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Are Power Plant Closures a Breath of Fresh Air? Air Pollution, Absences, and Achievement

Sarah Komisarow
Duke University

Emily L. Pakhtigian
Penn State University

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Are Power Plant Closures a Breath of Fresh Air? Air Pollution, Absences, and Achievement *

Sarah Komisarow and Emily L. Pakhtigian†

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Abstract

This paper examines the effects of three large, coal-fired power plant closures on student absences and achievement in the Chicago area. We find that schools near the plants experienced a 7 percent reduction in absences relative to those further away following the closures. Math achievement in these schools increased following the closures, although our estimates are imprecise. Using data on wind, air conditioning, and magnet schools, we show that schools with higher baseline pollution exposure experienced the greatest gains from the plant closures. Our analysis of mechanisms suggests that health is an important channel through which air pollution affects absences.

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†Komisarow: Sanford School of Public Policy, Duke University, Durham, NC 27708 (email: sarah.komisarow@duke.edu). Pakhtigian: School of Public Policy, Penn State University, University Park, PA 16802 (email: emilypakhtigian@psu.edu).

1 Introduction

During the past decade, coal consumption in the United States (U.S.) has declined dramatically. Fueled in part by increases in the hydraulic fracturing ("fracking") of natural gas and the use of renewable energy sources, coal consumption has fallen by 42 percent relative to its peak in 2005 (Mobilia and Comstock, 2019). Figure 1a depicts total energy consumption in the U.S by source between 2000 and 2018, illustrating declines in coal consumption and increases in natural gas consumption. Accompanying these changes in energy consumption have been dramatic changes in industrial infrastructure – and particularly in the number of operational coal-fired power plants in the U.S. Figures 1b and 1c illustrate the total number of operational coal-fired power plants and coal-fired power plant capacity in the U.S. between 2004 and 2016, respectively, where there are notable and steep declines in both beginning around 2013. The confluence of increases in the supply of natural gas, increased stringency in emissions standards for coal-fired power plants, and flat growth in demand for electricity have all contributed to record numbers of coal-fired power plant closures across the country (MacIntyre and Jell, 2018; Mobilia and Comstock, 2019; Johnson and Chau, 2019).

Despite record numbers of coal-fired power plant closures, many people in the U.S. – particularly children – are still affected by coal-fired power plant emissions. In this paper, we focus on one previously unexplored dimension of children's exposure to emissions from coal-fired power plants: namely, exposure emanating from elementary schools' proximities to operational coal-fired power plants. Figure 2a illustrates the locations of operational coal-fired power plants in the U.S. using the most recent year of data (2016) following these large-scale changes. Coal-fired power plant locations depicted in blue indicate no public schools near the plant (within 10 kilometers), while locations depicted in red indicate the presence of public schools nearby (within 10 kilometers). Figure 2b enriches this illustration by scaling the red dots (operational coal-fired power plants) to indicate the number of students attending school in close proximity (within 10 kilometers). In total, we estimate that in 2016 around 2.3 million elementary school-aged children (grades kindergarten through eighth) attended a public school located within 10 kilometers of an operational coal-fired power plant, which accounts for around 7 percent of the public school population in this age range. Among these 2.3 million children, we document striking disparities by family income: 81 percent were eligible for free/reduced-price lunch, meaning they come from families with incomes at or below 185 percent of the federal poverty line.

Extensive literatures in public health and medicine document the negative correlation between exposure to air pollution and morbidity and mortality.[1] These associations are reinforced by a growing quasi-experimental literature that documents the causal effects of exposure to air pollution on morbidity and mortality outcomes.[2] The growing quasi-experimental literature has also contributed evidence on the negative effects of exposure to air pollution by examining a wider range of social and economic outcomes, including educational attainment, health stock, labor market outcomes, and criminal behavior. These papers find that exposure to air pollution – particularly *in utero* or during early childhood – negatively affects educational attainment, earnings, worker productivity, long-term health stock, and labor supply and leads to increases in criminal behavior (Sanders, 2012; Isen et al., 2017; Chang et al., 2016; Hanna and Oliva, 2015; Herrnstadt and Muehlegger, 2015; Rosales-Rueda and Triyana, 2018; Tan Soo and Pattanayak, 2019; Bharadwaj et al., 2017).

While much of the current work in this area focuses on the effects of exposure to air pollution on infants and adults, relatively less has investigated effects on children.[3] Children are particularly vulnerable to the negative effects of exposure to air pollution for a number of reasons including

[1]Exposure to air pollution is associated with low birthweight and prematurity (Bobak, 2000; Sagiv et al., 2005), infant mortality (Glinianaia et al., 2004), cardiovascular events and diseases (Dominici et al., 2006; Brook et al., 2018), respiratory illness and diminished pulmonary function (Brunekreef et al., 1997; Muhlfeld et al., 2008; Wang et al., 2019), diseases of the central nervous system (Block and Caldern-Garcidueas, 2009), and mortality (Pope and Dockery, 2006; Di et al., 2017).

[2]See, for example, Chay and Greenstone (2003), Deryugina et al. (2016), Beatty and Shimshack (2011). For evidence regarding this link from the developing world, see work on forest fires and birth outcomes in Jayachandran (2009) and Rangel and Vogl (2018).

[3]This is also true of literature examining air pollution effects on health in the developing world. Frankenberg et al. (2005) examine the impacts of emissions from forest fire activity in Indonesia, finding health consequences among elderly populations; Jayachandran (2009) and Rangel and Vogl (2018) examine *in utero* emissions exposures in Indonesia and Brazil, respectively, finding evidence of increased instances of fetal and infant mortality and decreased birthweight as a result of these exposures. Further, Ghosh and Mukherji (2014) examine urban air pollution on health in India and find links between exposure to fine particulates and respiratory ailments among children under the age of 5.

their developmental status, breathing patterns, time spent outdoors, and time spent in activities that raise ventilation (breathing) rates (Gauderman et al., 2004; Schwartz, 2004; Bateson and Schwartz, 2007). Existing work on the effects of exposure to air pollution on children includes growing literatures that focus on children's health and education outcomes. While the evidence on health outcomes is consistently negative (Neidell, 2004; Beatty and Shimshack, 2011; Austin et al., 2019), there is less consensus on whether, how, and to what extent air pollution exposure affects education outcomes such as absences, test scores, and behavior in school.[4]

We contribute new evidence to the growing literature on the effects of air pollution exposure on absences and achievement by exploiting variation from a previously unexamined context and source of exposure: coal-fired power plant closures. Specifically, we leverage variation in exposure to air pollution induced by the nearly-simultaneous closures of three large, coal-fired power plants located within 15 miles of one another. The Crawford, Fisk Street, and State Line Generating Stations, which were located in or near Chicago, Illinois, were all closed abruptly within a six-month period of 2012 after decades of continuous operations. At the time of their closures, these three plants were among some of the largest coal-fired power plants operating in the U.S. We use this natural experiment to estimate the effect of exposure to air pollution on absences and achievement using data from fifteen Illinois school districts that were located in close proximity to the three power plants. This unique setting – in which large industrial sources abruptly closed after several decades of operation – allows us to sharply identify short- and medium-term impacts on students who attended schools near the three power plants.

This natural experiment is an ideal setting in which to study the effects of exposure to air pollution on student outcomes for three reasons. First, the power plant closures happened unexpectedly and in advance of previously announced timelines that had been shared publicly by the two companies that owned the plants (Tweh, 2010; Saltanovitz, 2011; Schneider Kirk, 2012; Lydersen, 2012; Hawthorne, 2012). Aside from the qualitative evidence supporting this claim, we show, later in the paper, that none of the three plants exhibited evidence of drawing-down or reducing output

[4] See, for example, Currie et al. (2009), Ebenstein et al. (2016), Marcotte (2017), Austin et al. (2019), and Heissel et al. (2019).

in advance of the closures. This lends credibility to our claim that the changes in exposure to air pollution are plausibly exogenous and mitigates concerns about migration to affected areas in advance of the closures, which would tend to bias our estimates toward zero. Second, the change in exposure to air pollution induced by the three power plant closures was large and meaningful. Specifically because the three plants in question were among some of the oldest coal-fired power plants in the U.S., they were subject to less stringent regulation and had more limited pollution controls relative to other coal-fired power plants that were operating at the time (Laasby, 2010a; Hawthorne, 2010a; Wernau, 2011).[5] We provide empirical evidence to substantiate this claim later in the paper by examining ground-level concentrations of fine particulates from two high-resolution data sources. Finally, this natural experiment provides an uncontaminated setting in which to study impacts of exposure to air pollution on children without concerns about offsetting or countervailing effects emanating from parental or community job loss. At the time of the closures, the three plants collectively employed around 280 people, which is a negligible share of total employment in the Chicago metropolitan area (Lydersen, 2012; Wernau, 2012c). This effectively shuts down competing effects on children through affected parents or other community-level impacts, which have been shown to be important in other contexts (Ananat et al., 2011; Coelli, 2011; Levine, 2011; Rege et al., 2011).

We estimate the causal effect of coal-fired power plant closures on student outcomes using difference-in-differences and event-study approaches. These identification strategies exploit temporal changes in exposure to air pollution induced by the three coal-fired power plant closures paired with spatial variation in schools' proximities to the plants. In the full sample of elementary schools, we find that school-level rates of student absences decreased by around 0.395 percentage points (7 percent) in schools located near the plants (within 10 kilometers) following the closures. In more readily interpretable units, this reduction translates into around 372 fewer student absence-days annually for the typical-sized (median) treated elementary school in our sample, or around

[5] A federal lawsuit against Midwest Generation – the owner of the Crawford and Fisk Street Generating Stations – accused the company of unfairly avoiding the installation of additional pollution control technologies on their plants (Hawthorne, 2005, 2007, 2010b).

0.71 fewer absence-days per student per year. The magnitude of this effect is larger than other estimates in the pollution literature, although we note that the shock to air quality induced by the three power plant closures is likely much larger than the shocks exploited by other papers that are typical of this literature. For several reasons that we discuss in more detail later, we believe that our estimates are still likely to be lower bounds.

In addition to our results for student absences overall, we also investigate effects on absences for student subgroups by gender, race/ethnicity, and family income. We consistently find evidence to suggest that absence reductions are larger in terms of magnitude for boys than for girls. This is the first paper in the literature to document this finding. We believe this pattern of results is consistent with well-documented differences in asthma prevalence by gender (prevalence is higher in boys than girls in this age range) and with differential patterns of time-use by gender (boys spend more time outside than girls and more time engaged in moderate and vigorous physical activities, which raise breathing rates) (Akinbami et al., 2009; Nader et al., 2008; U.S. Environmental Protection Agency, 2008). We find weaker evidence to suggest that absence reductions are larger in terms of magnitude for black students than for Hispanic students, although we acknowledge that our estimates for subgroups by race/ethnicity are less precise and more sensitive to model specification. This result is somewhat at odds with previous findings in the literature; however, we note that the contexts of the previous work are all quite different. As a final exploration of treatment effect heterogeneity, we find that estimated effects for low-income students are similar to those for the full sample, which is consistent results reported in the existing literature.

Following our presentation of results for student absences, we investigate effects on student achievement. Although we do not find any statistically significant effects on student achievement, our point estimates in math are nearly identical to magnitudes suggested by previous education literature linking absences and math test scores.[6] We find a noisier and less clear pattern of results for effects on student achievement in reading, although this also aligns with previous education literature linking absences and reading test scores.

[6] See, for example, Sims (2008), Fitzpatrick et al. (2011), and Aucejo and Romano (2016).

To provide evidence to support the internal validity of our estimated effects on absences and achievement, we investigate treatment heterogeneity on the basis of differential exposure to air pollution among treated schools. *Ex ante* we expect larger effects (in absolute terms) in schools where pre-closure exposure to emissions from coal-fired power plants was higher. To explore this hypothesis, we partition treated schools in our sample on the basis of exposure using three distinct ways to characterize "high" versus "low" exposure schools: wind intensity, air conditioning, and magnet status. Our three approaches yield a pattern of results that are remarkably consistent with one another: namely, that reductions in absences (or increases in achievement) were larger in "high" exposure versus "low" exposure schools. This exercise lends credibility to our identification strategy by ruling out that the possibility that schools near the plants were affected by other, unmeasured positive shocks to school quality, student enrollment, or other unobservables that improved student outcomes independently, even in the absence of coal-fired power plant closures.

To gain insight into the specific mechanisms underlying our estimated effects on student absences, we explore three channels suggested by previous literature: First, we present results from an investigation into the possibility that the coal-fired power plant closures led to changes in the composition of students enrolled in treated schools. If higher income families moved into the neighborhoods surrounding the coal-fired power plants following the closures, then our estimates of would overstate the effects of power plant closures on absenteeism. We find no evidence to suggest these changes in student enrollment or composition occurred. Second, to investigate whether improvements in students' health could explain reductions in absences, we examine how emergency department (ED) visits for asthma-related conditions (among 5-18 year-old children) responded to power plant closures. Difference-in-difference and event-study estimates using zip-code level data suggest large and meaningful reductions in ED visits for asthma-related conditions in zip codes near the plants relative to those further away following the closures. We conclude with an examination of whether and how ground-level concentrations of fine particulates changed in treated schools relative to control schools following the power plant closures. We do this by drawing on high-resolution estimates of average annual concentrations of fine particulates (PM

2.5) corresponding to the locations of all schools in our sample. Using two new, high-resolution sources of data on annual, ground-level concentrations of fine particulate matter, we document significant reductions in annual concentrations of fine particulates in areas near the three power plants relative to areas further away following the three plant closures. We believe that these three pieces of evidence – when considered with the existing medical and public health literatures on the effects of exposure to fine particulates – point strongly to improved respiratory health emanating from reduced exposure to fine particulates as a primary channel through student absences were reduced following the plant closures.

This paper contributes to the broad literature on the effects of exposure to air pollution on children's outcomes and specifically to the emerging work that focuses on absences and achievement in school. Given the unique context of our work – in which we observe a large, positive shock to air pollution exposure – and trends in energy generation in the U.S., our paper provides insight into the impacts of coal-fired power plant closures and suggests that the gains from reduced exposure to coal-fired power plant emissions may be sizable and particularly beneficial for young children.

2 Background

2.1 Coal-Fired Power Plant Closures

In the six-month period spanning March to August of 2012, three large, coal-fired power plants located in or very near the city of Chicago, Illinois were retired in short succession. At the time of their closures, two of the power plants – the Crawford and Fisk Street Generating Stations – were located within Chicago's city limits (see Figure 3), making them the only two operational, coal-fired power plants within the borders of a major U.S. city (Hawthorne, 2012). Opened in the early 1900s, the Crawford and Fisk Street Generating Stations were located on the north bank of the South Branch of the Chicago River (Wernau, 2012a). The third power plant – the State Line Generating Station – was located in Hammond, Indiana, a city in Lake County Indiana located directly adjacent to the Illinois state (and Chicago city) line (Lydersen, 2012).

Prior to their closures, the Crawford, Fisk Street, and State Line Generating Stations were among some of the largest operational coal-fired power plants in the country. Panel (a) of Appendix Figure A1 depicts the three plants' positions in the national distribution of coal-fired power plant capacity in 2009. The plants were in the 70th (State Line), 69th (Crawford), and 59th (Fisk Street) percentiles of the national distribution. Panel (b) of Appendix Figure A1 depicts the distribution of net reductions in nameplate capacity at the county-level for all U.S. counties between 2004 and 2016 (excluding zeroes). We note that Cook (IL) and Lake (IN) counties both fall in the right tail. Panel (c) of Appendix Figure A1 aggregates these net reductions to the city-level.[7] The net reduction in capacity from the three closures placed Chicago in the extreme right-tail of the distribution – only two other cities experienced larger reductions between 2004 and 2016: Cincinnati, Ohio and Las Vegas, Nevada, although in both cases the plants were located outside of the city centers.[8] In the months leading up to their unexpected closures, all three plants were in regular operation, which we document by plotting their monthly capacity factors (see Appendix Figure A2).

The three plants underwent numerous modifications to add pollution controls over time, particularly for nitrogen oxide (a precursor to ozone) and mercury (Laasby, 2010b; Wernau, 2012a; Hawthorne, 2012). Despite these efforts, there were some limitations on what could be added to the plants – particularly in the cases of the Crawford and Fisk Street Generating Stations – due to the constrained size and location of the plants' physical sites (Wernau, 2012a). This meant that prior to their closures, the three plants were among some of largest emitters of pollutants in the U.S. (Laasby, 2010a; Hawthorne, 2010a; Wernau, 2011).

In March 2012, the State Line Generating Station was closed unexpectedly, in advance of a previously announced closure date of 2014 (Tweh, 2010; Saltanovitz, 2011; Schneider Kirk, 2012). The 83-year-old plant in Hammond, Indiana was built in 1929 and was for many years the

[7] We define cities based on the U.S. Office of Management and Budget's definition of Consolidated Statistical Areas (CSAs), which represent linked metropolitan and micropolitan statistical areas that share substantial economic activity.

[8] In Cincinnati, the plant was located 18 miles outside of the city, and in Las Vegas, the plant was located 50 miles outside of the city.

largest coal-fired power plant in the U.S. (Hawthorne, 2010a). The introduction of more stringent environmental regulation from the Obama Administration combined with declining natural gas prices induced by hydraulic-fracturing ("fracking") contributed to the decision to close the plant in 2012 (Lydersen, 2012).

Six months later, in August 2012, the Crawford and Fisk Street Generating Stations were also retired unexpectedly and in advance of previously announced timelines. The parent company cited an inability to make the financial investments necessary to upgrade pollution control technologies and ongoing negotiations with environmental groups and state regulators regarding the company's portfolio of power plants across the state (Wernau, 2012b).

2.2 Children and Exposure to Air Pollution

Due to ongoing development, children are more susceptible to harm from exposure to air pollution than adults and may experience harm at levels of exposure that pose no threat to adults (World Health Organization, 2011). Children's lungs and immune systems are less developed than adults', which means they are more vulnerable to permanent damage from air pollution (Bateson and Schwartz, 2007). In addition, children breathe differently than adults, which may influence the amount of exposure and the penetration of fine particles within the lungs. While adults commonly breathe through their noses, children often breathe through their mouths, decreasing air filtering and increasing exposure, even in the same ambient environment (Bateson and Schwartz, 2007; Foos et al., 2007). Even conditional on nasal breathing – which increases with age – children's noses may be less effective at air filtering due to differences in the anatomical structures of the nasal passage (Foos et al., 2007). A final difference comes from potentially higher rates of deposition of particles into the lower respiratory tract of the lungs, due to conditions such as obesity, hay fever (allergic rhinitis), and asthma (Foos et al., 2007).

Children's activity patterns may also increase their exposure to air pollution both because they spend more time outdoors than adults and because they partake in activities more likely to increase ventilation (breathing) rates, which increases their exposure to air pollution (Klepeis et al., 2001;

Schwartz, 2004; Bateson and Schwartz, 2007). In particular, time spent outdoors is highest among children ages 6-11 relative to children in other age ranges, suggesting potential differences in exposure to air pollution among elementary-aged children compared to their older or younger peers (U.S. Environmental Protection Agency, 2008).

2.3 Previous Work

Some of the earliest quasi-experimental evidence on exposure to air pollution and education outcomes came from Ransom and Pope (1992). In this paper, the authors investigated the association between PM10 exposure and student absences in the context of a steel mill shutdown in Provo, Utah in the mid-1980s. They found that a 100 microgram per cubic meter (μ/m^3) increase in PM10 (28-day average) was associated with a 2 percentage point (40 percent) increase in student absences. They further documented that effects were larger for students enrolled in grades 1-3 versus grades 4-6 and that the effects on absences persisted for several weeks. Building on these findings, Currie et al. (2009) developed a framework to consider exposure to multiple pollutants including carbon monoxide (CO), PM10, and ozone. Using data from thirty-nine school districts in Texas, the authors estimated the effect of the one extra day of exposure to poor air quality on student absences, finding that, for CO, an increased day of exposure increased absences by between 5 and 9 percentage points, depending on the severity of pollution.

In recent work, Heissel et al. (2019) employed a difference-in-differences approach to leverage student school transitions to "upwind" versus "downwind" schools near highways. They found suggestive evidence of effects on student absence rates: when students transitioned to an upwind school, their absence rate increased by 0.5 percentage points (10 percent increase relative to baseline), although this effect is only marginally statistically significant. In another recent paper, Austin et al. (2019) exploit variation in exposure to air pollution emanating from a school bus retrofitting program in the state of Georgia. School bus retrofitting dramatically reduces diesel emissions from school buses, which contain nitrogen oxide and fine particulates. The authors did not find statistically significant effects of retrofitting on district-level attendance rates, although they note that attendance rates were very high at baseline. Furthermore, changes in exposure to air pollution induced by retrofits could be time-limited and localized.

Two additional recent papers investigate the effect of exposure to particulate matter on student absences in China, where air pollution levels are typically much higher than those observed in the U.S. Chen et al. (2018) use an instrumental variables framework to assess the effect of exposure to air pollution in Guangzhou City on absences. Using temperature inversions as an instrument for air quality, the authors find that a one standard deviation increase in daily Air Quality Index (AQI) levels leads to a 7 percent increase in absence rates. Using detailed student-level data that contains information on reasons for absences, they find that absences on days with poor air quality are mostly driven by an increased in respiratory-related conditions, suggesting the importance of health mechanisms. Consistent with Chen et al. (2018), Liu and Salvo (2018) find that increased exposure to PM2.5 leads to increases in absences among students enrolled in international schools in a major urban center in north China. Specifically, they find that PM2.5 levels in excess of 200 micrograms per cubic meter (24-hour average) on the previous day increases the likelihood of an absence by 0.9 percentage points, or 14 percent in relative terms.

3 Data

3.1 School Data

We obtained information on student absences and other student characteristics aggregated to the school-level from the Illinois State Board of Education (ISBE) Report Card Data Library.[9] These data provide the annual aggregate student absence rate for total enrolled students and for several student subgroups. The annual aggregate student absence rate is a ratio of the sum of all student absence days (summed across all students enrolled in the school) to the sum of all student enrollment days (summed across all students in the school).[10] The Illinois Report Card program also contains

[9] These data are publicly-available here: https://www.isbe.net/ilreportcarddata.

[10] Let a_{ist} be the number of absence days for student i enrolled in school s in year t and let e_{ist} be the number of enrollment days for student i enrolled in school s in year t. Note that $e_{ist} \leq 180$, since some students may enroll (transfer in) after the first day or may disenroll (transfer out) prior to the end of the school year. The annual aggregate

time-varying school characteristics: total enrollment, percent black, percent Hispanic, and percent low-income. We obtained information on two time-varying policy controls relevant to the Chicago Public Schools (CPS) context during this period: Safe Passage status (0/1) and Welcoming School status (0/1). These special programs were introduced at a select number of schools in the school district following the mass closings in CPS at the end of the 2012/13 school year.

We obtained student-level test score information from the Illinois State Board of Education (ISBE) using a Freedom of Information Act Request (FOIA).[11] Unlike other administrative education data, this student-level data contained only the following information: a randomized student identification number (created solely for the purpose of fulfilling the FOIA request and not linkable to other administrative data), the student's school and grade level, the school year, and a scale score for the math, reading, science, and writing subject tests of the Illinois Standards Achievement Test (ISAT).[12] We normalized scale scores by grade, subject, and year using the scores of all students in Illinois who were not enrolled in one of our fifteen sample districts (mean zero and unit standard deviation). We then collapsed the normalized student-level scores from math and reading subject tests into school-by-year cells or school-by-grade-by-year cells.

To define our treatment and control groups, we obtained addresses for each traditional public elementary school in our nine school districts from published versions of the state's Directory of Educational Entities.[13] We merged school address information with the ISBE Report Card Data, geocoded all addresses, and calculated the linear distance between each school and each of the three power plants. In our main specifications, we define schools as treated if they are within 10 kilometers of one of the power plants; if they are outside the 10 kilometers radius, we define them

student absence rate is then given by: $A_{st} = \Sigma_{i=1}^{N_g} a_{ist}/e_{ist}$, where g denotes student group (either all students in the school, male students, female students, or low-income students.

[11] We submitted a Freedom of Information Act (FOIA) request to the Illinois State Board of Education (ISBE) on September 14, 2017.

[12] We do not use the writing or science tests, since these are not administered to all grade levels nor were they administered during all of the years in our sample.

[13] The Illinois Directory of Educational Entities is available here: https://www.isbe.net/Pages/Data-Analysis-Directories.aspx. It contains information on all public entities that provide educational services to K-12 students in Illinois. The directory is updated continuously; snapshots are preserved each school year. The Illinois State Board of Education (ISBE) was unable to provide the snapshot for the 2015/16 school year, however, so we imputed school addresses for this school year based on the address listed in the previous school year.

as controls.

3.2 Sample

Our sample is a balanced panel of 457 traditional public elementary schools from fifteen school districts in Illinois.[14] These fifteen districts were chosen because they all contain at least one school within 10 kilometers of at least one of the three plants, per our treatment definition. We restrict our attention to traditional public elementary schools that did not change locations during the 2008/09-2015/16 school years. We drop charter schools and schools that opened (or closed) during this time period from our analysis. Approximately 85 percent of the schools in our sample belong to one single school district, the City of Chicago Public Schools (CPS). CPS is the third largest school district in the United States and the single largest school district in Illinois. CPS schools account for roughly 18 percent of schools and 25 of student enrollment at the elementary school level in Illinois.[15]

3.3 Descriptive Statistics

Table 1 presents baseline information at the school-level for school characteristics, absences, and student achievement for elementary schools in our sample. Columns (1) and (2) present mean estimates and standard errors for the 457 elementary schools during the 2008/09 school year. Columns (2) and (3) disaggregate the full sample and present the same descriptive information for our treatment (Near) and control (Far) groups. Column (4) presents the difference in means between these two groups and the associated standard errors. Column (5) presents the p-value from a two-tailed t-test of the difference in means.

At baseline, elementary schools located in close proximity to at least one of the three plants

[14] The districts in our sample include: Forest Park School District, Riverside School District, Oak Park Elementary School District, Berwyn North School District, Cicero School District, Berwyn South School District, Lyons School District, Summit School District, Central Stickney School District, Burbank School District, Oak Lawn-Hometown School District, Dolton School District, Burnham School District, Calumet City School District, and City of Chicago Public Schools.

[15] Authors' calculations from the 2008/09 school year.

(Near) differed on numerous observable dimensions when compared to elementary schools located further away (Far). Prior to the plant closures, elementary schools in close proximity had higher percentages of Black students (16 percentage points), higher percentages of low-income students (12 percentage points), and were more likely to be designated as Safe Passage schools (12 percentage points) relative to elementary schools slightly further away (Panel (A)). All of these differences are statistically significant at the 5 percent-level. We do not find evidence of statistically significant differences in enrollment, the percentage of Hispanic students enrolled in the school, or the likelihood Welcoming School designation.

We also find that elementary schools located in close proximity to at least one of the three plants had worse absence (Panel (B)) and worse test score (Panel (C)) outcomes at baseline compared to elementary schools further away. Elementary schools in close proximity had worse aggregate absence rates for students overall (0.60 percentage points higher) and for all of the following subgroups: male students (1.02 percentage points higher), female students (0.96 percentage points higher), black students (1.07 percentage points higher), Hispanic students (1.34 percentage points higher), and low-income students (0.86 percentage points higher). Finally, elementary schools in close proximity had relatively worse school-level test scores outcomes: math test scores were approximately 0.28 standard deviations lower on average, while reading test scores were around 0.30 standard deviations lower on average.

4 Empirical Strategy

We use difference-in-differences and event-study approaches to estimate the effect of coal-fired power plant closures on student absences and test scores. Both empirical approaches exploit spatial variation in schools' proximity to the Crawford, Fisk Street, and State Line Generating Stations and temporal variation induced by the nearly-simultaneous, closures of the three plants. We define a school as treated if it is located within 10 kilometers of at least one of the three plants. We chose this distance because it is the median distance in our fifteen district sample of elementary schools, although we demonstrate that our results are not sensitive to this choice. As power plant emissions may travel much further than 10 kilometers, we acknowledge that students attending elementary schools in the control group could have also been exposed to pollution emitted from the three plants. This possibility of control group contamination means that our estimates should be interpreted as lower bounds.

4.1 Difference-in-Differences Specification

Our difference-in-differences strategy assumes parallel trends in observable and unobservable determinants of absences and test scores in our treatment and control groups in the years preceding the plant closures. This assumption is required in order for the control group (Far) schools to provide a valid counterfactual for how absence and test score outcomes in the treatment group (Near) schools would have evolved in the absence of the plant closures. Even though this is not directly testable, we later provide evidence in support of the assumption and thus the validity of our identification strategy.

Our difference-in-differences estimates are based on an equation of the following form:

$$Y_{st} = \alpha + \beta \times (Near \times Post)_{st} + \delta_t + \phi_s + X_{st} \cdot \theta + \varepsilon_{st} \tag{1}$$

Y_{st} is a school-level absence or test score outcome for school s in year t. $(Near \times Post)_{st}$ is a binary indicator that takes the value of one for all schools in the treatment group in school years $t = 2013, ..., 2016$. We include a vector of year fixed-effects, δ_t, to control for factors that are common across all elementary schools in the sample within specific school years, such as local economic conditions, state-level school policy changes, and weather. We include a vector of school fixed-effects, ϕ_s, to control for time-invariant school-level factors such as the local environment, curricular differences, school policies, and neighborhood characteristics. X_{st} is a vector of time-varying school characteristics and policy controls, including the natural logarithm of total enrollment, the share of black students, the share of Hispanic students, the share of low-income students, whether the school was designated as a Safe Passage school (0/1), and whether the school was designated as a Welcoming School (0/1). We report heteroskedasticity-robust standard errors clustered at the school level and weight all regressions by total enrollment to increase precision.

4.2 Event-Study Specification

To further investigate the validity of the parallel trends assumption and to explore dynamic effects of the treatment, we modify our differences-in-differences specification by interacting the indicator variable for schools in the treatment group, $Near_s$, with event-time indicators. This flexible approach allows for more detailed investigation of changes in school-level absence and test score outcomes around the year of the plant closures. We present results based on estimating the following equation:

$$Y_{st} = \sum_{\substack{j=-3 \\ j \neq -1}}^{4} \left[\pi_j \cdot Near_s \cdot \mathbf{1} \cdot \left(t - 2012 = j \right) \right] + \phi_s + \delta_t + X_{st} \cdot \theta + \varepsilon_{st} \tag{2}$$

All components of Equation (2) are the same as the previous specification, although we now interact $Near_s$ with event-time dummies. The sequence of π_j coefficients for $j = -3, ..., 4$ ($j = -1$ omitted) trace out the evolution of relative differences in school-level absence and test score outcomes in treatment (Near) and control (Far) schools. In the plots we produce based on this equation, we set $j = 0$ for the 2011/12 school year. The State Line Generating Station closed in March 2012 – three months prior to the end of the 2011/12 school year. Thus, to be conservative we consider this school year to be "partially treated" since elementary schools in the vicinity of the State Line Generating Station had improved air quality for nearly one-quarter of the school year. We expect coefficient estimates from π_0 therefore to be nonzero but smaller in magnitude than those in the following school years, since only one of the three plants had retired, for only part of the school year.

5 Main Results

5.1 Absences

Column (1) of Table 2 presents results for Equation (1) for absences among the full sample of elementary schools. The point estimate indicates that aggregate absence rates were 0.395 percentage points lower in treatment schools relative to control schools in the school years following the three power plant closures. This reduction in absences represents a 7 percent decline relative to the baseline mean of 5.809 percent. For the typical (median) treated elementary school with 525 enrolled students, this absence rate decline represents a reduction of around 372 student-absence days per year, or around 0.71 absences per student per year.[16]

Panel (A) of Figure 4 plots the coefficients and associated ninety-five percent confidence intervals from estimating Equation (2) for the same group of schools. Coefficient estimates corresponding to $j = -3$ and $j = -2$ depict differences between the treatment and control groups in the years prior to the plant closures ($j = -1$ is omitted). We cannot reject the null hypothesis that both coefficients are jointly equal to zero ($p = 0.76$). This visual evidence illustrates that absence outcomes were trending similarly in treatment versus control schools prior to the plant closures. The coefficient on $j = 0$ comes from the 2011/12 school year, which we consider to be partially treated due to the closure of the State Line Generating Station prior to the end of the school year. The coefficient is negative but statistically indistinguishable from zero and is then followed by a sequence of coefficients that become substantially more negative over time.

Columns (2)-(6) of Table 2 present estimation results separately by student subgroup, including by gender, race/ethnicity, and family income. While we find suggestive evidence of heterogeneous treatment effects by gender and by race/ethnicity, we do not find any evidence of heterogeneous effects by family income. Columns (2) and (3) results separately for male and female students. Although we are unable to directly test whether the two effects are statistically different, we consistently find that effects on male students are larger than effects on female students (the boot-

[16]To covert the percentage point reduction in the aggregate absence rate at the school-level into absences per student per year, we assume that all students are enrolled for the duration of the 180-day school year.

strapped p-value on this difference is $p = 0.038$). Aggregate absence rates were around 0.440 percentage points lower for males in treatment schools versus control schools and 0.349 percentage points lower for female students in the school years following the plant closures. In relative terms, these translate into 7 percent and 6 percent reductions. For the typical (median) treated elementary school with enrollment split evenly between males and females, these declines represent reductions of 207 and 165 student-absence days per year, or around 0.79 and 0.63 fewer absences per student per year among males and females, respectively. The visual evidence in Panels (B) and (C) of Figure 4 are similar to the results for the full sample, although once again effects are larger for males than for females.

Columns (4) and (5) of Table 2 present estimation results separately for black and Hispanic students.[17] These results reveal suggestive – albeit weaker – evidence of larger effects on black students relative to Hispanic students. Aggregate absence rates were around 0.431 percentage points lower for black students in treatment schools versus control schools and 0.197 percentage points lower for Hispanic students in the years following the plant closures (the bootstrapped p-value on this difference is $p = 0.209$). In relative terms, these translate into 7 percent and 3 percent reductions, respectively. The visual evidence Panels (D) in Figure 4 reveal a pattern of effects on black students that are similar to the pattern observed in the full sample, but the pattern of results for Hispanic students in Panel (E) is quite different. The effects on Hispanic students are relatively constant in all of the years following the plant closures, unlike the pattern of increasingly negative effects observed for all other groups. Column (6) of Table 2 presents results for students from low-income families. We find that the results are very similar to our results for the full sample. Aggregate absence rates among low-income students were around 0.337 percentage points lower in treatment schools versus control schools in the years following the plant closures. In relative terms, this translates into a 6 percent reduction in absences.

[17] We are unable to obtain results for other racial/ethnic groups due to high levels of non-reporting of other subgroup absence rates at the school-level in our panel.

5.2 Achievement

Table 3 presents results for Equation (1) for math and reading achievement test scores among the full sample of elementary school students. In addition to estimating effects on average test scores within schools, we also estimate effects at the 10th, 25th, 50th, 75th, and 90th percentiles of the within-school test score distribution. Unlike the results for absences, our data do not allow us to identify student subgroups in the test score data. In this table we collapse test scores by subject to the school-year level and pool across grades 3-8. We present the same results separately by grade and subject in Online Appendix C.

The results for math achievement appear in Columns (1) through (6) of Panel (A). Although our point estimate in Column (1) is statistically insignificant, its magnitude of 0.007 standard deviation units is in line with what would be suggested by the existing literature linking reductions in absences and math test scores (Sims, 2008; Fitzpatrick et al., 2011; Aucejo and Romano, 2016). Columns (2)-(6) present our results for other moments in the test score distribution, none of which are significant. Columns (1)-(6) of Panel (B) presents the same results for reading achievement test scores. As with math scores, we find no evidence of any statistically significant effects. Our point estimate for reading achievement in Column (1) is actually negative, although we note that the link between absences and reading test scores established in the previous education literature is much weaker. Figure 5 plots the event-study coefficients for math and reading achievement test scores in Panels (A) and (B), respectively.

5.3 Dose-Response Relationship

Table 4 presents results from three exercises designed to detect the presence of a dose-response relationship. In Panel (A) reports results from the first exercise, in which we partitioned schools in the treatment group into two groups: those located in close proximity to one plant and those located in close proximity to two plants (no schools are located within 10 kilometers of all three plants). We find very limited evidence of a dose-response relationship that takes this form. Although we find that in most cases the effect is larger in magnitude for the group of schools located in close proximity to two plants relative to those located in close proximity to one plant, in most cases we cannot reject null hypothesis that the effects are equal. The one exception appears in Column (4), where we find significant evidence of a stronger effect on absences for black students who attend schools that are in close proximity to two plants versus one plant. We repeat this analysis for achievement test scores in math and reading and present the results in Panel (A) of Appendix Table A10. We consistently find that the point estimates are larger in magnitude for the group of schools located in close proximity to two plants relative to the group of schools located in close proximity to one plant, but our estimates are imprecise.

As a second means to explore the presence of a dose-response relationship, we assign all of our treated schools to one of three groups based on the power plant to which they are closest: Crawford, Fisk Street, or State Line. Because the three power plants had different capacities, we view this exercise as a way to investigate whether the size of the plant – and hence its emissions "dose" – influenced the magnitude of the treatment effect.[18] We do not find evidence of a monotonic relationship between plant size and the magnitude of the treatment effect. Instead, we find a fairly consistent pattern of effects that are largest at State Line, followed by Fisk, followed by Crawford, although this does not hold for all subgroups and in most cases we cannot reject the null hypothesis that the effects are equal across plants. Once again we repeat this analysis for achievement test scores, which we present in Panel (B) of Appendix Table A10.

As a final exercise, we partition schools in the treatment group into two groups based on distance to the nearest of the three plants: the first group is comprised of schools located within 5 kilometers of the nearest plant, while the second group is comprised of schools located between 5 and 10 kilometers of the nearest plant. We do not find any evidence of an increasing dose-response relationship based on proximity; rather, we find robust evidence of larger effects on absences in schools located between 5 and 10 kilometers from the nearest plant. We believe this is likely explained by dispersion patterns that result from a combination of tall stacks and wind. We find similar pattern in the magnitudes of our estimates for math and reading achievement test scores,

[18] State Line Generating Station was the largest (614 MWh), followed by Crawford (597 MWh), and Fisk (374 MWh).

which we present in Panel (C) of Appendix Table A10, noting, once again, that our effects on achievement are imprecisely estimated.

5.4 Robustness, Falsification, and Inference

In addition to our estimating equation outlined in Equation (1), we report estimates from two specification checks designed to assess the robustness of our results to changes in model specification. First, to assess the sensitivity of our estimates to unobserved sources of heterogeneity, we report results from Equation (1) augmented with the addition of district-specific linear trends. Our results, which we report for absences in Appendix Table A2 and for achievement test scores in Appendix Table A6, are essentially unchanged. Second, to provide insight into whether effects are heterogeneous with respect to school size, we report results from unweighted regressions. Our results, which we report for absences in Appendix Table A4 and for test scores in Appendix Table A8, are very similar to our main results.

To assess the sensitivity of our results to our decision to use a 10-kilometer radius to define the treatment group, we re-estimated our main model and allowed this radius to vary. We plot the resulting coefficients and their associated ninety-five percent confidence intervals for 1 kilometer increments ranging from 5 to 15 kilometers in Appendix Figure A3. Our treatment effect estimate is slightly positive for the radius of 5 kilometers, due to substantial control group contamination, but then crosses zero and becomes increasingly negative as we allow the radius to increase. We note that expanding the treatment radius past 10 kilometers does very little to the estimated treatment effect. We repeat this exercise for math and reading achievement test scores and plot the resulting treatment effects for radii ranging from 5 to 15 kilometers in Panels (A) and (B) of Appendix Figure A4.

To assess whether and how our results depend on our choice of sample, we re-estimate all of our results for the subsample of elementary schools that are from Chicago Public Schools (CPS). In the cases of both absences and achievement test scores, we find patterns of results that are similar to those obtained for the full sample. We note, however, that in most cases the point estimates from the subsample of CPS schools are larger in magnitude (i.e., larger reductions in absences and larger increases in achievement test scores). For completeness, we present these results in Online Appendix D.

We perform several falsification exercises to reinforce the causal interpretation of our absence results. To do this, we estimate Equation (1) on school-level outcomes that we expect to be unaffected by plant closures. Appendix Table A11 presents estimation results for following outcomes: average class size and the average number of minutes per day spent on Math and English instruction.[19] The point estimates in Columns (1)-(3) are small and statistically insignificant. The ninety-five percent confidence intervals are narrow enough to rule out meaningful effects on these outcomes in either the positive or negative direction. This strengthens the causal interpretation of our absence results by demonstrating that we are not picking up the effects of other unobserved improvements in treated schools that coincided with the plant closures.

To assess the sensitivity of our conclusions regarding the statistical significance of our estimates, we present two alternative approaches to inference. First, we cluster our standard errors at the 5-digit zip code to allow for arbitrary serial correlation in error terms among a larger set of schools. As expected the standard errors from this clustering are larger, but our conclusions regarding the statistical significance are unaffected. We present these results for absences in Appendix Table A3 and for achievement test scores in Appendix Table A7. Second, we report p-values from non-parametric permutation tests in Appendix Tables A5 and A9. These p-values characterize uncertainty in our estimates that arises from the assignment of schools to treatment and control groups, rather than sampling. We calculated these p-values by randomly re-assigning treatment at the school-level, re-estimating our model to obtain an estimate of this "placebo" effect, and then obtaining the associated (false) treatment effect. We repeated this process 1,000 times and then computed the share of estimates that were more extreme (in the absolute sense) than our actual estimate. All permutation p-values fall below the conventional 0.05-level, leaving our conclusions about the statistical significant of our estimated effects unchanged.

[19]These classroom outcomes are averaged at the school-level among sixth grade classrooms. We chose this grade because the majority of the schools in our sample serve sixth grade students.

6 Heterogeneous Effects by Exposure

To provide further evidence supporting the internal validity of our estimated effects, we investigate treatment heterogeneity on the basis of differential exposure to air pollution. We expect, *ex ante*, that the effects of closures will be larger (in absolute terms) in schools with higher, pre-closure levels of exposure. We partition treated schools on the basis of exposure (e.g., "high" vs. "low" exposure schools) using three distinct characteristics: wind intensity, air conditioning, and magnet status. Our three approaches yield results that are remarkably consistent with one another, despite the fact that these school-level characteristics are essentially uncorrelated with each other and with the share of students in the school who are low-income.[20] Specifically, we find that the magnitude of our estimated effects (in terms of reductions in absences or increases in achievement) are larger in "high" exposure versus "low" exposure schools.

6.1 Wind Intensity

To investigate treatment heterogeneity on the basis of exposure, we first use daily wind data from the 2008/09 school year (baseline) to split treated schools into two groups: "High Wind" and "Low Wind." We created these two groups based sample median (45 days) of the total number of days during the school year on which the school was directly in the wind path of the nearest plant (for a visual depiction of this classification, see Appendix Figure A5).[21] We then re-estimated Equation (1) with an interaction that allowed the treatment effect to vary between these two groups of schools. We report results in Panel (A) of Table 5. Our absence results in Columns (1)-(6) almost uniformly demonstrate that reductions in absence rates were larger in High Wind relative to Low Wind schools. The lone exception is for black students in Column (4). Our achievement test score results in Columns (7) and (8) also reveal a pattern of estimates that suggest that improvements in test scores were larger in High Wind schools relative to Low Wind schools.

[20]For cross-sectional correlations between school-level air conditioning (percent), number of wind days, magnet status (0/1), and the percentage of low-income in the school, see Appendix Table A12.

[21]For more information on Wind Data sources, please see Appendix B.

6.2 Air Conditioning

As a second means to investigate treatment heterogeneity on the basis of exposure, we divide treated schools in our sample based on the percent of the school building that is air-conditioned.[22] The presence of air conditioning within schools is likely to affect exposure in two ways: First, schools with air conditioning are less likely to have open windows on hot days, thus limiting the potential for outdoor air to circulate inside. Second, air conditioners (and HVAC systems more generally) have basic air filtration capacities (Parker et al., 2008). We find evidence of the same pattern in Panel (B) of Table 5, where the point estimates for schools with low levels of air conditioning are consistently larger (in magnitude) than those for high levels of air conditioning. The lone exception is, once again, for black students in Column (4). Our achievement test score results in Columns (7) and (8) also reveal a pattern of point estimates that suggest that improvements in test scores were larger in low air conditioning schools where exposure to air pollution was likely to be higher.

6.3 Magnet Schools

As a final means to investigate treatment heterogeneity on the basis of exposure, we divide treated schools in our sample based on their magnet status. We expect larger effects in non-magnet schools (i.e., schools with designated attendance boundaries) since those schools draw from local neighborhoods and thus are more likely to have students living nearby. Consistent with our previous findings, we once again find evidence of larger effects in high exposure (i.e., non-magnet) schools in Table 6. Columns (1)-(6) present results for absences, while Columns (7) and (8) present results for test scores. In all cases, our estimates are larger in magnitude among schools we consider to be high exposure.

[22] We obtained data on air conditioning in CPS schools from an Energy Star Audit in 2012.

7 Mechanisms

To provide evidence on the mechanisms underlying the reduced-form effects presented in the previous sections, we first report results from an investigation into the possibility that the coal-fired power plant closures led to changes in the composition of students enrolled in treated schools. Second, we investigate effects on children's health by examining whether and how emergency department (ED) visits for asthma- related conditions among 5-18 year-old children responded to power plant closures. We conclude with an examination of whether and how ground-level concentrations of fine particulates changed in treated schools relative to control schools following the power plant closures. We do this by drawing on high-resolution estimates of concentrations of fine particulates (PM 2.5) corresponding to the locations of all schools in our sample.

7.1 Ruling Out Changes in Enrollment and the Composition of Students

To investigate whether power plant closures led to changes in enrollment or the composition of students who attended treated schools following the power plant closures, we estimate Equation (1) with school-level characteristics on the left-hand side and report the results in Table 7. If it were the case that higher income or more advantaged families moved to the neighborhoods of treated schools following the power plant closures, then our estimates of would overstate the effects of power plant closures on absenteeism. The results in Columns (1)-(4) demonstrate that observable school-level characteristics were unaffected by the plant closures. We find no evidence of any statistically significant effects of the plant closures on the natural logarithm of enrollment, the percentage of black students enrolled in the school, the percentage of Hispanic students enrolled in the school, or the percentage of low-income students enrolled in the school. All of the point estimates are small in magnitude and statistically insignificant. Moreover, the associated ninety-five percent confidence intervals are narrow enough to rule out meaningful effects on school-level enrollment and student characteristics in both the positive and negative directions. The results in Columns (4) and (5) present results for dependent variables measuring the share of students who took tests in math and reading at the school-level.[23] These measures provide additional evidence to suggest that the composition of students did not change in response to the power plant closures.

7.2 ED Visits for Asthma-Related Conditions

To provide evidence that our observed reductions in absences are generated through improvements in student health, we present results from a series of regressions utilizing a difference-in-differences specification similar to Equation (1) but estimated at the zip-code level.[24] This analysis investigates the effects of the plant closures on rates of emergency department (ED) visits for asthma-related conditions among 5-18 year olds. Table 8 presents estimation results from a specification similar to Equation (1) with either the crude rate or age-specific rate of ED visits for asthma-related conditions among 5-18 year olds on the left-hand side.[25] Columns (1)-(3) report results for the crude rate of ED visits for asthma-related conditions, where we find that ED visits decreased in zip codes close to the power plants by around 2 visits per thousand residents per year (8 percent) following the closures. As a robustness check, we present results for age-specific rates in Columns (4)-(6), where we find that ED visits decreased in zip codes close to the power plants by around 8.5 visits per thousand residents in the same age range per year (8 percent). We present event-study results for the same dependent variables in Figures 6a and 6b.

7.3 Particulate Pollution

We also examine changes to fine particulate pollution following the power plant closures. To do this, we exploit high-resolution data on annual ground-level concentrations of fine particulates from two unique sources. These sources are satellite-derived concentrations of PM2.5 (van Donkelaar et al., 2019) and estimates from the atmospheric dispersion model Downscaler, which

[23] We note that baseline levels of the share of tested students are low (around 0.54), which reflects the fact that standardized tests are not administered to students in all grades.

[24] Appendix Figure A6 depicts the "near" and "far" zip code designations used in this analysis.

[25] The crude rate measures the number of ED visits for asthma-related conditions among 5-18 year-olds per one thousands residents in the zip code. The age-specific rate measures the number of ED visits for asthma-related conditions among 5-18 year-olds per one thousands residents in same age range in the zip code.

are produced the by U.S. Environmental Protection Agency (EPA) and the U.S. Centers for Disease Control (CDC).[26] Figure B1 plots the values of $PM_{2.5}$ derived from these two sources against station measurements of $PM_{2.5}$ at four air pollution monitoring sites in Chicago. These figures demonstrate that our measures of air pollution are highly correlated with available station data; the correlation is stronger between station data and satellite data, so the satellite data are our preferred source of air pollution measures.[27]

Table 9 presents estimation results from Equation (1) in which we use school-specific measures of PM2.5 concentrations on the left-hand side. We find consistent evidence of decreased ambient concentrations of fine particulates for treatment schools relative to control schools in the years following the plant closures. The point estimate in Column (1) indicates that the three plant closures resulted in concentrations of fine particulates that were around 0.059 μg/m^3 lower in treatment schools in the post period. Relative to the baseline mean of 13.169 μg/m^3 , this represents a 0.4 percent decline in fine particulates following the plant closures.

8 Conclusion

In this paper we estimate the causal effect of three, nearly-simultaneous coal-fired power plant closures on student absences and achievement. We use this natural experiment to estimate the effect of exposure to air pollution on absences and achievement using data from fifteen Illinois school districts that were located in close proximity to the three power plants. This unique context – in which large industrial sources abruptly closed after several decades of operation – allows us to sharply identify short-run and medium-run effects on students who attended schools near the three power plants.

We find that power plant closures decreased student absences at the school-level by around 0.395 percentage points (7 percent). This translates into around 372 fewer student absence-days for the typical-sized (median) elementary school in our sample, or around 0.71 fewer absence-

[26]For more detailed information about these sources, please see Appendix B.

[27]The correlation coefficients between station, satellite, and Downscaler measures in our data are 0.87 (station-satellite correlation), 0.49 (station-Downscaler correlation), and 0.58 (satellite-Downscaler correlation).

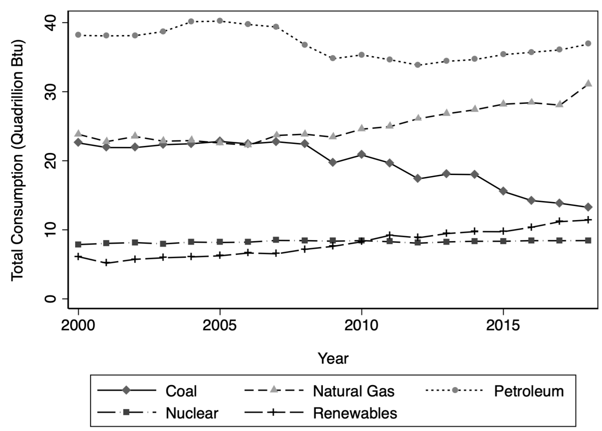
days per student per year. Although much of the previous literature in the economics of education would suggest that reductions in absences should translate into improvements in student test scores, we do not find any statistically significant evidence of effects on student achievement in math or reading. In math, the magnitudes of our findings are consistent with what we would expect based on previous literature.

Our investigation into treatment heterogeneity on the basis of differential exposure to air pollution reveals larger effects in schools where pre-closure exposure to emissions from coal-fired power plants was higher. Our three approaches – using data on wind, air conditioning, and magnet schools – yield a consistent pattern of results: specifically, we find that reductions in absences and increases in achievement were larger in schools with higher baseline exposure to emissions from coal-fired power plants. These in turn help us to rule out that the possibility that treated schools (near the plants) were affected by other, unobserved shocks.

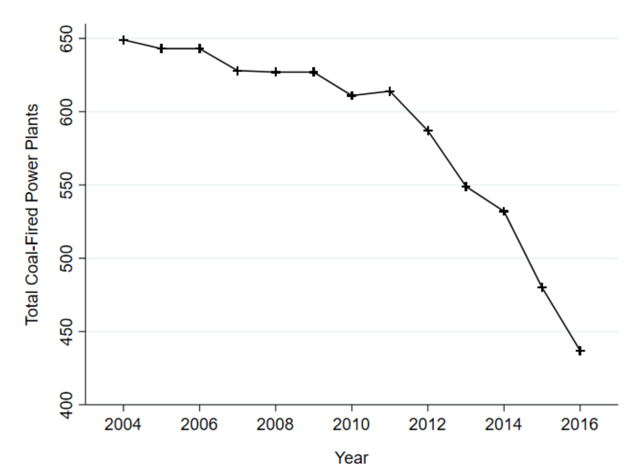
We gain insight into the mechanisms underlying our estimated effects on student absences by exploring changes in student enrollment and composition, effects on children's health, and ground-level concentrations of fine particulates. When considered together, these results from these three exercises strongly suggest improved respiratory health as a primary absence-reducing channel.

This paper contributes to the emerging literature on the effects of exposure to air pollution on children's outcomes and – more specifically – to the emerging body of evidence that focuses on absences and achievement in school. Our unique setting – in which we exploit variation in exposure to air pollution emanating from a large, positive shock – and trends in energy generation in the U.S., our paper provides insight into the impacts of coal-fired power plant closures and suggests that the gains from reduced exposure to coal-fired power plant emissions may be sizable and particularly beneficial for young children.

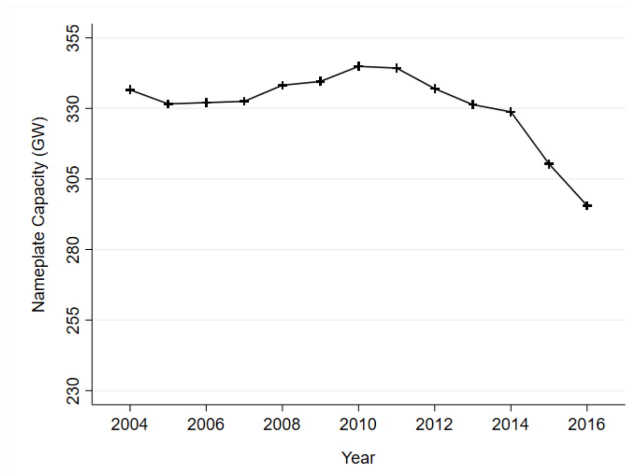
Figures



(a) Sources of Energy in the United States



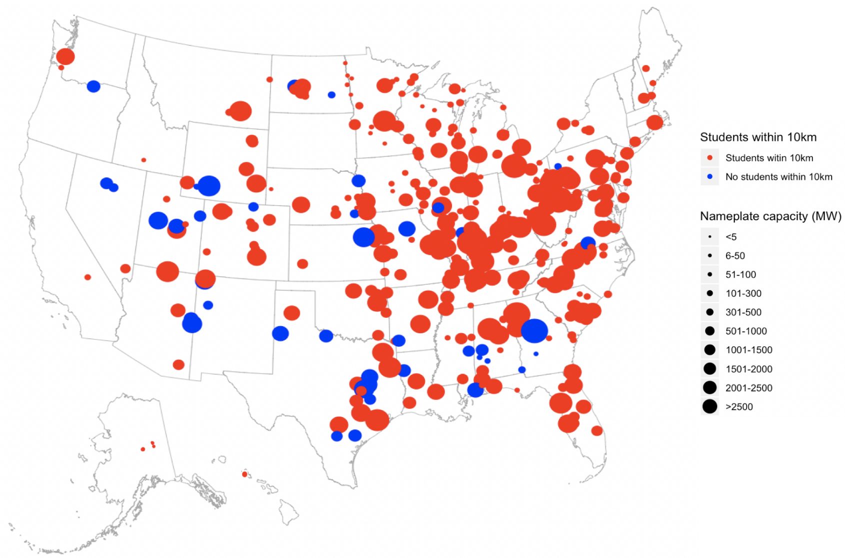
(b) Number of Coal-Fired Power Plants in the United States



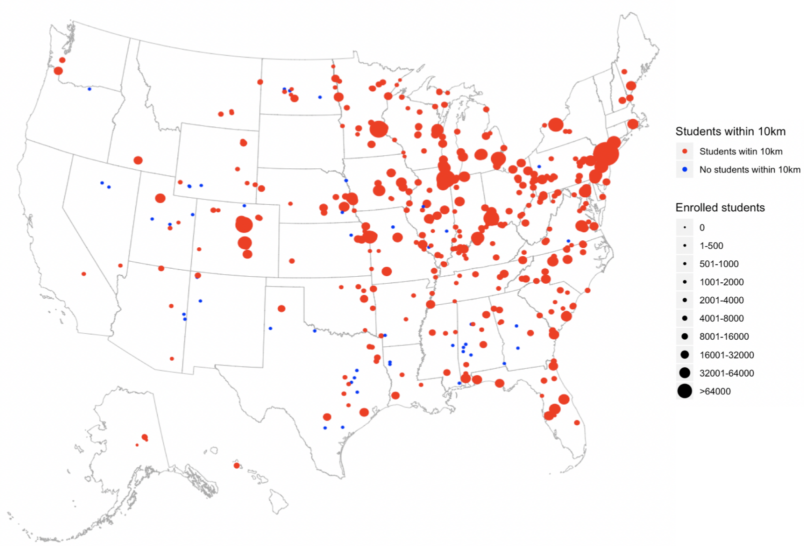
(c) Capacity (Gigawatts)

Figure 1: Energy Consumption, Operational Coal-Fired Power Plants, and Coal-Fired Power Plant Capacity in the United States

Notes: Panel (a) depicts energy consumption in the United States, separately by source, between 2000 and 2018. Panel (b) depicts the number of operational coal-fired power plants in the United States between 2004 and 2016. Panel (c) depicts the total capacity (Gigawatts) of operational coal-fired power plants in the United States between 2004 and 2016. Authors' calculations based on data from the United States Energy Information Administration (U.S. EIA).



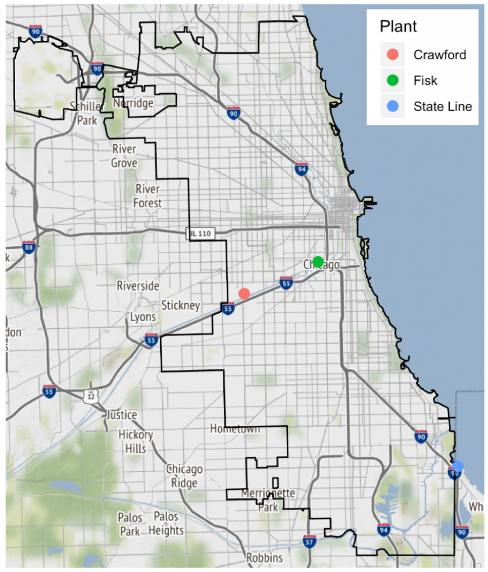
(a) Coal-Fired Power Plant Capacity in the United States, 2016



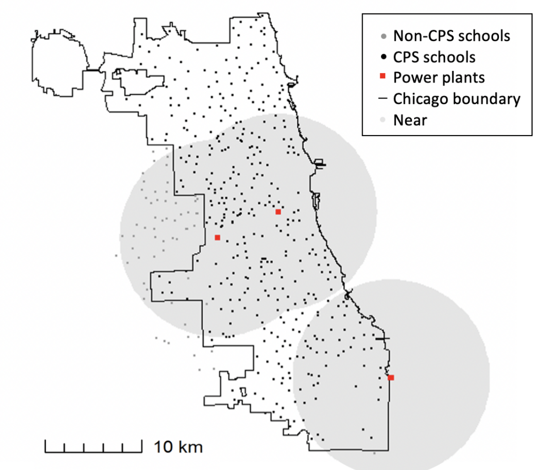
(b) K-8 Enrollment Near Coal-Fired Power Plants in the United States, 2016

Figure 2: Coal-Fired Power Plant Capacity and K-8 Public School Enrollment in the United States, 2016

Notes: This figure depicts the locations of operational coal-fired power plants in the United States in 2016. The size of each dot represents the number of K-8 students enrolled in a public school located within 10 kilometers (km) of the plant. Power plants depicted in red have public schools (K-8) within 10 km of their operation; power plants depicted in blue do not. Power plant locations, energy sources, and operational status come from the United States Energy Information Administration (EIA) Form EIA-860. Public school locations and enrollments come from the Elementary and Secondary Information System (ElSi) of the National Center for Education Statistics (NCES) of the United States Department of Education.



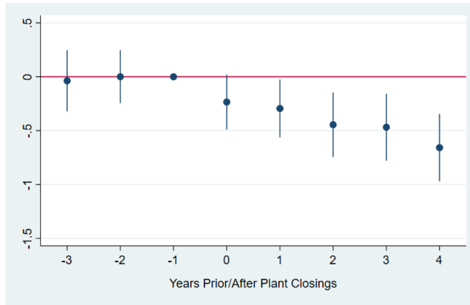
(a) Locations of Three Coal-Fired Power Plants



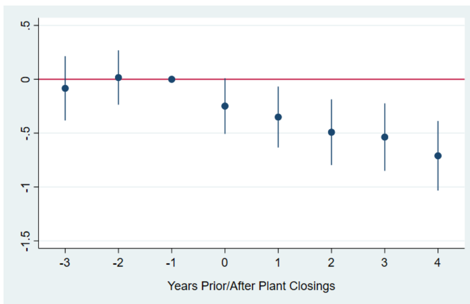
(b) Sample Schools

Figure 3: Coal-Fired Power Plants In and Near Chicago, IL

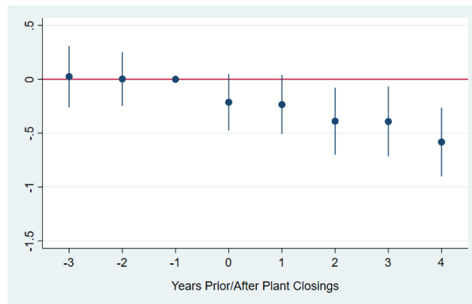
Notes: Panel (a) depicts the locations of the Crawford, Fisk Street, and State Line Generating Stations. Panel (b) depicts the locations of all schools in our sample and their proximities to the Crawford, Fisk, and State Line coal-fired power plants. Schools located within the gray shaded areas are within 10 kilometers of at least one of the coal-fired power plants. Schools in the Chicago Public School (CPS) district are indicated in black; non-CPS schools are indicated in dark gray.



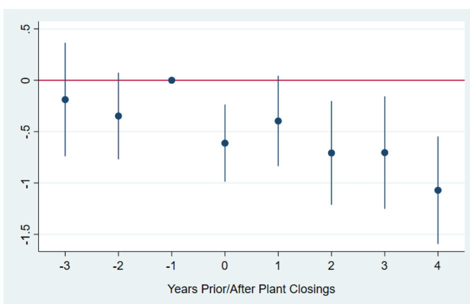
(a) All



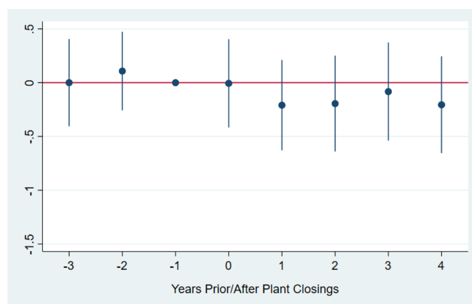
(b) Male



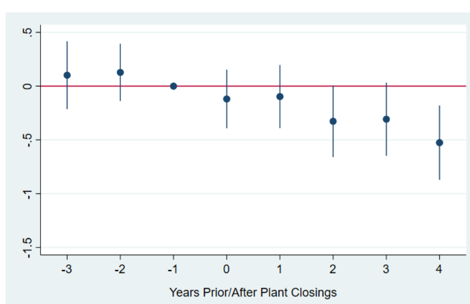
(c) Female



(d) Black



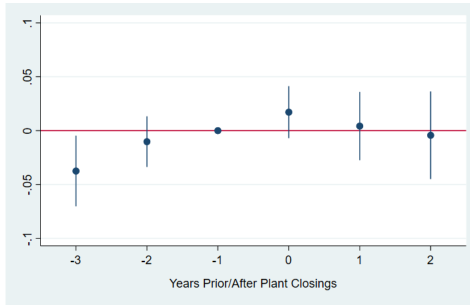
(e) Hispanic



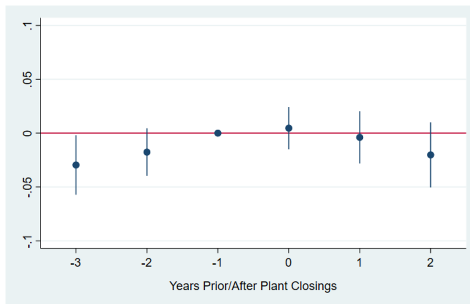
(f) Low-Income

Figure 4: Event-Study Estimates, Absences

Notes: The panels in this figure depict event-study results for absences in fifteen Illinois school districts. Each plot depicts coefficient estimates from Equation (2) and their associated ninety-five percent confidence intervals. $t = 0$ is the 2011/12 school year (partially treated) and $t = -1$ is omitted. The event-study specification includes school fixed-effects, year fixed-effects, the natural logarithm of enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). The regression is weighted by student enrollment. Heteroskedasticity-robust standard errors are clustered at the school-level.



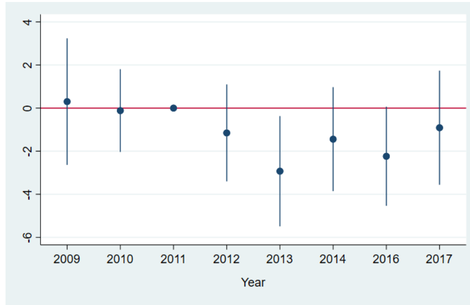
(a) Math



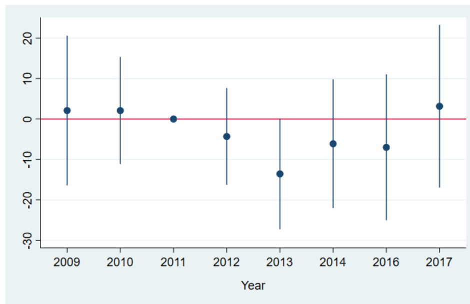
(b) Reading

Figure 5: Event-Study Estimates, Math and Reading Achievement

Notes: This figure depicts event-study results for math and reading achievement in fifteen Illinois school districts. The plot depicts coefficient estimates from Equation (2) and their associated ninety-five percent confidence intervals. $t = 0$ is the 2011/12 school year (partially treated) and $t = -1$ is omitted. The event-study specification includes school fixed-effects, year fixed-effects, the natural logarithm of enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). The regression is weighted by the number of test takers at the school-level. Heteroskedasticity-robust standard errors are clustered at the school-level.



(a) ED Visits for Asthma-Related Conditions, 5-18 Year-Olds, Crude Rate



(b) ED Visits for Asthma-Related Conditions, 5-18 Year-Olds, Age-Specific Rate

Figure 6: Event-Study Estimates, ED Visits for Asthma-Related Conditions, 5-18 Year Olds

Notes: This figure depicts event-study results for emergency department (ED) visits for asthma-related conditions among 5-18 year olds. The plot depicts coefficient estimates from Equation (2) and their associated ninety-five percent confidence intervals. The event-study specification includes zip code fixed-effects, year fixed-effects, and is weighted by population. Heteroskedasticity-robust standard errors are clustered at the school-level.

Tables

Table 1: Descriptive Statistics, Elementary Schools in Fifteen Illinois School Districts, 2008/09

	(1) Full Sample	(2) Near	(3) Far	(4) Diff.	(5) p-value
Panel A. School Characteristics					
Enrollment	608.16	593.19	645.81	-52.62	0.13
	(324.22)	(318.79)	(335.79)	(34.32)	
Percent Black	43.73	48.40	31.99	16.41***	0.00
	(42.75)	(43.39)	(38.86)	(4.17)	
Percent Hispanic	39.08	40.36	35.86	4.50	0.19
	(37.49)	(39.93)	(30.39)	(3.46)	
Percent Low-Income	78.02	81.53	69.20	12.33***	0.00
	(24.53)	(22.14)	(27.91)	(2.74)	
Panel B. Absence Rates					
	5.53	5.81	4.82	0.99***	0.00
All	(1.90)	(2.00)	(1.40)	(0.17)	
	5.71	6.00	4.99	1.02***	0.00
Male	(2.03)	(2.12)	(1.56)	(0.18)	
	5.34	5.61	4.65	0.96***	0.00
Female	(1.82)	(1.93)	(1.29)	(0.16)	
	6.64	6.95	5.88	1.07***	0.00
Black	(2.37)	(2.37)	(2.19)	(0.23)	
	5.55	5.94	4.60	1.34***	0.00
Hispanic	(4.75)	(5.37)	(2.47)	(0.38)	
	5.66	5.90	5.04	0.86***	0.00
Low-Income	(1.85)	(1.95)	(1.39)	(0.16)	
Panel C. Test Scores					
	-0.46	-0.54	-0.26	-0.28***	0.00
Math	(0.48)	(0.44)	(0.52)	(0.05)	
	-0.43	-0.52	-0.22	-0.30***	0.00
Reading	(0.47)	(0.43)	(0.50)	(0.05)	
Observations (Schools)	457	327	130		

Notes: Column (1) reports means and standard deviations for the full sample of elementary schools from fifteen schools districts in Illinois. The fifteen districts included in the full sample are: Forest Park School District, Riverside School District, Oak Park Elementary School District, Berwyn North School District, Cicero School District, Berwyn South School District, Lyons School District, Summit School District, Central Stickney School District, Burbank School District, Oak Lawn-Hometown School District, Dolton School District, Burnham School District, Calumet City School District, and City of Chicago Public Schools. Column (2) reports means and standard deviations for schools within 10 kilometers (km) of at least one of of of the following three coal-fired power plants: Crawford Generating Station, Fisk Street Generating Station, and State Line Generating Station. Column (3) reports means and standard deviations for schools located more than 10 kilometers (km) away. Column (4) reports the difference in means (Near - Far) and the associated standard error. Column (5) reports the p-value from a two-tailed t-test of the difference in means. Asterisks indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All	Male	Female	Black	Hispanic	Low-Income
	(1)	(2)	(3)	(4)	(5)	(6)
Near X Post	-0.395***	-0.440***	-0.349***	-0.431**	-0.197**	-0.337***
	(0.085)	(0.088)	(0.087)	(0.183)	(0.096)	(0.094)
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3635	3493	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	0.007	0.005	0.009	0.014	0.009	0.003
	(0.017)	(0.014)	(0.016)	(0.019)	(0.020)	(0.022)
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566
Panel B. Reading Achievement						
Near X Post	-0.002	-0.002	0.008	-0.003	-0.002	0.000
	(0.012)	(0.015)	(0.015)	(0.013)	(0.013)	(0.015)
Baseline Mean	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2668	2668	2668	2668	2668	2668

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Dose-Response Estimates of the Effect of Power Plant Closures on Student Absences, Overall and by Subgroup

	All (1)	Male (2)	Female (3)	Black (4)	Hispanic (5)	Low-Income (6)
Panel A. Number of Plants						
Near 1 Plant X Post	-0.366***	-0.418***	-0.316***	-0.235	-0.197*	-0.366***
	(0.104)	(0.109)	(0.107)	(0.211)	(0.102)	(0.120)
Near 2 Plants X Post	-0.419***	-0.458***	-0.377***	-0.702***	-0.198*	-0.316***
	(0.098)	(0.103)	(0.100)	(0.213)	(0.104)	(0.106)
p-value: 1 vs. 2 Plants	0.632	0.738	0.580	0.031	0.992	0.684
Panel B. Nearest Plant						
State Line (614 MWh) X Post	-0.549***	-0.606***	-0.498***	-0.306	-0.149	-0.535***
	(0.182)	(0.191)	(0.183)	(0.258)	(0.148)	(0.189)
Crawford (597 MWh) X Post	-0.271***	-0.319***	-0.222**	-0.482**	-0.118	-0.184*
	(0.095)	(0.100)	(0.098)	(0.230)	(0.099)	(0.105)
Fisk (374 MWh) X Post	-0.526***	-0.559***	-0.489***	-0.505**	-0.405***	-0.505***
	(0.117)	(0.124)	(0.117)	(0.232)	(0.129)	(0.129)
p-value: State Line vs. Crawford	0.125	0.131	0.128	0.520	0.812	0.061
p-value: Crawford vs. Fisk	0.040	0.071	0.029	0.926	0.011	0.017
p-value: Fisk vs. State Line	0.908	0.822	0.962	0.489	0.100	0.884
Panel C. Partition Treatment Group by Distance						
Within 5k X Post	-0.143	-0.171*	-0.123	-0.287	-0.083	-0.044
	(0.092)	(0.097)	(0.096)	(0.244)	(0.103)	(0.099)
Between 5k-10k X Post	-0.573***	-0.630***	-0.509***	-0.466**	-0.363***	-0.573***
	(0.102)	(0.106)	(0.105)	(0.193)	(0.109)	(0.114)
p-value: Under 5k vs. 5k-10k	0.000	0.000	0.000	0.431	0.003	0.000
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3635	3493	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Heterogeneous Effects of Power Plant Closures by Wind Intensity and School Air Conditioning

	All	Male	Female	Black	Hispanic	Low-Income	Math	Read
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Wind Path Intensity								
High Wind X Post	-0.452***	-0.506***	-0.399***	-0.370*	-0.370***	-0.385***	0.017	0.008
	(0.095)	(0.098)	(0.098)	(0.213)	(0.100)	(0.106)	(0.020)	(0.014)
Low Wind X Post	-0.316***	-0.351***	-0.278***	-0.550**	-0.037	-0.271**	-0.007	-0.016
	(0.105)	(0.111)	(0.106)	(0.217)	(0.105)	(0.115)	(0.020)	(0.014)
p-value: Low vs. High Wind	0.221	0.184	0.282	0.392	0.000	0.343	0.237	0.113
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899	-0.543	-0.518
Observations	3,656	3,654	3,654	3,635	3,493	3,652	2,668	2,668
Panel B. Air Conditioning								
High AC X Post	-0.414***	-0.437***	-0.387***	-0.491**	-0.187*	-0.331***	0.011	0.003
	(0.102)	(0.105)	(0.105)	(0.207)	(0.105)	(0.109)	(0.019)	(0.014)
Low AC X Post	-0.518***	-0.604***	-0.439***	-0.466**	-0.250*	-0.501***	0.039*	0.002
	(0.134)	(0.143)	(0.132)	(0.227)	(0.137)	(0.145)	(0.023)	(0.018)
p-value: Low vs. High AC	0.474	0.272	0.715	0.909	0.621	0.269	0.232	0.946
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899	-0.543	-0.518
Observations	3,128	3,126	3,126	3,111	2,966	3,125	2,319	2,319

Notes: Each cell reports results from a separate regression, where the dependent variable is the aggregate absence rate calculated among the full sample or student subgroup indicated in the column heading or average achievement in math or reading. All regression specifications include school fixed-effects, year fixed-effects, enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by student enrollment in the full sample or relevant subgroup or by the number of tested students. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneous Effects of Power Plant Closures by School Magnet Status

	All (1)	Male (2)	Female (3)	Black (4)	Hispanic (5)	Low-Income (6)	Math (7)	Read (8)
Not Magnet X Post	-0.427***	-0.463***	-0.380***	-0.652***	-0.217**	-0.357***	0.013	0.007
	(0.099)	(0.104)	(0.102)	(0.221)	(0.105)	(0.110)	(0.020)	(0.014)
Magnet X Post	-0.341***	-0.395***	-0.296***	-0.313	-0.186*	-0.297***	-0.001	-0.014
	(0.103)	(0.107)	(0.105)	(0.211)	(0.107)	(0.113)	(0.020)	(0.014)
p-value: Not Magnet vs. Magnet	0.449	0.566	0.462	0.112	0.736	0.626	0.493	0.152
Baseline Mean	5.799	5.990	5.606	6.934	5.934	5.887	-0.542	-0.516
Observations	3,624	3,622	3,622	3,604	3,462	3,620	2,647	2,647

Notes: Each cell reports results from a separate regression, where the dependent variable is the aggregate absence rate calculated among the full sample or student subgroup indicated in the column heading or average achievement in math or reading. All regression specifications include school fixed-effects, year fixed-effects, enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by student enrollment in the full sample or relevant subgroup or by the number of tested students. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Difference-in-Differences Estimates of the Effect of Power Plant Closures on Enrollment, Student Demographics, and the Share of Tested Students

	Log Enrollment (1)	Percent Black (2)	Percent Hispanic (3)	Perent Low-Income (4)	Share Math TT (5)	Share Read TT (6)
Near X Post	-0.037*	0.219	0.196	-0.195	0.006	0.005
	(0.021)	(0.263)	(0.352)	(0.465)	(0.010)	(0.010)
Baseline Mean	6.253	48.403	40.360	81.531	0.543	0.542
Observations	3656	3656	3656	3656	3656	3656

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level measure of enrollment, student characteristics, or the shared of tested students. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table 8: The Effect of Power Plant Closures on ED Visits for Asthma-Related Conditions Among 5-18 Year Olds

	(1)	(2)	(3)	(4)	(5)	(6)
	Crude Rate	Crude Rate	Crude Rate	Age-Spec.	Age-Spec.	Age-Spec.
Near X Post	-1.637**	-1.676**	-1.954*	-5.967	-8.491**	-12.809**
	(0.691)	(0.691)	(1.103)	(4.060)	(3.807)	(5.717)
Baseline Mean	21.241			101.764		
Observations	384	384	384	384	384	384
Year and Zip FE	X	X	X	X	X	X
Covariates		X	X		X	X
Zip Code Trends			X			X

Notes: Each cell reports results from a separate regression, where the dependent variable is the crude rate of asthma-related emergency department (ED) visits for the age group listed in the column heading. All regressions are weighted by population. Heteroskedasticity-robust standard errors are clustered at the zip code-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Difference-in-Differences Estimates of the Effect of Power Plant Closures on Particulate Pollution (PM2.5)

	Downscaler (1)	Satellite Point (2)	Satellite 1k Buffer (3)	Satellite 2k Buffer (4)
Near X Post	-0.059***	-0.025*	-0.026**	-0.027**
	(0.008)	(0.013)	(0.012)	(0.012)
Baseline Mean	13.169	12.767	12.767	12.764
Observations	2742	3656	3656	3656

Notes: Each column reports results from a separate regression, where the dependent variable is the average annual ground-level concentration of fine particulates (PM 2.5) in micrograms per cubic meter. All regression specifications include school fixed-effects, year fixed-effects, enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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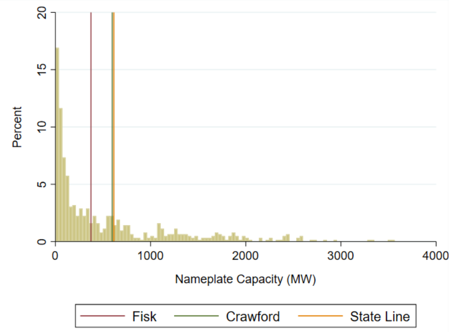
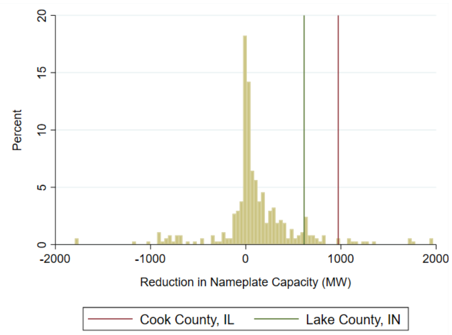
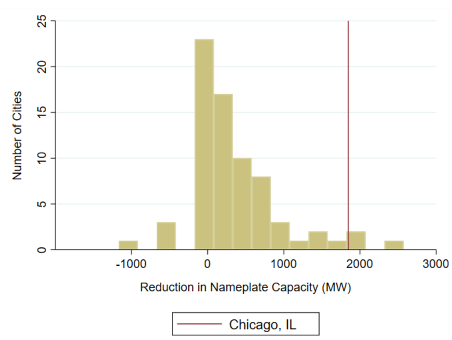
Appendix A: Supplemental Results



(a) Distribution of Coal-Fired Power Plant Capacity (Nameplate), 2009



(b) Distribution of Reductions in Nameplate Capacity at the County-Level, 2004-2016



(c) Distribution of Reductions in Nameplate Capacity at the City-Level, 2004-2016

Figure A1: Coal-Fired Power Plants and Reductions in Capacity in the United States

Notes:

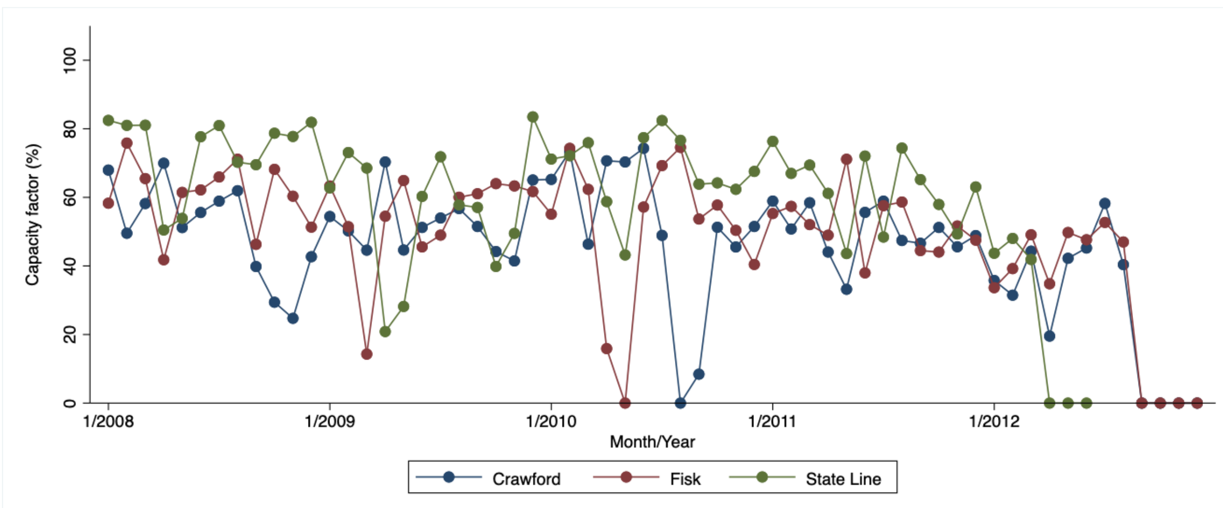
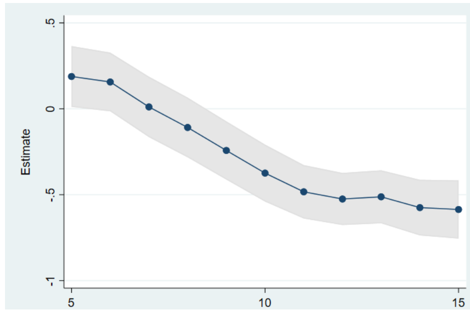
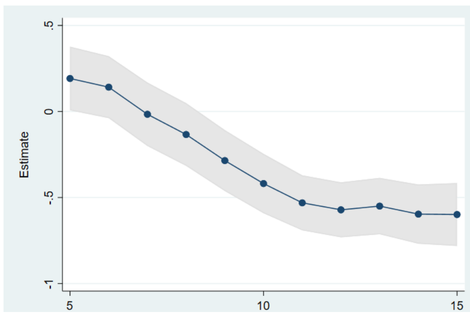


Figure A2: Monthly capacity factors for Crawford, Fisk Street, and State Line power plants

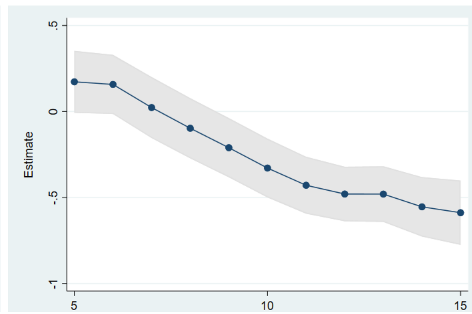
Notes: Monthly capacity factors are calculated as the ratio of actual energy generation (MWh) to potential energy generation (MWh) in each month. Data to calculate these factors come from the EPA's Air Markets Program Data.



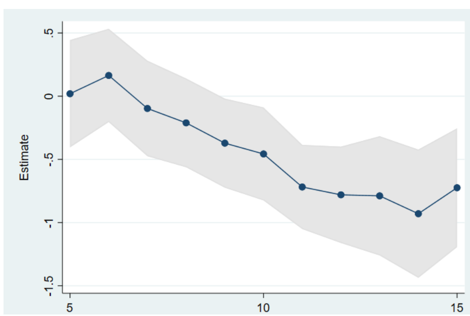
(a) All



(b) Male



(c) Female



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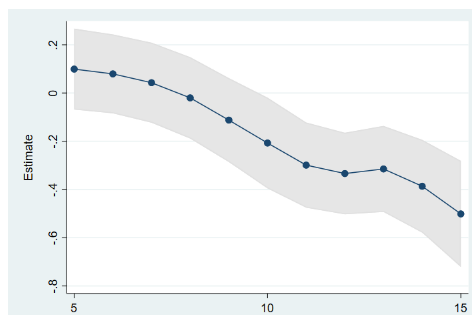
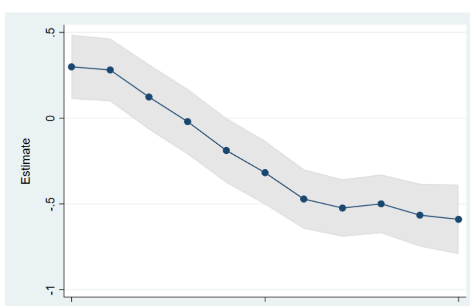


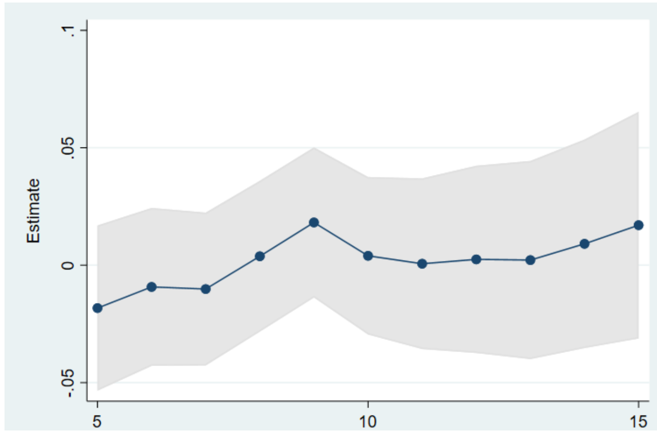
(e) Hispanic



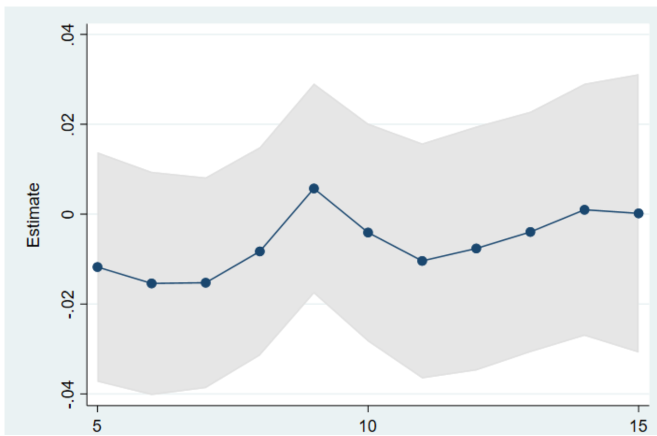
(f) Low-Income

Figure A3: Estimated Treatment Effects by Radius, Absences Overall and by Subgroup

Notes: This figure depicts estimated treatment effects for varying radii (in kilometers).



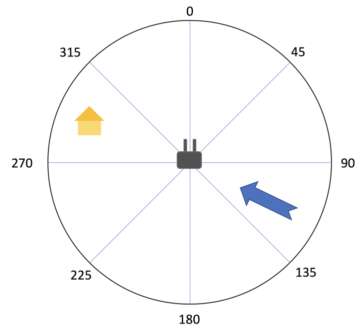
(a) Math



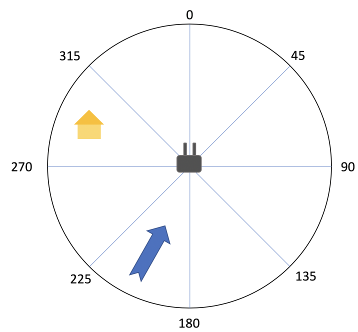
(b) Reading

Figure A4: Estimated Treatment Effects by Radius, Achievement in Math and Reading

Notes: This figure depicts estimated treatment effects for varying radii (in kilometers).



(a) School in Wind Path



(b) School Not in Wind Path

Figure A5: School in Wind Path versus Not in Wind Path

Notes: This figure illustrates how we classified High versus Low Wind school days. The blue arrow depicts the direction from which the day's wind originated.

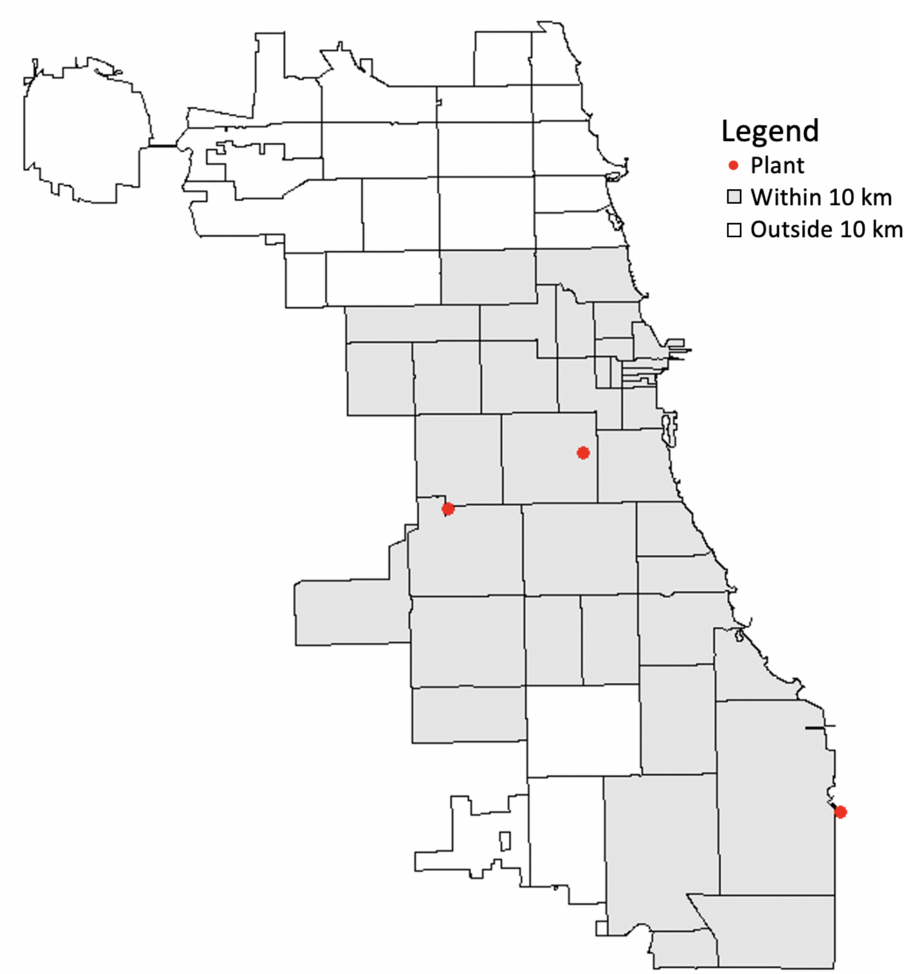


Figure A6: Map of “Near” and “Far” Zip Codes

Notes: This figure shows the zip codes designated as “near” (shaded in gray) and “far” (in white) used in the analysis of asthma-related ED visits.

Table A1: K-8 Students Enrolled in Public Schools Located Within 10km of Coal-Fired Power Plants in the United States, 2016

		Race/Ethnicity				Family Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	White	Black	Hispanic	Other	FRL	Non-FRL
Kindergarten	259,867	128,094	52,092	53,544	26,137		
	[100.00]	[49.29]	[20.05]	[20.60]	[10.06]		
1st Grade	268,473	130,392	55,268	56,309	26,504		
	[100.00]	[48.57]	[20.59]	[20.97]	[9.87]		
2nd Grade	270,296	131,763	54,823	56,971	26,739		
	[100.00]	[48.75]	[20.28]	[21.08]	[9.89]		
3rd Greade	269,021	131,364	54,468	57,071	26,118		
	[100.00]	[48.83]	[20.25]	[21.21]	[9.71]		
4th Grade	260,994	129,536	51,652	55,013	24,793		
	[100.00]	[49.63]	[19.79]	[21.08]	[9.50]		
5th Grade	251,808	126,386	49,589	52,526	23,307		
	[100.00]	[50.19]	[19.69]	[20.86]	[9.26]		
6th Grade	249,193	126,735	48,422	51,244	22,792		
	[100.00]	[50.86]	[19.43]	[20.56]	[9.15]		
7th Grade	247,020	128,030	48,273	48,777	21,940		
	[100.00]	[51.83]	[19.54]	[19.75]	[8.88]		
8th Grade	246,847	128,722	48,491	48,119	21,515		
	[100.00]	[52.15]	[19.64]	[19.49]	[8.72]		
Total in K-8	2,323,519	1,161,022	463,078	479,574	219,845	1,892,241	431,278
	[100.00]	[49.97]	[19.93]	[20.64]	[9.46]	[81.44]	[18.56]

Notes: Rows depict the number of K-8 public school students by grade enrolled in a public school located within 10 kilometers (km) of a power plant that utilizes coal in one or more of its generators. Columns present total enrollment and enrollment disaggregated by race/ethnicity and by free/reduced-price lunch eligibility. Results are presented as total number (first row for each grade) and row percentage (second row for each grade). Values in each percentage row in columns 2-5 sum to 100%; values in total K-8 percentage row in columns 6-7 sum to 100%. Data on free/reduced-price lunch eligibility only available at the school level. Power plant locations, energy sources, and operational status come from the United States Energy Information Administration (EIA) Form EIA-860. Public school locations and enrollments come from the Elementary and Secondary Information System (ElSi) of the National Center for Education Statistics (NCES) of the United States Department of Education.

Table A2: (District-Specific Trends) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All	Male	Female	Black	Hispanic	Low-Income
	(1)	(2)	(3)	(4)	(5)	(6)
Near X Post	-0.419***	-0.464***	-0.374***	-0.342*	-0.209**	-0.356***
	(0.088)	(0.092)	(0.090)	(0.175)	(0.098)	(0.098)
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3635	3493	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: (SEs Clustered at Zip Code Level) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All	Male	Female	Black	Hispanic	Low-Income
	(1)	(2)	(3)	(4)	(5)	(6)
Near X Post	-0.395***	-0.440***	-0.349***	-0.431**	-0.197*	-0.337**
	(0.121)	(0.118)	(0.125)	(0.216)	(0.116)	(0.140)
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3635	3493	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: (Unweighted) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All	Male	Female	Black	Hispanic	Low-Income
	(1)	(2)	(3)	(4)	(5)	(6)
Near X Post	-0.398***	-0.427***	-0.367***	-0.161	-0.483*	-0.357***
	(0.094)	(0.099)	(0.095)	(0.188)	(0.262)	(0.097)
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3638	3541	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table A5: (Randomization Inference) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All (1)	Male (2)	Female (3)	Black (4)	Hispanic (5)	Low-Income (6)
Near X Post	-0.395***	-0.440***	-0.349***	-0.431**	-0.197**	-0.337***
	[0.000]	[0.000]	[0.000]	[0.012]	[0.021]	[0.000]
Baseline Mean	5.809	6.004	5.611	6.948	5.939	5.899
Observations	3656	3654	3654	3635	3493	3652

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: (District-Specific Trends) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	0.014	0.010	0.013	0.020	0.019	0.015
	(0.017)	(0.014)	(0.016)	(0.019)	(0.020)	(0.022)
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566
Panel B. Reading Achievement						
Near X Post	0.001	0.000	0.010	-0.002	0.001	0.005
	(0.013)	(0.015)	(0.015)	(0.014)	(0.013)	(0.015)
Baseline Mean	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2668	2668	2668	2668	2668	2668

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: (SEs Clustered at Zip Code Level) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	0.007	0.005	0.009	0.014	0.009	0.003
	(0.016)	(0.012)	(0.015)	(0.018)	(0.019)	(0.021)
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566
Panel B. Reading Achievement						
Near X Post	-0.002	-0.002	0.008	-0.003	-0.002	0.000
	(0.013)	(0.014)	(0.016)	(0.014)	(0.014)	(0.014)
Baseline Mean	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2668	2668	2668	2668	2668	2668

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A8: (Unweighted) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	0.002	-0.002	0.003	0.008	0.004	-0.003
	(0.017)	(0.015)	(0.017)	(0.019)	(0.020)	(0.022)
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566
Panel B. Reading Achievement						
Near X Post	-0.009	-0.001	0.003	-0.003	-0.012	-0.015
	(0.014)	(0.017)	(0.017)	(0.015)	(0.015)	(0.016)
Baseline Mean	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2715	2715	2715	2715	2715	2715

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table A9: (Randomization Inference) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	0.007	0.005	0.009	0.014	0.009	0.003
	[0.665]	[0.663]	[0.543]	[0.442]	[0.637]	[0.878]
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566
Panel B. Reading Achievement						
Near X Post	-0.002	-0.002	0.008	-0.003	-0.002	0.000
	[0.868]	[0.918]	[0.576]	[0.807]	[0.876]	[0.998]
Baseline Mean	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2668	2668	2668	2668	2668	2668

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Dose-Response Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Math Mean (1)	Math 10th (2)	Math 25th (3)	Math Median (4)	Math 75th (5)	Math 90th (6)	Read Mean (7)	Read 10th (8)	Read 25th (9)	Read Median (10)	Read 75th (11)	Read 90th (12)
Panel A. Number of Plants												
Near 1 Plant X Post	-0.011	-0.003	-0.007	-0.003	-0.015	-0.025	-0.009	-0.013	-0.001	-0.009	-0.008	-0.010
	(0.019)	(0.016)	(0.018)	(0.021)	(0.022)	(0.024)	(0.015)	(0.018)	(0.017)	(0.015)	(0.016)	(0.017)
Near 2 Plants X Post	0.022	0.013	0.022	0.027	0.028	0.027	0.005	0.007	0.016	0.002	0.003	0.008
	(0.020)	(0.016)	(0.019)	(0.022)	(0.024)	(0.026)	(0.014)	(0.017)	(0.017)	(0.015)	(0.015)	(0.016)
p-value: 1 vs. 2 Plants	0.102	0.342	0.126	0.175	0.067	0.043	0.348	0.265	0.364	0.492	0.456	0.263
Panel B. Nearest Plant												
State Line (614 MWh) X Post	0.024	0.014	0.021	0.031	0.031	0.024	0.002	-0.011	0.002	0.006	0.017	0.010
	(0.030)	(0.025)	(0.029)	(0.033)	(0.033)	(0.034)	(0.022)	(0.025)	(0.026)	(0.023)	(0.023)	(0.024)
Crawford (597 MWh) X Post	-0.000	0.004	0.005	0.005	0.000	-0.009	-0.003	0.006	0.010	-0.008	-0.006	-0.005
	(0.019)	(0.015)	(0.018)	(0.021)	(0.023)	(0.026)	(0.014)	(0.017)	(0.017)	(0.015)	(0.015)	(0.017)
Fisk (374 MWh) X Post	0.010	0.003	0.010	0.018	0.011	0.012	-0.001	-0.008	0.009	-0.001	-0.005	0.003
	(0.023)	(0.019)	(0.022)	(0.025)	(0.026)	(0.029)	(0.016)	(0.020)	(0.019)	(0.017)	(0.017)	(0.018)
p-value: State Line vs. Crawford	0.410	0.717	0.564	0.426	0.341	0.352	0.821	0.511	0.782	0.567	0.314	0.522
p-value: Crawford vs. Fisk	0.665	0.945	0.826	0.618	0.675	0.495	0.856	0.506	0.955	0.693	0.969	0.648
p-value: Fisk vs. State Line	0.658	0.709	0.714	0.706	0.576	0.746	0.929	0.908	0.821	0.796	0.358	0.768
Panel C. Partition Treatment Group by Distance												
Within 5k X Post	-0.008	-0.008	0.002	-0.004	-0.004	-0.014	-0.009	-0.007	-0.008	-0.012	-0.010	-0.008
	(0.020)	(0.016)	(0.019)	(0.022)	(0.024)	(0.026)	(0.015)	(0.017)	(0.018)	(0.016)	(0.016)	(0.018)
Between 5k-10k X Post	0.018	0.015	0.015	0.026	0.018	0.015	0.004	0.002	0.019	0.003	0.003	0.005
	(0.019)	(0.016)	(0.018)	(0.021)	(0.022)	(0.025)	(0.014)	(0.018)	(0.017)	(0.015)	(0.015)	(0.016)
p-value: Under 5k vs. 5k-10k	0.207	0.174	0.507	0.179	0.357	0.265	0.379	0.622	0.152	0.329	0.400	0.423
Baseline Mean	-0.543	-1.610	-1.149	-0.582	0.015	0.566	-0.518	-1.747	-1.129	-0.471	0.113	0.615
Observations	2668	2668	2668	2668	2668	2668	2668	2668	2668	2668	2668	2668

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Difference-in-Differences Estimates of the Effect of Power Plant Closures on Other School-Level Outcomes

	Class Size	Math Minutes	English Minutes
	(1)	(2)	(3)
Near X Post	0.183	-0.841	0.466
	(0.192)	(0.913)	(1.100)
Baseline Mean	24.324	53.069	123.858
Observations	3656	3610	3610

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level measure of class size or the average number of minutes per day spent on Math or English instruction. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table A12: Correlation Matrix, School Characteristics Related to Exposure and Percentage of Low-Income Students

	Percent AC (1)	Wind Days (2)	Magnet (0/1) (3)	Percent Low-Income (4)
Percent AC	1.0000			
Wind Days	-0.0741	1.0000		
Magnet (0/1)	-0.0737	0.0030	1.0000	
Percent Low-Income	0.0121	-0.1887	-0.0306	1.0000

Notes: Each cell reports a correlation coefficient calculated in the baseline school year (2008/09) among all schools in the sample. Correlation coefficients involving school-level air conditioning are only calculated among the subsample of schools from Chicago Public Schools (CPS).

Appendix B: Other Data Sources

Downscaler Data

The Downscaler model, developed by the Environmental Protection Agency (EPA) and Centers for Disease Control (CDC), incorporates station monitoring data with atmospheric modeling data from the Community Multi-Scale Air Quality Model (CMAQ) to predict daily $PM_{2.5}$ exposure ($\mu g/m^3$) at the census tract level.The CMAQ models daily $PM_{2.5}$ dispersion as gridded averages across the United States, providing the advantage of pollution estimates in areas without station coverage. Monitoring station data are then used to calibrate the model to reduce modeling error.

We downloaded daily, census tract level $PM_{2.5}$ estimates from 2008 to 2014 from the publicly available Downscaler model.[28] We estimated academic year average $PM_{2.5}$ exposures starting with the 2008-09 school year through the 2013-14 school year for each census tract in our school sample. We extracted the census tract location for each school within our sample to merge together our sample of elementary schools and academic year $PM_{2.5}$ estimates from the Downscaler model. These data were processed using R statistical software.

Satellite Data

We downloaded satellite-derived, annual $PM_{2.5}$ values ($\mu g/m^3$) measured at a 0.01 by 0.01 degree grid resolution (approximately 1 km^2) as a second air pollution measure.[29] These estimates are derived using Aerosol Optical Depth (AOD) and the GEOS-Chem chemical transport model. The predictions of ground-level $PM_{2.5}$ generated by this model are calibrated by regional observations of $PM_{2.5}$ levels. The method used to generate and calibrate these predicted $PM_{2.5}$ values is described in van Donkelaar et al. (2019). Using R statistical software, we extracted the annual $PM_{2.5}$ raster value at each school location in our sample from 2008-2016. We generated school-year av-

[28] Daily Downscaler $PM_{2.5}$ data at the census tract level from 2001-2014 are available here https://ephtracking.cdc.gov/download.

[29] Annual satellite-derived $PM_{2.5}$ data at a resolution of 0.01 by 0.01 degrees from 2001-2016 covering the United States are publically available here http://fizz.phys.dal.ca/~atmos/martin/?page_id=140.

erages from these annualized values by weighting the average of two contiguous years by monthly contribution to the duration of the school year (e.x., to calculated a school year average for the 2008-09 school year, we calculated $0.4 \cdot \mathrm{PM2.5}_{2008} + 0.6 \cdot \mathrm{PM2.5}_{2009}$). In addition to extracting annualized $PM_{2.5}$ values at each school location, we also extracted average $PM_{2.5}$ values using 1 and 2 km buffers to check for any sensitivity based on the resolution of the satellite data.

Power Plant Data

We use power plant generator data from the U.S. Energy Information Association (EIA).[30] All electricity-generating plants with nameplate capacities at or above 1 megawatt (MW) annually complete a Form EIA-860, which catalogues information about all generators operated by the plant, including information about generator location, fuel source, and nameplate capacities. The data are available from 2001 to 2018; we used forms covering the years 2004-2016. In each year, we extracted any generators that utilize coal as a fuel source for electricity generation along with the generator's name plate capacity, its plant (as plants can operate more than one generator), and its parent utility (as utilities can operate more than one plant). In addition, we utilized the geographic information about each plant including latitude, longitude, county, and state. These geographical markers allowed us to calculate plant operations and generator capacities at the county, state, and national level from 2004 through 2016.

To aggregate power plant counts from the county level to the Metropolitan Statistical Area (MSA) level, we used the historical delineation files from the United States Census Bureau.[31]

Power Plant Emissions Data

We use monthly emissions data from the EPA's Air Markets Program Data.[32] These monthly generation data provide information about the current and historical patterns of operation of industrial

[30]Form EIA-860 data are available here https://www.eia.gov/electricity/data/eia860/.

[31]Data available at: https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/historical-delineation-files.html.

[32]Air Markets Program data are available here https://ampd.epa.gov/ampd/.

sites. For this paper, monthly generation data were used for the period of 2008-2012 to calculate monthly capacity factors for the Crawford, Fisk Street, and State Line generating stations.

Wind Data

We obtained daily wind data from the Global Historical Climatology Network (GHCN) of the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA).[33] These daily wind readings came from the land surface station located at Midway Airport (MDW) in Chicago, Illinois (station number: USW00014819). We used daily readings on the direction (in degrees) of the fastest 2-minute wind ($wdf2$).

Public School Enrollment Data

We used public school enrollment data from the Elementary/Secondary Information System (ElSi), a web application of the National Center for Education Statistics (NCES).[34] We downloaded data on all elementary schools (serving grades kindergarten-8) in the United States in 2016, including school name and location, number of students enrolled in each grade (K-8) in the following race/ethnicity groups–white, black, Hispanic, Asian, Native American, Pacific Islander, and two or more specified–, number of free or reduced-price lunch students enrolled, and school classification as city, suburb, town, or rural. We calculated the linear distance between each school location and each power plant operating in 2016 from the Form EIA-860 data. We calculated the number of K-8 students living within 10 km from any of the operational coal-fired power plants.

Air Conditioning Data in Chicago Public Schools (CPS)

We obtained information on air conditioning (AC) in CPS school buildings from a published report of the Chicago Public Schools (CPS). This report was generated using the United States Environ-

[33] These data are public-use and can be downloaded here: https://www.ncdc.noaa.gov/ghcn-daily-description.

[34] ElSi data are available here https://nces.ed.gov/ccd/elsi/.

mental Protection Agency (US EPA) Energy Star Portfolio Manager. The report contained building level information on the percent of the school with air conditioning from April 2011.

Data on Emergency Department (ED) Visits for Asthma-Related Conditions

We obtained annual counts of emergency department visits for children ages 0-18 and ages 0-4 for asthma-related conditions at the zip code level from the Chicago Health Atlas.[35] These annual counts were available for 48 zip codes (or zip code aggregates) for the years 2009-2017 (excluding 2015, when no data were made available). These data were derived from microdata from the Discharge Data, Division of Patient Safety and Quality, Illinois Department of Public Health.

We calculated crude and age-specific emergency department (ED) visit rates (per 10,000 inhabitants) for asthma-related conditions using zip-code level data from American Factfinder.[36] Crude rates were calculated for by adjusting annual counts of ED visits for asthma-related conditions by total population, and age-specific rates were calculated using the following age groups (0-4, 5-18, and 0-18). We used population estimates for the age group 5-19 to calculate the age-specific rate for children ages 5-18 and population estimates for the age group 0-19 to calculate the age-specific rate for children ages 0-18 because more granular data were not available. Population estimates (overall) and by age group came from the Decennial Census (2010) and the American Community Survey (ACS) 5-Year Estimates (2011-2017). Data for 2009 were linearly interpolated using the Decennial Censuses from 2000 and 2010.

Magnet School Status

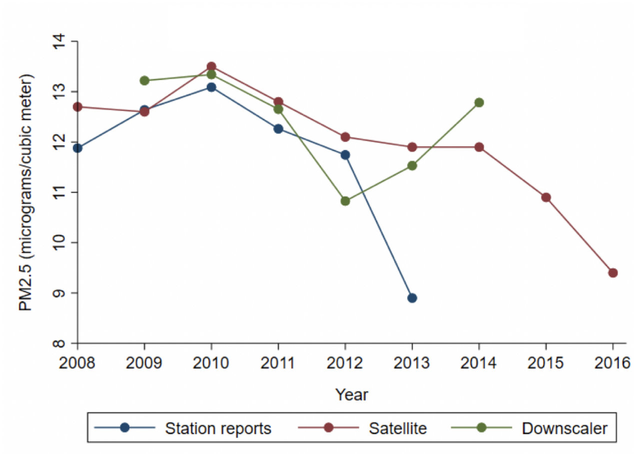
We obtained information on schools' magnet status from the Elementary/Secondary Information System (ElSi), a web application of the National Center for Education Statistics (NCES).[37] These data came from the 2008/09 school year. Magnet schools typically do not have attendance bound-

[35] These data are public-use and are available here: https://www.chicagohealthatlas.org/.

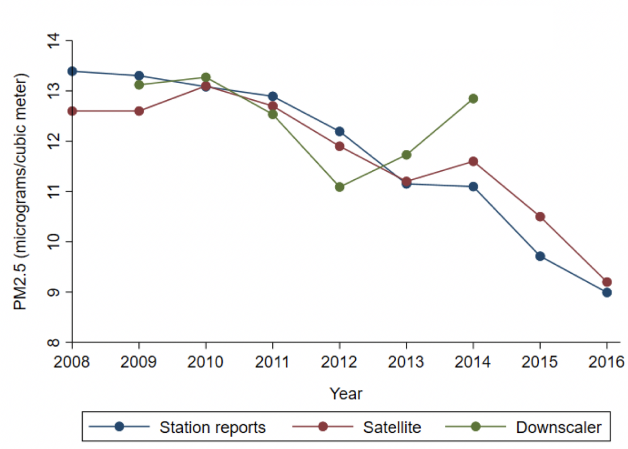
[36] There data are public-use and are available here: https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

[37] ElSi data are available here https://nces.ed.gov/ccd/elsi/.

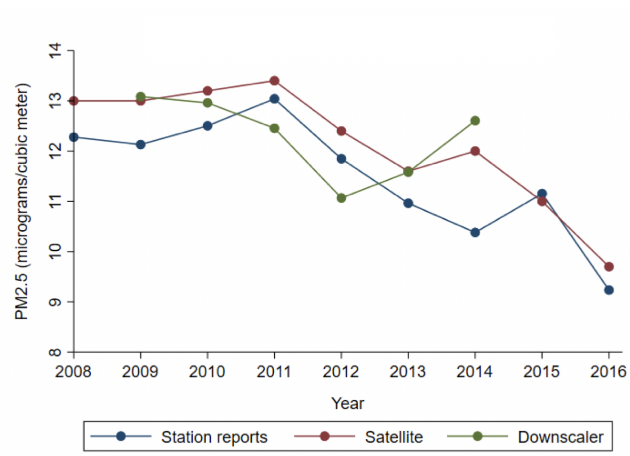
aries, and spaces in magnet schools are allocated on the basis of random lottery (following an application process).



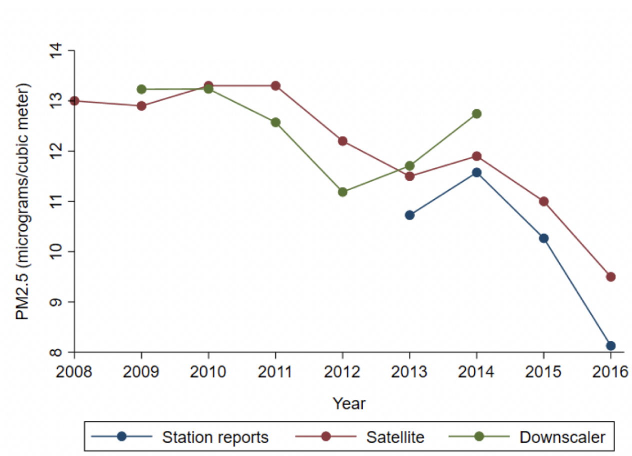
(a) Washington High School



(b) Com Ed Maintenance Building



(c) Springfield Pump

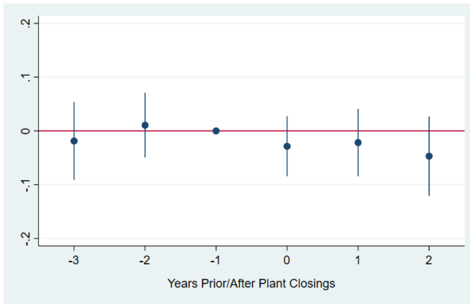


(d) Liberty School

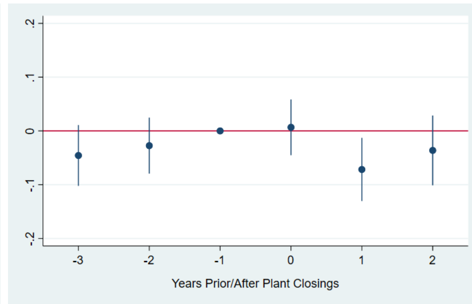
Figure B1: Estimated Treatment Effects by Radius, Absences

Notes: This figure depicts the correlations between measured $PM_{2.5}$ at four station locations throughout Chicago, satellite $PM_{2.5}$ at a 1 km^2 resolution, and Downscaler $PM_{2.5}$ at the census tract level (the census tracts containing these 4 stations range in area from 0.6 to 2.9 km^2). All $PM_{2.5}$ values are aggregated to annual means.

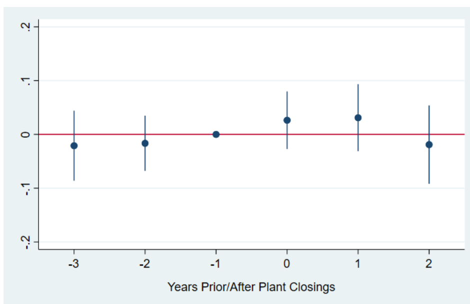
Online Appendix C: Supplemental Test Score Results by Subject and Grade



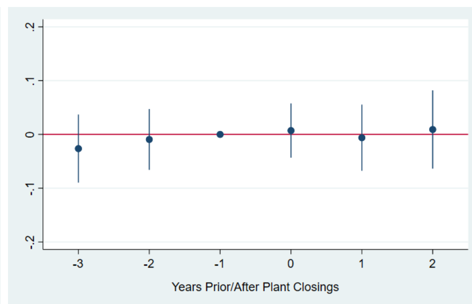
(a) 3rd Grade



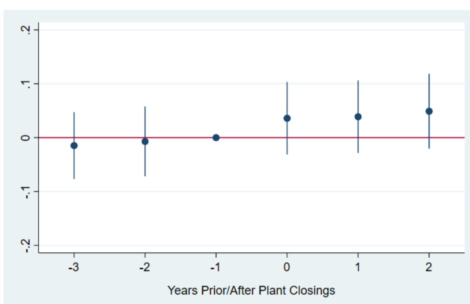
(b) 4th Grade



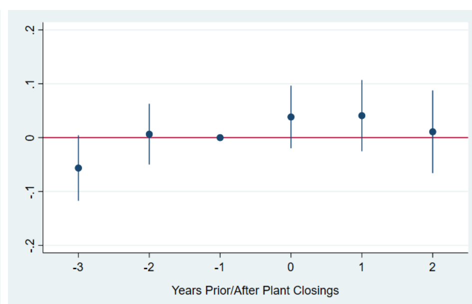
(c) 5th Grade



(d) 6th Grade



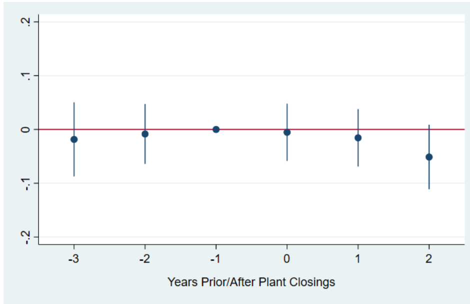
(e) 7th Grade



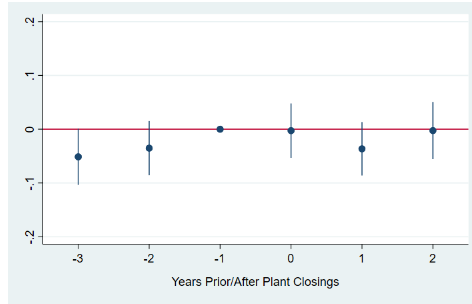
(f) 8th Grade

Figure C1: Event-Study, Math Achievement Test Scores

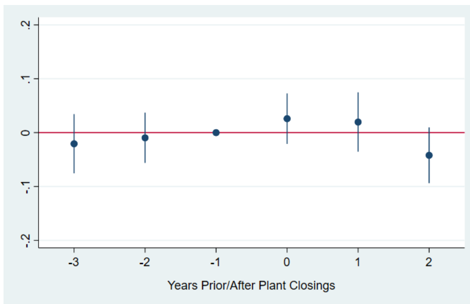
Notes: This figure depicts event-study results for absences in fifteen Illinois school districts. The plot depicts coefficient estimates and their associated ninety-five percent confidence intervals. $t = 0$ is the 2011/12 school year and $t = -1$ is omitted. The event-study specification includes school fixed-effects, year fixed-effects, the natural logarithm of enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). The regression is weighted by student enrollment. Heteroskedasticity-robust standard errors are clustered at the school-level.



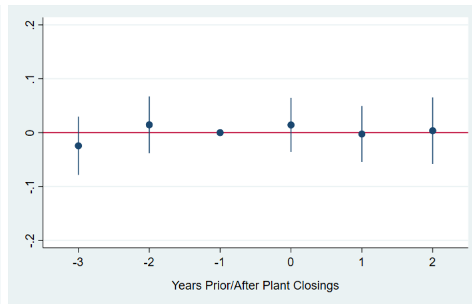
(a) 3rd Grade



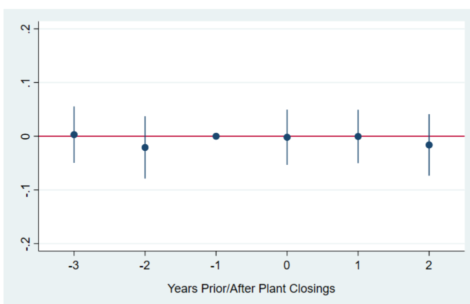
(b) 4th Grade



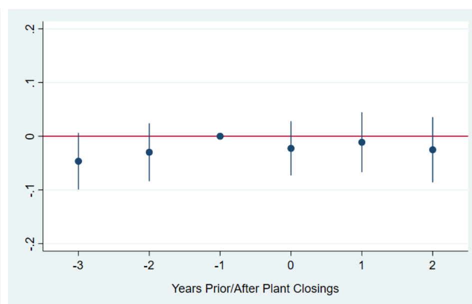
(c) 5th Grade



(d) 6th Grade



(e) 7th Grade



(f) 8th Grade

Figure C2: Event-Study, Reading Achievement Test Scores

Notes: This figure depicts event-study results for absences in fifteen Illinois school districts. The plot depicts coefficient estimates and their associated ninety-five percent confidence intervals ($t = -1$ is omitted). The event-study specification includes school fixed-effects, year fixed-effects, the natural logarithm of enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). The regression is weighted by student enrollment. Heteroskedasticity-robust standard errors are clustered at the school-level.

Table C1: (3rd Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	-0.014	-0.028	-0.008	-0.003	-0.009	0.003
	(0.029)	(0.030)	(0.028)	(0.031)	(0.034)	(0.041)
Baseline Mean	-0.589	-1.726	-1.226	-0.602	0.012	0.559
Panel B. Reading Achievement						
Near X Post	-0.029	-0.035	-0.029	-0.020	-0.036	-0.006
	(0.024)	(0.030)	(0.029)	(0.027)	(0.026)	(0.028)
Baseline Mean	-0.553	-1.768	-1.208	-0.510	0.114	0.587
Observations	2588	2588	2588	2588	2588	2588

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: (4th Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	-0.021	-0.010	0.009	-0.020	-0.041	-0.032
	(0.024)	(0.025)	(0.026)	(0.027)	(0.029)	(0.032)
Baseline Mean	-0.570	-1.606	-1.152	-0.589	-0.030	0.493
Panel B. Reading Achievement						
Near X Post	0.012	0.010	0.021	0.020	0.010	0.011
	(0.019)	(0.025)	(0.024)	(0.022)	(0.022)	(0.026)
Baseline Mean	-0.560	-1.743	-1.190	-0.541	0.061	0.595
Observations	2617	2617	2617	2617	2617	2617

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: (5th Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	0.018	0.019	0.043	0.030	0.016	0.016
	(0.027)	(0.027)	(0.027)	(0.030)	(0.032)	(0.037)
Baseline Mean	-0.591	-1.599	-1.177	-0.654	-0.064	0.474
Panel B. Reading Achievement						
Near X Post	-0.004	-0.024	0.001	-0.003	-0.005	0.016
	(0.020)	(0.027)	(0.024)	(0.020)	(0.024)	(0.029)
Baseline Mean	-0.592	-1.807	-1.211	-0.575	0.036	0.569
Observations	2602	2602	2602	2602	2602	2602

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: (6th Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	0.015	0.027	0.025	0.009	0.004	0.023
	(0.027)	(0.027)	(0.030)	(0.030)	(0.033)	(0.038)
Baseline Mean	-0.553	-1.568	-1.157	-0.600	-0.023	0.519
Panel B. Reading Achievement						
Near X Post	0.004	0.005	0.020	0.007	-0.015	0.002
	(0.022)	(0.031)	(0.026)	(0.022)	(0.024)	(0.032)
Baseline Mean	-0.572	-1.775	-1.164	-0.534	0.044	0.555
Observations	2349	2349	2349	2349	2349	2349

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C5: (7th Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	0.044*	0.042*	0.020	0.032	0.029	-0.019
	(0.025)	(0.025)	(0.028)	(0.032)	(0.034)	(0.041)
Baseline Mean	-0.583	-1.434	-1.052	-0.576	-0.023	0.506
Panel B. Reading Achievement						
Near X Post	-0.001	0.010	-0.016	0.000	0.006	0.034
	(0.019)	(0.032)	(0.024)	(0.021)	(0.022)	(0.029)
Baseline Mean	-0.483	-1.567	-0.918	-0.390	0.102	0.547
Observations	2153	2136	2136	2136	2136	2136

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table C6: (8th Grade) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement						
Near X Post	0.025	-0.028	-0.008	-0.003	-0.009	0.003
	(0.027)	(0.030)	(0.028)	(0.031)	(0.034)	(0.041)
Baseline Mean	-0.512	-1.726	-1.226	-0.602	0.012	0.559
Panel B. Reading Achievement						
Near X Post	0.004	-0.035	-0.029	-0.020	-0.036	-0.006
	(0.021)	(0.030)	(0.029)	(0.027)	(0.026)	(0.028)
Baseline Mean	-0.451	-1.768	-1.208	-0.510	0.114	0.587
Observations	2136	2588	2588	2588	2588	2588

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix D: Supplemental Results for CPS

Table D1: Descriptive Statistics, Elementary Schools in Chicago Public Schools, 2008/09

	(1) Full Sample	(2) Near	(3) Far	(4) Diff.	(5) p-value
Panel A. School Characteristics					
Enrollment	633.49	616.35	673.18	-56.83	0.13
	(331.39)	(325.53)	(342.72)	(37.35)	
Percent Black	48.42	55.54	31.91	23.63***	0.00
	(43.28)	(43.41)	(38.34)	(4.42)	
Percent Hispanic	37.46	37.33	37.76	-0.42	0.91
	(37.71)	(40.29)	(31.06)	(3.77)	
Percent Low-Income	82.13	86.84	71.22	15.62***	0.00
	(21.35)	(16.31)	(27.01)	(2.69)	
Panel B. Absence Rates					
	5.73	6.07	4.95	1.12***	0.00
All	(1.94)	(2.06)	(1.36)	(0.18)	
	5.94	6.29	5.12	1.17***	0.00
Male	(2.07)	(2.18)	(1.53)	(0.19)	
	5.52	5.84	4.76	1.08***	0.00
Female	(1.87)	(1.99)	(1.26)	(0.17)	
	6.86	7.20	6.08	1.12***	0.00
Black	(2.35)	(2.39)	(2.07)	(0.24)	
	5.83	6.29	4.79	1.50***	0.00
Hispanic	(5.11)	(5.88)	(2.47)	(0.44)	
	5.83	6.12	5.17	0.95***	0.00
Low-Income	(1.89)	(2.02)	(1.32)	(0.17)	
Panel C. Test Scores					
	-0.49	-0.60	-0.25	-0.34***	0.00
Math	(0.48)	(0.42)	(0.53)	(0.06)	
	-0.46	-0.56	-0.22	-0.34***	0.00
Reading	(0.46)	(0.40)	(0.51)	(0.05)	
Observations (Schools)	388	271	117		

Notes: Column (1) reports means and standard deviations for the full sample of elementary schools from Chicago Public Schools (CPS). Column (2) reports means and standard deviations for schools within 10 kilometers (km) of at least one of of the following three coal-fired power plants: Crawford Generating Station, Fisk Street Generating Station, and State Line Generating Station. Column (3) reports means and standard deviations for schools located more than 10 kilometers (km) away. Column (4) reports the difference in means (Near - Far) and the associated standard error. Column (5) reports the p-value from a two-tailed t-test of the difference in means. Asterisks indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: (Chicago Public Schools Sample) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Absences, Overall and by Subgroup

	All (1)	Male (2)	Female (3)	Black (4)	Hispanic (5)	Low-Income (6)
Near X Post	-0.440***	-0.487***	-0.398***	-0.383**	-0.200**	-0.379***
	(0.092)	(0.096)	(0.094)	(0.182)	(0.101)	(0.100)
Baseline Mean	6.071	6.293	5.841	7.200	6.294	6.123
Observations	3104	3102	3102	3087	2942	3102

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: (Chicago Public Schools Sample) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Mean (1)	10th (2)	25th (3)	Median (4)	75th (5)	90th (6)
Panel A. Math Achievement						
Near X Post	0.016	0.009	0.014	0.021	0.021	0.020
	(0.017)	(0.014)	(0.017)	(0.019)	(0.021)	(0.023)
Baseline Mean	-0.596	-1.648	-1.196	-0.637	-0.047	0.506
Panel B. Reading Achievement						
Near X Post	0.001	-0.001	0.013	-0.003	0.002	0.008
	(0.013)	(0.016)	(0.016)	(0.014)	(0.014)	(0.016)
Baseline Mean	-0.561	-1.783	-1.175	-0.515	0.066	0.571
Observations	2300	2300	2300	2300	2300	2300

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D4: (Chicago Public Schools Sample) Dose-Response Estimates of the Effect of Power Plant Closures on Student Absences, Overall and by Subgroup

	All	Male	Female	Black	Hispanic	Low-Income
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Number of Plants						
Near 1 Plant X Post	-0.433***	-0.491***	-0.387***	-0.194	-0.216**	-0.431***
	(0.122)	(0.128)	(0.123)	(0.214)	(0.109)	(0.134)
Near 2 Plants X Post	-0.445***	-0.484***	-0.405***	-0.618***	-0.194*	-0.347***
	(0.105)	(0.110)	(0.107)	(0.211)	(0.110)	(0.112)
p-value: 1 vs. 2 Plants	0.927	0.959	0.888	0.059	0.815	0.545
Panel B. Nearest Plant						
State Line (614 MWh) X Post	-0.583***	-0.654***	-0.527***	-0.266	-0.157	-0.570***
	(0.190)	(0.199)	(0.190)	(0.261)	(0.157)	(0.195)
Crawford (597 MWh) X Post	-0.320***	-0.368***	-0.274**	-0.471**	-0.096	-0.223*
	(0.114)	(0.119)	(0.116)	(0.239)	(0.107)	(0.119)
Fisk (374 MWh) X Post	-0.522***	-0.556***	-0.489***	-0.408*	-0.403***	-0.507***
	(0.118)	(0.125)	(0.118)	(0.228)	(0.130)	(0.130)
p-value: State Line vs. Crawford	0.180	0.165	0.195	0.473	0.674	0.083
p-value: Crawford vs. Fisk	0.143	0.201	0.112	0.803	0.010	0.050
p-value: Fisk vs. State Line	0.762	0.649	0.847	0.628	0.128	0.762
Panel C. Partition Treatment Group by Distance						
Within 5k X Post	-0.155	-0.188*	-0.138	-0.208	-0.080	-0.060
	(0.100)	(0.105)	(0.103)	(0.242)	(0.109)	(0.105)
Between 5k-10k X Post	-0.650***	-0.708***	-0.590***	-0.427**	-0.391***	-0.637***
	(0.114)	(0.119)	(0.116)	(0.193)	(0.120)	(0.123)
p-value: Under 5k vs. 5k-10k	0.000	0.000	0.000	0.343	0.005	0.000
Baseline Mean	6.071	6.293	5.841	7.200	6.294	6.123
Observations	3104	3102	3102	3087	2942	3102

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level absence rate calculated among the full sample or student subgroup indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by enrollment in the full sample or relevant subgroup. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D5: (Chicago Public Schools Sample) Dose-Response Estimates of the Effect of Power Plant Closures on Student Achievement in Math and Reading

	Math Mean (1)	Math 10th (2)	Math 25th (3)	Math Median (4)	Math 75th (5)	Math 90th (6)	Read Mean (7)	Read 10th (8)	Read 25th (9)	Read Median (10)	Read 75th (11)	Read 90th (12)
Panel A. Number of Plants												
Near 1 Plant X Post	0.001	0.002	0.000	0.009	0.002	-0.006	-0.005	-0.013	0.005	-0.009	-0.002	0.002
	(0.020)	(0.018)	(0.020)	(0.023)	(0.024)	(0.025)	(0.016)	(0.020)	(0.019)	(0.017)	(0.017)	(0.019)
Near 2 Plants X Post	0.027	0.015	0.023	0.030	0.036	0.039	0.006	0.008	0.018	0.002	0.005	0.012
	(0.021)	(0.017)	(0.020)	(0.023)	(0.024)	(0.027)	(0.015)	(0.018)	(0.018)	(0.016)	(0.015)	(0.017)
p-value: 1 vs. 2 Plants	0.228	0.464	0.257	0.388	0.164	0.089	0.487	0.297	0.507	0.552	0.711	0.550
Panel B. Nearest Plant												
State Line (614 MWh) X Post	0.026	0.012	0.021	0.032	0.033	0.028	0.002	-0.012	0.005	0.004	0.019	0.012
	(0.031)	(0.026)	(0.030)	(0.034)	(0.034)	(0.035)	(0.023)	(0.026)	(0.027)	(0.024)	(0.024)	(0.025)
Crawford (597 MWh) X Post	0.021	0.017	0.017	0.023	0.027	0.025	0.004	0.012	0.020	-0.004	0.002	0.009
	(0.020)	(0.016)	(0.019)	(0.023)	(0.025)	(0.027)	(0.016)	(0.019)	(0.020)	(0.017)	(0.016)	(0.019)
Fisk (374 MWh) X Post	0.006	-0.001	0.006	0.013	0.008	0.010	-0.002	-0.012	0.007	-0.003	-0.005	0.004
	(0.023)	(0.020)	(0.023)	(0.026)	(0.027)	(0.029)	(0.016)	(0.020)	(0.019)	(0.018)	(0.017)	(0.018)
p-value: State Line vs. Crawford	0.872	0.864	0.882	0.797	0.873	0.942	0.946	0.376	0.602	0.736	0.482	0.902
p-value: Crawford vs. Fisk	0.555	0.381	0.630	0.703	0.488	0.621	0.729	0.259	0.531	0.949	0.712	0.771
p-value: Fisk vs. State Line	0.566	0.643	0.630	0.607	0.503	0.648	0.848	0.982	0.962	0.775	0.338	0.729
Panel C. Partition Treatment Group by Distance												
Within 5k X Post	-0.001	-0.005	0.003	0.000	0.006	0.003	-0.008	-0.008	-0.005	-0.012	-0.007	-0.002
	(0.021)	(0.017)	(0.020)	(0.023)	(0.025)	(0.027)	(0.015)	(0.018)	(0.019)	(0.016)	(0.017)	(0.018)
Between 5k-10k X Post	0.029	0.019	0.021	0.037	0.032	0.032	0.008	0.004	0.026	0.004	0.009	0.014
	(0.020)	(0.017)	(0.019)	(0.022)	(0.023)	(0.026)	(0.015)	(0.019)	(0.018)	(0.016)	(0.016)	(0.017)
p-value: Under 5k vs. 5k-10k	0.171	0.188	0.389	0.128	0.311	0.285	0.330	0.536	0.127	0.352	0.340	0.354
Baseline Mean	-0.596	-1.648	-1.196	-0.637	-0.047	0.506	-0.561	-1.783	-1.175	-0.515	0.066	0.571
Observations	2300	2300	2300	2300	2300	2300	2300	2300	2300	2300	2300	2300

Notes: Each cell reports results from a separate regression, where the dependent variable is a school-level measure of student achievement for the moment indicated in the column heading. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by the number of test-takers in the school. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D6: (Chicago Public Schools Sample) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Enrollment, Student Demographics, and the Share of Tested Students

	Log Enrollment (1)	Percent Black (2)	Percent Hispanic (3)	Perent Low-Income (4)	Share Math TT (5)	Share Read TT (6)
Near X Post	-0.045*	0.272	0.181	-0.477	-0.004	-0.005
	(0.023)	(0.285)	(0.352)	(0.423)	(0.010)	(0.010)
Baseline Mean	6.300	55.542	37.334	86.837	0.584	0.583
Observations	3104	3104	3104	3104	3104	3104

Notes: Each column reports results from a separate regression, where the dependent variable is a school-level measure of enrollment, student characteristics, or the shared of tested students. All regression specifications include school fixed-effects, year fixed-effects, total enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * $p <0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table D7: (Chicago Public Schools Sample) Heterogeneous Effects of Power Plant Closures by Wind Intensity and School Air Conditioning

	All	Male	Female	Black	Hispanic	Low-Income	Math	Read
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Wind Path Intensity								
High Wind X Post	-0.543***	-0.603***	-0.486***	-0.338	-0.405***	-0.458***	0.038*	0.017
	(0.110)	(0.113)	(0.113)	(0.213)	(0.110)	(0.117)	(0.021)	(0.016)
Low Wind X Post	-0.336***	-0.370***	-0.305***	-0.447**	-0.035	-0.297**	-0.006	-0.016
	(0.110)	(0.116)	(0.111)	(0.212)	(0.108)	(0.119)	(0.020)	(0.015)
p-value: Low vs. High Wind	0.100	0.079	0.152	0.616	0.000	0.224	0.040	0.038
Baseline Mean	6.071	6.293	5.841	7.200	6.294	6.123	-0.596	-0.561
Observations	3,104	3,102	3,102	3,087	2,942	3,102	2,300	2,300
Panel B. Air Conditioning								
High AC X Post	-0.401***	-0.424***	-0.378***	-0.400*	-0.179*	-0.321***	0.006	0.003
	(0.104)	(0.107)	(0.108)	(0.205)	(0.107)	(0.111)	(0.019)	(0.014)
Low AC X Post	-0.507***	-0.594***	-0.432***	-0.380*	-0.243*	-0.491***	0.035	0.001
	(0.135)	(0.143)	(0.133)	(0.224)	(0.138)	(0.146)	(0.024)	(0.018)
p-value: Low vs. High AC	0.463	0.267	0.704	0.929	0.615	0.266	0.223	0.929
Baseline Mean	6.071	6.293	5.841	7.200	6.294	6.123	-0.596	-0.561
Observations	3,024	3,022	3,022	3,007	2,863	3,022	2,241	2,241

Notes: Each cell reports results from a separate regression, where the dependent variable is the aggregate absence rate calculated among the full sample or student subgroup indicated in the column heading or average achievement in math or reading. All regression specifications include school fixed-effects, year fixed-effects, enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). All regressions are weighted by student enrollment in the full sample or relevant subgroup or by the number of tested students. Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table D8: (Chicago Public Schools Sample) Difference-in-Differences Estimates of the Effect of Power Plant Closures on Particulate Pollution (PM2.5)

	Downscaler (1)	Satellite Point (2)	Satellite 1k Buffer (3)	Satellite 2k Buffer (4)
Near X Post	-0.062***	-0.024*	-0.024**	-0.027**
	(0.008)	(0.013)	(0.012)	(0.012)
Baseline Mean	13.173	12.772	12.771	12.769
Observations	2328	3104	3104	3104

Notes: Each column reports results from a separate regression, where the dependent variable is the average annual ground-level concentration of fine particulates (PM 2.5) in micrograms per cubic meter. All regression specifications include school fixed-effects, year fixed-effects, enrollment, percent black, percent Hispanic, percent low-income, Safe Passage (0/1), and Welcoming School (0/1). Heteroskedasticity-robust standard errors are clustered at the school-level. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.