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Coal Use and Student Performance

Valentina Duque
University of Sydney

Michael Gilraine
New York University

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Valentina Duque
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Abstract

This paper examines the effect of air pollution from power production on students' cognitive outcomes. To do so, we leverage variation in power production over time, wind patterns, and plant closures. We find that each one million megawatt hours of coal-fired power production decreases student performance in schools within ten kilometers by 0.02σ and 0.01σ in math and English, respectively. We find no such relationship for gas-fired plants. Extrapolating our results nationwide indicates that the decline in coal use in the United States from 2007 through 2018 increased student performance by 0.003σ and reduced the black-white test score gap by 0.002σ.

Keywords: Air Pollution; Coal Power; Education; Health.
JEL codes: Q53, II4, I24

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1 Introduction

Coal is the largest fuel source for electricity production worldwide and disproportionately contributes to the emissions related to energy production. In the United States, for instance, coal-fired power plants account for a third of power production, but 60% of all sulfur dioxide, 50% of mercury, 60% of arsenic, and 13% of nitrogen oxide emissions (US Environmental Protection Agency, 2018). As the Clean Air Task Force put it: "Among all industrial sources of air pollution, none poses greater risks to human health and the environment than coal-fired power plants."[1] Over the last decade, however, coal use in the United States has declined dramatically as it was replaced with cheaper and cleaner alternatives, especially natural gas.[2]

A large body of research has shown air pollution negatively affects health (see, for instance, Currie et al. (2014)) and student achievement (Ebenstein et al., 2016; Heissel et al., Forthcoming; Persico and Venator, 2019). Given the disproportionate emissions of coal-fired power plants, the precipitous decline in coal usage in the last decade has substantially improved air quality (Currie and Walker, 2019). Combined with the link between air pollution and cognition, the replacement of coal-fired power plants may represent a significant driver of student achievement over the past decade.

Using detailed data on students from the state of North Carolina in additional to school-level data throughout the United States, this paper calculates the improvement in student achievement over the past decade caused by replacing coal with cleaner sources of electricity generation. To do so, we leverage three sources of variation to estimate the impact of coal-fired power plant emissions on student performance. First, we use the fact that power production varies year-to-year to compare student performance in nearby schools in high-production years relative to low-production years. Second, we use the fact that emissions from power plants can

[1] Link: https://www.catf.us/resource/the-toll-from-coal/.

[2] In 2006, coal-fired power plants accounted for 49% of total electricity generation. By 2018, coal's share of electricity generation decreased to 27%. During the same period, the share of natural gas-fired electricity generation nearly doubled from 20% in 2006 to 36% in 2018.

be carried long distances by wind (Schneider et al., 2010; Zhang et al., 2017). This fact allows us to augment our first source of variation by comparing the production-induced performance changes in schools downwind relative to upwind of the plant. Third, we conduct an event-study that leverages ten coal-fired power plant closures.

We first implement our methods using administrative records from the universe of third to eighth grade public school students in North Carolina from 2000-01 through 2016-17. Along with detailed information on student-level demographic characteristics and test scores, the administrative data contain student identifiers which allow us to track students over time. We link these data to monthly power plant production data from the U.S. Energy Information Administration, which enable us to calculate energy production levels by fuel type for all academic years, 2000-01 to 2016-17. These data are then connected to wind patterns using information from eighty-one meteorological stations throughout North Carolina to ascertain whether schools are 'downwind' or 'upwind' from a power plant.

All three empirical designs indicate that each one million megawatts-hour (Mwh) increase in coal-fired power production – about a third of the average yearly production of a coal plant in our sample – lowers student performance in schools within $10km$ by 0.02σ and 0.01σ in math and English, respectively. The entirety of this effect is concentrated in schools downwind from the power plant. We find no such relationship for gas-fired power production.

We next extrapolate our estimates nationwide. Before doing so, we first ensure our results are not specific to North Carolina by repeating our analysis at the national level using school level proficiency data from the U.S. Department of Education. Our estimated nationwide effects are near-identical to those found in North Carolina. With the relationship between student achievement and coal and gas-fired power production confirmed at the national level, we then use our estimates from North Carolina to estimate the nationwide effect of reduced coal use on student achievement.

We calculate a sizeable decrease in coal-fired power production exposure over the last decade. During the school months of September-May in the 2006-07 school year, the average U.S. student was exposed to 195,000 Mwh of coal-fired power production occurring within 10km of their school. By 2017-18, this number had dropped to 61,000 Mwh (a 69 percent reduction). Given the estimated impact of coal-fired power production on student achievement, this decline indicates that the nationwide increase in test scores due to the decline in coal usage from 2006-07 to 2017-18 was 0.003σ (=0.02*(0.195-0.061)). This is a meaningful nationwide effect: Estimates from Krueger (1999) suggest that approximately 700 million dollars per year would be required to attain a similar nationwide test score increase through class size reduction.[3] The nationwide impact obscures substantial spatial variation: Midwestern states saw substantial impacts given their higher use of coal, while effects were minimal in Western states.

The decline in coal use also reduced inequality since underprivileged students are more likely to attend schools in polluted regions (Currie, Voorheis, and Walker, 2020). For instance, we estimate that the decline in coal use reduced the nationwide black-white test score gap by 0.002σ. Once again, there is substantial spatial variation. Illinois, for example, saw a decline of 0.02σ in their black-white test gap due to the decline in coal use whereas Texas saw little change. We treat our estimates as conservative since we only consider the impact of coal-fired production on schools within 10km of the plant; prior research has found that coal-fired plants can affect air quality 20-40 miles away (Yang and Chou, 2015; Jha and Muller, 2017).

Our paper contributes to the related literature in several ways. First, we provide the first causal estimates of the relationship between fossil fuel power production and student performance (to our knowledge). While power plants can increase lo-

[3] Krueger (1999) estimated that reducing class size by seven students (from 22 to 15 students per classroom) increases test scores by 0.22 standard deviations. Given this, a class size reduction of about one-eightieth of the seven student decline would yield a nationwide test score increase of 0.003σ. According to the National Center for Education Statistics, the United States currently has 56.6 million students and an average class size of 23.5 and so would require 8,900 new teachers to reduce class sizes by the required amount (=56.6 million/(23.5-7/80) - 56.6 million/23.5). With average teacher salaries being $60,477 plus an additional thirty percent in benefits, the class size reduction program would cost $700 million a year to deliver the same benefits as the reduction in coal use (neglecting facility costs).

cal economic activity (Greenstone et al., 2010), our research adds to the growing literature that these plants negatively affect nearby children (Currie et al., 2015; Yang and Chou, 2015; Murphy, 2017) indicating the need for mitigation or locating these plants far away from residential areas.[4] Second, we add to an emerging body of research that demonstrates the adverse effects of air pollution on cognition (Ebenstein et al., 2016; Roth, 2019; Persico and Venator, 2019; Heissel et al., Forthcoming; Gilraine, 2020). Third, we place in context the nationwide benefit of cleaner air, showing that the transition from coal to cleaner fuel sources led to a non-negligible increase in student performance and helped reduce inequality.

The rest of the paper is organized as follows: The next section describes the recent findings on the effects of pollution exposure on health and education along with a brief history of power production in the United States. Section 3 then sets out our empirical methodology and introduces the North Carolina data. These are followed by our results in Section 4, which are confirmed in the national data and extrapolated nationwide in Section 5. Section 6 concludes.

2 Background

This section reviews the literature related to the effect of air pollution on child health and cognition and some of the potential mechanisms that previous research has examined. We then describe power production in the United States, paying particular attention to recent trends in coal-fired power production.

2.1 Related Literature

Effects on children's health: An extensive literature in economics has linked air pollution to children's health, with the first quasi-experimental evidence coming from Ransom and Pope (1995). Focusing on a labour strike in Utah that forced the

[4]Research in epidemiology has also shown that child's neurodevelopment is associated with exposure to coal-fired power plant emissions, primarily particulate matter and polyaromatic hydrocarbon exposure (Amster and Lew Levy, 2019).

closure of a steel mill – a major local source of particulate matter – the authors showed that child hospitalizations fell when the mill closed. Additional evidence soon followed: Chay and Greenstone (2003a) exploit changes in environmental regulations arising from the Clean Air Act of 1970 and find that a 1-unit decline in particulates led to 8 fewer infant deaths per 100,000 live births. These findings have been echoed in recent studies using pollution variation arising from cars (Currie et al., 2009b; Currie and Walker, 2011; Knittel et al., 2016; Simeonova et al., Forthcoming), airplanes (Schlenker and Walker, 2016), local weather conditions (Deryugina et al., 2019; Heft-Neal et al., 2019), and industrial plant closures (Chay and Greenstone, 2003b; Currie et al., 2015). Given the strong association between early life conditions and future outcomes (see Almond et al. (2018) for a recent survey), studies have also linked early-life pollution exposure to reduced health and productivity in adulthood (Isen and Rossin-Slater, 2017; Grönqvist et al., 2017; Barreca et al., 2017).

Effects on children's test scores: Compared to the body of research on the air pollution effects on health outcomes, fewer studies examine the effects on child cognition. However, measuring air pollution effects beyond health is important as previous work has linked test score improvements with long-term gains in outcomes (Garces et al., 2002; Chetty et al., 2011).

Zweig et al. (2009) link changes in outdoor air pollution near Los Angeles schools with changes in students' test scores and find that a 10 percent decrease in outdoor PM2.5 and NO2 raises math test scores by 0.34 percent and 0.18 percent, respectively.[5] Similarly, Ebenstein et al. (2016) use variation in test day particulate pollution in Israel and find that every 10 percent increase in PM2.5 on the test day reduces test scores by 0.02 standard deviations. Using data from Santiago, Chile, Bharadwaj et al. (2017) show that prenatal exposure to carbon monoxide reduces fourth grade test scores by 0.04 standard deviations. Persico and Venator (2019)

[5]Most of the scientific literature focuses on the health effects of air pollution uses PM2.5 because fine particulate matter can penetrate lung tissue and get into the bloodstream (Pope III and Dockery, 2006; Dominici et al., 2014; Deryugina et al., 2020).

find that students attending schools within one mile of a Toxic Release Inventory site experienced a 0.024 standard deviations increase in test scores once the site closed relative to those attending schools between 1 and 2 miles away. Likewise, Heissel et al. (Forthcoming) show that students attending a school where the prevailing winds place it 'downwind' of a highway score 0.04 standard deviations below comparable students attending 'upwind' schools.

Potential mechanisms of air pollution: Pollution can affect students' test scores through several mechanisms. First, air pollution can lower the availability of oxygen in the environment thereby limiting the oxygen required for the appropriate functioning of the brain. Studies have shown that short-term exposure to air pollution is associated with inflammation and oxidative stress in the brain (Kleinman and Campbell, 2014), cerebro-vascular dysfunction, and alterations in the blood-brain barrier of the central nervous system (Genc et al., 2012), negatively impacting an individual's concentration and decision-making (Heyes et al., 2016). Second, air pollution is associated with contemporaneous health conditions such as eye or nose irritation or child's asthma (Neidell, 2004; Alexander and Currie, 2017; Simeonova et al., Forthcoming; Ward, 2015; Lleras-Muney, 2010), which may impede a child's learning in school. Third, polluted air can also increase students' (and teachers') school absences (Currie et al., 2009a; Persico and Venator, 2019), and these absences can in turn cause lower grades (Goodman, 2014).

2.2 Energy Production in the United States

Coal has been used to generate electricity in the United States since the very start of electricity generation in the country: Pearl Street Station, the first commercial power plant, used coal for electricity generation when it began operating in Manhattan in 1882 (Bennion, 1940). Coal maintained its dominance as the leading fuel for electricity generation throughout the rapid electrification of the country. By the end of the 20th century, coal generated over half the country's electricity.

The start of the 21st century, however, has seen a precipitous decline in coal-fired electricity generation: The average share of electricity generated from coal in the United States dropped from 49% in 2006 to 27% in 2018. The leading culprit in the decline of coal was the emergence of shale gas due to advances in hydraulic fracturing extraction techniques, which caused gas prices to fall making natural gas a cheaper alternative to coal (Joskow, 2013; Knittel et al., 2015; Fell and Kaffine, 2018). Given this, the same period saw a substantial rise in the share of electricity produced by natural gas: its share of electricity generation nearly doubled from 20% in 2006 to 36% in 2018. The decline in coal was also abetted by increased environmental regulation, namely the Cross State Air Pollution Rule and the Mercury and Air Toxics Standards which were both established in 2011 (Burtraw et al., 2012; US Environmental Protection Agency, 2015).

Coal plants are considered a 'dirty' fossil fuel, releasing large amounts of airborne pollutants such as particulates, carbon dioxide, carbon monoxide, sulfur dioxide, and nitrogen oxide as well as airborne toxins in the form of mercury, lead, and various other heavy metals (e.g., arsenic, cadmium, cobalt). In contrast, natural gas is known as a 'clean' fossil fuel, since it emits roughly half the carbon dioxide and one-quarter the nitrogen oxide of coal and almost no sulfur dioxide, carbon monoxide, black carbon, particulates, and mercury (Nature, 2009). Given coal's outsized emission of airborne pollutants, research has linked the decline in coal use to significant improvements in airborne pollution across the United States over the last fifteen years, including decreased mercury, carbon dioxide, nitrogen oxides, and sulfur dioxides (Venkatesh et al., 2012; De Gouw et al., 2014; Zhang et al., 2016).

Table B.2 reports emissions of carbon dioxide, sulfur dioxide and nitrogen oxides from coal and gas-fired power plants from 2013 to 2018 for the United States.[6] Comparing emissions from coal and natural gas plants per million Mwh produced, we see that natural gas plants release virtually no sulfur dioxide and less than half the carbon dioxide emissions of coal-fired plants. We also see improvements in coal-fired power plant emission efficiency nationwide over the last five years, as

[6]Unfortunately, plant-level emissions data are only available from 2013 onwards.

sulfur dioxide and nitrogen oxides emissions per million Mwh have fallen by roughly half. These improvements have been driven by a combination of retirement of less efficient coal plants, increased use of low-sulfur coal, and the installation of pollution abatement technologies such as flue gas desulfurization scrubbers.

North Carolina's energy sector mimics national trends in energy production. Coal provided roughly sixty percent of North Carolina's electricity generation until 2010, when natural gas generation began to rise rapidly. As in the rest of the country, this was driven by the decline in natural gas prices due to advances in hydraulic fracturing increasing gas production in states such as Texas, North Dakota, Colorado, and Wyoming. From 2010 to 2017 coal's share of electricity generation dropped from 60% to 27%, while the share of electricity generation from natural gas increased six-fold from 5% in 2010 to 30% in 2017. During this time, nuclear power remained the only other major source of power and its share of electricity generation was remarkably stable, representing 32% of electricity generation in 2001 and 33% in 2017. In contrast to national trends, North Carolina has seen a *decrease* in emission efficiency in its coal power plants (see Table B.2), likely because plant-level efficiency has declined due to increased cycling.[7]

An additional catalyst for the decline in coal use in North Carolina comes from the fact its largest energy producer, Duke Energy, was subject to an ongoing lawsuit from 2000-2015 by the United States Justice Department on behalf of the Environmental Protection Agency. The lawsuit claimed that Duke Energy violated federal clean air laws by modifying thirteen coal-fired power generators without the required equipment to control air pollution. During the fifteen year lawsuit, Duke Energy shut down eleven of these units by closing four power plants and eventually settled in 2015 by agreeing to plead guilty to nine criminal violations of the Clean Water Act, pay a civil penalty, and shut down the remaining two offending units

[7]Utilization rates of North Carolina's coal-fired power plants have declined over time, with nine coal plants operating at less than fifty percent capacity in 2018. Duke Energy has stated that "cycling" plants – whereby plants' energy production is scaled down during the day to accommodate solar energy to the power grid and then scaled back up at night – decreases emission efficiency as forced stops and starts can temporarily disable emission controls.

by 2024.[8]

3 Methods and Data

Our empirical strategy to estimate the effect of air pollution caused by coal-fired power production on student achievement relies on three 'quasi-experiments' that leverage separate sources of variation. This section describes each of these quasi-experiments and then introduces the data set that we have assembled.

3.1 Empirical Strategies

Quasi-experiment 1: Production Variation. Our first quasi-experiment uses the fact that power production at individual plants varies significantly year-to-year, allowing us to compare student performance in schools nearby during high production years to low production years. Since higher power production is associated with increased plant-level pollution, we expect student performance in nearby schools to suffer in years of high power production.

We investigate the relationship between power production and student performance through the following regression:

$$y_{igs(p)t} = \alpha + \beta prod_{s(p)t} + \phi Z_{igs(p)t} + \gamma_{s(p)} + \theta_i + \lambda_{gt} + \epsilon_{igs(p)t} \ , \quad for \ X_{s(p)} \leq \bar{X} \ , \tag{1}$$

where $y_{igs(p)t}$ is the test score of student i in grade g at the end of school year t who attends school s that is nearest to power plant p, $prod_{s(p)t}$ represents the annual power production (in millions of Mwh) of plant p near school s during school year t, and $Z_{igs(p)t}$ includes student demographic controls (e.g., free or reduced price lunch status, English learner status, disability, and gifted status). θ_i is an individual fixed effect to account for time-invariant student-level characteristics, $\gamma_{s(p)}$ is a school fixed effect which absorbs time-invariant school-level characteristics such as school

[8]The Washington Post, September 2015, Link: https://www.washingtonpost.com/national/duke-energy-to-settle-federal-lawsuit-over-claims-of-clean-air-law-violations/2015/09/10/953adeca-57fc-11e5-8bb1-b488d231bba2_story.html

location, and λ_{gt} are grade-by-year fixed effects, accounting for temporal shocks that are common to all students in a particular grade-year (e.g., state-level curriculum reform). $X_{s(p)}$ denotes the distance of school s to power plant p and $\bar{X}$ is our 'radius of interest' whereby we restrict our regression to only include schools within $\bar{X}$ of a power plant. We bracket the p subscript to indicate that schools are always assigned to one power plant (and so school fixed effects subsume power plant fixed effects). Standard errors are clustered at the school level to account for within-school serial correlation in the observations.[9] β is our coefficient of interest and represents the effect of a one million Mwh increase in annual power plant production on student test scores.

Although the prior literature has indicated that coal-fired power plants can affect air quality 20-40 miles away (Yang and Chou, 2015; Jha and Muller, 2017), we set $\bar{X} = 10km$ (6.2 miles) throughout so that we focus on regions near the power plant that are likely to face similar economic shocks in a given year. We also establish the impact of power production on student performance as a function of distance to the power plant by plotting the relationship between power production and student performance for various $2.5km$ distance bins (see Figure 3). Doing so, we find significant declines in student performance among bins below $10km$, with no significant declines in performance observed in bins above $10km$, in line with expectations that the impact of power plant emissions diminishes with distance.[10]

Quasi-experiment 2: Wind *and* Production Variation. Our second quasi-experiment introduces an additional level of variation coming from the fact that wind carries air pollutants downwind from power plants. This second fact allows us to introduce an additional level of variation, which alleviates concerns that would arise if we used *solely* power production as it might be correlated with other local factors (e.g., employment or wages) that could also affect student achievement.

Intuitively, wind variation allows us to compare student performance in years

[9] Clustering at the school level also leads to the most conservative standard errors.

[10] Given the spatial distribution of power plants in North Carolina, setting $\bar{X} = 10km$ has the additional benefit that schools are not treated by more than one power plant.

of high and low power production for schools that are relatively 'downwind' versus 'upwind' of the power plant. Since both 'downwind' and 'upwind' schools are nearby the power plant, any unobserved variables that might affect student achievement and are correlated to power production (e.g., income shocks, weather, etc.) should similarly affect students attending either type of school. Therefore, any differential effect of the increased power production between 'downwind' relative to 'upwind' schools can be attributed to the fact that pollution travels downwind (as in Deryugina et al. (2019); Anderson (Forthcoming); Heissel et al. (Forthcoming)), and so students in downwind schools are more affected by the higher pollution levels caused by increased power production.

We leverage both wind and year-to-year power production variation by estimating the following regression:

$$\begin{aligned} y_{igs(p)t} &= \alpha + \beta prod_{s(p)t} * downwind_{s(p)} + \delta prod_{s(p)t} \\ &\quad + \phi Z_{igs(p)t} + \gamma_{s(p)} + \theta_i + \lambda_{gt} + \epsilon_{igs(p)t}\,,\ for\ X_{s(p)} \leq \bar{X}\,, \end{aligned} \tag{2}$$

where all the terms are the same as in equation (1), with the additional term $downwind_{s(p)}$ denoting our measure of how 'downwind' school s is from plant p (formally defined later in equation (6)). β is our coefficient of interest and represents the marginal effect of a one million Mwh increase in annual power plant production in downwind relative to upwind schools on student test scores.

Quasi-experiment 3: Coal Plant Closures. Our third identification strategy leverages coal plant closures in North Carolina, using six coal plant closures and four coal plant conversions into natural gas plants as natural experiments. Given that we do not find any relation between natural gas energy production and student achievement (as we show later in Tables 2 and B.3), we do not distinguish between coal plant conversions or closures, leaving us with ten events. Of these, four occurred in 2010-11, leaving 2011-12 to be the first year of no nearby coal-fired power production for almost half our sample.

We use an event-study approach to estimate the effects of coal plant closures on students' test scores using the following equation:

$$y_{igs(p)t} = \alpha + \beta post_{s(p)t} + \delta pre{*}close_{s(p)t} + \phi Z_{igs(p)t} + \gamma_{s(p)} + \theta_i + \epsilon_{igs(p)t},\ for\ X_{s(p)} \leq \bar{X}, \quad (3)$$

where $close_{s(p)t}$ denotes time in years relative to the plant closure (i.e., event time), $post_{s(p)t} \equiv \mathbb{1}\{close_{s(p)t} \geq 0\}$ indicates that plant p closest to school s has closed and $pre{*}close_{s(p)t} \equiv (1 - post_{s(p)t}) * close_{s(p)t}$ controls for the (linear) trend in test scores in the years leading up to a plant closure. All other terms are the same as those in equation (1).

We also assess the validity of the event study by plotting event-time coefficients using the following regression:

$$\begin{aligned} y_{igs(p)t} =& \alpha_0 + \sum_{j=-4}^{-2} \gamma_j \cdot \mathbb{1}\{Plant\ Closure_{s(p)t} = j\} + \sum_{j=0}^{3} \beta_j \cdot \mathbb{1}\{Plant\ Closure_{s(p)t} = j\} \\ &+ \phi Z_{igs(p)t} + \gamma_{s(p)} + \theta_i + \epsilon_{igs(p)t}\ ,\ for\ X_{s(p)} \leq \bar{X}\ , \end{aligned} \quad (4)$$

where $\mathbb{1}\{Plant\ Closure_{s(p)t} = j\}$ is an indicator variable equal to one if school s near plant p is in event time j, and equal to zero otherwise. This specification is a non-parametric version of equation (3) and allows for non-parametric estimation of the time path of the estimated effects of the coal plant closure at different periods. The event-time coefficients γ_j show how student test scores evolve in the years leading up to the plant closure and β_j display the development of test scores after the plant closure. Period $j = -1$ in event-time (i.e., the year before the plant closes) is the omitted category. Given the inclusion of student fixed effects, the sample is restricted to four periods pre- and post-closure to ensure that we observe the same student both before and after the plant closure.

3.2 Data

We now describe the data we use for estimation. Our data combines three distinct data sources to construct a student-level data set that captures students' exposure to nearby power plants both in relation to power production levels and wind direction.

Power Plant Data: Our three quasi-experiments require information on power plant location and production. These data come from the U.S. Energy Information Administration (EIA) Monthly Generation and Fuel Consumption Time Series File (EIA-923) and its pre-2008 predecessor (EIA-906).[11] These data report monthly power production by plant and type of fuel for all large power plants across the United States for the calendar years 2001-2018, which we use as our analysis period.

The EIA data cover all power producing locations, including those relying on renewable energy sources (e.g., hydroelectric) as well as small power producing locations (e.g., crematoriums, factories, mills) that are unlikely to significantly affect individuals by themselves given their low level of power production. We thus restrict our sample to large coal and natural gas fired power plants with average power production levels of over 250,000 Mwh during the academic year over their period of operation. The 250,000 Mwh threshold restricts the majority of our sample to large power stations, although our data also includes the world's largest tobacco factory (at the time).

To match the academic calendar, we sum power production generated from September to May[12] for each plant by fossil fuel type. Each plant-year is classified as being coal or natural gas based on the majority fuel type used in that academic year. These designations are clear in the data: coal plants on average generate 98 percent of their electricity using coal, with the remainder being produced using natural gas, oil, or biomass. Similarly, natural gas plants on average generate 97 percent of their electricity using natural gas. Given this, total power production for each plant for each academic year is defined as the power produced at that plant

[11] Available at https://www.eia.gov/electricity/data/eia923/.

[12] School calendars vary across school districts, but the academic year usually runs from the last week of August to the first week of June.

coming from its main fossil fuel (i.e., coal or natural gas) from September-May.

We are left with a sample of twenty-one coal and natural gas plants, of which – as four coal plants converted to natural gas – seventeen operated as coal plants and eight operated as gas plants at some point during our period of interest (2001-2017). Of the remaining thirteen coal plants that did not convert to natural gas, six closed during our analysis period. Figure 1 shows the location of all twenty-one power plants across the state of North Carolina along with their production type and Table B.1 lists all power plants along with their location, dates of operation, production characteristics, and distance to nearest wind station (see below).

Wind Data: With our sample of power plants in hand, we now construct a measure of wind direction for each power plant. To do so, we obtain information on wind patterns from the National Oceanic and Atmospheric Administration's Surface Hourly Global data.[13] These data report wind speed and direction every five minutes from eighty-one meteorological stations across the state of North Carolina. Because the number of wind stations has been increasing over time and wind patterns are consistent year-to-year, we proxy wind direction for the earlier years (i.e., 2001-2013) with data from 2014-2017. We then restrict the wind observations to those: (i) that occur during school hours,[14] and (ii) with non-negligible wind speeds to ensure that the wind is pushing pollutants in a given direction.[15]

The data are then collapsed by angle of wind according to an 8-directional wind-rose. The wind data thus represents the proportion of time wind blows *toward* one of four cardinal directions (N, E, S, W) plus the four intercardinal directions (NE, SE, SW, NW) during school hours. Formally, given N observations per wind station w, the proportion of time the wind blows *toward* direction D during school hours

[13] Available at https://www7.ncdc.noaa.gov/CDO/cdopoemain.cmd?datasetabbv=DS3505&countryabbv=&georegionabbv=&resolution=40

[14] We assume that school hours run from 8am through 3pm, although school hours do vary by district.

[15] Specifically, only observations where the wind speed is 5mph or greater are included. We also omit observations where the wind direction cannot be determined as the wind is bi-directional.

is expressed as follows:

$$wind_{w(p)D} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}\{wind_i = D\}\ ,\ D \in \{N, NE, E, SE, S, SW, W, NW\}\,. \quad (5)$$

Power plants are then matched to the nearest wind station according to physical distance. The closest wind station is usually within twenty kilometers of the power plant (see Table B.1), which should adequately capture the direction wind is blowing at the power plant given that wind direction is highly spatially correlated. In fact, prevailing wind directions are fairly consistent across North Carolina, with the wind generally blowing toward the North and, to a lesser extent, the South. Only a small portion of the state has wind predominantly blowing from the East or West.

School Location Data: We combine our plant-level production and wind direction data with geocoded location data on every public school in North Carolina (including charter schools). Using these data, we first calculate the distance of a school relative to the nearest power plant, giving us a unique school-power plant combination.[16] We then use the coordinates of both the school and its nearby power plant to calculate the *direction* of the school relative to the power plant. Once again, we discretize the direction the school is located relative to the power plant into one of four cardinal directions (N, E, S, W) plus the four intercardinal directions (NE, SE, SW, NW).

Next, we calculate the proportion of time the wind is blowing from a given power plant toward a given school during school hours. There is no clear-cut way to calculate this measure. We choose one method we believe is reasonable, and then show robustness to this measure (see Figure B.2). Specifically, denote D' as the directions adjacent to a given direction D (e.g., if $D = N$, then $D' = \{NE, NW\}$).

[16] Given the spacing of power plants (see Figure 1), there are no cases where schools are within 10km of two power plants and so the school-power plant combination is unique.

We define the degree 'downwind' school s is from plant p as:

$$downwind_{s(p)} = \mathbb{1}\{School\ Location_{s(p)} = D\} * wind_{w(p)D} + \frac{1}{2}\mathbb{1}\{School\ Location_{s(p)} = D\} * wind_{w(p)D'}\,. \quad (6)$$

Effectively, this measure captures the proportion of time the wind is blowing from power plant p toward school s either directly or from an adjacent direction, with adjacent directions given half the weight.

Figure 2 provides an example of a typical wind rose – a diagram often used by meteorologists to summarize the distribution of wind direction – to provide intuition for our wind measure. The circular format of the wind rose shows the direction the winds is blowing *toward*[17] and the length of each "spoke" around the circle shows the proportion of time the wind blows toward that particular direction during school hours. For instance, the dark blue 'spoke' in Figure 2 shows that the wind blows towards the North 27.5 percent of the time.

As is typical in North Carolina, Figure 2 indicates wind generally blows *toward* the North, with little wind blowing East or West. The 'downwind' measure for a school located North of the power plant will incorporate all three spokes colored blue (N, NW, NE), with the lighter blue spokes (NW,NE) being given half weight. The school's 'downwind' measure is thus 0.4375 ($= 0.275 + \frac{1}{2}0.1625 + \frac{1}{2}0.1625$), which is relatively high. Likewise, a school located to the East of the power plant has a relatively low 'downwind' measure of only 0.16875 ($= 0.05 + \frac{1}{2}0.1625 + \frac{1}{2}0.075$).

Administrative Student Data: Our data now consist of all public schools in North Carolina, distance of each public school to the nearest power plant, and a measure of how often the wind blows from the power plant toward the school. Next, we incorporate detailed administrative data from the North Carolina Education Research Center (NCERDC) and assign students to schools based on attendance. Our student-level data include information on all public school students in the state

[17] Usually, wind roses indicate the direction the wind blows *from*. We reverse this and show the direction wind is blowing *toward* to help with intuition.

for the 2000-01 to 2016-17 academic years. Importantly, the NCERDC data contain unique student identifiers, allowing us to track students over time.

The student-level data contain test scores for each student in mathematics and English for grades two through eight from standardized tests in math and English that are administered at the end of each school year in the state.[18] Test scores are reported on a developmental scale, which is designed such that each additional point represents the same knowledge gain, regardless of the student's grade or baseline ability. To create comparability of test scores across grades and years, we standardize this scale at the student level to have a mean of zero and a variance of one for each grade-year. Student-level demographics are also observed, including sex, race/ethnicity, free or reduced price lunch status, English learner status, disability, and gifted status.

Summary statistics are reported in Table 1. Column (1) shows student characteristics for all students in the sample ($N = 2.5$ million, or 9.2 million student-year observations). North Carolina has a white student plurality and a substantial black minority population (28 percent), with Hispanic and Asian students making up a further eleven and three percent of the student body, respectively. Almost half are eligible for free or reduced price lunch, ten percent report having a disability, and fifteen percent are gifted.

Columns (2)-(4) present summary statistics for the samples of our three quasi-experiments. Column (2) restricts the data to students in schools located within $10km$ of a coal power plant, which corresponds to the sample used in the first and second quasi-experiments. While less than ten percent of the full sample attend schools within $10km$ of a coal plant, these students appear similar to the full student body both in terms of test scores and demographics. Column (3) restricts the sample to students who attend a school within $10km$ of a natural gas plant, while column (4) restricts the sample to students in schools within $10km$ of a coal plant that

[18]With the exception of the second grade test which is administered at the start of the school year for students in third grade. In addition, the second grade test was discontinued after 2007-08 and is not available in either 2005-06 for math nor 2007-08 for English.

shuts down or converts to natural gas during the period of interest. The samples in both columns (3) and (4) consist of lower performing students that come from more disadvantaged backgrounds. A large reason for these differences is that three of the coal plants that converted to natural gas are located near highly-disadvantaged neighborhoods.

4 Results

This section provides estimates of the effect of coal-fired power production on student performance using our three quasi-experiments that leverage variation in production, wind, and plant closures. We also use the first two methodologies to measure the impact of natural gas power plants.[19]

Quasi-experiment 1: Production Variation. Our first quasi-experiment compares student performance in schools near power plants in years when power production is high to years when power production is low. Figure 3 nonparametrically plots the relationship between power production and student math performance by distance to the plant. To do so, it groups schools into 2.5km bins and reports the results of equation (1) for schools within those bins.[20]

Figure 3(a) plots the relationship for schools near coal-fired power plants. Schools that are less than 10km from the coal-fired power plant experience approximately a 0.02σ decline in math scores for each million Mwh increase in power production at the nearby power plant. After 10km, the relationship between increased power production and test scores disappears, providing empirical support for our decision to restrict the effect of coal-fired power production to schools within 10km for our main analysis. Figure 3(b) plots the same relationship for natural gas fired power production. Visually, there is no clear relationship between natural gas power production and student performance.

[19] We do not have enough natural gas plant openings or closings to use the third source of variation.

[20] We combine the 0-2.5km and 2.5-5km bins as there are few schools within 2.5km of a power plant.

Panel A of Table 2 reports the results of equation (1) for schools within $10km$ of a coal-fired power plant for both math and English. In line with the visual evidence, results indicate that a one million Mwh increase in coal-fired power production is associated with a 0.02σ decline in math test scores, which is statistically significant at the one percent level. The impact on English scores is about half of the math score effect and is statistically significant at the five percent level.

Panel B of Table 2 estimates the same equation, but for schools within $10km$ of a natural gas power plant. Given that natural gas-fired power production generates substantially lower levels of harmful emissions, we expect a smaller relationship between natural gas production and student performance. Indeed, our point estimates indicate no clear relationship between natural gas power production and student performance.

Quasi-experiment 2: Wind *and* Production Variation. Our second quasi-experiment incorporates wind variation into our first quasi-experiment. To start, Figure 4 nonparametrically plots the relationship between coal-fired power production and student math performance by distance to the plant *and* by whether the plant is 'downwind' or 'upwind' of the power plant. To do so, we delineate schools as 'downwind' or 'upwind' based on whether the school faces above or below median wind blowing from the power plant according our downwind measure (see equation (6)) and then group schools into $2.5km$ bins and report the results of equation (1) for schools within those bins. For schools 'downwind' and within $10km$ of the power plant, students experience approximately a 0.03σ decline in math scores for each one million Mwh increase in production at the nearby power plant. For 'downwind' schools further than $10km$, there is no clear relationship between test performance and power production. Schools 'upwind' of the power plant do not appear to be substantially affected by increased coal-fired power production.

Table 3 reports the results of equation (1) for schools within $10km$ that are 'downwind' (Panel A) and 'upwind' (Panel B) of the coal-fired plant for both math and English. As expected, we see that a one million Mwh increase in power production leads to large and statistically significant declines in math scores of 0.03σ for schools that are 'downwind' of the coal-fired plant. For schools 'upwind' of the plant, there is no clear relationship between power production and student performance.

Panel C then interacts coal-fired power production with our continuous measure of how downwind a school is from the plant as described by equation (2). To help interpret these point estimates, we divide our downwind measure by 0.15 to make the scale of the estimates roughly comparable to the differences between Panels A and B given that our wind measure is about 0.15 units higher for schools 'downwind' relative to 'upwind' of the power plant. Our estimates yield near-identical effect sizes to our simple 'upwind' relative to 'downwind' comparison. Once again, estimates for English are about half of those for math. Table B.3 repeats the quasi-experiment for natural gas plants and finds no clear relationship between natural gas power production and student performance in either 'downwind' or 'upwind' schools.

Quasi-experiment 3: Coal Plant Closures. Our third quasi-experiment leverages coal-fired plant closures and conversions to natural gas. Given that we find no evidence that power production using natural gas lowers student performance (see Tables 2 and B.3), we do not distinguish between a coal plant closure or conversion to natural gas. Our study therefore incorporates ten events: six coal plant closures and four conversions to natural gas. The closure/conversion date we use for each plant is given in Table B.1.

Figure 5 plots estimates from equation (4) for schools 'downwind' (Figure 5(a)) and 'upwind' (Figure 5(b)) of the plant which show the evolution of student performance in the years leading up to and after the plant closure. In the years leading up to the coal plant closure, we see that student performance is stable for both schools 'downwind' and 'upwind' of the plant. Given this, there appears to be no evidence of a differential pre-trend among students in schools near plants about to close relative to those in schools near plants that will close in the future (or have closed).

After the plant closes at event time zero, however, we see a jump in student performance among schools 'downwind' from the plant. Test scores continue to increase somewhat after plant closure, likely as some of our 'closed' plants continue to produce some coal-based electricity for a year or two afterward.[21] No such jump in test scores after plant closure is observed for schools 'upwind' of the plant.

Table 4 reports results from the event study defined by equation (3). The point estimates indicate that a coal-fired power plant closure leads to a 0.05-0.06σ increase in both math and English performance among schools within 10km of the power plant. Panels A and B delineate these results into schools that are 'downwind' (Panel A) and 'upwind' (Panel B) of the coal-fired power plant. As expected, the majority of the effect is driven by schools downwind of the power plant.

The average coal plant closure in the sample had coal power production of about one and a half million Mwh pre-closure, implying that our estimates in the event-study design are about 1.5-2 times those found in our first two quasi-experimental designs. While these differences are not statistical significant, one driver may be that the closed coal plants were older and less efficient (in terms of pollution) than the coal plants that remained open.

4.1 Robustness

Placebo Test: Although unlikely, one might be concerned that power plants may jointly reduce production due to a statewide shock (e.g., the Great Recession) that happens to differently affect students living downwind relative to upwind of power plants. To alleviate this concern, Figure B.1 conducts a placebo test where we estimate equation (2) but randomly assign the power production of a coal-fired plant that of a different coal-fired plant. The figure shows that the point estimates from these placebo tests are centered around zero and only once does it exceed the estimate found in Panel C of Table 3, as one would expect by chance. The placebo

[21] We consider a plant closed if they experience greater than a seventy-five percent drop in their production. For most plants this indicates their complete closure, but some plants kept a boiler in operation for a few ensuing years. For example, we consider Riverbend to have closed after 2010-11 when it retired four of its boilers, but the plant kept one boiler in operation for the subsequent two years.

test clearly indicates that our results are driven by production changes in nearby power plants.

Functional Form: Table B.4 recreates our main results from Table 3 using logged power production rather than production in millions of Mwh. This helps alleviate concerns that our results are solely driven by large power plants with substantial production variation in levels as the log specification captures the effect of a percentage change in power production instead. Results are qualitatively similar when the log specification is used.

Wind Measure: Our 'downwind' measure defined in equation (6) gives half weight to adjacent wind directions. Figure B.2 graphs the point estimate from our second quasi-experimental design that interacts power production with wind direction when different weights are applied to adjacent wind directions. The point estimate is remarkably stable when zero through equal weights are given to adjacent wind directions.

5 Nationwide Results

Our results indicate that coal-fired power production in North Carolina causes a substantial and significant decline in test scores. Given that *nationwide* coal use declined by 45 percent from 2007 to 2018,[22] we expect the performance of students throughout the country to have benefited from reduced coal use. This section takes our results from North Carolina and extrapolates them nationwide.

5.1 Repeating our Quasi-Experiment Using National Data

As a first step, we confirm our results in North Carolina using national performance data from the U.S. Department of Education.[23] While our power plant data are available nationwide are so are easily adapted, the performance data only detail

[22] Total electric power generation from industrial sources using coal fell from 2.02 billion Mwh in 2007 to 1.15 billion Mwh in 2018 according to the EIA.

[23] Available at https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html.

school level proficiency rates. These proficiency rates vary substantially across states due to different testing regimes and also within-state due to changes in testing over time. To deal with this, we construct school proficiency rankings within each state-year cell and use this measure as our outcome.[24] Appendix A.1 provides a detailed description of our data sources and the construction of our national data set.

With nationwide data in hand, we alter equation (1) and run the following regression:

$$y_{s(p)t} = \alpha + \beta prod_{s(p)t} + \phi Z_{s(p)t} + \gamma_{s(p)} + \lambda_t + \epsilon_{s(p)t} \,, \quad for \, X_{s(p)t} \leq \bar{X} \,, \tag{7}$$

where $y_{s(p)t}$ is the statewide school proficiency ranking of school s that is nearest to power plant p in school year t, $prod_{s(p)t}$ represents the annual power production (in millions of Mwh) of plant p near school s during school year t, $Z_{s(p)t}$ includes time-varying school controls (e.g., student-teacher ratio, testing rate, enrollment, percent free or reduced price lunch, percent female, and percent from different ethnicity groups), and $\gamma_{s(p)}$ and λ_t are school and year fixed effects, respectively. As before, $X_{s(p)}$ denotes the distance of school s to power plant p and $\bar{X}$ is our 'radius of interest', which we set to $10km$ as in our main specification. β is our coefficient of interest and represents the effect of a one million Mwh increase in power plant production on a school's statewide proficiency ranking.

Figure 6(a) plots the relationship between increased coal-fired power production and the school's statewide proficiency ranking in math, grouping schools into $5km$ bins and reporting the results of equation (7) within those bins.[25] As in North Carolina, we observe a negative relationship between power production and performance among schools within $10km$ of the coal plant. Beyond $10km$, no such

[24] Alternatively, we could use proficiency rates directly and include state-year fixed effects. We use within-state rankings instead for two reasons: (i) state-year fixed effects are collinear with production variation in states with one power plant, and (ii) proficiency thresholds vary substantially across states and so an identical (homogeneous) effect could lead to differential proficiency rate increases in different states. Results are qualitatively similar when we employ this alternative method: we find that a one million Mwh increase in coal-fired power production decreases the percent of students scoring proficient by 0.26 (statistically significant at the five percent level).

[25] We lack precision to graph results by $2.5km$ bins as done for North Carolina.

relationship is evident. As before, we find no statistically significant relationship between power production and test scores for natural gas plants (Figure 6(b)).

Table B.6 reports the results from equation (7). We find that every one million Mwh increase in coal-fired power production decreases the statewide math proficiency rank of schools within $10km$ by 0.3-0.4 percentile ranks. For comparison, if we run regression (7) using our North Carolina data we find a point estimate of 0.42, indicating that our nationwide results are similar to those found in North Carolina. This gives us confidence that our North Carolina results can be extrapolated nationwide.

5.2 Calculating Nationwide Effect

We calculate the nationwide impact of reduced coal usage on student performance by multiplying the estimated impact of one million Mwh of coal-fired power production on student performance (-0.02σ) by the enrollment weighted change in exposure to coal-fired power generation within $10km$ of a school from 2006-07 to 2017-18. See Appendix A.2 for details on the construction of our coal-fired exposure measure.

For this calculation to be valid, several strong assumptions are required, although we believe these assumptions are conservative and so our estimated effect is a lower bound of the impact of reduced coal use on student cognition. First, we assume only students attending schools within $10km$ of a coal-fired power plant are affected, in line with results from Figure 3(a). Second, students are assumed to not be affected by coal-fired power generation in the summer months. Third, the impact of emissions from coal-fired power production is linear and homogeneous within $10km$. Fourth, the efficiency of coal-fired power plants has been constant over time, which Table B.2 indicates is conservative as coal power plant efficiency has improved from 2013 to 2018. Fifth, replacement sources of electricity do not impact student performance. As discussed previously, coal-fired power production was predominantly replaced by natural gas and we find no relationship between natural gas power production and student performance (see Figure 3(b)), providing support for this assumption.[26]

Total Effect: In the 2006-07 school year, the average student had 195,000 Mwh of coal-fired power production occurring within $10km$ of their school during the school months of September-May. By 2017-18, this number had dropped to 61,000 Mwh. Our point estimates indicate that a one million Mwh increase in coal-fired power production reduces test scores by 0.02σ. Given this, we calculate that the nationwide increase in test scores due to the decline in coal usage from 2006-07 to 2017-18 was 0.003σ (=0.02*(0.195-0.061)).

Spatial Variation: The impacts from the decline in coal use feature a high degree of spatial variation. Figure 7(a) presents our estimate of the increase in test scores from 2006-07 to 2017-18 due to the decline in coal usage by state. On one hand, Western states had extremely low levels of coal usage in 2006-07 and so the decline in coal had little effect in these states. Midwestern states, on the other hand, saw steep declines in coal usage. In the most affected state of Illinois, for instance, students' average coal-fired power production exposure dropped almost ten-fold from 800,000 Mwh in 2007 to 90,000 Mwh in 2017-18.[27] According to our calculation, the decline in coal usage increased statewide test scores in Illinois by 0.014σ.

Inequality: The decline in coal use also had substantial impacts on inequality since underprivileged students are more likely to attend schools in polluted regions (Currie, Voorheis, and Walker, 2020). For instance, we estimate that the decline in coal use reduced the nationwide black-white test score gap by 0.002σ and reduced the socioeconomic test score gap by 0.001σ.[28] The decline in these gaps also occurred within-state, with Figure 7(b) exhibiting the change in the black-white test score gap by state due to the decline in coal use.

[26] Increased renewable energy use has also supplanted coal-fired power production; it is unlikely these sources would impact student performance given that they are emissions-free.

[27] One reason for the large change in coal exposure in Illinois is the closure of three coal-fired power plants in 2010 (Fisk, Crawford, and State Line) that where near or within the city limits of Chicago.

[28] We define the socioeconomic test score gap as the difference in test scores between students who are and who are not free or reduced price eligible.

6 Conclusion

The last decade years has seen a precipitous decline in coal-fired power production, causing dramatic improvements in air quality across the United States. This paper quantifies the impact of the shift from coal-fired power production to cleaner sources such as natural gas on student performance.

To do so, we leverage three sources of variation to estimate the impact of coal-fired power plant emissions on student performance: (i) year-to-year production, (ii) wind, and (iii) plant closures. Quasi-experiments leveraging each source of variation indicate that every one million Mwh of increased coal-fired power plant production lowers student performance in schools within $10km$ by around 0.02σ. Nearly the entirety of this effect is concentrated in schools downwind from the power plant.

We find no such relationship between natural gas power production and student performance, indicating that the switch from coal to natural gas has generated substantial improvements in student achievement. Given the spatial distribution of schools and power plants across the United States combined with our estimates from North Carolina, we calculate that the drop in coal-fired power production from 2006-07 to 2017-18 led to a nationwide math test score increase of 0.003σ and reduced the black-white test score gap by 0.002σ. The boost to cognition exhibits a high degree of spatial variation, with Midwestern states receiving substantial test score boosts while western states experienced little change.

Our estimates suggest a new lever that policymakers can use to improve the perilous state of education in the United States. Even though coal use has declined in the United States, more than 40 percent of people in the U.S. still live in areas with unhealthy levels of air pollution (American Lung Association, 2019), indicating that air quality improvements or mitigation (Gilraine, 2020) can generate further educational gains. In addition, given that underprivileged children are more likely to live in polluted areas (Currie et al., 2020), policies that reduce exposure to airborne pollutants can also reduce the pervasive test score gaps in education.

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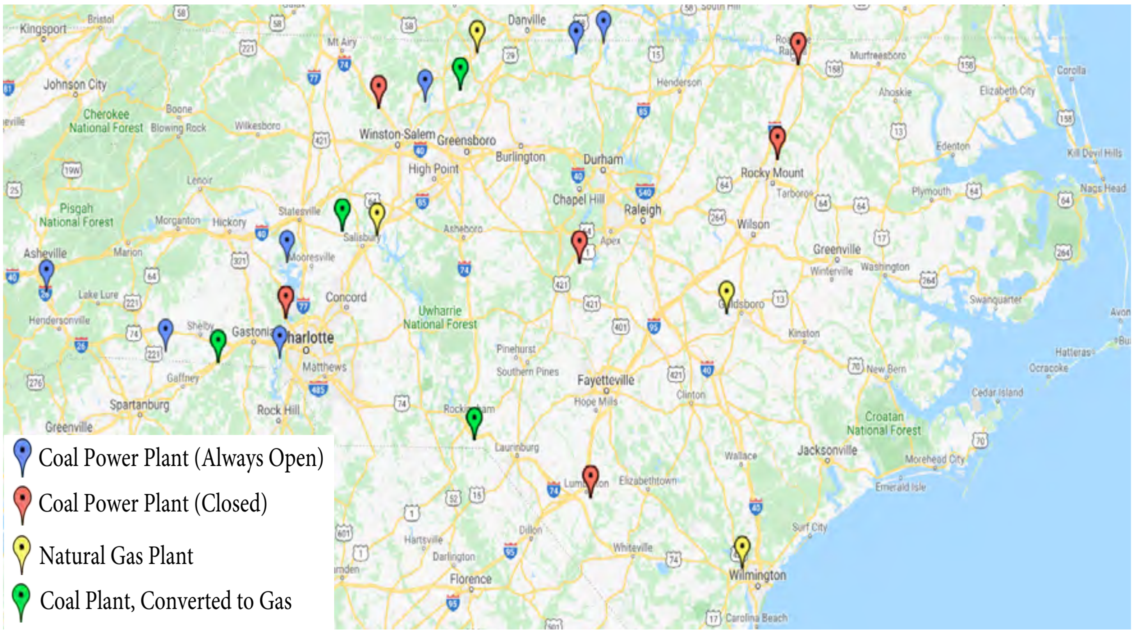
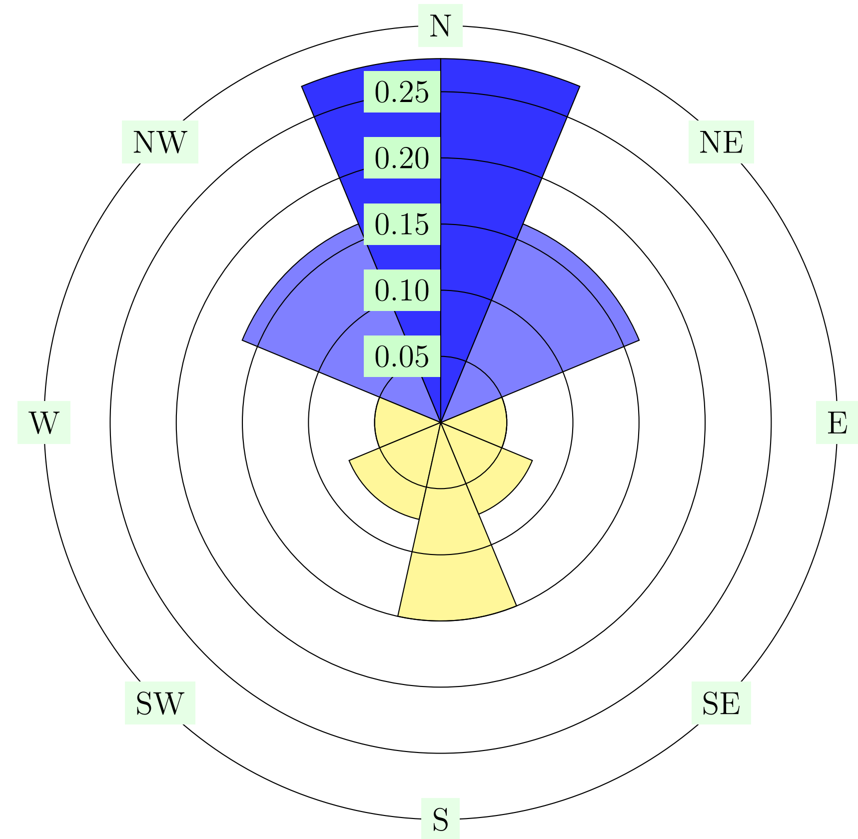
Figure 1: Large Coal and Natural Gas Plants in North Carolina 2001-2017



Notes: This figure shows the geographic location of North Carolina's twenty-one large coal and natural gas plants. Out of seventeen coal plants in our sample, four converted to natural gas (denoted by green marker) and six closed outright (denoted by the red marker). We therefore have a total of seventeen coal plants (of which six closed and four converted to natural gas) and eight natural gas plants operating over our period of interest (2001-2017). Table B.1 reports the period of operation for these plants, along with distance to the nearest wind station, production statistics, and their closure or conversion date.

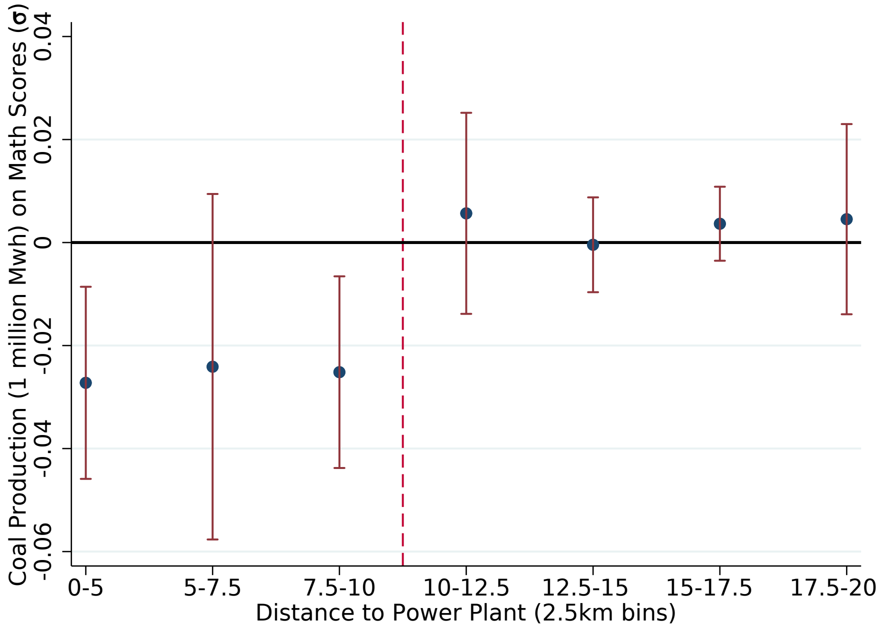
Figure 2: Constructing 'Downwind' Measure: Example



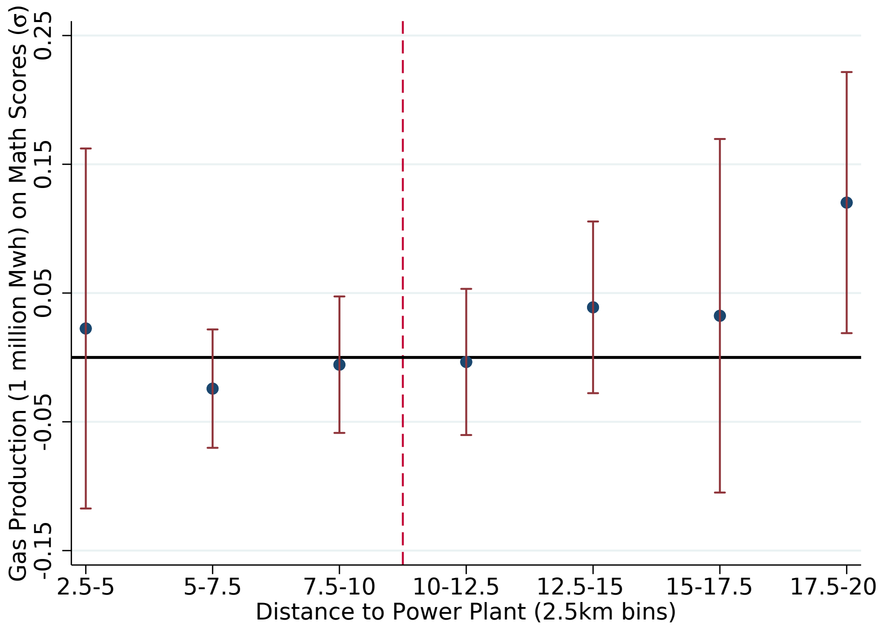
Notes: This figure provides an example of a typical wind rose in North Carolina. The circular format of the wind rose shows the direction the winds is blowing *toward* and the length of each "spoke" around the circle shows the proportion of time the wind blows toward that particular direction during school hours. For instance, the dark blue 'spoke' indicates that the wind blows towards the North 27.5 percent of the time. The 'downwind' measure for a school located North of the power plant incorporates all three spokes colored blue (N, NW, NE), with the lighter blue spokes (NW, NE) being given half weight. The school's 'downwind' measure is thus 0.4375 ($= 0.275 + \frac{1}{2}0.1625 + \frac{1}{2}0.1625$), which is relatively high. Likewise, a school located to the East of the power plant has a relatively low 'downwind' measure of only 0.16875 ($= 0.05 + \frac{1}{2}0.1625 + \frac{1}{2}0.075$).

Figure 3: Effect of Power Production on Student Math Scores by Distance and Source

(a) Coal-Fired Power Production



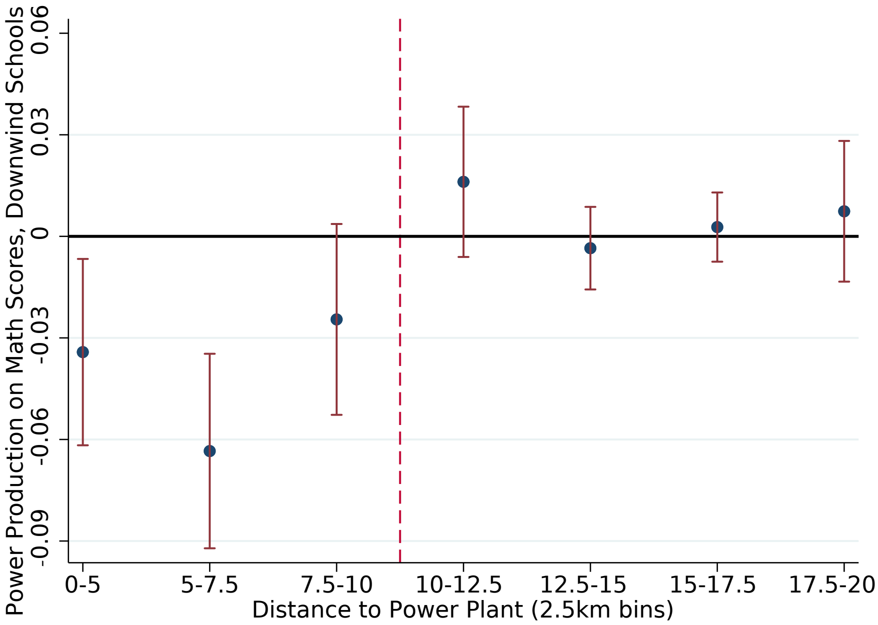
(b) Natural Gas Fired Power Production



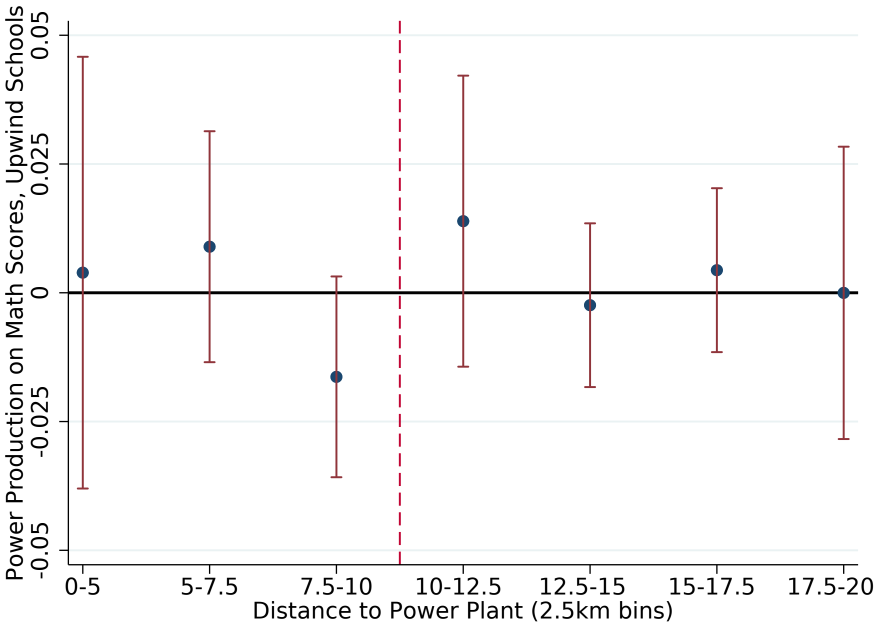
Notes: These figures use year-to-year power plant production variation to look at the effect of power production on test scores by estimating equation (1) for different distance bins and by fuel type. Effect sizes are in terms of standard deviations of the student test score distribution. Each point represents the result of a separate regression of equation (1) and includes controls for demographics and student, school, and grade-year fixed effects. Given these controls, the figures mimic the results from column (2) of Table 2. The two bins less than $5km$ are combined as there are few observations within 2.5km of a power plant. The solid horizontal line denotes a point estimate of zero while the vertical dashed line delineates observations closer to 10 kilometers from the power plant, which are the observations used in the main analysis. The whiskers represent 90 percent confidence intervals with standard errors clustered at the school level.

Figure 4: Effect of Coal-Fired Power Production on Student Math Scores by Distance and whether School is 'Downwind' or 'Upwind' of Power Plant

(b) 'Downwind' from Coal-Fired Power Plant



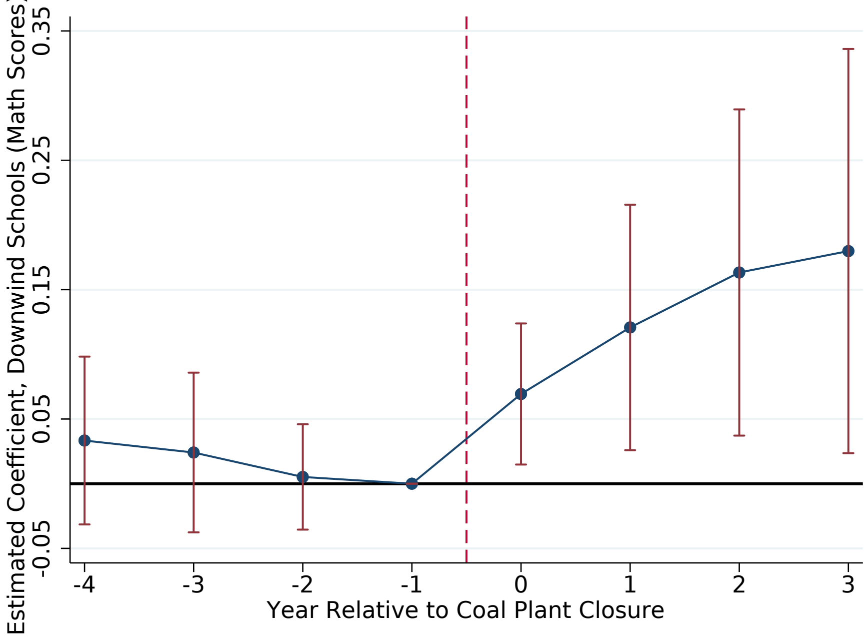
(b) 'Upwind' from Coal-Fired Power Plant



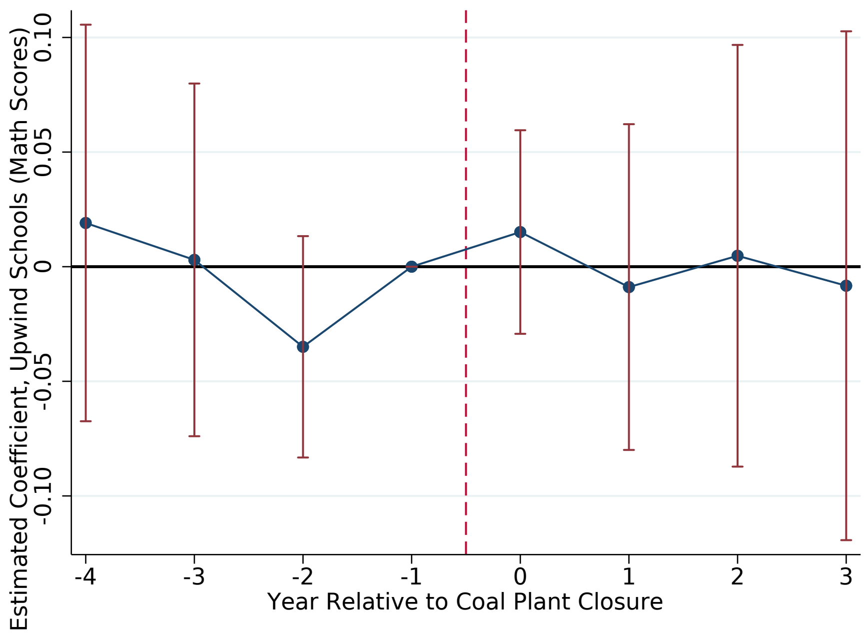
Notes: Figures estimate the effect of coal-fired power production on student performance by estimating equation (1) for different distance bins. Results are subdivided by whether the school is 'downwind' (Panel A) or 'upwind' (Panel B) of the coal-fired plant. 'Downwind' status is defined as facing above median wind, while 'upwind' schools face below median wind levels according to our downwind measure (see equation (6)) with the sample split occurring at the school level so that there are an equal number of schools in both panels for each distance bin. Effect sizes are in terms of standard deviations of the student test score distribution. Each point represents the result of a separate regression of equation (1) and includes controls for student demographics and student, school, and grade-year fixed effects. Given these controls, the figures mimic the results from column (2) of Table 3. The two bins less than $5km$ are combined as there are few observations within 2.5km of a power plant. The solid horizontal line denotes a point estimate of zero while the vertical dashed line delineates observations closer to 10 kilometers from the power plant, which are the observations used in the main analysis. The whiskers represent 90 percent confidence intervals with standard errors clustered at the school level.

FIGURE 5: Event-Study Estimates of the Effects of Coal Plant Closures on Students' Test Scores by Downwind and Upwind Status

(a) 'Downwind' from Coal-Fired Power Plant



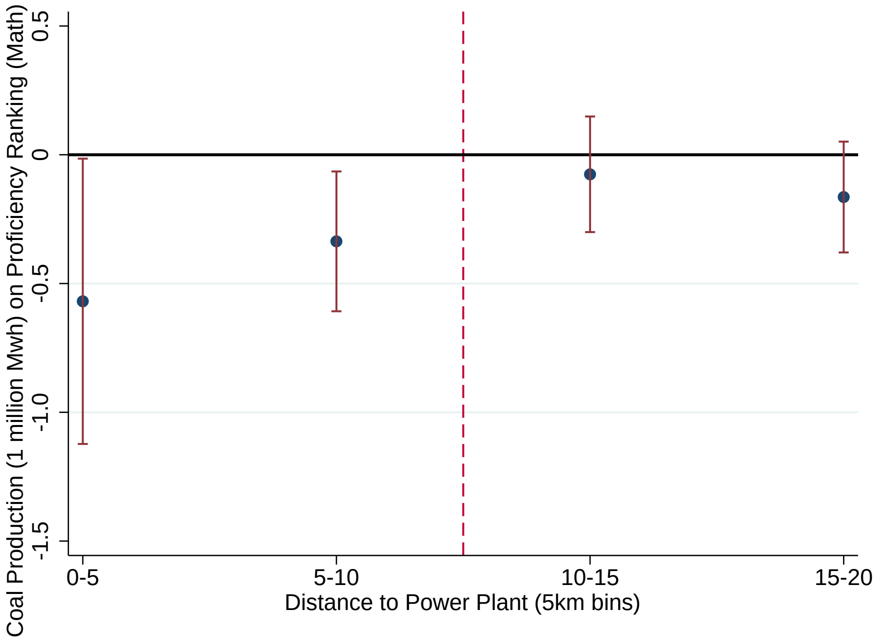
(b) 'Upwind' from Coal-Fired Power Plant



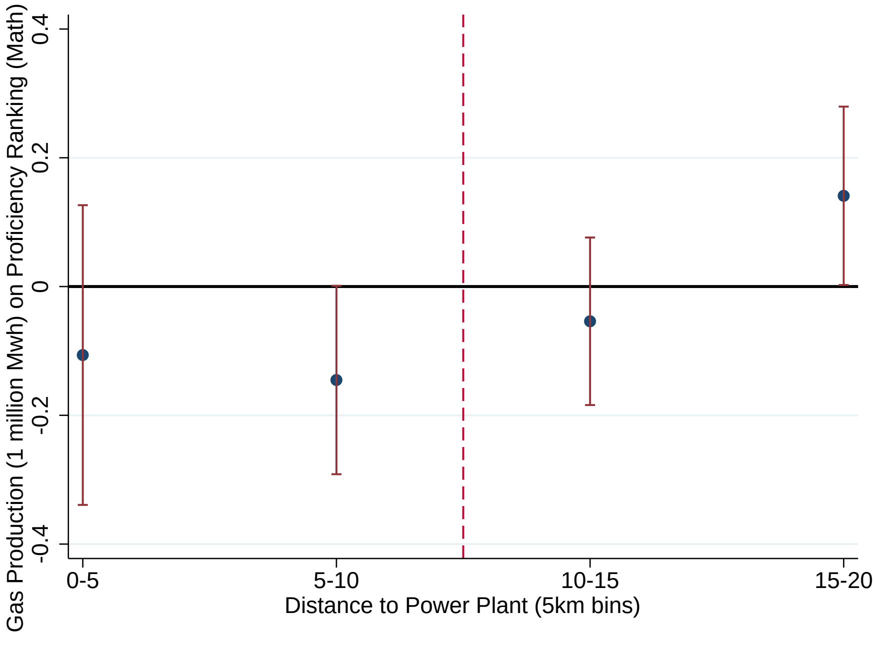
Notes: The above figures plot estimates from equation (4) and show the evolution of student performance in the years leading up to and after the plant closure. Results are subdivided by whether the school is 'downwind' (Panel A) or 'upwind' (Panel B) of the coal-fired plant. 'Downwind' status is defined as facing above median wind, while 'upwind' schools face below median wind levels according to our downwind measure (see equation (6)) with the sample split occurring at the school level so that there are an equal number of schools in both panels. Regressions include controls for student demographics and student, school, and grade-year fixed effects. Given these controls, the figures mimic the results from column (2) of Table 4. The solid horizontal line denotes a point estimate of zero while the vertical dashed line delineates the periods before and after the coal-fired power plant closed. The whiskers represent 90 percent confidence intervals with standard errors clustered at the school level.

FIGURE 6: Effect of Power Production on Math Proficiency by Distance and Source: **National** Data

(a) Coal-Fired Power Production



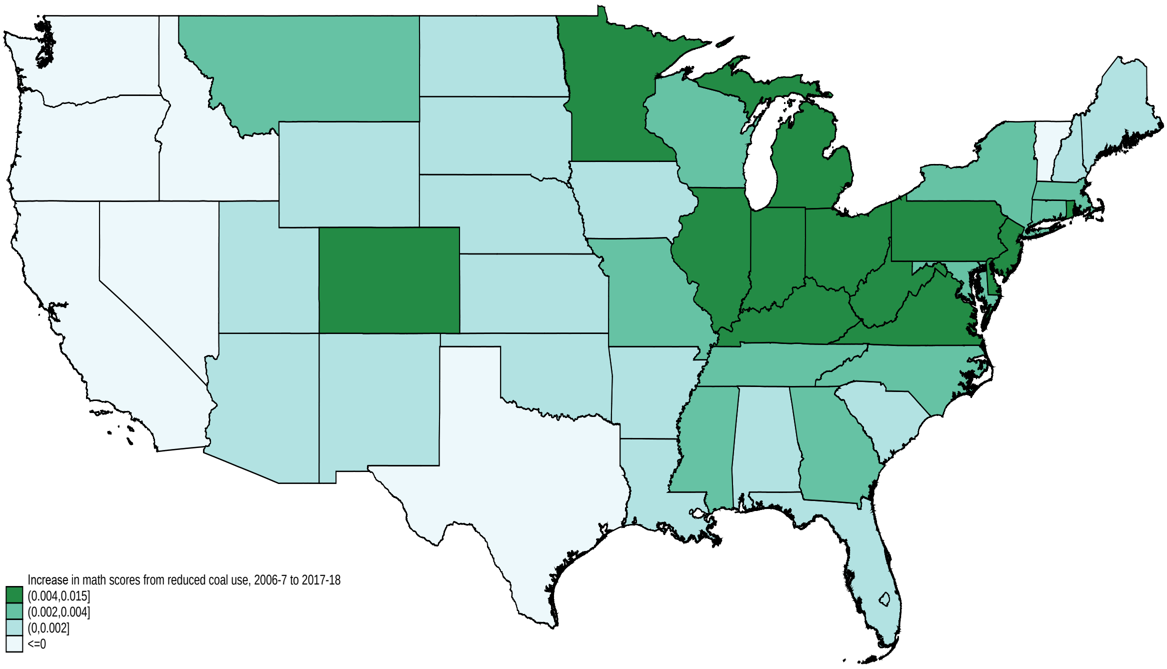
(b) Natural Gas Fired Power Production



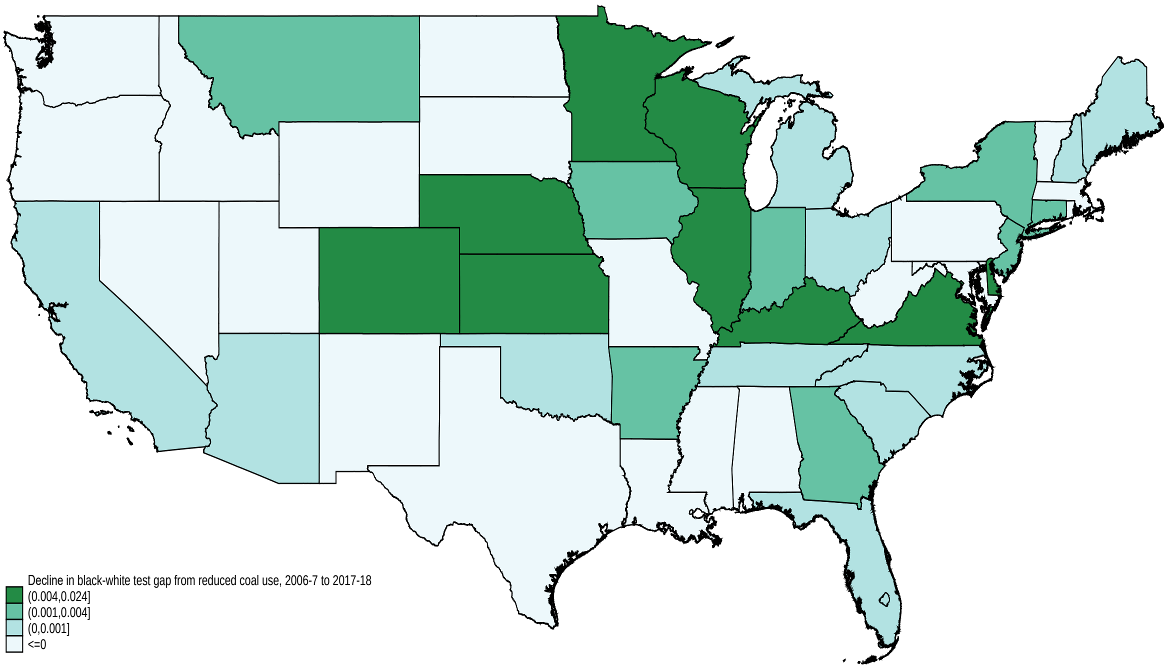
Notes: These figures use year-to-year power plant production variation to look at the effect of power production on test scores by estimating equation equation (7) which identifies the effect of a one million megawatt hour (Mwh) increase in power production on student performance using the nationwide data (see Appendix A.1). The outcome variable is defined as the school's ranking based on their school wide proficiency rate in their state. Each point represents the result of a separate regression of equation (7) and includes controls for lag state proficiency rank, school demographics, and school and year fixed effects. Given these controls, the figures mimic the results from column (3) of Table B.6. The solid horizontal line denotes a point estimate of zero while the vertical dashed line delineates observations closer to 10 kilometers from the power plant, which are the observations used in the main analysis. The whiskers represent 90 percent confidence intervals with standard errors clustered at the school level.

Figure 7: Spatial Variation in Impact of Reduced Coal Use from 2006-07 to 2017-18

(a) Aggregate Achievement (Math)



(b) Black-White Test Score Gap (Math)



Notes: These figures show spatial variation in the nationwide impact of reduced coal usage from 2006-07 through 2017-18. Figure 7(a) shows the aggregate improvement in student achievement by state, while Figure 7(b) shows the decline in the black-white test score gap by state. Effect sizes are in terms of standard deviations of the student test score distribution. We determine aggregate effects by calculating the average enrollment-weighted change in coal-fired power production within $10km$ of schools from 2006-07 to 2017-18 and multiply that number by our estimated effect of 0.02σ. For the black-white test score gap, we similarly calculate the average enrollment-weighted change in coal-fired power production within $10km$ of schools for black students relative to white students from 2006-07 to 2017-18 and multiply that number by our estimated effect of 0.02σ. Alaska and Hawaii are excluded for visual clarity.

Table 1. Summary Statistics

	Full Sample[1] (1)	Within 10 km of Coal Plant (2)	Within 10 km of Gas Plant (3)	Event Study Sample (4)
Mean of Student Characteristics				
Math Score (σ)	0.00	-0.01	-0.28	-0.22
Reading Score (σ)	0.00	-0.03	-0.25	-0.21
Lagged Math Score (σ)[2]	0.02	0.01	-0.25	-0.19
Lagged Reading Score (σ)[2]	0.02	0.00	-0.23	-0.18
% White	54.6	55.7	49.3	44.7
% Black	27.6	30.4	34.0	39.8
% Hispanic	10.8	7.3	10.3	7.9
% Asian	2.5	2.3	0.8	1.5
% Free or Reduced Price Lunch	47.9	46.8	64.0	59.5
% English Learners	4.4	3.2	3.2	3.7
% with Disability	9.7	7.0	12.4	9.5
% Gifted	15.4	13.5	13.7	9.6
% Repeating Grade	1.0	1.1	0.8	1.2
Distance to Power Plant (km)	36.8	6.8	6.2	6.7
Downwind Measure	0.24	0.24	0.25	0.24
# of Plants	21	17	8	10
# of Students	2,509,400	178,065	31,606	78,251
Observations (student-year)	9,247,841	469,095	72,335	191,965

[1] Data coverage: grades 3-8 from 2000-01 through 2016-17. Third grade lagged test scores are not available after 2008-09 (inclusive) due to the end of the grade 3 pre-test nor during 2005-06 (math) and 2007-08 (English). Grade-years lacking lagged own subject test scores are dropped. Summary statistics are reported for the math sample.

[2] Lagged test scores are generally missing for about ten percent of the sample.

Table 2. Effect of Power Production Using Production Variation by Plant Type

	Math Scores (σ)			English Scores (σ)		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Coal-fired Plants						
Production	-0.021***	-0.021***	-0.019**	-0.008*	-0.009**	-0.009**
(1 million Mwh)	(0.009)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)
Observations	469,095	469,095	434,602	466,947	466,947	433,020
# of Students	178,065	178,065	162,923	177,067	177,067	161,942
B. Natural Gas Plants						
Production	0.012	0.007	0.006	0.000	-0.008	-0.007
(1 million Mwh)	(0.016)	(0.015)	(0.019)	(0.008)	(0.008)	(0.006)
Observations	72,335	72,335	68,479	72,266	72,266	68,305
# of Students	31,606	31,606	29,694	31,584	31,584	29,654
Demographics Controls	No	Yes	Yes	No	Yes	Yes
Lagged Test Scores	No	No	Yes	No	No	Yes

Notes: This table reports estimates from equation (1) which identifies the effect of a one million megawatt hour (Mwh) increase in power production on student performance. Panel A reports estimates for schools nearby a coal-fired power plant, while Panel B does so for schools neighboring a natural gas power plant. The sample is restricted to schools within $10km$ of a power plant and to years that the power plant was in operation. Table B.1 reports the power plants used in the analysis by type and their period of operation. Effect sizes are in terms of standard deviations of the student test score distribution. Each cell represents the result of a separate regression of equation (1) and includes student, school, and grade-year fixed effects. 'Demographic controls' include student level demographics and mean demographics at the school-grade level and include: ethnicity, gender, free or reduced price meal status, disability status, gifted status, English learner status, and grade repeating status. Missing indicators are used for students with missing demographics. 'Lagged test scores' consist of a cubic polynomial in prior lagged math and reading scores interacted with grade dummies along with average lagged school-grade test scores. Students with missing lagged own-subject scores are dropped while a missing indicator is used for those missing a lagged other subject score. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3. Effect of **Coal** Power Plant Production Using Production and Wind Variation

	Math Scores (σ)			*English Scores (σ)*		
	(1)	(2)	(3)	(4)	(5)	(6)
A. 'Downwind' from Coal-fired Plant						
Production	-0.033***	-0.033**	-0.033***	-0.009	-0.009	-0.011*
(1 million Mwh)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)
B. 'Upwind' from Coal-fired Plant						
Production	-0.004	-0.004	-0.002	-0.005	-0.006	-0.006
(1 million Mwh)	(0.012)	(0.012)	(0.012)	(0.005)	(0.005)	(0.005)
C. Continuous Wind Measure						
Production	-0.030**	-0.031**	-0.030**	-0.018**	-0.020**	-0.021**
$*$downwind÷0.15	(0.014)	(0.014)	(0.014)	(0.008)	(0.009)	(0.009)
Demographics Controls	No	Yes	Yes	No	Yes	Yes
Lagged Test Scores	No	No	Yes	No	No	Yes
Observations	469,095	469,095	434,602	466,947	466,947	433,020
# of Students	178,065	178,065	162,923	177,067	177,067	161,942

Notes: Panels A and B contrast the effect of increased coal-fired power production for schools that are 'downwind' relative to 'upwind' of the coal-fired power plant according to our downwind measure (see equation (6)). Specifically, Panel A estimates equation (1) for 'downwind' schools facing above median wind, while Panel B does so for 'upwind' schools with below median wind levels. Splitting the sample into 'downwind' and 'upwind' schools is done at the school level so that there are an equal number of schools in both panels. Panel C reports results from equation (2) which uses year-to-year variation in coal-fired power production along with across school variation in our continuous wind measure. We divide our continuous wind measure by 0.15 to make our estimates comparable to the contrast between Panel A and B as, on average, our wind measure is about 0.15 units higher for 'downwind' schools relative to 'upwind' schools. Effect sizes in Panels A and B report the change in standardized test scores for a one million megawatt hour (Mwh) increase in power production. Given the additional differencing layer, Panel C reports the change in standardized test scores for a one million megawatt hour (Mwh) increase in power production *combined* with a 0.15 unit increase in our wind measure. The sample is restricted to schools within 10km of a power plant and to years that the power plant was in operation (as a coal plant). Table B.1 reports the power plants and their period of operation. Each cell represents the result of a separate regression and includes student, school, and grade-year fixed effects. 'Demographic controls' include student level demographics and mean demographics at the school-grade level and include: ethnicity, gender, free or reduced price meal status, disability status, gifted status, English learner status, and grade repeating status. Missing indicators are used for students with missing demographics. 'Lagged test scores' consist of a cubic polynomial in prior lagged math and reading scores interacted with grade dummies along with average lagged school-grade test scores. Students with missing lagged own-subject scores are dropped while a missing indicator is used for those missing a lagged other subject score. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.

TABLE 4. Event-Study of Coal-Fired Plant Closures

	Math Scores (σ)			*English Scores (σ)*		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Event-Study						
post	0.065***	0.060***	0.048**	0.056***	0.055***	0.061***
	(0.022)	(0.021)	(0.021)	(0.016)	(0.016)	(0.015)
B. 'Downwind' from Coal-fired Plant						
post	0.093***	0.090**	0.103***	0.076**	0.069**	0.081**
	(0.035)	(0.035)	(0.036)	(0.033)	(0.034)	(0.032)
C. 'Upwind' from Coal-fired Plant						
post	0.031	0.031	0.016	0.038*	0.041**	0.052***
	(0.028)	(0.027)	(0.022)	(0.022)	(0.020)	(0.018)
Demographics Controls	No	Yes	Yes	No	Yes	Yes
Lagged Test Scores	No	No	Yes	No	No	Yes
Observations	191,965	191,965	159,200	191,338	191,338	158,741
# of Students	78,251	78,251	66,879	78,202	78,202	66,648

Notes: Panel A estimates results from the event study quasi-experiment defined by equation (3). The event-study utilizes ten coal plant closures and conversions; the names of these plants along with the date of the event are reported in Table B.1. Panels B and C estimate results from the event study quasi-experiment defined by equation (3) for schools that are 'downwind' relative to 'upwind' of the coal-fired power plant. Specifically, Panels B and C estimate equation (3) for 'downwind' schools facing above median wind and 'upwind' schools with below median wind levels according to our downwind measure (see equation 6). Splitting the sample into 'downwind' and 'upwind' is done at the school level so that there are an equal number of schools in both panels. The sample is restricted to schools within 10km of one of the ten power plants that closed or converted to natural gas during our period of study (2001-2017). Each cell represents the result of a separate regression of equation and includes student, school, and grade-year fixed effects. 'Demographic controls' include student level demographics and mean demographics at the school-grade level and include: ethnicity, gender, free or reduced price meal status, disability status, gifted status, English learner status, and grade repeating status. Missing indicators are used for students with missing demographics. 'Lagged test scores' consist of a cubic polynomial in prior lagged math and reading scores interacted with grade dummies along with average lagged school-grade test scores. Students with missing lagged own-subject scores are dropped while a missing indicator is used for those missing a lagged other subject score. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.

A Nationwide Analysis

Our nationwide analysis supplements our North Carolina study by extending our design to utilize nationwide performance data on school proficiency rates. Here, we detail the data construction for our nationwide sample.

A.1 Data

School Performance Data: For performance data with nationwide coverage we draw on school level proficiency data reported by the U.S. Department of Education.[29] These data report mathematics and English proficiency rates on the state assessment by school from 2009-10 through 2017-18 and are (to the authors' knowledge) the only school level performance data with national coverage.[30] Proficiency rates vary substantially across states with math proficiency rates ranging from thirty percent in New Mexico to almost eighty percent in Iowa. Given that each state uses a different test, these differential proficiency rates for the most part capture differences in the difficulty of each state's standardized test rather than differences in student performance across states. Furthermore, state proficiency rates vary substantially within states across time due to changes in statewide testing regimes. Notably, many states adopted Common Core standards during this time period, often causing large declines in statewide proficiency rates. While school fixed effects (which subsume state fixed effects) account for across state differences in test difficulty, we deal with within-state changes in testing regimes by constructing school proficiency rankings within each state-year cell. State proficiency rankings have the benefit of being relatively consistent under different testing regimes, allowing us to utilize within state-year variation even for states with one power plant (which is not the case if we include state-year fixed effects).

Data report school level proficiency rates, although for privacy reasons restrict

[29]Available at https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html.

[30]While the Stanford Education Data Archive contain school level performance data, these data are not disaggregated by year which is required to use the time variation inherent in our empirical strategy.

reporting to schools with more than five students and 'blur' the proficiency rates for schools up to three-hundred students by reporting achievement ranges (e.g., 5-10 percent proficient). When achievement ranges are reported, the midpoint of the achievement range is assigned as the school level proficiency rate (e.g., 5-10 percent proficient is assigned as 7.5 percent proficient). The data also separates out the number of test takers by grade, with high school state standardized tests reported as a separate category. High school testing differs substantially from testing in lower grades due to the fact that students can select different high school exams (e.g., 'Foundations of Math' rather than 'Algebra II') whereas all students generally must take the same exam in third through eighth grade. We therefore create a separate statewide proficiency ranking for high schools and omit schools that serve both elementary and high school students (e.g., K-12 schools). Our results (available upon request) are similar if high schools are dropped or K-12 schools are included.[31]

School Demographic Data: School demographic data from 2009-10 through 2017-18 is collected from the National Center for Education Statistics (NCES).[32] Data is collected on: enrollment, ethnicity, gender, free or reduced price lunch status, and the ratio of students to full time equivalent teachers. These data allow us to construct the following school year level controls: enrollment, percent of students that are male, percent belonging to a given ethnicity group (e.g., African-American, Asian, Hispanic, and White), percent eligible for free or reduced price lunch, and the student-teacher ratio. We also use the number of test takers from the performance data to calculate school level test-taking rates. This data is then merged to the school performance data using the NCES school id, with 98.3 percent of schools with performance data being matched to the student demographics data.

Power Plant Data: As in our North Carolina analysis, data on national power plant locations and production are drawn from the EIA Monthly Generation and Fuel Consumption Time Series File (EIA-923) for 2009 through 2018. We mimic

[31]Three-quarters of the schools in our data are elementary and middle schools that have no high school tests conducted. Fifteen percent of our schools are high schools and the remaining ten percent are schools that have both middle school and high school grades (e.g., K-12 schools).

[32]Available at https://nces.ed.gov/ccd/.

the restrictions we used for North Carolina whereby we only include plants with average power production levels using fossil fuels of over 250,000 megawatts-hour (Mwh) during the academic year over their period of operation. Once again, we match the monthly power production to the academic year by summing power production generated from September to May for each plant by fuel type.

The national data requires some additional data cleaning relative to our North Carolina analysis. First, unique plants in the EIA data are sometimes on the same industrial site as another plant. We combine these plants together by manually investigating all power plants withing $3km$ of each other and assigning them an identical plant identifier if there are no residential areas between them. Second, the national data includes power plants with significant power production from oil or biomass fuels, which we code as a third plant type in addition to our coal and natural gas plants. Third, several power plants produce electricity using both coal and natural gas. In our main results, we assign the plant type using the predominant fossil fuel, although we also drop these combined fuel source plants in column (4) of Table B.6. Fourth, power plants can sometimes be in close proximity to each other making it difficult to attribute the effect of increased power production to a single plant. We drop these cases in column (5) of Table B.6. Schools are then matched to the nearest power plant according to physical distance,[33] which creates our main analysis sample of 88,626 schools matched to 922 power plants.

Summary Statistics: Table B.5 reports summary statistics from our nationwide sample. Column (1) shows the summary statistics for schools across the nation, with column (2) restricting the data to schools within $10km$ of a coal power plant. Compared to the nation at large, schools near coal power plants perform worse and have students that come from a more disadvantaged background. Column (3) reports the data for schools within $10km$ of a natural gas plant; these schools are somewhat higher performing and feature substantially more Hispanic students rel-

[33]We calculate the distance to five closest power plants so that we can make the appropriate sample restrictions to exclude schools that are near two power plants that have substantial fossil fuel power production in the same school year.

ative to the coal plant sample. Differences between the coal and gas plant samples are likely driven by the geographic location of plants: coal plants dominate in the Midwest, for instance, where there are relatively few Hispanic students.

A.2 Calculating Nationwide Effect

To calculate the national impact of reduced coal usage on student performance we multiply the estimated impact of one million Mwh of coal-fired power production on student performance (-0.02σ) by the enrollment weighted change in exposure to coal-fired power generation within $10km$ of a school from 2006-07 to 2017-18. We construct the change in coal-fired production exposure by once again drawing on national power plant production from the EIA Monthly Generation and Fuel Consumption Time Series File (EIA-923 for the 2017-18 data, EIA-906/920 for the 2006-2007 data). This time, we do not restrict attention only to plants with production above $250,000$ Mwh during the school year. Instead, we consider all coal producing plants in the United States, summing September to May power production by plant to obtain overall academic year production. Plant location data is then drawn from the EIA-860 generator information series. We match each plant operating in the 2017-2018 academic year to the 2018 location data, and match each plant operating in the 2006-07 academic year to the 2012 location data, which is the earliest available. For plants operating in 2006-07 which are not included in the 2012 location data, we obtain their locations from the United States Environmental Protection Agency (EPA) 2007 Emissions and Generation Resource Integrated Database (eGRID).[34] The final sample contains 665 plants in 2006-07 and 390 plants in 2017-18. There are 363 plants which are operational in both time periods.

We then combine our national plant-level coal production data with school-level data from the National Center for Education Statistics (NCES) Elementary

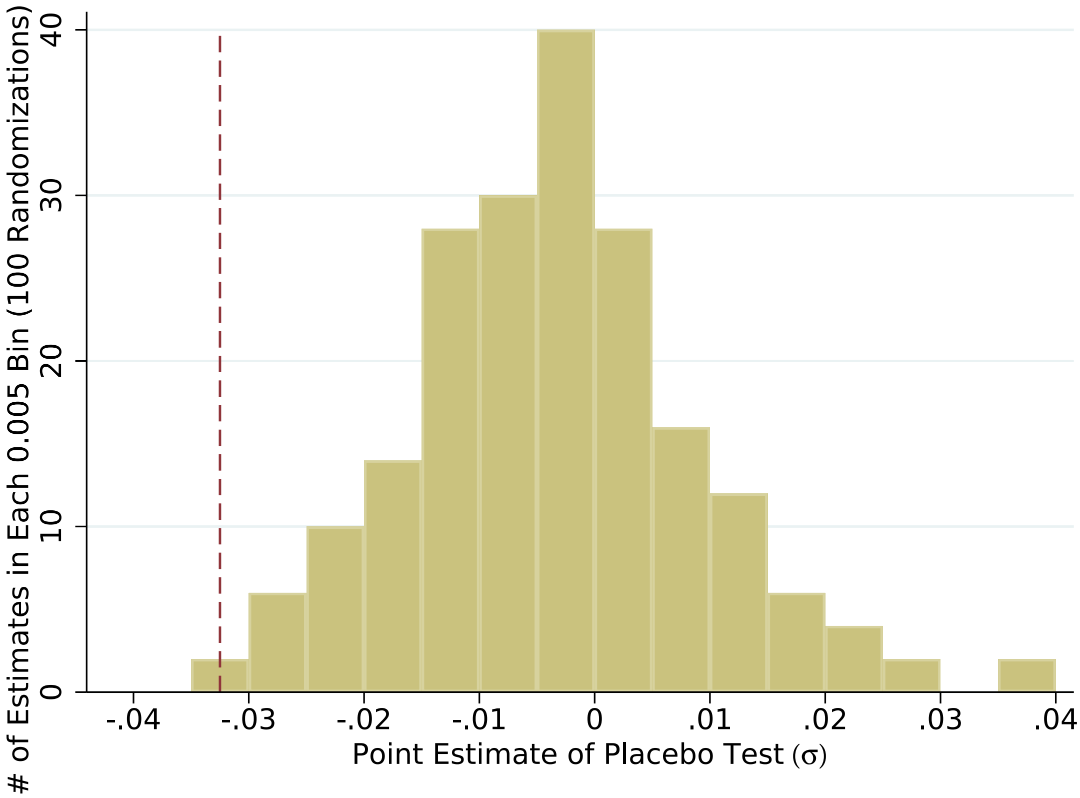
[34] Available at https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid.

and Secondary Information System (ELSI)[35] for the 2006-07 and 2017-18 academic years, which itself comes from the Department of Education's Common Core of Data survey. For each public school in the United States, our data contains a school name, state, latitude and longitude, as well as total enrollments broken down by race and reduced price/free lunch eligibility. The final sample contains $94,164$ schools in 2006-07 and $95,256$ schools in 2017-18. There are $80,328$ schools which had positive enrolments in both 2006-07 and 2017-18. Each school is matched to all coal plants within a 10 kilometer radius separately in each academic year. This allows us to sum the total coal production of all plants within these radii, identifying the total Mwh generated in the vicinity of each school, which we code in increments of one million Mwh. National or state averages, weighted by total or subgroup-specific enrollment, of coal production within a school's vicinity are then calculated. Subtracting the 2017-18 values from those obtained in 2006-07 gives us the enrollment weighted change in exposure to coal-fired power generation within $10km$ of a school from 2006-07 to 2017-18.

[35] Available at `https://nces.ed.gov/ccd/elsi/tableGenerator.aspx`.

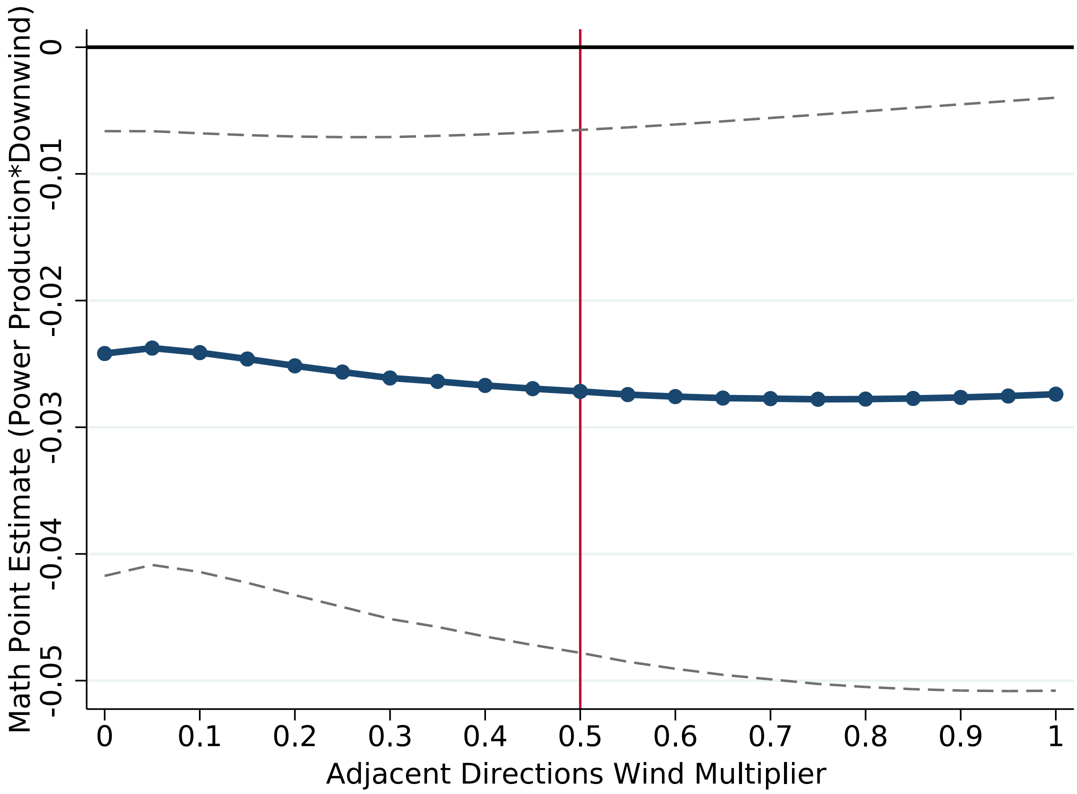
B Appendix Figures and Tables

Figure B.1: Placebo Test



Notes: This figure reports the results of a placebo test where we estimate equation (2) (using standardized math scores as the outcome) but randomly assign the power production of a coal-fired plant that of a different coal-fired plant. This is done to alleviate concerns that power plants may jointly reduce production due to a statewide shock (e.g., the Great Recession) that happens to differently affect students living downwind relative to upwind of power plants. The sample is restricted to schools within $10km$ of a power plant and to years that the power plant was in operation (as a coal plant). Table B.1 reports the power plants and their period of operation. The placebo test is run 100 times, with the point estimates for each placebo placed in bins of 0.005σ. The x-axis denotes these 0.005σ bins while the y-axis indicates the number of placebo tests with a point estimate falling in that bin. Regressions include controls for student demographics and student, school, and grade-year fixed effects and our continuous wind measure is divided by 0.15 to make our estimates comparable to those reported in column (2) of Panel C in Table 3. The dashed vertical line represents the point estimate of -0.031σ found in column (2) of Panel C Table 3.

Figure B.2: Robustness to Wind Measure



Notes: This figure reports results from equation (2) which uses year-to-year variation in coal-fired power production along with across school variation in our continuous wind measure when different weights are given to adjacent wind directions in the calculation of our downwind measure (see equation (6)). Specifically, the x-axis indicates the weight given to adjacent wind directions, with zero denoting no weight and one denoting equal weight. The continuous wind measure is divided by the difference between the downwind measure in 'downwind' schools relative to 'upwind' schools (split by above or below median according to the downwind measure) to keep point estimates consistent for the various 'downwind' definitions. The sample is restricted to schools within $10km$ of a power plant and to years that the power plant was in operation (as a coal plant). Table B.1 reports the power plants and their period of operation. Regressions include controls for student demographics and student, school, and grade-year fixed effects. The point estimate when adjacent wind directions are given half weight – denoted by the vertical line – effectively reports the same estimate as that reported in column (2) of panel C in Table 3, although it is slightly smaller as the difference between 'upwind' and 'downwind' schools is 0.13 rather than the 0.15 unit difference used to scale point estimates in Table 3.

Table B.1. Large Coal and Gas Power Plants in North Carolina

Plant Name (PlantID)	Fuel Type	Dates of Operation	(Lat, Lon)	Mean Production [Min-Max]	Km to Wind Station	Closure/Conversion Notes
Asheville Energy Plant (2706)	Coal	All years	(35.4731, -82.5417)	1,407,923 [883,586-1,824,702]	4.6	N/A
Cape Fear (2708)	Coal	2000-01 to 2010-11	(35.595, -79.0495)	1,271,130 [616,218-1,497,818]	4.9	Officially retired in October 2012, but retired 2 (of 4) coal-fired units in 2011 leading to a major decline in coal-fired energy production. Given 2011-12 production was less than one-quarter of that in 2010-11, 2011-12 is coded as first post-closure academic year.
H.F. Lee (2709)	Coal/Gas (Converted)	Coal: 2000-01 to 2011-12 Gas: 2012-13 to 2016-17	(35.3799, -78.0878)	Coal: 1,246,328 [702,694-1,566,722] Gas: 4,406,655 [2,736,551-5,100,208]	11.8	Retired all coal-fired units in September 2012 and so 2012-13 is coded as first post-closure academic year. Replaced by gas-fired combined cycle plant which started production in December 2012.
Roxboro (2712)	Coal	All years	(36.4833, -79.0731)	9,130,228 [3,520,377-11,632,098]	23.4	N/A
LV Sutton (2713)	Coal/Gas (Converted)	Coal: 2000-01 to 2012-13 Gas: 2013-14 to 2016-17	(34.2831, -77.9853)	Coal: 1,676,127 [754,695-2,368,378] Gas: 2,893,843 [2,006,652-3,311,531]	8.0	Coal-fired units were retired in November 2013 and so 2013-14 is coded as first post-closure academic year. Replaced by gas-fired combined-cycle plant that came online in late-2013.
W.H. Weather-spoon (2716)	Coal	2000-01 to 2010-11	(34.5875, -78.9755)	439,230 [218,852-648,041]	8.0	Plant retired in September 2011 and so 2011-12 is coded as first post-closure academic year.
GG Allen (2718)	Coal	All years	(35.1897, -81.0122)	2,946,652 [336,182-5,537,831]	6.4	N/A

Buck (2720)	Coal/Gas (Converted)	Coal: 2000-01 to 2010-11 Gas: 2011-12 to 2016-17	(35.7133, -80.3767)	Coal: 916,882 [383,752-1,418,080] Gas: 3,048,455 [1,717,465-3,711,169]	10.0	Officially retired April 2013, but 2 (of 4) coal-fired units were retired in mid-2011. Plant experienced a severe decline in production in 2009 (>75%) and its production levels never recovered. Given that, 2008-09 is coded as first post-closure academic year. Replaced by gas-fired combined-cycle plant that started production in 2011-12.
Cliffside (2721)	Coal	All years	(35.22, -81.7594)	2,546,192 [916,173-4,101,390]	14.9	N/A
Dan River (2723)	Coal/Gas (Converted)	Coal: 2000-01 to 2007-08 Gas: 2012-13 to 2016-17	(36.4862, -79.7208)	Coal: 460,957 [251,109-928,976] Gas: 2,873,443 [1,778,531-3,650,357]	12.9	Coal-fired plant officially retired on April 1, 2012, but major production effectively ceased after 2007-08 with production levels in 2008-09 being below 200,000Mwh, less than one-fifth 2007-08 production. 2008-09 is thus coded as first post-closure year. Natural gas plant opened in December 2012.
Marshall (2727)	Coal	All years	(35.5975, -80.9658)	8,429,976 [4,942,812-11,637,477]	18.6	N/A
Riverbend (2732)	Coal	2000-01 to 2010-11	(35.36, -80.9742)	1,074,186 [420,822-1,795,004]	15.2	Although officially retired on April 1, 2013, major power production ended on October 2012 with the retirement of four turbines in October 2012 with production in 2011-12 being below 40,000Mwh. Given this, 2011-12 is coded as the first post-closure year.
Mayo (6250)	Coal	All years	(36.5278, -78.8917)	2,599,171 [1,036,881-3,526,635]	28.2	N/A
Richmond/Smith Energy (7805)	Gas	2001-02 to 2016-17	(34.8392, -79.7406)	3,407,601 [287,921-8,753,174]	6.0	Began operation late-2001, and had a large expansion in late-2011.

Rowan (7826)	Gas	2003-04 to 2016-17	(35.7314, -80.6019)	1,245,976 [78,189-3,013,099]	12.0	Main energy production started in 2003-04 (although there had been a small amount of since 2001). Large expansion in 2008-09.
Belews Creek (8042)	Coal	All years	(36.2811, -80.0603)	9,715,447 [5,503,389-11,990,858]	21.9	N/A
Edgecombe Genco (10384)	Coal	2000-01 to 2010-11	(36.0373, -77.7533)	513,661 [339,506,693,125]	21.7	Continued producing some electricity until 2014-15, but production in 2011-12 fell by over two-thirds to below 140,000Mwh. 2011-12 is therefore coded as first post-closure year.
RJ Reynolds Tobaccoville (50221)	Coal	2000-01 to 2002-03	(36.2521, -80.3638)	201,242 [118,498-264,569]	18.3	Closed on March 1, 2004. 2003-04 is coded as first post-closure year as production for 2004-05 school year fell by over fifty percent (and production ceased in March of that year).
Roanoke Valley I (54035)	Coal	2000-01 to 2013-14	(36.4364, -77.6167)	1,122,406 [675,799-1,312,637]	11.9	Closed in 2017, but effectively ended major production in 2014, with 2014-15 production almost one-tenth of 2013-14 production. 2014-15 is therefore coded as first post-closure year.
Rockingham County CT (55116)	Gas	2011-12 to 2016-17	(36.3297, -79.8297)	385,307 [90,263-775,481]	12.1	Always open, but only generated significant energy production (>120k) after 2010-11.
Cleveland County Generating Facility (57029)	Gas	2013-14 to 2016-17	(35.1705, -81.4166)	458,470 [230,472-660,632]	19.3	Natural gas plant opened March 2013.

Table B.2. Plant Efficiency Over Time: Average Emissions (Tons) per Million Mwh

(a) Coal Producing Plants, North Carolina

Calendar Year	# of Plants	CO2 per Million Mwh	SO2 per Million Mwh	NOx per Million Mwh
2013	19	2092	8.28	2.83
2014	16	2449	6.78	2.85
2015	16	2444	6.33	3.10
2016	16	3094	5.89	4.57
2017	13	3507	8.10	6.38
2018	14	3910	11.07	7.08

(b) Coal Producing Plants, United States

Calendar Year	# of Plants	CO2 per Million Mwh	SO2 per Million Mwh	NOx per Million Mwh
2013	547	2568	13.79	4.24
2014	515	2392	13.89	3.72
2015	470	2150	10.99	3.12
2016	433	2203	9.34	3.04
2017	382	2045	7.13	2.68
2018	374	2145	7.05	2.87

(c) Gas Producing Plants, United States

Calendar Year	# of Plants	CO2 per Million Mwh	SO2 per Million Mwh	NOx per Million Mwh
2013	1711	1076	0.008	2.76
2014	1688	1060	0.006	2.90
2015	1655	1111	0.012	3.02
2016	1792	1084	0.012	2.70
2017	1771	1064	0.004	2.74
2018	1825	1034	0.006	2.74

Notes: Plant level emissions data were obtained from the EIA, available from 2013 onwards. We obtain the total annual power generation from coal and gas for each plant, combining the annual records from different prime movers or fuel codes if a particular plant used multiple coal or gas sources. We restrict attention to plants generating more than 1,000,000 Mwh in a given year and record the number of plants satisfying this criteria in each year. We then take the total emissions of each greenhouse gas for each plant, recorded in imperial tons, and divide it by the the coal or gas generation of that plant, recorded in million Mwh increments. We report the average across all plants in each year for each pollutant in the table above.

Table B.3. Effect of **Natural Gas** Power Plant Production Using Production and Wind Variation

	Math Scores (σ)			*English Scores (σ)*		
	(1)	(2)	(3)	(4)	(5)	(6)
A. 'Downwind' from Natural Gas-fired Plant						
Production	0.001	-0.005	-0.007	0.018	0.000	0.001
(1 million Mwh)	(0.014)	(0.020)	(0.022)	(0.019)	(0.017)	(0.016)
B. 'Upwind' from Natural Gas-fired Plant						
Production	0.048	0.035	0.027	0.030	0.012	0.010
(1 million Mwh)	(0.061)	(0.052)	(0.053)	(0.047)	(0.026)	(0.027)
C. Continuous Wind Measure						
Production	0.024	0.017	0.019	0.019	0.018	0.009
∗downwind÷0.15	(0.033)	(0.032)	(0.032)	(0.019)	(0.018)	(0.017)
Distance Controls	No	Yes	Yes	No	Yes	Yes
Lagged Test Scores	No	No	Yes	No	No	Yes
Observations	72,335	72,335	68,479	72,266	72,266	68,305
# of Students	178,065	178,065	29,694	31,584	31,584	29,654

Notes: Panels A and B contrast the effect of increased natural gas-fired power production for schools that are 'downwind' relative to 'upwind' of the natural gas-fired power plant according to our downwind measure (see equation (6)). Specifically, Panel A estimates equation (1) for 'downwind' schools facing above median wind, while Panel B does so for 'upwind' schools with below median wind levels. Splitting the sample into 'downwind' and 'upwind' schools is done at the school level so that there are an equal number of schools in both panels. Panel C reports results from equation (2) which uses year-to-year variation in coal-fired power production along with across school variation in our continuous wind measure. We divide our continuous wind measure by 0.15 to make our estimates comparable to the contrast between Panel A and B as, on average, our wind measure is about 0.15 units higher for 'downwind' schools relative to 'upwind' schools. Effect sizes in Panels A and B report the change in standardized test scores for a one million megawatt hour (Mwh) increase in power production. Given the additional differencing layer, Panel C reports the change in standardized test scores for a one million megawatt hour (Mwh) increase in power production *combined* with a 0.15 unit increase in our wind measure. The sample is restricted to schools within $10km$ of a power plant and to years that the power plant was in operation (as a coal plant). Table B.1 reports the power plants and their period of operation. Each cell represents the result of a separate regression of equation and includes student, school, and grade-year fixed effects. 'Demographic controls' include student level demographics and mean demographics at the school-grade level and include: ethnicity, gender, free or reduced price meal status, disability status, gifted status, English learner status, and grade repeating status. Missing indicators are used for students with missing demographics. 'Lagged test scores' consist of a cubic polynomial in prior lagged math and reading scores interacted with grade dummies along with average lagged school-grade test scores. Students with missing lagged own-subject scores are dropped while a missing indicator is used for those missing a lagged other subject score. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table B.4. Effect of **Coal** Power Plant Production Using **Log** Production and Wind Variation

	Math Scores (σ)			*English Scores (σ)*		
	(1)	(2)	(3)	(4)	(5)	(6)
A. 'Downwind' from Coal-fired Plant						
log(production)	-0.081***	-0.080***	-0.079***	-0.052***	-0.052***	-0.052***
	(0.023)	(0.023)	(0.022)	(0.013)	(0.014)	(0.014)
B. 'Upwind' from Coal-fired Plant						
log(production)	-0.002	-0.002	0.002	0.005	0.004	0.006
	(0.024)	(0.024)	(0.025)	(0.011)	(0.011)	(0.012)
C. Continuous Wind Measure						
log(production)	-0.056***	-0.057***	-0.055***	-0.040***	-0.043***	-0.043***
∗downwind÷0.15	(0.020)	(0.020)	(0.019)	(0.012)	(0.012)	(0.011)
Demographics Controls	No	Yes	Yes	No	Yes	Yes
Lagged Test Scores	No	No	Yes	No	No	Yes
Observations	469,095	469,095	434,602	466,947	466,947	433,020
# of Students	178,065	178,065	162,923	177,067	177,067	161,942

Notes: This table recreates Table 3 using log(production) rather than production in millions of Mwh. Panels A and B contrast the effect of increased coal-fired power production for schools that are 'downwind' relative to 'upwind' of the coal-fired power plant according to our downwind measure (see equation (6)). Specifically, Panel A estimates equation (1) for 'downwind' schools facing above median wind, while Panel B does so for 'upwind' schools with below median wind levels. Splitting the sample into 'downwind' and 'upwind' schools is done at the school level so that there are an equal number of schools in both panels. Panel C reports results from equation (2) which uses year-to-year variation in coal-fired power production along with across school variation in our continuous wind measure. We divide our continuous wind measure by 0.15 to make our estimates comparable to the contrast between Panel A and B as, on average, our wind measure is about 0.15 units higher for 'downwind' schools relative to 'upwind' schools. Effect sizes in Panels A and B report the change in standardized test scores for a one hundred percent increase in power production. Given the additional differencing layer, Panel C reports the change in standardized test scores for a one hundred percent increase in power production *combined* with a 0.15 unit increase in our wind measure. The sample is restricted to schools within $10km$ of a power plant and to years that the power plant was in operation (as a coal plant). Table B.1 reports the power plants and their period of operation. Each cell represents the result of a separate regression and includes student, school, and grade-year fixed effects. 'Demographic controls' include student level demographics and mean demographics at the school-grade level and include: ethnicity, gender, free or reduced price meal status, disability status, gifted status, English learner status, and grade repeating status. Missing indicators are used for students with missing demographics. 'Lagged test scores' consist of a cubic polynomial in prior lagged math and reading scores interacted with grade dummies along with average lagged school-grade test scores. Students with missing lagged own-subject scores are dropped while a missing indicator is used for those missing a lagged other subject score. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.

TABLE B.5. Summary Statistics: **National** Data

	All Schools[1]	Within 10 km of Coal Plant[2]	Within 10 km of Gas Plant[3]
	(1)	(2)	(3)
Mean of School Characteristics			
State Proficiency Rank (Math)	48.5	39.2	42.4
State Proficiency Rank (English)	48.3	38.7	41.7
Enrollment	587.2	569.4	660.6
% White	53.7	47.5	31.8
% Black	15.8	24.8	21.5
% Hispanic	22.0	20.9	36.4
% Asian	4.1	2.8	6.5
% Free/Reduced Price Lunch	52.6	59.6	61.4
Student-Teacher Ratio	17.0	16.5	17.5
Distance to Power Plant (km)	33.2	6.3	6.1
# of Plants[4]	922	351	523
# of Schools	88,626	5,607	14,582
Observations (school year)	665,511	42,824	106,911

[1] Data coverage: 2009-10 through 2017-18. Includes all schools, regardless of distance to nearby power plant.
[2] Includes all schools within 10km of a coal-fired power plant that produced more than 250,000 Mwh of electricity from coal during at least one school year from 2009-10 through 2017-18.
[3] Includes all schools within 10km of a natural gas fired power plant that produced more than 250,000 Mwh of electricity from natural gas during at least one school year from 2009-10 through 2017-18.
[4] Includes any power plant that produced more than 250,000 Mwh of electricity from coal, natural gas, oil, or biomass during at least one school year from 2009-10 through 2017-18.

Table B.6. Effect of Power Production on Math Proficiency Rank Using Production and Wind Variation by Plant Type: **National** Data

	All Plants (1)	All Plants (2)	All Plants (3)	Primary Fuel Only Plants (4)	No Other Nearby Plants (5)
A. Coal-fired Plants					
Production	-0.39**	-0.32**	-0.39***	-0.46***	-0.32**
(1 million Mwh)	(0.16)	(0.16)	(0.15)	(0.17)	(0.16)
Observations	42,824	39,507	33,937	28,211	29,752
# of Schools	5,607	5,525	5,319	4,866	4,873
B. Natural Gas Plants					
Production	-0.05	-0.11	-0.12	-0.11	-0.08
(1 million Mwh)	(0.09)	(0.09)	(0.008)	(0.09)	(0.09)
Observations	106,911	96,209	82,218	75,131	62,679
# of Students	14,582	14,223	13,602	13,197	10,914
Demographics Controls	No	Yes	Yes	Yes	Yes
Lag State Prof. Rank	No	No	Yes	Yes	Yes

Notes: This table reports estimates from equation (7) which identifies the effect of a one million megawatt hour (Mwh) increase in power production on student performance using the nationwide data (see Appendix A.1). Panel A reports estimates for schools nearby a coal-fired power plant, while Panel B does so for schools neighboring a natural gas power plant. The sample is restricted to schools within $10km$ of a power plant the produced at least 250,000 Mwh over school months for one school year using that fossil fuel (coal for Panel A and natural gas for Panel B). Column (4) restricts the sample to power plants where no more than 250,000 Mwh of power is produced by an alternative fossil fuel, while column (5) restricts the sample to schools with only one power plant within $10km$ of them. The outcome variable is defined as the school's ranking based on their school wide proficiency rate in their state. Each cell represents the result of a separate regression and includes school and year fixed effects. 'Demographic controls' include school level controls for: ethnicity, gender, free or reduced price meal status, class size, and enrollment. 'Lag State Prof. Rank' consist of a cubic polynomial in prior lagged statewide proficiency rank in math and reading scores interacted with state dummies. Standard errors are clustered at school level. ***,** and * denote significance at the 1%, 5% and 10% levels, respectively.