ton)	24.25	(1.51)	22.62	(1.61)	1.63	(0.35)***
Heat content in Sub-Bituminous Coal (MMBtu/ton)	17.72	(0.90)	17.91	(1.27)	-0.19	(0.17)
Heat content in Other Coal (MMBtu/ton)	18.38	(5.70)	15.73	(4.38)	2.65	(1.66)

Notes: Table shows the means and standard deviations of plant characteristics for the year 2005, by CAIR and non-CAIR facilities. Unit-level fuel shares and technology stock are averaged over facility to arrive at facility-level data. All facility-level data is then collapsed by year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.5: Fuel price to coal ratio (price/mmBtu) by CAIR



Notes: The figures plot the ratio of oil, gas and petroleum costs (per unit of heat content) on the average costs of coals (per unit of heat content). Data are retrieved from the EIA monthly-frequency and state-level dataset on fuel prices delivered at fossil fuel power plants. Plain lines correspond to these ratios in states covered by the CAIR, and the dotted lines correspond to data in non-CAIR states.

Demographics

Figure B.6: Block groups and 1 mile radii circles

Notes: Figure illustrates how demographic variables are constructed. The background map shows block group level boundaries. The three red dots represents three different power plants. The blue circles encapsulating the power plants are 1 mile radii circles. To construct demographics for the 1 mile radii circles, we first identify the block groups that intersect with the circle. We then calculate the size of the intersected areas (in m^2). Next, by assuming a uniform distribution of population, we can calculate the number of people per m^2 within each block group. Multiplying this population density (pop/m^2) by the size of the intersected areas (in m^2), we get the number of people living within the intersected areas. Taking the population within each intersected area and dividing it by the total population within the 1 mile circle, we get population-weighted shares for each intersected area. These population weights are used to create average demographic variables for the 1 mile circles around power plants.

Table B.5: Demographics in power plants neighborhoods v. all country

	Count	Mean	SD	Min	Max
Panel A: All block groups in the US					
Median household income (USD 1000)	209272	54.20	30.26	2.50	250.00
Top income (above USD 100 000) (%)	211274	0.18	0.18	0.00	1.00
Below poverty line (%)	209697	0.12	0.09	0.00	0.50
High school or less (%)	211274	0.47	0.21	0.00	1.00
College degree (%)	211274	0.32	0.20	0.00	1.00
Population (1000)	211274	1.45	1.24	0.00	55.28
Median house value (USD 1000)	204199	230.82	196.11	5.40	1,000.00
Panel B: 1 mile radius circles around power plants					
Median household income (USD 1000)	394	50.12	16.94	12.07	127.97
Top income (above USD 100 000) (%)	394	0.15	0.11	0.00	0.65
Below poverty line (%)	394	0.13	0.09	0.00	0.65
High school or less (%)	394	0.53	0.14	0.12	0.84
College degree (%)	394	0.26	0.12	0.05	0.73
Population within 1 mile (1000)	394	2.38	14.53	0.00	225.34
Median house value (USD 1000)	394	147.06	98.73	29.40	727.52

Notes: Table shows summary statistics of demographic variables from the 2005-2009 American Community Survey (ACS). Panel (a) shows an unweighted average of demographics for all block groups in the US Panel (b) shows population-weighted averages for a 1 mile radius circle around non-gas power plants.

Table B.6: Demographics, by CAIR and non-CAIR

	CAIR		non-CAIR		Difference	
	Mean	(sd)	Mean	(sd)	Mean	(se)
Census year(s): 2005-2009 (1 mile radius)						
Median household income (USD 1000)	49.26	(17.27)	52.93	(15.58)	-3.67	(1.90)*
Top income (above USD 100 000) (%)	0.15	(0.11)	0.16	(0.10)	-0.01	(0.01)
Below poverty line (%)	0.13	(0.09)	0.12	(0.09)	0.01	(0.01)
High school or less (%)	0.55	(0.14)	0.48	(0.12)	0.07	(0.01)***
College degree (%)	0.25	(0.12)	0.29	(0.11)	-0.03	(0.01)**
Population within 1 mile (1000)	2.70	(16.54)	1.34	(2.88)	1.35	(1.00)
Median house value (USD 1000)	143.12	(102.97)	159.83	(82.75)	-16.71	(10.43)
Census year(s): 2010-2014 (1 mile radius)						
Median household income (USD 1000)	53.07	(18.31)	55.63	(15.89)	-2.56	(1.96)
Top income (above USD 100 000) (%)	0.19	(0.10)	0.17	(0.10)	0.02	(0.01)
Below poverty line (%)	0.14	(0.09)	0.13	(0.10)	0.01	(0.01)
High school or less (%)	0.50	(0.14)	0.45	(0.12)	0.05	(0.01)***
College degree (%)	0.29	(0.13)	0.32	(0.12)	-0.03	(0.01)**
Population within 1 mile (1000)	2.68	(16.51)	1.40	(3.09)	1.27	(1.00)
Median house value (USD 1000)	142.84	(95.63)	158.84	(69.88)	-15.99	(9.10)*
Air quality index (AQI) (100 mile radius)						
SO_2 AQI	16.26	(1.97)	12.82	(2.33)	3.43	(0.27)***
NO_x AQI	23.77	(1.20)	23.53	(1.30)	0.24	(0.15)
Ozone AQI	37.15	(0.79)	37.24	(0.96)	-0.09	(0.11)
Non-attainment (county level)						
Non-attainment (2004)	0.37	(0.48)	0.20	(0.41)	0.16	(0.05)***
Count of pollutants violating NAAQS (2004)	0.53	(0.78)	0.41	(0.85)	0.12	(0.10)
Time-varying covariates (state level)						
Cooling degree day (cdd)	123.78	(65.21)	80.41	(64.98)	43.36	(7.71)***
Heating degree day (hdd)	386.31	(154.35)	511.28	(168.50)	-124.97	(19.60)***
GDP (real), 1000 USD	427.68	(296.23)	153.18	(102.38)	274.50	(20.08)***

Notes: Table shows the means and standard deviations, by CAIR and non-CAIR facilities. Unless stated otherwise, values are for the year 2005. The two last columns show the difference in means and the standard errors from a t-test on the equality of means. The sample is balanced over the period 2003-2014 and is restricted to non-gas units.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Plant characteristics, by high and low median income

	Below 25th pct		Above 75th pct		Difference
	Mean	(sd)	Mean	(sd)	
SO_2 (tons)	1,926	(2,540)	2,249	(2,534)	-323
NO_x (tons)	689	(786)	608	(505)	81
log SO_2 (tons)	6.49	(1.95)	6.80	(2.01)	-0.31
log NO_x (tons)	5.74	(1.53)	5.88	(1.41)	-0.13
SO_2 rate (tons/GWh)	4.83	(3.70)	5.27	(4.72)	-0.44
NO_x rate (tons/GWh)	1.74	(0.95)	1.49	(0.78)	0.25^{*}
Gross load (GWh)	437	(476)	441	(400)	-4
Heat input (MMBtu)	4,256	(4,279)	4,376	(3,628)	-120
Coal (primary)	0.91	(0.29)	0.77	(0.40)	0.14^{**}
Oil (primary)	0.08	(0.27)	0.23	(0.40)	-0.15^{***}
Gas (secondary)	0.28	(0.45)	0.35	(0.46)	-0.08
Oil (secondary)	0.23	(0.42)	0.24	(0.42)	-0.01
Startyear	1972	(14)	1970	(12)	1.3
SO_2 technology (any)	0.24	(0.42)	0.19	(0.37)	0.05
NO_x technology (any)	0.81	(0.38)	0.85	(0.31)	-0.04
Number of facilities	77		72		
Number of states	21		21		

Notes: Balanced sample for the years 2003-2014. Only CAIR units. Only non-gas. Year 2005. Observations are collapsed by year and facility.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Demographics. Summary statistics, by gas and non-gas.

	Coal/Oil	Gas	Difference
Census year(s): 2005-2009 (1 mile radius)			
Median household income (USD 1000)	49.26	49.44	-0.18
Below poverty line (%)	0.13	0.15	-0.02**
Top income (above USD 100 000) (%)	0.15	0.16	-0.00
High school or less (%)	0.55	0.56	-0.01
College degree (%)	0.25	0.24	0.01
Population within 1 mile (1000)	2.68	3.85	-1.17
Median house value (USD 1000)	143.12	150.54	-7.42
Census year(s): 2010-2014 (1 mile radius)			
Median household income (USD 1000)	53.07	50.61	2.46*
Top income (above USD 100 000) (%)	0.19	0.20	-0.02**
Below poverty line (%)	0.14	0.17	-0.02***
High school or less (%)	0.50	0.53	-0.03**
College degree (%)	0.29	0.26	0.02**
Population within 1 mile (1000)	2.68	3.85	-1.17
Median house value (USD 1000)	142.84	144.81	-1.97

Notes: Balanced sample (2003-2014). Demographic data is from the 2005-2009 and 2010-2014 American Community Survey. The one mile circle data is constructed using population-weighted block group level data.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Home-ownership rate, by median income

	Below 25^{th} pct		Above 75^{th} pct		Difference
	Mean	(sd)	Mean	(sd)	
Home-ownership rate (05-09)	0.70	(0.18)	0.86	(0.09)	-0.15***

Notes: The table shows the mean of home-ownership rate in the 1 mile radius circle surrounding each power plant. The sample is split into a low-income group and a high income group. *Below* 25^{th} *pct* indicates neighborhoods with median income below the 25^{th} percentile, while *Above* 75^{th} *pct* indicate neighborhoods with median income above the 75^{th} percentile. The sample is restricted to CAIR facilities. Median income and the home-ownership rate is from the 2005-2009 American Community Survey (ACS).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Robustness checks: average effects

To test the sensitivity of the average treatment effects, we run a battery of robustness checks. The tests are summarized in Table B.10. More detailed tables and figures are provided in the following subsections.

Table B.10: The effect of the CAIR markets on emissions. Robustness checks

		SO_2		NO_x			
		DiD		DiD		DiDiD	
No.	Different specifications:	level	log	level	log	level	log
1	Baseline	-945.8***	-0.456**	-201.0**	-0.369**	-323.1***	-0.427***
2	Control for hdd and cdd	-943.1***	-0.454**	-200.8**	-0.365**	-325.4***	-0.433***
3	Control for gdp	-986.0***	-0.393*	-214.8***	-0.290*	-323.5***	-0.426***
4	Both coal and gas plants	-546.4***	-0.300*	-150.4**	-0.224**	-168.9***	-0.224***
5	Only gas plants	-5.913	0.0539	-1.656	0.101	-0.205	0.00111
6	Exclude border states (c)	-1021.8***	-0.552**	-196.6**	-0.492***	-333.4***	-0.473***
7	Exclude border states (t)	-1369.5***	-0.516**	-301.5***	-0.402**	-429.7***	-0.546***
8	Exclude border states (c and t)	-1446.0***	-0.611**	-297.1***	-0.524***	-439.9***	-0.592***
9	Placebo (border states)	-168.7	0.0340	9.846	-0.000673	-17.70	-0.0601
10	Only former NBP (t)	-1213.6***	-0.525**	-286.5***	-0.421***	-468.4***	-0.591***
11	Unbalanced	-927.5***	-0.461**	-180.5**	-0.375**	-294.2***	-0.389***
12	Unbalanced and impute zeros	-938.2***	-0.587***	-188.8**	-0.441***	-294.8***	-0.391***
13	Drop bottom and top 1 pct	-864.2***	-0.466**	-149.1**	-0.390***	-268.4***	-0.425***
14	Drop bottom and top 5 pct	-578.2***	-0.390***	-128.8***	-0.386***	-186.3***	-0.378***
15	Drop bottom and top 10 pct	-375.4***	-0.256**	-122.7***	-0.375***	-167.0***	-0.359***
16	Exclude deregulated plants	-971.3***	-0.792***	-212.7**	-0.635***	-316.9***	-0.411***

Notes: Each row shows the estimated treatment effect from either equation 2.3 (DiD) or 2.5 (DiDiD). The baseline sample is a balanced sample (2003-2014) of non-gas power plants (unless stated otherwise). We restrict the sample to the years 2004-2005 (pre) and 2009-2014 (post). For NO_x DiD we only use the winter months. All regressions include facility fixed effects and month-year fixed effects. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We might worry that lower emissions in the CAIR region led to higher emissions in the non-CAIR region. In other words, there could be emissions leakage to the control group, which would overstate effects of the policy. One potential leakage channel could be that lower electricity production under CAIR is offset by higher electricity production in the non-CAIR region. If this is the case, we would expect leakage to be most pronounced for CAIR facilities sharing an electricity grid with facilities not covered by CAIR. To test for this, we restrict the sample by (i) excluding control states that border CAIR states (row 6), excluding treated states bordering non-CAIR states (row 7), or both (row 8). Restricting the sample actually leads to higher estimated treatment effects, suggesting that leakage is not leading us to overestimate the effects of the trading programs.

We also try to restrict the sample to power plants that were also part of the former NO_x Budget Trading Program. In principle, the triple difference strategy should only work for these facilities, as they exhibit a pre-treatment difference in summer and wintertime emissions. Overall, the treatment effect is somewhat larger when only looking at former NO_x Budget Trading Program units (row 10).

Next, we use an unbalanced version of the dataset, meaning that we include plants that open up or shut down during the period 2003-2014. Using an unbalanced panel has small effects on the treatment estimates (see row 11). When plants shut down, they exit dataset. This could mean that the overall effect of CAIR is understated, as plants that shut down in principle generate zero emissions. To take this into account, we construct a modified dataset where we impute zero SO_2 and NO_x emissions for plants that shut down (see row 12). Imputing the zeros leads to a slightly higher treatment effect for SO_2 (compared to the unbalanced panel), while the effect on NO_x is mixed.

The density curves in Figure B.4 show that there is not a complete overlap in the outcome variables across the treatment and control group. To try to account for this, we restrict the sample by dropping the top and bottom 1, 5 and 10 percentiles of the distribution (see rows 13-15). Overall, the treatment effects in log points in the different samples are somewhat lower than the baseline. The treatment effects in levels are substantially lower, partly due to a lower pre-treatment mean of the dependent variable.

B.4 Robustness checks: heterogeneous effects

B.4.1 Summary of robustness checks

Table B.11 presents results from a battery of robustness checks. Each row in the table reports the slope $\hat{\beta}_2$ estimated from equation 2.7.

Table B.11: Heterogeneous effects, by median income. Robustness checks.

		Heterogeneous effect	
No.	Specification	log SO_2	log NO_x
1	Baseline	-0.0142***	-0.00466**
2	Control for pre emissions level	-0.0141***	-0.00539**
3	Drop bottom and top 1 pct	-0.0147***	-0.00623**
4	Drop bottom and top 5 pct	-0.0173***	-0.00671***
5	Drop bottom and top 10 pct	-0.0159**	-0.00660***
6	0.5 mile radius	-0.0130***	-0.00483**
7	2 mile radius	-0.0168***	-0.00404
8	3 mile radius	-0.0190***	-0.00435
9	10-14 Census	-0.0111**	-0.00322
10	2000 Census	-0.0119*	-0.00187
11	Control for high school	-0.0147***	-0.00639
12	Control for college degree	-0.0135**	-0.00564
13	Control for % Blacks	-0.0151***	-0.00523**
14	Control for % Hispanics	-0.0145***	-0.00501**
15	Control for SO2 AQI	-0.0150***	-0.00458*
16	Control for O3 AQI	-0.0161***	-0.00473*
17	Control for population density	-0.0139***	-0.00487**
18	Exclude deregulated plants	-0.0174***	-0.00305

Notes: Each row shows the interaction term $\beta_2 CAIR_{j,t} \times Demo_j$ estimated from equation 2.7. The baseline sample is a balanced sample (2003-2014) of non-gas units. We restrict the sample to the years 2004-2005 (pre) and 2009-2014 (post). For NO_x we only use the winter months. All regressions include facility fixed effects and month-year fixed effects. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Including an interaction term between pre-treatment emissions levels and $post$ have minor effects on the estimate (see row 2). Restricting the sample by excluding the top and bottom 1, 5 and 10 percentiles slightly increase the estimated interaction terms (see rows 3-5). Expanding the circle radius around the power plants to 2 and 3 miles increases the estimated slope for SO_2 somewhat, while shrinking the circle to 0.5 mile lowers the estimate (see rows 6-8).[10] For NO_x, the interaction term is less precisely estimated when expanding the radius to 2 and 3 miles.

Using the 2014 American Community Survey, which is based on the 5-year average from 2010-2014, leads to a slightly less steep but still significant slope coefficient for SO_2 (see row 9). For NO_x the interaction term is no longer statistically significant. The American Community Surveys only dates back to 2009, which provides an average from 2005-2009. However, before this there were decennial surveys. The last one was conducted in they year 2000, and reports values from 1999. Using the median income from the 2000 Census, the interaction term for SO_2 is about the same as for the 2014 ACS (see row 10). The coefficient, however, is less precisely estimated. For NO_x there is no heterogeneous effect when using the 2000 Census.

Next, we include controls for education and share of minorities to see to what degree the different variables are picking up the same effects. Controlling for education has small impacts for SO_2, while it lowers the precision for NO_x (see rows 11-12). Controlling for minorities (% blacks and % Hispanics) also has little effect on the interaction term (see rows 13-14). This suggests that income and race/ethnicity may have separate effects.

What is more, we control for measures of the ambient air quality and population density, which can be seen as proxies for the marginal damage of pollution in the area around the power plants. This has minor effects of the estimated slope coefficients (see rows 15-17)

Lastly, we exclude all deregulated plants from the sample to ensure that differential ownership structure across neighborhoods is not driving the results.[11] This leads to a slightly stronger heterogeneous effect for SO_2, while the slope coefficient for NO_x is smaller and insignificant (see row 18).

Overall, the heterogeneous effect is large and robust for SO_2, while small and not very

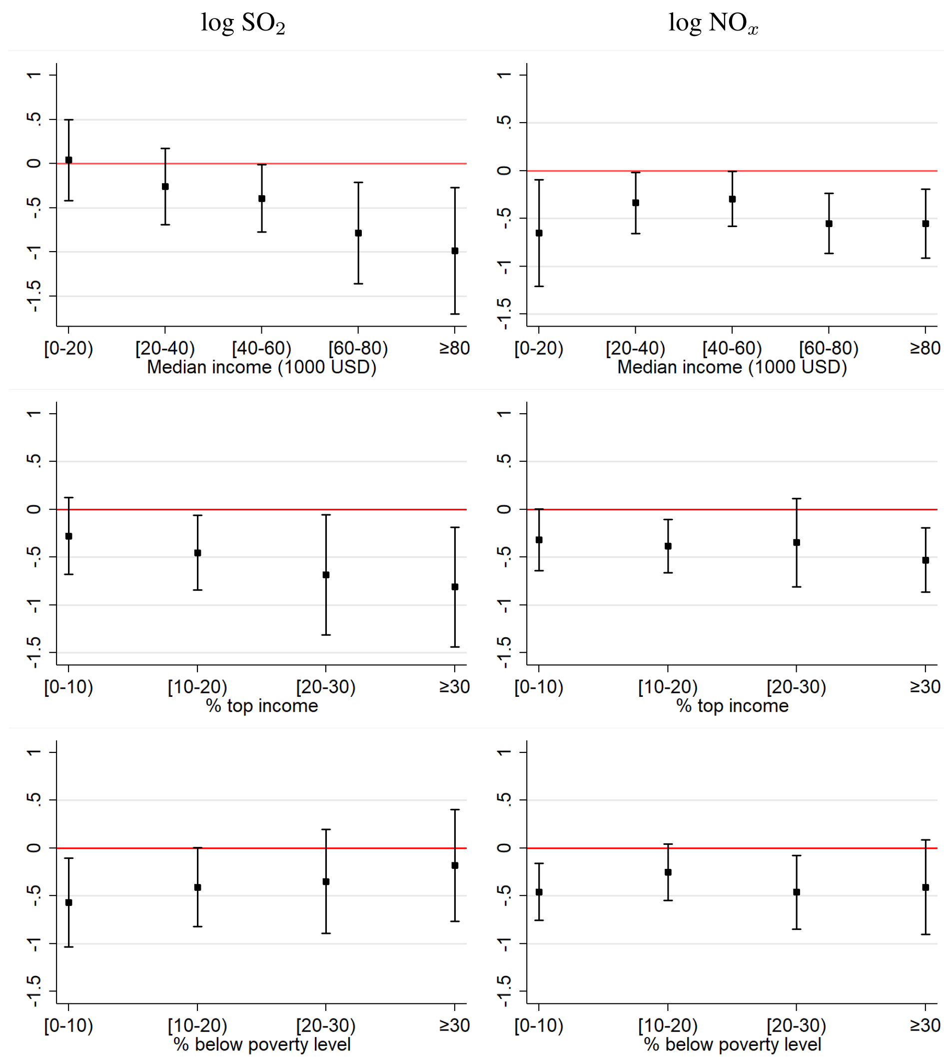
[10]Expanding the circle radius means that we calculate weighted neighborhood characteristics for a larger area around the power plant.

[11]As previously noted, deregulated plants tend to react differently to stricter regulation than publicly owned ones (Fowlie, 2010; Cicala, 2015).

robust for NO_x. In addition to the robustness checks presented above, we estimate non-linear versions of the heterogeneous effects for the three income measures. The results are presented in Appendix B.4.2, and show similar patterns as the linear specification.

B.4.2 Non-linear specifications

Figure B.7: Non-linear effects of CAIR on emissions, by three income measures.



Notes: Figures plot the treatment effects for different income bins estimated from equation 2.9. The dependent variable $y_{j,t}$ is log SO_2 emissions (first column) or log NO_x emissions (second column). The horizontal axis indicates different values of the demographic variable $Demo_j$. The y-axis reports the net treatment effects. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the state level in all regressions. The sample is balanced over the period 2003-2014, restricted to non-gas units and to the years 2004-2005 (pre period) and 2009-2014 (post period). Demographic variables are from the 2005-2009 American Community Survey (ACS).

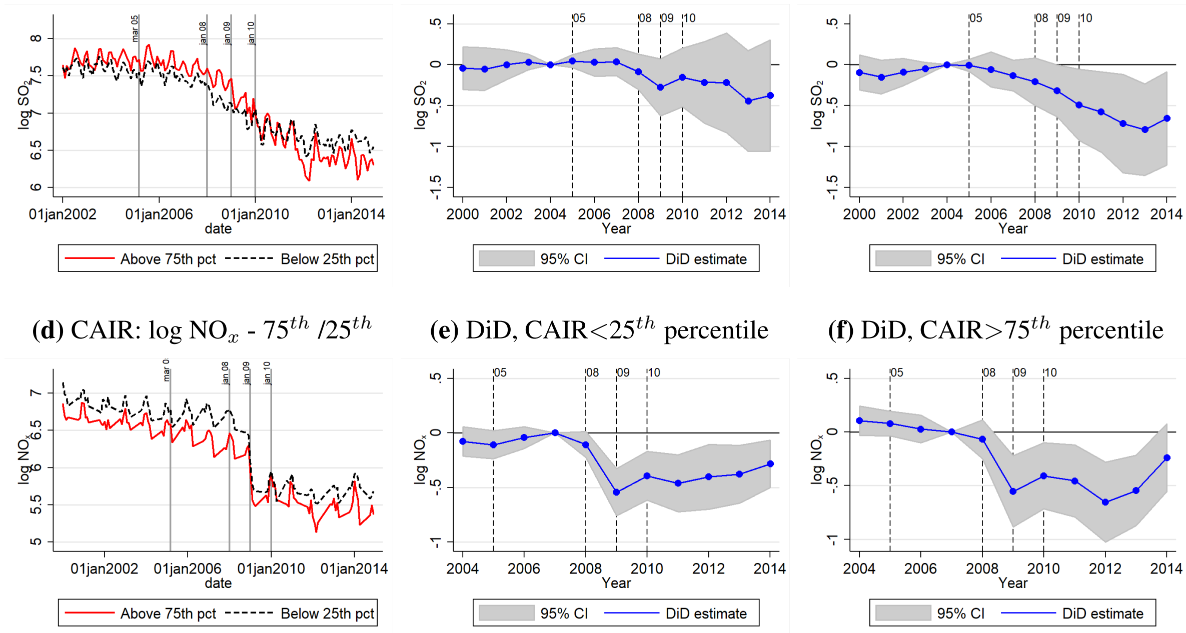
B.4.3 Investigating group-specific pre-trends

One might worry that low and high income neighborhoods were on very different paths prior to the policy implementation. If this was the case, the heterogeneous effects might merely reflect an underlying trend for the two groups. To investigate this, we focus on CAIR facilities located in neighborhoods with a median income either below the 25^{th} percentile or above the 75^{th} percentile. We then plot the development in mean emission levels of facilities in the two groups, as well as estimate the leads and lags versions of the DiD (equation 2.4) for the two groups separately. The results are shown in Figure B.8. Panel (a) reveals fairly similar pre-treatment trends for the two income groups. Panels (b) and (c) show that the Rule induced larger reductions in SO_2 emissions for the high income group. For NO_x there was a significant treatment effect for both the high and low income groups (see panel (e) and (f)).

Figure B.8: Trends in emissions and average yearly treatment effects, by high and low median income

(a) CAIR: log SO_2 - $75^{th}/25^{th}$ **(b)** DiD, CAIR<25^{th} percentile **(c)** DiD, CAIR>75^{th} percentile

(d) CAIR: log NO_x - 75^{th} /25^{th} **(e)** DiD, CAIR<25^{th} percentile **(f)** DiD, CAIR>75^{th} percentile



Notes: Panel (a) shows the mean of log SO_2 emissions by month-year for CAIR facilities located in neighborhoods with median income in the 25^{th} percentile (dashed line) and median income in the 75^{th} percentile (solid line). Panel (d) depicts the same for log NO_x emissions. Panel (b) and (c) reports the coefficients $\sum_{m=0}^{M} \hat{\beta}_{-m}$ and $\sum_{k=1}^{K} \hat{\beta}_{+k}$ estimated from equation 2.4 (DiD), but where we restrict the treatment group to facilities located in neighborhoods with median income in the lower 25^{th} percentile (b) or in the upper 75^{th} percentile (c). Panel (e) and (f) shows the same, only for log NO_x emissions. Standard errors in all regressions are clustered at the state level. The gray areas are 95% confidence intervals. The sample is balanced over the period 2003-2014 and is restricted to non-gas units. Demographic variables are from the 2005-2009 American Community Survey (ACS).

B.4.4 Taking into account plant shutdown

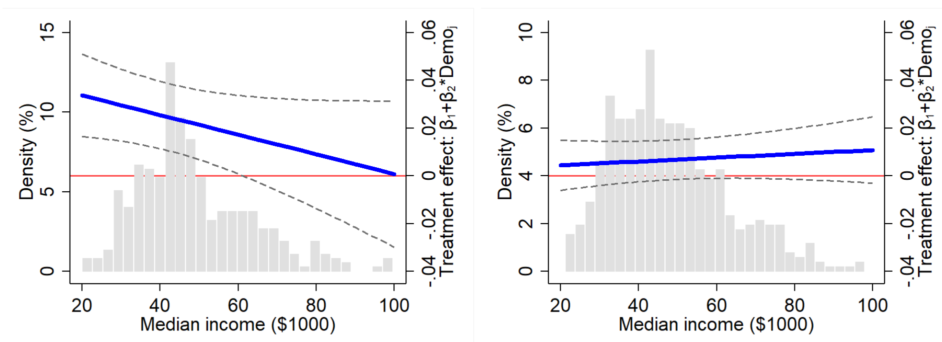
Up until now, the analysis has focused on plants that did not shut down during the treatment period. In the following subsections, we investigate effects of the CAIR on the probability of a plant shutting down, and whether this probability varies with neighborhood demographics. We then test if results on emissions are robust to the inclusion of power plants that shut down.

Are power plants in low-income areas more likely to shut down?

To investigate the effects of the CAIR on plants retiring, we construct a time-varying, binary variable labeled *shutdown* that takes the value of 0 if a plant is operative in a given year and a value of 1 if the plant shuts down in a given year. Using a linear probability model, we estimate the effect of CAIR on the probability of a plant shutting down in a given year. Results from the estimation are presented in Figure B.9, and reveal that non-gas plants located in low-income neighborhoods are more likely to shut down. For high-income neighborhoods, the probability is close to zero and not statistically significant. For gas power plants, the CAIR did not affect the probability of a plant shutting down (see Figure B.9b).[12]

Figure B.9: Heterogeneous treatment effects on facility shutdowns, by median income

(a) Pr(coal/oil shutting down) **(b)** Pr(gas shutting down)



Notes: Panel (a) shows the estimated probability of a coal or oil plant shutting down, while panel (b) shows the estimated probability of a gas plant shutting down. The solid blue lines in both figures are the estimated net treatment effects using the empirical specification in equation 2.7, i.e., $\beta_1 + \beta_2 \times Demo_j$. The solid black lines hence show the estimated net treatment effect given the different values of the demographic variable indicated on the horizontal axis. The outcome variable is a binary variable indicating plant shutdown in a given year. Standard errors are clustered at the state level. The histogram of the demographic variable is shown in the background. Dashed lines represent 95 percent confidence intervals. Demographic variables are from the 2005-2009 American Community Survey (ACS). All demographics are constructed for 1 mile radii circles around the power plant.

Why are plants in poorer areas more likely to shut down?

Owners may decide to shut down their power plants as a response to the CAIR. They could make such a decision if under any positive retirement date ($T_{r,i}$), the cost minimization problem yields zero or negative present value profits. Given uncertainty around the price profile of allowances (p_t), owners may find upfront investments in abatement technology too expen-

[12]We also estimate the effects of non-gas and gas plants opening up, and find that the CAIR lowered the probability of a non-gas plant opening up, but the effect does not vary with income. For gas plants, the effect is not statistically different from zero.

sive or too risky.[13] Power plants located in poorer areas could face such constraints in higher proportion than plants in higher income neighborhoods.[14] Beyond financial constraints, the local population may also put pressure on plant owners to install technology instead of shutting down, as the latter could result in job losses. If such pressure is stronger in more affluence neighborhoods, it could help explain the lower probability of shutdown in higher income areas. These proposed explanations remain conjectures, as it is difficult to test for such mechanisms.

B.4.5 Different circle radii. Reduced form

Table B.12: Effects of CAIR markets on socioeconomic variables. 0.5 mile radii

	House	Rent	Income	Poor	College	PopDen
Coal*post	0.0580**	-0.000863	0.0339	-0.0128	0.00973**	-0.00134
	(0.0221)	(0.0328)	(0.0253)	(0.00819)	(0.00455)	(0.00371)
Obs	1284	1168	1286	1286	1302	1300
Number of facilities	642	584	643	643	651	650
Clusters (state)	24	24	24	24	24	24
Mean dep.var (pre)	11.67	6.571	3.850	0.131	0.215	0.148

Notes: Balanced sample (2003-2014). Both non-gas and gas units. Units are averaged over facility. The outcome variable is the log of demographics variables from the 2009 and 2014 American Community Survey (ACS). All regressions include an interaction term between *post* and state ID and *post* and log of the demographic variable. Standard errors clustered at the state level in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[13] Only 15% of plants shutting down during the CAIR had installed scrubbers.

[14] E.g., they may face higher costs of upgrading technology, or binding budget constraints.

Table B.13: Effects of CAIR markets on socioeconomic variables. 2 mile radii

	House	Rent	Income	Poor	College	PopDen
Coal*post	0.0374**	0.00470	0.0359**	-0.0115**	0.00883**	-0.00157
	(0.0151)	(0.0201)	(0.0141)	(0.00504)	(0.00418)	(0.00226)
Obs	1308	1282	1302	1298	1306	1302
Number of facilities	654	641	651	649	653	651
Clusters (state)	24	24	24	24	24	24
Mean dep.var (pre)	11.74	6.599	3.905	0.126	0.229	0.216

Notes: Balanced sample (2003-2014). Both non-gas and gas units. Units are averaged over facility. The outcome variable is the log of demographics variables from the 2009 and 2014 American Community Survey (ACS). All regressions include an interaction term between *post* and state ID and *post* and log of the demographic variable. Standard errors clustered at the state level in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14: Effects of CAIR markets on socioeconomic variables. 3 mile radii

	House	Rent	Income	Poor	College	PopDen
Coal*post	0.0216	0.00138	0.0207	-0.00946**	0.00642	-0.00111
	(0.0132)	(0.0173)	(0.0131)	(0.00381)	(0.00420)	(0.00185)
Obs	1306	1296	1300	1298	1308	1300
Number of facilities	653	648	650	649	654	650
Clusters (state)	24	24	24	24	24	24
Mean dep.var (pre)	11.76	6.608	3.928	0.122	0.235	0.223

Notes: Balanced sample (2003-2014). Both non-gas and gas units. Units are averaged over facility. The outcome variable is the log of demographics variables from the 2009 and 2014 American Community Survey (ACS). All regressions include an interaction term between *post* and state ID and *post* and log of the demographic variable. Standard errors clustered at the state level in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Heterogeneous effects: potential explanations

In this section, we investigate potential hypotheses as to why policy-induced reductions in SO_2 emissions are smaller in low-income, poorly-educated and minority neighborhoods.

Pre-policy power plant characteristics

In theory, a cap-and-trade system will lead plants with lower marginal abatement costs to reduce their emissions and sell unused allowances on the market to plants with higher abatement costs. Marginal abatement costs can depend on e.g., the age, size, fuel mix, and installed abatement technologies of the power plant. Initial levels of emissions may also be correlated with a higher potential for emissions reductions (Fowlie et al., 2012). As the geographic distribution of socioeconomic groups is not random, we might expect systematic differences in plant characteristics across neighborhoods.[15]

Table B.15: Heterogeneous treatment effects when controlling for plant characteristics

	Heterogeneous effect	
Independent variable: $CAIR_{j,t} \times$ *median income*$_j$	log SO2	log NOx
Baseline	-0.0142***	-0.00466**
Control for pre emissions level	-0.0141***	-0.00539**
Control for pre gross load	-0.0137***	-0.00440*
Control for start year	-0.0134***	-0.00412**
Control for pre intensity	-0.0140**	-0.00676***
Control for pre technology	-0.0127***	-0.00432*
Control for pre non-coal	-0.0112**	-0.00445*

Notes: Table reports the results from 7 different regressions: each row reports the coefficient $\hat{\beta}_2$ estimated from equation 2.7, but where we control for different plant characteristics. The plant characteristics are controlled for by including an interaction terms between $CAIR_{j,t}$ and the level of the plant characteristics in the year 2005. All regressions include facility fixed effects and month-year fixed effects. Standard errors are clustered at the state level. The sample is balanced over the period 2003-2014, includes only non-gas units and is restricted to the years 2004-2005 (pre period) and 2009-2014 (post period). Only winter months are included in the DiD estimation for NO_x. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

To see if systematic differences in plant characteristics can explain the pattern of smaller SO_2 reductions in low-income neighborhoods, we re-estimate equation 2.7 for median in-

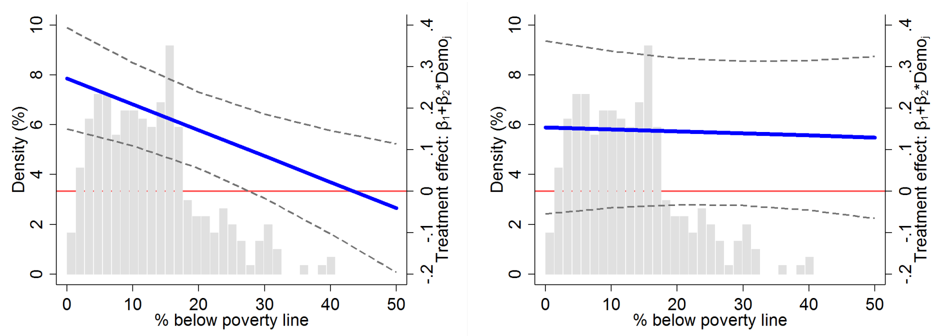
[15] In particular, previous studies have found that lower socioeconomic groups tend to scatter around dirtier emissions sources (Hanlon, 2014; **?**). If dirtier emissions sources also have higher marginal abatement costs, the finding that the new rule triggered larger reductions of SO_2 emissions for power plants located in relatively richer neighborhoods may reflect such historical sorting.

come, but control for a variety of plant characteristics that are likely to be associated with abatement costs. Specifically, we include separate interaction terms between the treatment variable ($CAIR_{jt}$) and initial plant characteristics. The coefficients of the interaction term $CAIR_{jt} \times Demo_j$ for different regressions are presented in Table B.15.[16] The results suggest that plant characteristics cannot account for the observed heterogeneity in reductions of SO_2 emissions under the CAIR. Controlling for pre-policy emissions levels, gross load, age, emissions intensity and technology stock all have minor effects on the slope $\hat{\beta}_2$ estimated from equation 2.7. However, controlling for the primary fuel category (oil versus coal) slightly attenuates the effect of income. This suggests that the income variable is partly picking up on systematic differences in fuel input. If the marginal abatement cost is lower for oil plants than coal plants, this could explain some of the differences across facilities located in rich and poor neighborhoods.

[16]Summary statistics by high and low median income is provided in Table B.7, and show that plant characteristics for the two groups are very similar. The only variables that are statistically different across the two groups are the share of facilities using coal or oil as their primary input: relatively richer neighborhoods have a higher share of facilities relying on oil instead of coal as the primary input.

Figure B.10: Heterogeneous treatment effects on technology adoption, by poverty rate

(a) SO_2 technology (any) **(b)** NO_x technology (any)



Notes: Figures show the estimated treatment effect of the CAIR on technology adoption. The solid blue lines in both figures are the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$ estimated from equation 2.7 (DiD). The dependent variable $y_{j,t}$ is a binary variable indicating the installation of any SO_2-specific technology (panel a) or NO_x-specific technology (panel b). Both regressions include an interaction term between $CAIR_{j,t}$ and the pre-treatment technology stock. The horizontal axis indicates different values of the demographic variable $Demo_j$, where a histogram of the variable is shown in the background. The left y-axis reports the density of $Demo_j$ in percent, while the right y-axis reports the net treatment effects $\hat{\beta}_1 + \hat{\beta}_2 \times Demo_j$. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the state level in all regressions. The sample is balanced over the period 2003-2014, includes only non-gas units and is restricted to the years 2004-2005 (pre period) and 2009-2014 (post period). Demographic variables are from the 2005-2009 American Community Survey (ACS). Below poverty level is defined at the share of people living below the poverty level within a 1 mile radius of the power plant. The demographic variable is constructed for 1 mile radii circles around the power plants.

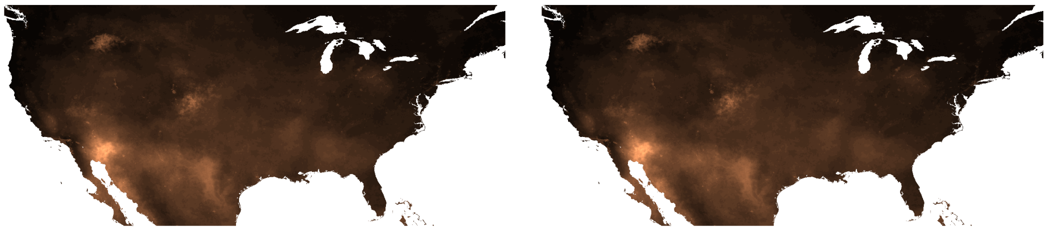
Appendix C

Appendix to Chapter 3

C.1 Additional figures and tables

Figure C.1: The geography of local air pollution improvements

(a) Mineral Dust



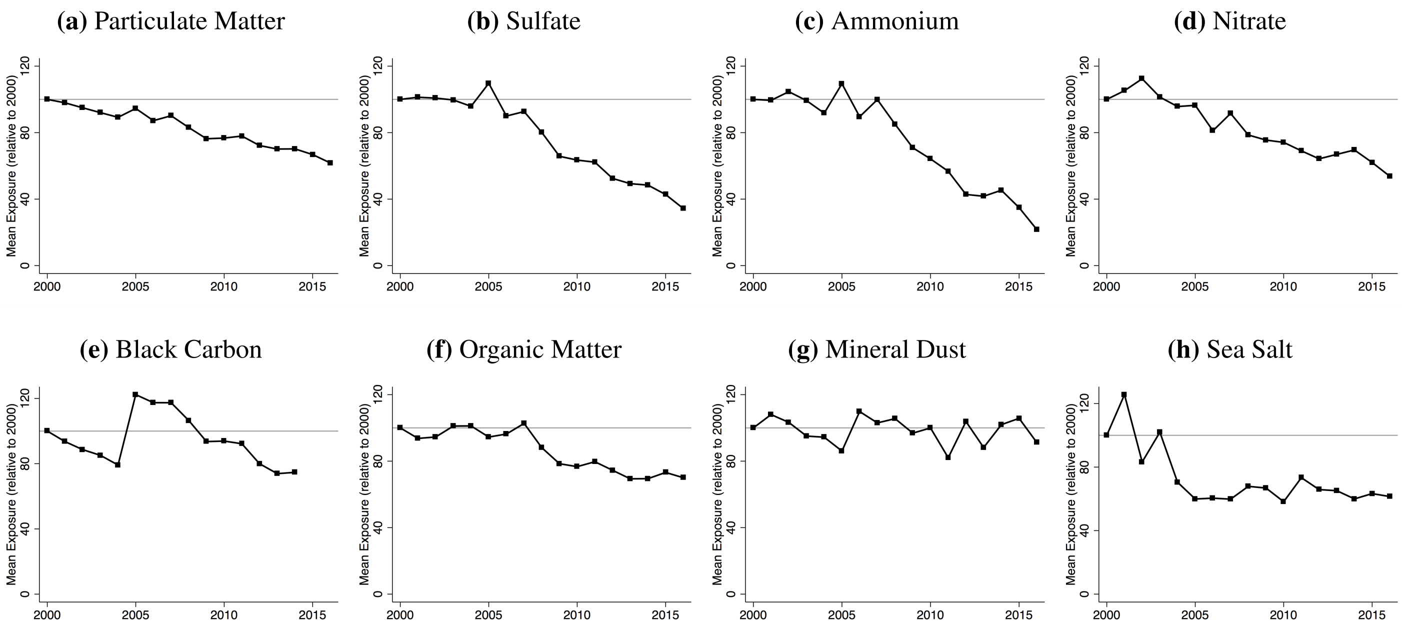
(b) Sea Salt

(c) Black Carbon

(d) Organic Matter

Notes: The maps display air concentrations of major air pollutants produced by industrial activity. The left panels represent yearly average air concentrations in the year 2000, and the right panels represent yearly average air concentrations for year 2016. For each pollutant, scales for left and right panels are identical. Geographic resolution is of 0.01 by 0.01 degrees (approximately 1km by 1km).

Figure C.2: Evolution of US population exposure to air pollution



Notes: The figures display the population-weighted averages over the contiguous United States.

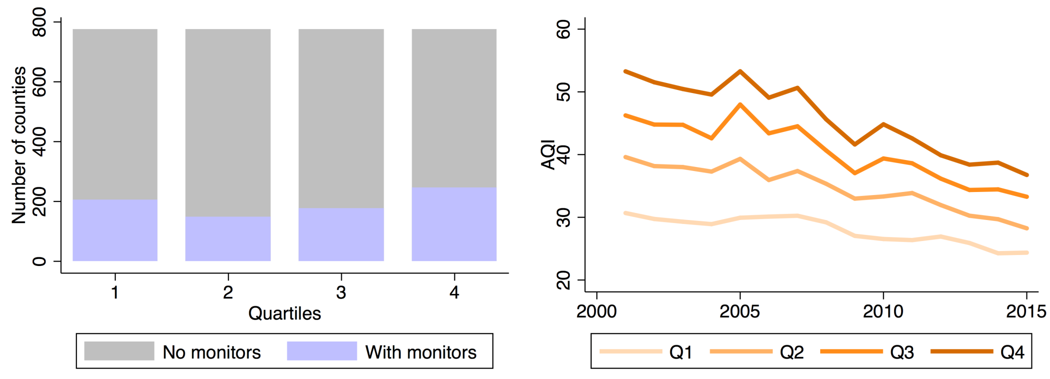
Table C.1: Correlations between pollutants—across years

Pollutant	Particulate Matter	Nitrate	Sulfate	Ammonium	Black Carbon	Organic Matter	Mineral Dust	Sea Salt
Particulate Matter	1							
Sulfate	0.709	1						
Ammonium	0.864	0.800	1					
Nitrate	0.697	0.175	0.669	1				
Black Carbon	0.727	0.207	0.533	0.690	1			
Organic Matter	0.668	0.146	0.425	0.671	0.846	1		
Mineral Dust	0.159	-0.121	-0.079	0.093	0.239	0.312	1	
Sea Salt	0.170	-0.079	-0.037	0.153	0.146	0.211	0.074	1

Notes: The table displays correlations between every pollutant in the dataset. Correlations were computed across block-groups from the 2010 census, and across years 2000 to 2016. Data are derived from

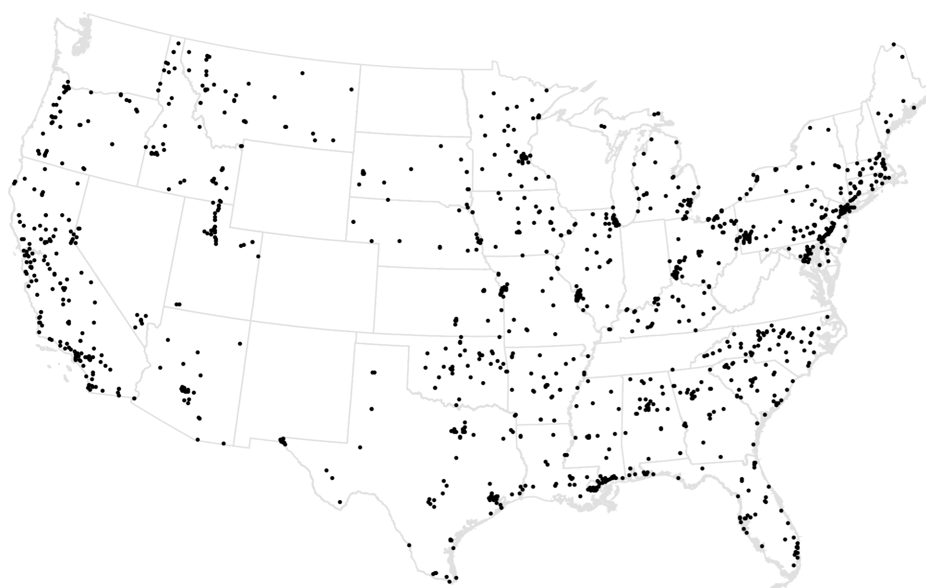
Figure C.3: Monitoring stations measurements

(a) Number of Monitoring Stations **(b)** Evolution of Monitoring Stations Measures



Notes: Subfigure (a) plots the number of counties that have at least one monitor for $PM_{2.5}$ (in blue) and the number of counties with no monitors (black). The x-axis represent the quartiles of counties, ranked by satellite imagery pollution measures in 2005. Subfigure (b) plots the average monitoring station measures for $PM_{2.5}$ pollution for counties that have monitors in each of the quartiles of the distribution of satellite imagery pollution measures across years.

Figure C.4: Location of monitoring stations — $PM_{2.5}$



Notes: Each dot represents the location of one EPA monitoring station taking measurements of $PM_{2.5}$ concentrations.

C.2 Additional results

Table C.2: Treatment effects of $PM_{2.5}$ concentration on real estate prices—County

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Corelogic/Satellite						
House Prices	-1.159***	-1.378***	-1.291***	-1.291***	-1.291***	-1.157***
	(0.095)	(0.114)	(0.082)	(0.082)	(0.082)	(0.091)
N	31,874	31,874	31,874	31,874	31,874	27,443
Adjusted R^2	0.01	0.09	0.10	0.10	0.10	0.07
Number of Units	2,296	2,296	2,296	2,296	2,296	2,290
Number of Clusters	48	48	48	48	48	48
Panel B - Corelogic/Monitoring Stations						
House Prices	-1.064***	-1.259***	-0.751***	-0.751***	-0.751***	-0.529***
	(0.131)	(0.139)	(0.143)	(0.143)	(0.143)	(0.128)
N	7,335	7,335	7,335	7,335	7,335	6,809
Adjusted R^2	0.02	0.06	0.07	0.07	0.07	0.07
Number of Units	698	698	698	698	698	693
Number of Clusters	48	48	48	48	48	48
County FE		X	X	X	X	X
State Trends					X	X
Temperatures Data			X	X	X	X
Demographics				X	X	X
NAAQS dummies						X

Notes: This table reports regression coefficients from 12 separate regressions, 6 per panel. The dependent variable is the log of the county-average sale prices from corelogic. The independent variables includes measures of $PM_{2.5}$ concentrations derived from satellite imagery (Panel A) or monitoring stations measures (Panel B). I restrict monitoring stations measures derived from the Federal Reference Method, to allow comparison accross monitors. All variables are averaged at the county-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Treatment effects of $PM_{2.5}$ concentration on real estate prices—Block

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Controlling for all other pollutants									
House Values	-0.973***	0.758**	-1.109***	-1.109***	-0.005	-0.799***	-0.799***	-0.654***	0.040
	(0.009)	(0.326)	(0.181)	(0.181)	(0.088)	(0.216)	(0.216)	(0.192)	(0.075)
N	1,802,716	1,802,334	1,800,263	1,800,263	1,799,855	1,796,353	1,796,353	1,796,353	1,795,945
Adjusted R^2	0.02	0.43	0.64	0.64	0.72	0.64	0.64	0.64	0.72
Number of Units	149,652	149,650	147,199	147,199	147,172	146,905	146,905	146,905	146,878
Number of Clusters	47	47	47	47	47	47	47	47	47
Block Group FE			X	X	X	X	X	X	X
CBSA FE				X		X	X	X	X
CBSA Trends		X			X				X
Temperatures Data						X	X	X	X
Demographics							X	X	X
NAAQS dummies									X

Notes: This table reports regression coefficients from 9 separate regressions from equation 3.1. Controls for measures of all pollutants in the satellite-derived dataset are included. Coefficients are reported for $PM_{2.5}$, controlling for concentrations of black carbon, amonium, nitrate, sea salt, dust, organic matter and sulfate.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.