Pollution and Learning

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Abstract

Exposure to PM2.5 pollution is detrimental to health and cognitive function, and at early ages, inhibits learning. Using standardized achievement data at the school-district-grade level for 3rd- through 8th-grade students for the entire United States from 2009-2016, we show that variations in ambient PM2.5 concentrations and particularly polluted days reduce student learning. For a school district at the 90th percentile of PM2.5 concentrations, we find an approximate 7.5% of a standard deviation reduction in achievement due to pollution. We further find that cumulative and year-round exposure matters in determining the full effect of PM2.5 on student learning, and that younger students in particular are harmed. Our results provide external validity to the received literature that has been limited in its geographic scope.

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1 Introduction

Pollution is bad. This is intuitive to almost everyone, but economists can muddy the water by also considering the 'good' that pollution can bring in terms of new job creation or the provision of products that are essential to many industries. The benefit side of this calculation has, historically, been easier to calculate – for example, we can conveniently count production quantities or document salaries and jobs. The cost side of this equation is more difficult to pin down because beyond the literal input costs to produce a good like electricity, pollution creates negative externalities that are not captured in the decision-making of firms. With advances in monitoring and data collection, we can now better calculate the true costs of these activities. This research shows how small particulate matter pollution affects learning and achievement on yearly standardized tests in mathematics and language arts for students across the United States.

Recent causal research has shown that there are a myriad of harmful effects due to nearby pollution[1] and fine partculate matter (PM2.5) specifically[2] with health effects including premature death, increased incidence of Alzheimer's disease, and low birth weight among infants. Beyond the direct health outcomes, particulate matter pollution has also hampered real-time cognitive ability, inequality, crime, and educational outcomes. With each new study, this growing list of consistent negative findings builds a body of evidence that points to the *true* negative effects of small particle pollution. And yet, there is still a very limited amount of research done using nationwide data. This paper provides empirical evidence of the negative relationship between small particle pollution and student achievement, using school-district-grade-level standardized test score data for 3rd- to 8th-graders across the United States from 2009-2016 – nearly one million separate observations. The panel structure

[1] Deryugina et al. (2019); Heutel and Ruhm (2016); Hollingsworth et al. (2021); Godzinski and Suarez Castillo (2021); Persico et al. (2020)

[2] Burnett et al. (2018); Burke et al. (2021); Choma et al. (2021); DeCicca and Malak (2020); Shang and Sun (2018); Jones (2020) Jones and Goodkind (2019)

of these data allows us to control for important unobserved heterogeneity over time and, most importantly, to show how variations in the amount of PM2.5 pollution locally affect student learning and achievement.

In our study, we are able to measure the learning effects of pollution over such an extensive geographic range by using daily population-weighted predictions of PM2.5 levels that are informed by satellite data and meteorological conditions. As of 2019, nearly 75% of counties did not have land-based monitoring. The reasons behind this dearth of monitoring stations are ample, and certainly include the expense necessary to install and maintain the equipment, but endogenous political concerns are part of the problem, too. Zou (2021) highlights just how monitoring and measurement are subject to political constraints. Sullivan and Krupnick (2018) discuss the issue as well. Put simply, there are incentives to reduce (or remove entirely) poor air quality readings so that a county is not at risk of non-attainment and subject to regulation under Clean Air Act standards. Moreover, policy-makers may be selective in their adoption of particulate matter monitoring equipment in the first place over fears of how regulation would affect local businesses. Thus, making use of satellite-based modeled particulate matter readings not only helps overcome these selection bias issues but also allows us to make national comparisons and connect these data with standardized learning and achievement data.

We consistently find that higher PM2.5 concentrations negatively affect student learning outcomes. To do this, we use two methods to capture pollution exposure along the extensive and intensive margins. First, we consider how average school-day concentrations of PM2.5 affect learning and find that each microgram per cubic meter above approximately 9 $\mu g/m^3$ results in a decrease in student achievement. This result is in line with the EPA's guidance that days above 12 $\mu g/m^3$ can no longer be considered 'good' for human health. In fact, our finding implies that the EPA's threshold should perhaps be lower. Our second indicator of pollution exposure is the number of polluted days in a school year.[3] This intensive margin measure also consistently points to harmful effects on learning. Specifically, we find that students exposed to 50 or more days with PM2.5 concentrations above 12 $\mu g/m^3$ have lower achievement.

In addition to our main analysis, we also wrangle our models into forms that highlight the relative impact of pollution exposure on student learning by student race, gender, and age. Additionally, we investigate how adaptation and the timing of pollution exposure affects student learning. In these latter models, we ask how persistent exposure and adaptation may already be factored into the built environment at the school district level. To do so, we estimate our primary model using subsamples that reflect different levels of exposure, and gauge how year-round exposure differs from school-day exposure and how prior-year exposure affects learning. The consistent story across all specifications (and both measures of exposure) is that small particulate matter pollution is harmful to learning.

1.1 Prior Work

The negative health effects of exposure to fine particulate matter (PM2.5) are well documented and represent a consensus view of how harmful they can be to those that are young (Jones and Goodkind (2019); Jones (2020); DeCicca and Malak (2020)) and those that are older (Godzinski and Suarez Castillo (2021); Deryugina et al. (2019); Wang et al. (2022); Hollingsworth et al. (2021)). Aragón et al. (2017) have even shown that particulate pollution reduces labor supply because household members must change their routines to care for these at-risk younger and older populations. Beyond the health effects that are documented and recognized later in life as Alzheimer's or reduced cognitive ability, PM2.5 pollution stands to impact learning and development fundamentally through physiological channels, which we may see at younger ages. Fine particulate matter disturbs normal brain chemistry and

[3] Number of school days with pollution readings above 12 $\mu g/m^3$.

function by moving from air passageways into folds in the brain. Once there, the body's immune system beings to 'attack' the foreign objects, causing damage that has been connected to dementia at older ages (Wang et al. (2022)). That is to say, fine particulates are able to cross the blood-brain barrier and cause neuroinflammation. At earlier ages, there is evidence that this manifests through impaired cognitive function and is even expressed through increased crime rates. Archsmith et al. (2018) use a quasi-experimental setup to show how highly-skilled umpires make more mistakes when there is greater PM pollution. Specifically, they find that a 10 $\mu g/m^3$ change in PM2.5 concentrations increases missed calls by about 3%. Künn et al. (2019) also show how cognitive function is impaired by coupling information on indoor PM concentrations with chess tournament performance. They find that a 10 $\mu g/m^3$ increase in the indoor concentration of fine particulate matter increases a player's probability of making an erroneous move by 26.3%. Pear packers also exhibit lower productivity in the face of more particle pollution (Chang et al. (2016)). Negotiations go poorly, too. Qin et al. (2019) find that transaction prices are 0.65% higher on severely polluted days. Hausman and Stolper (2021) discusses this issue of exposure to pollution and how 'hidden' pollution leads to further inequality. Crime outcomes have also been connected with fine particulate pollution (Burkhardt et al. (2019); Jones (2022)). These immediate effects are likely all due to cognitive delays and poorer decision-making in the face of high pollution. Bedi et al. (2021) use experimental evidence from 54 lab sessions over three years testing participants' simple attention, complex attention, arithmetic processing speed, working memory, and fluid reasoning. These authors find that high levels of PM2.5 reduce performance on fluid reasoning.[4]

The connection from PM2.5 pollution to direct education outcomes is more tenuous due to the time horizon between pollution exposure and test-taking. However, a few studies have found well-identified negative effects on learning and school absences. Heissel et al. (2020)

[4]They do not find evidence of PM2.5 affecting the other tests but note that they are underpowered to detect modest effects.

use variation in wind direction, proximity to major highways, and student school switching to identify the effect of traffic pollution, which includes PM2.5, on student learning and behavior outcomes. They find that test scores decrease, and both absences and behavioral incidents increase. Similarly, Persico and Venator (2019) use proximity to Toxic Release Inventory sites that open or close to show that being exposed to air pollution is associated with a 0.024 of a standard deviation lower test score. In China, Chen et al. (2018) uses information from over 3,000 schools in Guangzhou City to show that air pollution made worse by temperature inversions leads to more absences and illnesses. Bharadwaj et al. (2017) study siblings in Santiago, Chile and find that variation in fetal exposure to air pollution and PM10 leads to lower math and language skills measured in fourth grade. In Chicago, Komisarow and Pakhtigian (2022) find that coal plant closures have improved education outcomes.

Our work adds to this building body of evidence by providing the first nationwide-scale evidence of particulate matter pollution harming education outcomes. We are able to use local variation in the amount of particulate matter pollution to see how student achievement changes for students attending the same school over time. After accounting for unobserved fixed features of a community or school over time, we consistently find that higher particulate matter concentrations are associated with lower scores. We also separately discuss how demographic groups are affected, whether or not adaptation is occurring, and how year-round versus school-day pollution exposure matters. In these latter robustness models, we still find that pollution exposure harms learning. If anything, we see that learning and achievement fall even more when we subset to only the heaviest polluting areas or consider longer time horizons of pollution exposure.

2 Empirical Strategy

Our goal is to understand how pollution exposure affects learning and cognition. To answer this, we connect variation in the amount of pollution witnessed by students in each grade from

3rd through 8th at the school district level over time, and determine how this affects their performance on state standardized tests. The structure of these data allows us to account for important fixed factors specific to each school district that impact student learning, such as proximity to highways or power plants, as well as idiosyncratic changes that may be state, year, or county specific. Consider two illustrative examples: First, consider the effect that a state-wide teacher strike would have on student performance. PM2.5 pollution is transboundary and does not stop at state lines. So, if this hypothetical strike were to happen in a year that happened to have especially high PM2.5 concentrations, then failing to include these fixed effects would cause our estimates to be biased. Our modeling strategy allows us to account for this type of shock to student learning by including state-by-year fixed effects. Second, consider the role of pre-existing trends in determining student learning outcomes. Suppose that funding for education has increased year-over-year for schools due to higher tax remittances. Moreover, it is also the case that PM2.5 concentrations slightly decline each year over the entire sample for many school districts. Failure to account for these unobserved trends would falsely lead us to conclude that falling PM2.5 concentrations were the sole factor in improving scores.

In addition to these analyses, we also modify our primary model to highlight the relative impact of variation in pollution exposure on student learning. We investigate differences based on demographic groups, the intensity of exposure, and differences in long-term exposure. In the latter robustness check, we ask how persistent exposure and adaptation may already be factored into the built environment at the school district level. To do so, we estimate our primary model using subsamples that reflect different levels of exposure and alternative methods of measuring pollution exposure. In one model, we only use school districts with annual PM2.5 exposure in the bottom quintile or the top quintile (always heavy pollution or never heavy pollution). We also include binned quintile indicators, lagged (prior years) PM2.5 readings, and change how we construct our exposure measure to include summer and weekend PM2.5 readings as well. Regardless of the modeling strategy, we see that PM2.5 harms learning, and can dispel the notion that adaptation to this pollution has occurred.

2.1 Data Description

2.1.1 Education data

Our outcome variable of interest is a measure of student learning and achievement over the school year that is conformable across state lines. In this paper, we use the Stanford Education Data Archive (SEDA) 4.1 achievement data, which is constructed using data from the EDFacts data system housed by the U.S. Department of Education. The underlying data behind SEDA are collected from aggregated test score data from each state's standardized testing program as reported by individual schools or 'Local Education Agencies'. By law, each state is required to test every student in grades 3 through 8 in both math and reading/language arts each year, though states have the flexibility to select or design a test of their choice to measure student achievement relative to the state's standards. States set their own benchmarks or thresholds for the levels of performance, e.g., "proficient," in each grade and subject. States select 2 to 5 performance levels, where one or more levels represent "proficient" grade-level achievement. From this point, a measure of mean proficiency that is conformable across the entire EDFacts data system is constructed for each school, grade level, and year. These data are then aggregated to the geographic school district level for each grade level and year from 2009-2016. The geographic school district is the most granular geographic data available with a panel structure. Within each geographic school district, there are separate observations for each grade level, so we can also control for changes over time within a school district as students progress from 3rd to 8th grade.[5]

[5] A more detailed description of the construction of the mean measure of proficiency is available in the data codebook here: https://stacks.stanford.edu/file/druid:db586ns4974/seda_documentation_4.1.pdf

Mean proficiency is our outcome variable in all regressions. The unit of observation, then, is the mean proficiency for a grade level within a geographic school district over time. Further, the SEDA data also construct proficiency measures by gender and race, thus, we are able to disaggregate to these subgroups and determine if there are differential effects of pollution on learning. All regressions are weighted by the number of test-takers.

2.1.2 Pollution data

We collect PM2.5 pollution data from the CDC National Environmental Public Health Tracking Network.[6] This data set provides daily modeled, population-weighted predictions of PM2.5 levels at the county level. From this data, we calculate two measures of PM2.5 exposure that capture changes at the extensive and intensive margins. First, we aggregate the daily PM2.5 data to the annual school year average PM2.5 concentration for each county. For this exposure measure, we only include PM2.5 data for Monday through Friday during non-summer months. This extensive margin measure reflects how changes in average exposure affect learning, and variation in this variable can capture departures from long-term trends in PM pollution. Second, we calculate the number of polluted days during the year by counting the days with a PM2.5 reading greater than 12 $\mu g/m^3$, the EPA's upper threshold for "Good" air quality. This intensive margin measure reflects how changes in the intensity of PM pollution may impact learning. We exclude non-school days (summers and weekends) in calculating both these variables, but later relax this assumption to determine how year-long exposure affects student learning and achievement. Estimates that include weekends and summer month exposure to PM pollution yield larger effect sizes of pollution on learning.

[6]Visit `https://www.cdc.gov/nceh/tracking/topics/AirQuality.htm` for more information.

2.2 Econometric Specification

We use standard panel data methodology to identify the link between pollution exposure and student learning. Our outcome variable of interest is the cohort-scale mean achievement on state standardized tests, which is observable at the school district-year-grade-subject level. Our primary covariate of interest is the two pollution exposure measures described above to capture differences in exposure at the extensive and intensive margins. We also include a few control variables which we toggle on and off for robustness. These are the median income within the geographic school district, and the percent of students that belong to different race or ethnicity groups.[7] A consistent finding using these data is that there are achievement gaps by race, so we include the percent of students in each grade level that are black, white, Hispanic, and Asian.

Our benchmark specification also includes a variety of fixed effects that control for unobservable time-invariant differences in student learning outcomes specific to each school district, grade, or year. For example, the district fixed effects account for the fact that some districts may have highways or heavy industrial activity nearby while others do not. The inclusion of year fixed effects account for nonlinear aggregate shocks to student outcomes that are common across all school districts – for instance, the onset of a pandemic that moves learning online. We also include state-by-year fixed effects and state-specific trend variables which catch broader effects that may be shared by school districts in a state due to changes in education policy.[8] Thus, our identification of the effect of PM2.5 pollution on learning relies on conditional exogeneity. Conditional on district, grade, year, and other controls and state-specific variables in the model, any remaining impacts on student learning outcomes

[7] There are a multitude of other control variables we considered including: the number of students receiving free or reduced lunch, percent of families receiving SNAP benefits, etc. Ultimately, we decided to exclude these and instead include variables capturing the race of students because we fear that many of these other control variables are 'colliders' and would add bias into the estimation. Regardless, estimates using these alternate controls instead of student body race percentages yield the same conclusions.

[8] We toggle the inclusion of these variables and our fixed effects for robustness as well, but note that the estimated effect of PM2.5 pollution on learning is highly consistent across all model specifications.

are likely random. Our primary estimating equation is shown below:

$$\begin{aligned} Score_{igdy} &= \beta_0 + \beta_1 Pollution_{dy} + \beta_2 MedianIncome_{dy} + \sum_{r=0}^{n} \pi_r RacePercent_{r,dgy} \\ &+ \phi_i + \gamma_g + \mu_d + \omega_y + \xi_{s,y} + y * \zeta_s + \epsilon_{sgdy} \end{aligned} \quad (1)$$

where i, g, d, y stand for subject, grade, district and year. Our dependent variable, $Score_{igdy}$ is the mean achievement score in subject i for grade g in district d during year y. Our primary independent variable, $Pollution_{dy}$, measures the exposure to PM2.5 pollution of students in district d during year y. $MedianIncome_{dy}$ and $RacePercent_{r,dgy}$ capture district median income and race composition in each district. $\phi_i, \gamma_g, \mu_d, \omega_y, \xi_{s,y}$ stand for the subject, grade, district, year, and state-by-year fixed effects. $y * \zeta_s$ captures the states-specific time trend. Finally, ϵ_{sgdy} denotes the standard errors, which are clustered at the grade-district levels.

3 Results

Column 1 of Table 1 reports the estimation results from our preferred model. Columns (2)-(5) toggle the inclusion of covariates, the state-specific time trend, and subject, grade, year, district, and state-by-year fixed effects. The top panel reports estimates using average school day PM2.5 levels as the pollution exposure variable, and the bottom panel uses the number of school days above the EPA's threshold for 'good' air quality of 12 $\mu g/m^3$.

We find that pollution exposure is associated with lower student achievement across all models. For average school day exposure (top panel), the effect of one more microgram per cubic meter is -0.0025, or 0.6% of a standard deviation. Notice that the effect size increases when we remove control variables (column 2) or when we remove the state-by-year fixed effect. This leads us to conclude that these variables are capturing important determinants in student learning outcomes, so their exclusion would yield biased estimates. We also see that the school districts' race composition is an important determinant in student achievement, a consistent finding across papers that use SEDA data. To put our results in context, our finding that a one microgram increase in ambient PM2.5 levels reduces student learning by 0.0025 or 0.64% of a standard deviation is in the same range as Persico et al. (2020) who show a decrease of 0.024 standard deviations. Other authors have noted that a 10 $\mu g/m^3$ change is associated with 3% change in missed calls (Archsmith et al. (2018) or a 26.3% increase in the probability of an erroneous move in chess (Künn et al. (2019). We should not expect that year-round averages for PM2.5 to increase by such a large magnitude relative to 'normal' PM2.5 levels, but for example, this would imply a 6.4% of a standard deviation reduction. A better comparison is evaluating how PM2.5 lowers learning at high pollution levels. For a school district at the 90th percentile of PM2.5 concentrations, we expect to see an approximate 0.03 reduction in achievement due to pollution (7.5% of a standard deviation). In later robustness models, we test whether or not these effects are truly linear, or the effects grow in magnitude over exposure levels by including squares of our exposure variables. In essence, this allows us to determine if there are threshold effects. Section 4 below explores how marginal effects depend on average ambient PM2.5 levels. To preview results, we find that learning begins to be harmed when taverage school day exposure exceeds 9 micrograms. Thus, one immediate policy implication from our research is that the EPA should consider lowering the threshold on what they deem 'good' air quality.

The bottom half of Table 1 shows how student learning is affected by more days above the EPA's threshold for good air quality. While this exposure measure and the prior average school-year of estimates are correlated, this specification helps answer questions similar to that of Archsmith et al. (2018) and Künn et al. (2019) which focus on real-time pollution levels and cognitive outcomes. We do not have information on the testing dates for each school district, grade, or state.[9] However, we believe this intensive margin measure helps to

[9]For the states and school districts we could find precise information on test dates there is, in fact, a

capture acute changes in PM2.5 levels on education outcomes. In general, we see that each additional school day with PM2.5 levels above 12 micrograms yields lower learning. For an average school district in our sample, this is a -0.01 decrease or 2.3% of a standard deviation. Put differently, each 10 school days above 12 micrograms reduces achievement and learning by about 0.5% of a standard deviation.

4 Robustness: Alternative Specifications

4.1 Differences by Race, Gender, and Grade-level

Here, we measure how exposure to pollution affects different populations of students. We begin by exploring achievement data by the students' race, and then we analyze whether or not male and female students have different outcomes. Lastly, we divide the sample to only look at young students (3rd-5th grades) and older students (6th-8th grades). In all models, we use the same specification found in column 1 of table 1.[10]

Figure 1 shows the coefficients associated with pollution exposure for each subgroup and their 95% confidence intervals. The top panel contains the coefficients on average PM2.5 exposure, and the bottom panel shows the coefficients on the number of particularly polluted days. The first bar shows our overall estimate from column (1) in table 1. The next grouping shows breakdowns by student race, the third grouping by gender, and the final grouping by student grade level. We find that white and black students are both negatively affected by pollution exposure, which applies to both measures of pollution exposure. It is noteworthy that the point estimate for black students is below even the 95% confidence interval found for white students. However, the confidence interval for black students is wider due to the smaller sample size, so we cannot distinguish the two effect sizes statistically. For Hispanic and Asian students, the effect is not distinguishable from zero, though this is driven by the

surprising amount of variation within states both across grade levels, school districts, and from year to year.

[10] All fixed effects, time trends, and covariates.

Table 1: Primary results

	(1)	(2)	(3)	(4)	(5)
Average PM2.5, school days	-0.0025**	-0.0037***	-0.0244***	-0.0045***	-0.0025**
	(0.0010)	(0.0010)	(0.0016)	(0.0005)	(0.0010)
Median income	0.1259***		0.5174***	0.1263***	0.1259***
	(0.0093)		(0.0060)	(0.0092)	(0.0093)
% White	0.2481***		0.8222***	0.2616***	0.2481***
	(0.0297)		(0.0177)	(0.0303)	(0.0297)
% Black	-0.5405***		0.2714***	-0.5427***	-0.5405***
	(0.0457)		(0.0213)	(0.0469)	(0.0457)
% Hispanic	-0.1781***		0.2913***	-0.1584***	-0.1781***
	(0.0382)		(0.0239)	(0.0393)	(0.0382)
% Asian	0.6287***		1.1527***	0.6444***	0.6287***
	(0.0519)		(0.0417)	(0.0522)	(0.0519)
Constant	-1.3796***	0.0333***	-6.0203***	-1.3775***	-1.3796***
	(0.1077)	(0.0097)	(0.0631)	(0.1060)	(0.1077)
Polluted school days	-0.0002***	-0.0002***	-0.0018***	-0.0002***	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Median income	0.1262***		0.5206***	0.1265***	0.1262***
	(0.0093)		(0.0060)	(0.0092)	(0.0093)
% White	0.2482***		0.8138***	0.2621***	0.2482***
	(0.0297)		(0.0172)	(0.0304)	(0.0297)
% Black	-0.5407***		0.2620***	-0.5413***	-0.5407***
	(0.0457)		(0.0206)	(0.0469)	(0.0457)
% Hispanic	-0.1781***		0.2684***	-0.1595***	-0.1781***
	(0.0383)		(0.0229)	(0.0394)	(0.0383)
% Asian	0.6284***		1.1370***	0.6430***	0.6284***
	(0.0519)		(0.0417)	(0.0522)	(0.0519)
Constant	-1.3994***	0.0082***	-6.1912***	-1.4125***	-1.3994***
	(0.1072)	(0.0027)	(0.0644)	(0.1059)	(0.1072)
Observations	903,581	908,015	903,599	903,581	903,581
Subject, Grade, Year, District FEs	Y	Y	N	Y	Y
State×Year FE	Y	Y	N	N	Y
State time trend	Y	Y	N	Y	N

Note: *,**,*** denote significance at the 10, 5, 1% levels. Numbers in parentheses are standard errors, which are clustered at the grade-district levels. The dependent variable is the test score per district-year-grade-subject and all estimations are weighted by the number of test-takers.

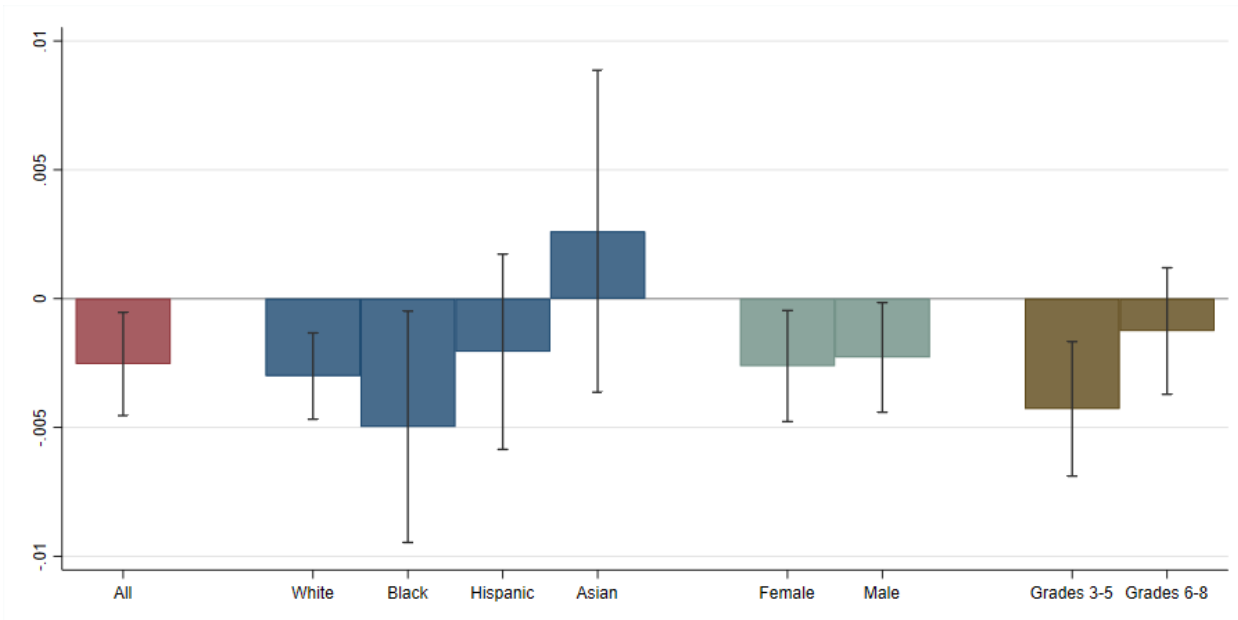
fact that this estimate is noisier due to smaller sample sizes. We note that when we later include full-year observations for PM2.5 exposure rather than just school-day exposure, the effect for Hispanic students is negative and statistically significant. Moving on to differences by gender, we again see a negative effect for both exposure measures, and this does not break along gender lines. Finally, when we compare young students with older students, we see that the effect is concentrated among younger students. For 3rd-5th graders, we find a large negative effect due to pollution exposure, but for 6th-8th graders, this effect is not statistically distinguishable regardless of our exposure measure. Moreover, this effect continues to hold in robustness models when we consider year-round exposure. While we are unable to determine the mechanism behind this through our available data, there are a few mechanisms that deserve mentioning. The first one is physiological. Most health studies finding a negative effect of small particle pollution show concentrated effects among the very young and very old. For the young, it is related to their smaller body mass. Given prior medical studies, it makes sense that we find concentrated education effects in younger students. The second mechanism involves the classroom environment that younger students attend. It is not uncommon for elementary school buildings to be among the oldest vintage school buildings in a district. This is because schools that had originally been designed as a high school or middle school are no longer large enough to accommodate a community's growth, so new buildings are made for older grade levels and the smaller schools are 'handed down' to the younger students because they are adequately sized. These older buildings can have old or outdated air ventilation and filtration. The use of temporary outdoor classrooms or 'portables' may also be a factor. For example, students in 6th-8th grades are typically placed in an entirely different building than their elementary peers (middle school). As a local area's population grows, the number of students in a single elementary school can begin to push the capacity of these buildings, and only the older students are trusted to be moved into portables. While many middle schools likely use portables as well, they are more likely to be used across all grades instead of being concentrated with the older students in the school (e.g., 5th graders at an elementary school). Thus, it may be the case that even though PM2.5 pollution is the same each year at the school-district level for all grades, actual exposure to this pollution depends on which grade-level the student is in and what types of classrooms they are attending (e.g. old buildings with poor ventilation, or strictly indoor versus partly outdoor portables). We should also note that when we include weekends and summer month exposure to PM2.5, this effect becomes negative and marginally significant for these higher grade-level students, though not to the same degree we notice with younger students.

4.2 Adaptation and Threshold Effects

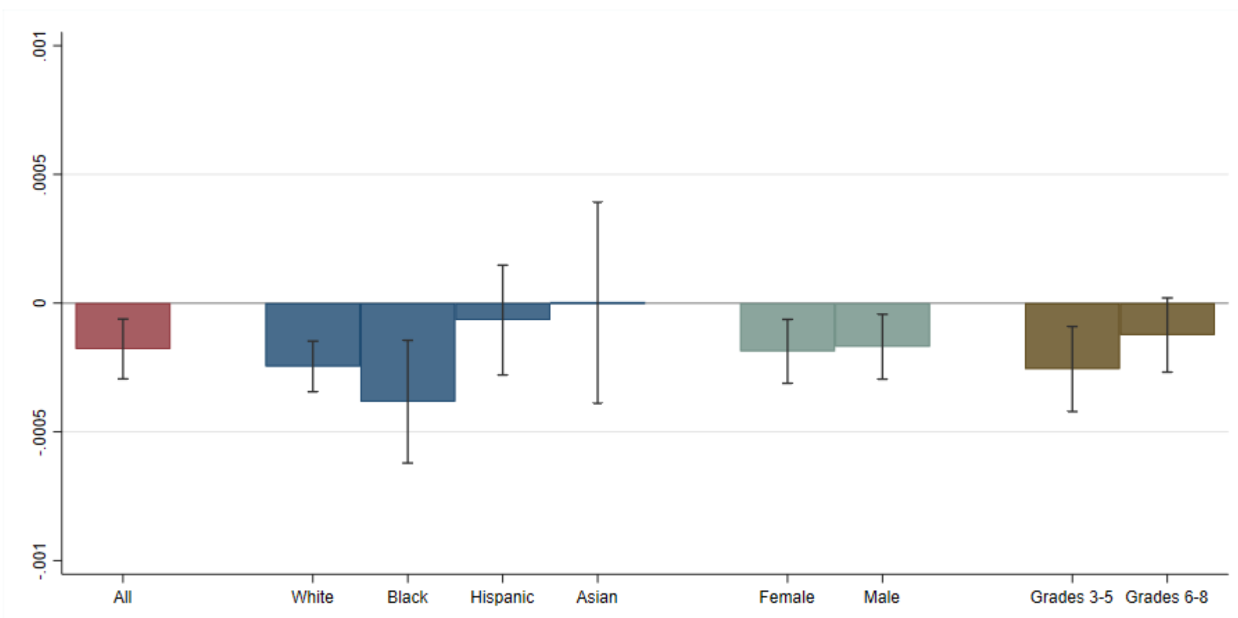
It is important to consider that educators and parents in school districts likely know how polluted their areas are; therefore, they may have already invested in mediation and air filtration for their students. Our prior estimates can be thought of as the effect of pollution evaluated at the mean. In this section, we are interested in determining how pollution affects learning in the most and least heavily polluted school districts. If we believe adaptation may be biasing our results, we may expect to see limited to no effect of additional pollution in the most polluted areas. To study this, we estimate our primary models using subsamples that reflect different levels of exposure. In one model, we only use school districts whose annual PM2.5 exposure is always in the bottom or top quintile (always heavy pollution or never heavy pollution). As expected, PM2.5 has no statistical effect for schools that are always in the bottom quintile. If schools have adapted to a high level of exposure each year (always in the top quintile), we would expect our coefficient of interest to be statistically zero. This is not the case. We find that each incremental unit of average PM2.5 exposure in a year reduces student learning in the top quintile and that the effect size is nearly four times greater. Moreover, we see the effect of additional heavy pollution days nearly doubles

Figure 1: Impact of pollution on test scores by demographics

(a) Average PM2.5



(b) Polluted days



in magnitude, and the conditional average achievement level is statistically different (more negative) compared to the least-polluted districts. These results are shown in Table 2.

We also consider a few 'non-linear' ways of modeling pollution exposure and its effect on student learning. First, we replace the continuous measure of mean pollution exposure with a set of indicator variables that equals 1 if pollution exposure in a year belongs to a certain quintile. We use the bottom quintile observations as our reference group, so each coefficient is relative to this lowest pollution group reading. Appendix figure A3 plots these coefficients. We see that observations in the 20-40% quintile are not statistically different than the least polluted areas but that schools with PM2.5 reading in the 40-60% quintile experience statistically significant lower test scores. Additionally, the point estimate keeps falling, indicating a greater effect of pollution on learning in the top quintile. Next, we consider how the marginal effect of more pollution changes according to the current pollution level. For example, we may expect that a unit increase in PM2.5 concentrations to have little to no effect on learning when moving from 3 to 4 micrograms, but a larger effect when moving from 13 to 14 micrograms. We evaluate these marginal effects for both mean pollution exposure and the number of polluted days based on equation 1, and also include squares of these variables to account for non-linear effects. Appendix figures A4 and A5 show the estimated marginal effects in graphic form. We see that there are indeed threshold effects in our model, but the size of these effects is not sensitive to whether we include the square of the exposure variable or not. Considering mean pollution exposure, we see that learning begins to decrease once PM2.5 crosses 9 micrograms and that each additional unit of exposure harms student learning. Turning to the number of especially polluted days, we see that learning begins to decrease once the number of polluted school days reaches 40 and continues to decrease as more polluted days occur. When we include the squared polluted days, the threshold point is near 50 days above 12mg, but with statistically similar effect sizes to the linear model.

Table 2: Results for most vs. least polluted districts

	Most polluted districts		Least polluted districts	
	(1)	(2)	(3)	(4)
PM2.5, Mean	-0.0091**		-0.0009	
	(0.0042)		(0.0070)	
Polluted school days		-0.0005***		0.0009
		(0.0002)		(0.0006)
Median income	0.1671***	0.1686***	-0.1160***	-0.1190***
	(0.0346)	(0.0349)	(0.0325)	(0.0327)
% White	0.8824***	0.8782***	0.6173***	0.6168***
	(0.1704)	(0.1708)	(0.1060)	(0.1061)
% Black	0.1725	0.1719	-0.9340***	-0.9254***
	(0.1779)	(0.1788)	(0.2991)	(0.2994)
% Hispanic	0.4442***	0.4428***	0.1225	0.1224
	(0.1217)	(0.1215)	(0.1080)	(0.1080)
% Asian	1.2737***	1.2741***	0.4822*	0.4876*
	(0.1722)	(0.1721)	(0.2787)	(0.2788)
Constant	-2.4224***	-2.5040***	1.0590***	1.0785***
	(0.4101)	(0.4182)	(0.3792)	(0.3722)
N	52405	52405	40085	40085
Adjusted R^2	0.8986	0.8986	0.7973	0.7973
Subject, grade, year, district FE	Y	Y	Y	Y
State × year FE	Y	Y	Y	Y
State time trend	Y	Y	Y	Y

Note: *,**,*** denote significance at the 10, 5, 1% levels. Numbers in parentheses are standard errors, which are clustered at the grade-district levels. The dependent variable is the test score per district-year-grade-subject and all estimations are weighted by the number of test-takers.

4.3 Cumulative Exposure and Lagged effects

Our last angle to investigate is the cumulative effect of pollution on learning and achievement. In our primary model, we make a limiting assumption about pollution exposure and only consider the effect of school-day exposure on learning. In other words, we calculate the mean exposure and the number of especially polluted days using only observations from Monday-Friday during school months. This is done in part to investigate phenomena similar to that shown in Archsmith et al. (2018); Huang et al. (2020); and Qin et al. (2019). Table 3 shows how our estimates change when we instead measure pollution exposure over the school year[11], and when we calculate mean exposure and polluted days over the entire year. A stylized fact derived from this table when looking at average PM2.5 concentrations is that the effect size of pollution on learning grows when more pollution data is considered (all-year exposure). For comparison, the coefficient on mean PM2.5 concentration during school days is -0.0025, while it is -0.0042 when pollution readings for the whole year are included – nearly double in size. This holds for all race, gender, and grade-level subcategories.[12] Looking to how particularly polluted days impact student learning, we see an opposite trend. When more pollution exposure observations are added (weekends and summers), the effect size slightly decreases. We believe this is consistent with the work of Archsmith et al. (2018) and Künn et al. (2019) who are looking at same-day effects of PM pollution and monitoring intensive margin changes.

[11]include weekends, but exclude summer pollution

[12]Interestingly, we now find a statistically significant negative effect of pollution on learning for Hispanic students that we did not see before.

Timing of pollution

	(1) All	(2) White	(3) Black	(4) Hispanic	(5) Asian	(6) Female	(7) Male	(8) Grades 3-5	(9) Grades 6-8
Average pollution									
School days	-0.0025**	-0.0030***	-0.0050**	-0.0021	0.0026	-0.0026**	-0.0023**	-0.0043***	-0.0013
	(0.0010)	(0.0009)	(0.0023)	(0.0019)	(0.0032)	(0.0011)	(0.0011)	(0.0013)	(0.0013)
School year	-0.0034***	-0.0035***	-0.0054**	-0.0044**	0.0025	-0.0033***	-0.0034***	-0.0051***	-0.0024*
	(0.0011)	(0.0009)	(0.0024)	(0.0021)	(0.0034)	(0.0012)	(0.0012)	(0.0014)	(0.0013)
All year	-0.0042***	-0.0038***	-0.0059**	-0.0064***	-0.0039	-0.0038***	-0.0045***	-0.0061***	-0.0022
	(0.0011)	(0.0010)	(0.0026)	(0.0019)	(0.0035)	(0.0012)	(0.0012)	(0.0015)	(0.0014)
Number of polluted days									
School days	-0.0002***	-0.0002***	-0.0004***	-0.0001	0.0000	-0.0002***	-0.0002***	-0.0003***	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
School year	-0.0001**	-0.0002***	-0.0002*	-0.0001	-0.0000	-0.0001**	-0.0001**	-0.0002***	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
All year	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002**	-0.0001***	-0.0001***	-0.0002***	-0.0001**
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
N	903581	807165	203158	251257	96035	754118	765651	467214	436350
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject, grade, year, dist. FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State× Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State time trend	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: *,**,*** denote significance at the 10, 5, 1% levels. Numbers in parentheses are standard errors, which are clustered at the grade-district levels. The dependent variable is the test score per district-year-grade-subject and all estimations are weighted by the number of test-takers.

Our next question in this section is how exposure on school days over prior years affects learning in the current year. We have pollution data going back to 2000 even though our education data starts in 2009, so the number of observations is not affected after adding lags of pollution exposure. We measure the effect of up to four prior years because this is when 3rd graders at the start of our sample would be kindergarteners. Here we see that PM2.5 exposure over the prior 2-3 years is important and negatively affects learning. Looking just to the prior year, we see that learning is reduced by as much as 0.004-0.0051 (1-1.3% of a standard deviation) due to increasing average PM2.5 concentration or polluted day counts in the prior year. Together with estimates shown in Table 3, we conclude that year-round and cumulative exposure to PM2.5 harm learning. The larger effect size found when we use full-year data on pollution is nearly identical to the effect size found for the prior year. Moreover, these findings support the notion that either adaptation is not happening or that adaptation by improving or limiting school exposure is not enough to offset the effect of PM2.5 on children at other times of the year or over prior years.

5 Conclusions and Policy Discussion

Small particulate matter pollution is detrimental to human health and has been linked to dementia and early mortality. More recently, advances in monitoring have allowed researchers to tie ambient PM2.5 levels with cognitive performance and even education outcomes. The consistent finding across this body of work is that students are worse off in the face of more pollution. Much of the work in this literature is well-identified, but it is limited in geographic scope and subject to concerns of external validity. Here, we explore the connection between PM2.5 pollution and learning using achievement on state standardized tests for students in 3rd through 8th grades for the entire United States. These data are at a yearly interval at grade and school district levels, which yields a panel of nearly one million observations that face varying PM2.5 exposure and shocks over time.

Table 3: Lagged effects

	(1)	(2)	(3)	(4)	(5)
Average pollution					
Current year	-0.0025**	-0.0007	-0.0006	-0.0008	-0.0007
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
1 year before		-0.0051***	-0.0043***	-0.0041***	-0.0040***
		(0.0010)	(0.0009)	(0.0009)	(0.0009)
2 years before			-0.0034***	-0.0028***	-0.0029***
			(0.0010)	(0.0009)	(0.0009)
3 years before				-0.0023**	-0.0026***
				(0.0010)	(0.0009)
4 years before					0.0013
					(0.0010)
Polluted days					
Current year	-0.0002***	-0.0001**	-0.0001*	-0.0001*	-0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
1 year before		-0.0003***	-0.0003***	-0.0003***	-0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
2 years before			-0.0002***	-0.0002***	-0.0002***
			(0.0001)	(0.0001)	(0.0001)
3 years before				0.0000	-0.0001
				(0.0001)	(0.0001)
4 years before					0.0003***
					(0.0001)
N	903581	903581	903581	903581	903581
Subject, grade, year, district FE	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y
State time trend	Y	Y	Y	Y	Y

Note: *,**,*** denote significance at the 10, 5, 1% levels. Numbers in parentheses are standard errors, which are clustered at the grade-district levels. The dependent variable is the test score per district-year-grade-subject and all estimations are weighted by the number of test-takers.

Regardless of how we measure PM2.5 exposure, either in average ambient concentrations over the school year or the number of particularly polluted school days, we find that PM2.5 harms learning. We find that each microgram increase in PM2.5 concentration reduces students learning by 0.6% of a standard deviation. This result is in line with findings by Heissel et al. (2020) and Persico and Venator (2019). Moreover, we find that this harm to education outcomes begins when average concentrations cross approximately 9 micrograms per cubic meter. This is below the EPA's own threshold for good air quality of 12 micrograms per cubic meter. We also investigate differences in harm based on demographic groups, intensity of exposure, and differences in long-term exposure. These models are intended to capture the adaptation and cumulative effects of persistent pollution. We find that these models point to an even larger effect of PM2.5 on learning.

The most 'shelf-ready' policy most would expect is to improve indoor air quality with better filtration of fine particles. However, to the extent that this adaptation has already occurred in highly polluted areas, we do not find evidence that it has been effective. We find that pollution throughout the year matters greatly, with effect sizes from full-year pollution exposure nearly twice those of school-day-only pollution exposure. Even prior years' exposure harms learning. Our estimates generally support the notion that the EPA's threshold for 'good' air quality should be lowered. Or, in the very least, future cost-benefit analyses must take into account that learning and achievement begin to deteriorate when ambient concentrations are above 9 $\mu g/m^3$, or there are 40-50+ days with 12 $\mu g/m^3$ concentrations.

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Appendix

Figure A1: Mean PM2.5 (top) Average Scores (bottom)

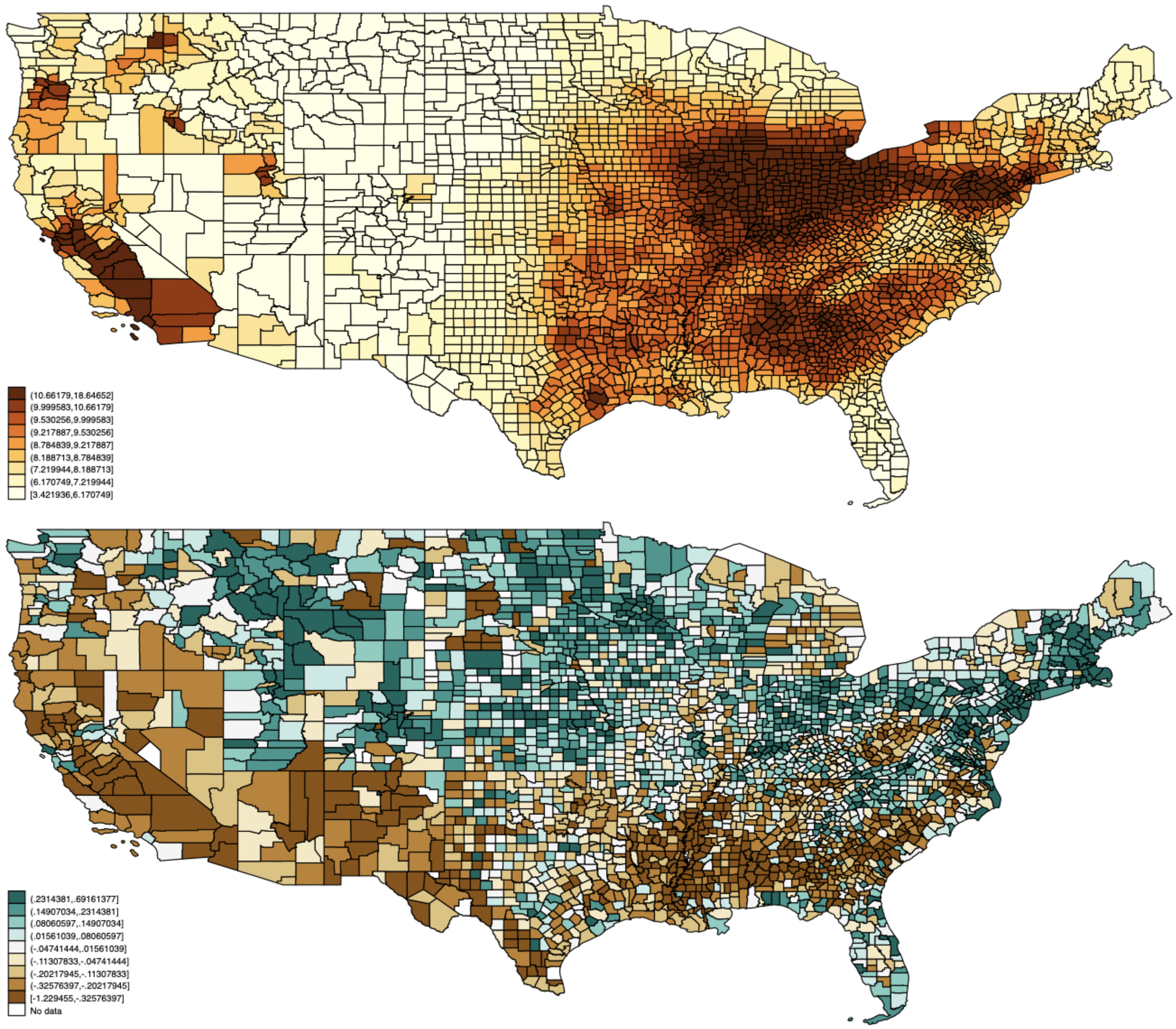
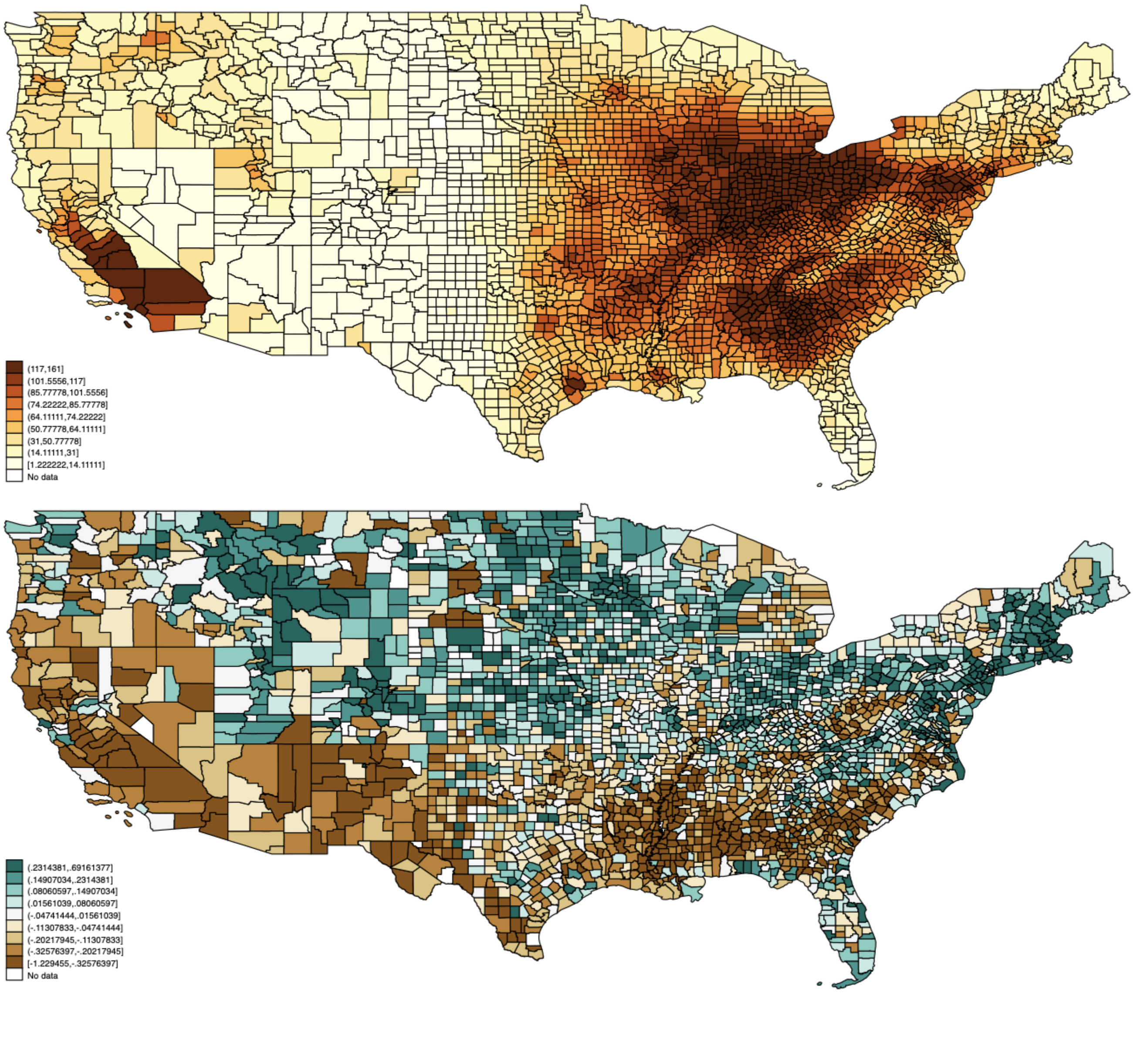


Figure A2: Days over 12 $\mu g/m^3$ (top) Average Scores (bottom)



A.1 Robustness Models: Non-linear effects, Pollution Timing

Figure A.3: Quantile Coefficients

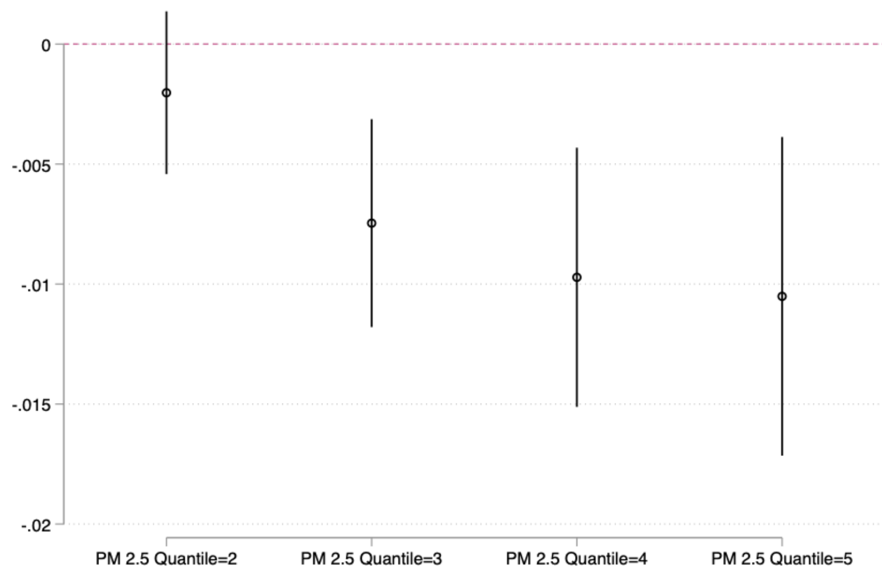
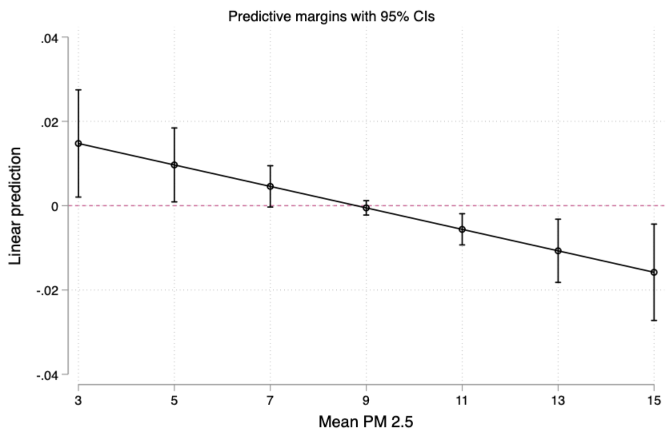


Figure A.4: Marginal Effects - Average PM2.5

(a) Linear



(b) Quadratic

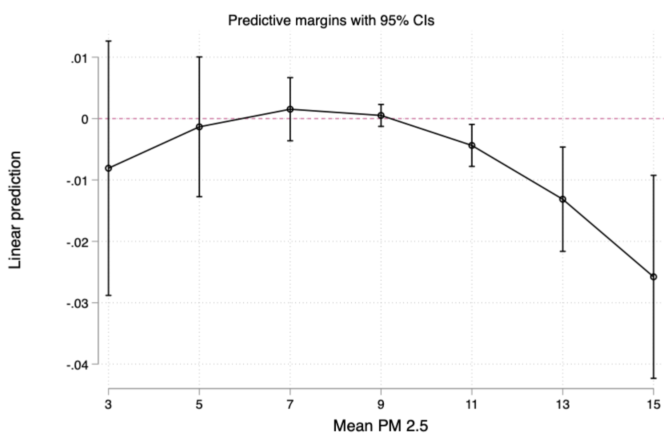
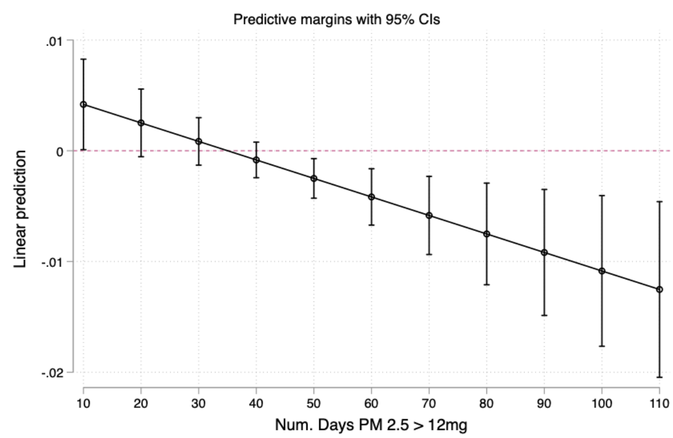


Figure A.5: Marginal Effects - Polluted Days

(a) Linear



(b) Quadratic