QUANTIFYING THE IMPACTS OF POLLUTION EXPOSURE
ON ACADEMIC ACHIEVEMENT IN CALIFORNIA

A Culminating Project Presented to the Department of Public Policy and Administration
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MASTER OF PUBLIC POLICY AND ADMINISTRATION

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**Executive Summary**

My Culminating Project presents original research that examines whether exposure to various forms of environmental pollution had a negative impact on the average standardized test performance for $6^{th}$ graders at California public school districts from 2009-2018. Public health research suggests that children exposed to certain types of pollution (such as fine particulate matter in ambient air or toxic heavy metals in drinking water) may suffer from impaired brain development or chronic conditions such as asthma that are exacerbated when pollution levels are high. Relative to their peers who do not experience these environmental stressors, students with pollution-induced health conditions may face attendance issues and struggle to focus, learn, and demonstrate their knowledge on test day. My research assesses whether these adverse health outcomes are resulting in measurable learning loss across the population.

I apply a fixed-effects panel regression analysis to examine the effect of selected pollution variables on average school district test scores for math and English Language Arts (ELA). My analysis connects test score data and school district covariates from the Stanford Education Data Archive (SEDA) with Census tract pollution scores from CalEnviroScreen (CES), a tool used by California state agencies to identify pollution burdens and prioritize investment of environmental program funds. To assemble my model, I used GIS mapping to match every California public school in the SEDA dataset to the appropriate Census tract, and then used corresponding school pollution scores to derive district averages. With nine years of test score data and three iterations of pollution data that cover similar time periods, I was able to assemble a panel model with school district and year fixed effects that account for more of the overall variation in test scores than is possible with a single-year cross-sectional regression.

My analysis focuses on the following subset of CES pollution variables to identify any measurable impacts on standardized test scores: Fine Particulate Matter (PM 2.5), Traffic, Toxic Cleanup Sites, Hazardous Waste Facilities, Solid Waste Facilities (including landfills), Impaired Water Bodies, and Groundwater Threats (a collection of pollution sources which may have water quality impacts). Of these seven pollution variables, I find a small but meaningful effect on standardized test scores from PM

2.5, Solid Waste Facilities, and Groundwater Threats. I do not find statistically significant relationships for the other pollution variables, despite some theoretical support for the effect of these variables in public health literature. My results are robust to a number of adjusted regression specifications and include important statistical corrections for multicollinearity and heteroskedasticity. However, I also find that these effects depend on the test subject, and appear to also vary based on levels of certain geographic and demographic indicators. Future research is needed to investigate these differing effects and to further explore the complex web of causal mechanisms that connect various forms of pollution exposure to academic outcomes.

While my results for Solid Waste Facilities and Groundwater Threats appear to be largely novel findings, the effect I find for PM 2.5 is supported by existing research that connects test score performance with poor air quality. Some of these prior studies take a time-dependent, quasi-experimental approach to show that both short- and long-term PM 2.5 exposure harms test performance, and that mitigating pollution exposure produces immediate benefits (i.e., the physical and cognitive harms from PM 2.5 are largely reversible). This dynamic suggests that policy intervention to improve classroom air quality may be an effective tool to boost student achievement. In fact, prior studies such as Gilraine (2020) and Stafford (2015) suggest that the per-dollar test-score benefits of classroom air filtration exceed more commonly prescribed educational interventions such as class-size reduction programs. The magnitude of the effect I find for PM 2.5 similarly supports this conclusion.

Finally, my research supports the notion that pollution reduction has an equitable distribution of benefits, as low-income communities of color face disproportionate pollution burdens, higher rates of pollution-induced illness, and lagging academic outcomes. And since academic achievement is a strong predictor of economic resources (and vice versa), these benefits compound across generations. Thus, the academic effects of pollution exposure are an essential consideration for policymakers seeking to address these persistent societal disparities, whether through regulating pollution sources, prioritizing mitigation efforts, or allocating funds to reduce student exposure.

**Acknowledgements**

I would like to express my gratitude for the superb education I received from the Department of Public Policy and Administration at California State University, Sacramento, and for the guidance I received from Dr. Rob Wassmer, who asks tough questions. I would also like to thank my fellow students, my professional colleagues and mentors, and my family, whose support is unwavering and always statistically significant.

I dedicate this project to my late father, a career teacher in Sacramento's under-resourced school districts who understood the value of a well-ventilated classroom.

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**Abstract**

Children exposed to pollution may face chronic issues such as asthma or impaired brain development, or may experience acute impairment from elevated pollution levels at certain times of the year. These health impacts from pollution exposure may also hinder a child's ability to succeed in the classroom, which has implications for educational attainment, lifetime earnings, and persistent disparities in educational and economic outcomes. In this paper, I use a fixed-effects panel regression analysis to compare nine years of test score data from California school districts with several pollution variables and quantify the long-term impacts of these pollutants on academic achievement. I find a statistically significant negative effect on either reading or math test scores from 1) levels of fine particulate matter in ambient air, 2) proximity to solid waste facilities, and 3) exposure to a group of pollution sources linked to poor drinking water quality. A one-standard-deviation increase in fine particulate matter decreases average reading scores by 2.75%. A one-standard-deviation increase in solid waste facilities and water quality threats decreases math scores by 1.75% and 0.96%, respectively. These results are robust to different regression specifications. Interaction effects show that the incremental academic impact of these pollutants varies considerably depending on a district's geographic and demographic characteristics.

## 1. Introduction

Researchers have examined a broad range of factors that may influence student performance in the classroom. These factors range from direct elements of the classroom experience, such as class sizes and teacher experience levels (Cho et al., 2012; Leigh, 2010), to more indirect socioeconomic factors like race/ethnicity and parental income (Bali & Alvarez, 2003; White et al., 2016; Akee et al., 2010; Conwell, 2021). Researchers have also determined that components of students' living and learning environments, like nutrition (Taras, 2005), textbook quality (Van Den Ham & Heinze, 2018), and even tree cover on campus (Sivarajah et al., 2018) influence their educational outcomes. Understanding the effect of these various factors is critical, as students' ability to succeed in school is a strong predictor of future earnings and economic mobility (Chetty et al., 2011; Aber et al., 2012). This paper, used to satisfy the culminating experience for my MPPA degree from CSU Sacramento, furthers the understanding of educational determinants by examining the extent to which district-wide exposure to environmental pollution influences average district-wide performance on standardized tests. In the remainder of this introduction, I offer a summary of the causal mechanisms connecting various types of pollution to academic achievement, explore the factors driving the observed correlation between pollution and other determinants, and provide an overview of this study's methodological approach.

Environmental pollution sources often originate from human activity and are highly localized. Exposure to environmental pollutants is known to have negative impacts on several markers of physical health and cognitive ability. For example, particulate matter, ozone, and nitrous oxides are the primary components of "smog" that has plagued urban areas and led to increased incidences of asthma, lung cancer, and heart disease (Manisalidis et al., 2020; Beeson et al., 1998; Nuvolone et al., 2018; Anenberg et al., 2018). Various estimates show that fine particulate matter (PM 2.5) alone contributes to thousands of premature deaths in California each year (Wang et al., 2019; Zhang et al., 2018; California Air Resources Board, n.d. -a). Emerging research also points to the harmful effects of air pollution on cognitive function, as studied in groups such as chess players (Künn et al., 2019), baseball umpires (Archsmith et al., 2018), stock traders (Meyer & Pagel, 2017), politicians (Heyes et al., 2019), and general office workers (Allen et al., 2016). The effect of air pollution on academic performance in children may thus be multifaceted, as chronic exposure in daily life can harm development and cause attendance issues, while acute exposure at school may impair cognitive function on test day. Other pollutants also have known impacts on children's health, development, and ability to learn. Examples include the well-studied effects of lead poisoning (Canfield et al., 2003; Eubig et al., 2010; Ha et al., 2009; Surkan et al., 2007), pre-natal exposure to pollutants from EPA Superfund sites (Persico et al., 2020; Baibergenova et al., 2003), and proximity to certain industrial facilities (Mohai et al., 2011; Pastor, Sadd, & Morello-Frosch, 2004; Choi et al., 2006). The long-term effects of growing up in a polluted environment, even when pollution concentrations are within legally established limits, appear to have lasting harms that warrant further study and may justify further policy intervention.

Pollution data indicate vast differences in exposure across geographies, as the modern pollution burden falls disproportionately on low-income communities of color (California Environmental Protection Agency (CalEPA), 2021a). Researchers have traced these differences to historic (often discriminatory) practices in environmental and land use regulation (CalEPA, 2021b; Lane et al., 2022; Gonzalez et al., 2022), which are likely also reflected in modern depressed property values (Chay & Greenstone, 2005; Hanna, 2007). The "urban renewal" programs in the U.S. during the 1950s and 60s razed sections of black and brown neighborhoods to install interstate highways, and discriminatory housing policies such as redlining restricted these same affected people from moving to wealthier, less polluted neighborhoods (Karas, 2015; Houston et al., 2004; Lane et al., 2022). Additionally, decades of individual facility siting decisions disproportionately placed polluting industries in minority neighborhoods (Mohai et al., 2015; Pastor et al., 2001), and the resulting hedonic property devaluation in these areas may have further attracted low-income residents (Been, 1994).

This analysis connects nine years of average test score data from California public school districts compiled by the Stanford Education Data Archive (SEDA; Reardon et al., 2021) with overlapping sets of pollution data compiled in CalEnviroScreen (CES), a tool developed by the California Office of Environmental Health Hazard Assessment (OEHHA, 2022) to identify "disadvantaged" communities for targeted environmental remediation. Using this data in a simple bi-variate correlation shows that an increase in one form of localized pollution (PM 2.5) correlates negatively with English Language Arts (ELA) test scores. Simultaneously, PM 2.5 is positively correlated with school district percent non-White students, and district percent non-White is negatively correlated with ELA test scores (see Figures 1, 2, and 3). Thus, the observed relationship between pollution exposure and test scores may merely be reflecting the academic effects of highly-correlated demographic variables. However, the multivariate regression analysis that follows finds that, in California, the observed relationship between certain pollution variables and standardized test scores continues to hold true even after controlling for potential confounding factors.

The remainder of this paper offers: 1) a brief literature review that explores causal mechanisms and lists prior studies on the relationship between pollution and test scores, 2) descriptive information on the datasets supporting my analysis, 3) the theoretical framework supporting my fixed effects panel regression model and several key methodological considerations, 4) the results of my analysis and the robustness of my findings, 5) a discussion of my results, including an analysis of effect sizes, comparison to prior studies, implications for policymakers, and the basis for future research, and 6) concluding remarks that highlight key findings and recommendations.

**Figure 1:** Simple Correlation between District PM 2.5 Concentration and Mean ELA Test Scores

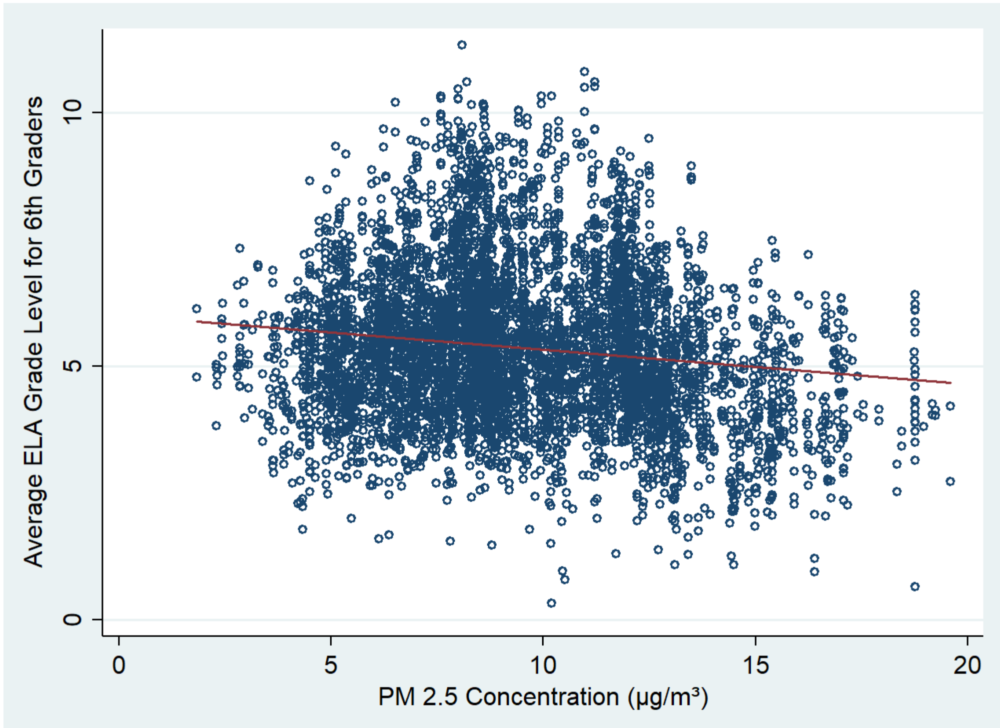



**Figure 2:** Simple Correlation between PM 2.5 Concentration and District Percent Non-White Students

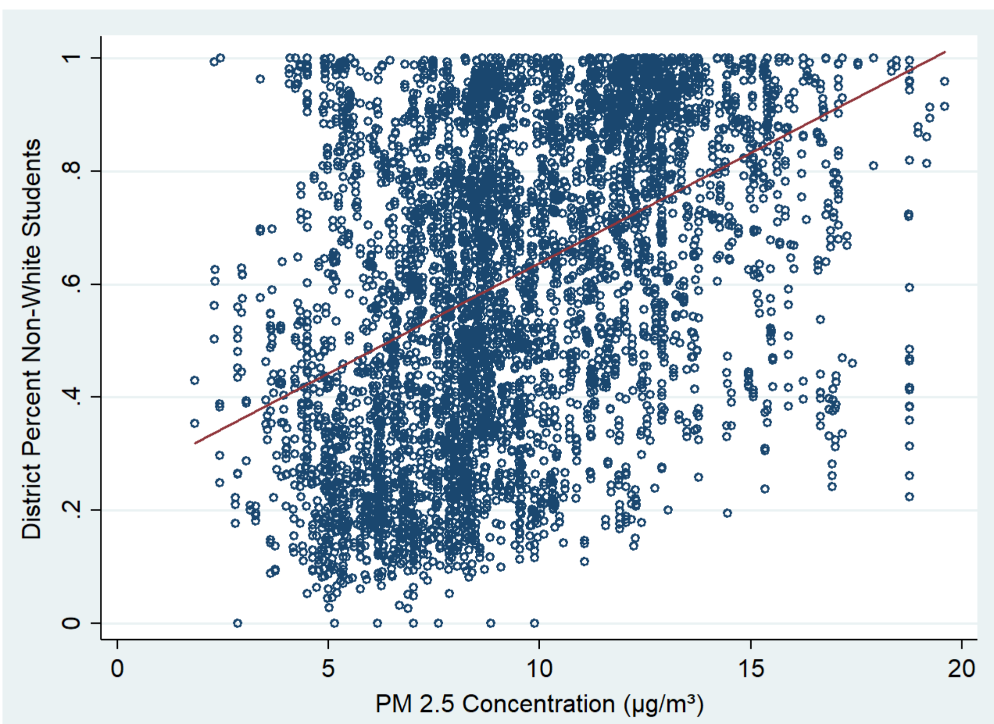
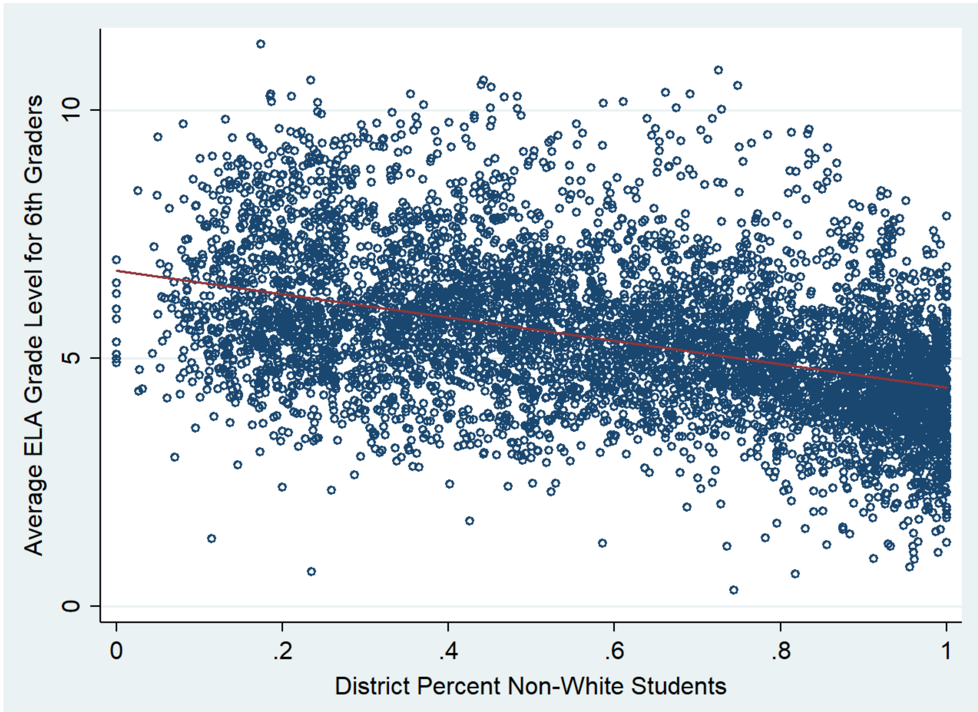


**Figure 3:** Simple Correlation between District Percent Non-White Students and Mean ELA Test Scores




## 2. Literature Review

Physical and cognitive impairments from pollution exposure could potentially have profound effects on a child's life, as academic success is a strong predictor of education attainment and future earnings (Chetty et al., 2011; Chamberlain, 2013). Both pollution exposure and education outcomes also vary strongly by race and income and likely exacerbate longstanding racial/ethnic and socioeconomic disparities. While standardized test scores are not a perfect reflection of a student's abilities or future potential, they still serve as a reasonable proxy for academic success and economic outcomes even in early grade levels. This literature review offers further detail on the causal relationship between pollution and test scores as supported by relevant public health and economic literature, and then explores the findings and limitations of prior studies that specifically examine this relationship. I choose to sort these studies into two methodological approaches—regression studies and natural experiments.

*Causal Mechanisms*

The effect of pollution exposure on test scores theoretically occurs through multiple causal pathways. As detailed in Table A1, air pollutants such as PM 2.5 can cause chronic respiratory illness such as asthma that lead to fatigue and school absences and impair learning. Exposure to various pollution sources may also impair long-term brain development, and even short-term pollution exposure may cause cognitive impairment that affects classroom performance regardless of development or health status. This relationship is complex, and the methodology of studies which examine these interactions may only capture a subset of possible causal pathways. Quasi-experimental studies are more robust to omitted variable bias, but their short-term temporal limitations imply that their results only reflect the *marginal* impact of changes in pollution exposure over the time window in question (whether through cognitive impairment or exacerbated chronic illness). The impact of air pollution on test day (Amanzadeh et al., 2019) or only in the time following decreased coal plant operation (Gilraine, 2022) is likely much weaker than the cumulative impact of exposure throughout a child's development. Conversely, observational studies with multiple years of data and enough controls likely capture a more holistic picture of pollution impacts, but are less able to distinguish between short- and long-term effects.

*Regression Studies*

One subset of existing studies uses a single cross-section of observations and Ordinary-Least-Squares (OLS) regression analysis to examine test scores across a combination of various pollutants, physical settings, and timeframes and attempts to isolate the effect of pollution by including an appropriate suite of control variables. Mohai et al. (2011) geographically overlaps Michigan public schools with the federal EPA's Toxic Release Inventory for industrial facilities and finds that, after controlling for confounding variables like race and socioeconomic status, students at schools in the highest quintile of toxic pollution exposure have higher absence rates and are less likely to meet state testing standards than students at schools with average levels of toxic pollution exposure. Pastor, Sadd, & Morello-Frosch (2004) use a comparable methodology and find similar results for Los Angeles area schools within one mile of industrial facilities that release toxins tracked by the EPA's 33/50 Program.

However, these studies both only include one year of data and do not control for school or school district fixed effects, rendering their results less robust against potential omitted variable bias. Ham et al. (2011) examines California public elementary schools by Census tract and finds statistically significant negative effects of ozone, fine particulate matter (PM 2.5), and coarse particulate matter (PM 10) for both math and ELA scores. This study estimates that reducing PM 10 exposure at low-SES schools to the levels faced by high-SES schools would close the proficiency gap in ELA by 0.34% and in math by 0.5%. Ham et al. (2011) includes multiple years of data and appropriately controls for school-level fixed effects. Other studies using this multivariate regression approach, with variation in the techniques used to control for confounding factors, include Stayhorn, J.C. & Strayhorn J.N. (2012) and Kim et al. (2009) which find ongoing detrimental impacts of elevated childhood blood levels of lead and manganese.

*Natural Experiments*

Another subset of existing studies attempts to isolate the effect of pollution on test scores by taking a quasi-experimental approach, where clear temporal variation in pollution exposure more directly demonstrates that subsequent changes in test scores are not merely reflecting confounding factors. Amanzadeh et al. (2019) analyze short-run temporal variation in PM 10 and find that a one standard deviation increase in PM 10 levels on test day at Iranian high schools lowers aggregate test scores by 0.64%, while a one standard deviation increase in PM 2.5 lowers aggregate test scores by 0.20%. Austin, Heutel, & Kreisman (2019) examine a Georgia school district that retrofitted school buses to mitigate emissions from diesel combustion and find that students who rode the cleaner buses saw their ELA scores improve by 0.09 standard deviations, which approximately equates to the expected performance gains from an additional five years of teacher experience. Heissel, Persico, & Simon (2019) use wind patterns along a major highway in Florida to show that children transitioning from elementary/middle to middle/high school had lower test scores and more absences and behavioral incidents if they moved to a school that is downwind of major traffic pollution. Gilraine (2020) examines air filters installed in 18 schools in response to the 2015 Aliso Canyon natural gas leak in Southern California and finds that the schools which received the filters saw math scores improve by 0.2 standard deviations over the following four months. Gilraine (2022) subsequently uses nationwide coal power plant operation times as an exogenous instrumental variable to estimate that each microgram-per-cubic-meter reduction in ambient PM 2.5 concentration improves average test scores for math and ELA by 0.02 standard deviations.

*Remaining Questions*

As described above, existing studies generally find modest but statistically significant effects of various pollutants on standardized test scores. However, these effects are not necessarily linear and may vary across student groups and test types. Amanzadeh et al. (2019) finds that high levels of ambient PM2.5 and PM10 on test day affects male students more than female students, and math scores more than ELA scores. In contrast, Austin, Heutel, & Kreisman (2019) find a statistically significant effect of diesel exhaust only on ELA scores and not math scores. Ham et al. (2011) and Mohai et al. (2011) find statistically significant effects of air pollution on both ELA and math scores, but the per-unit effect of pollution may be non-linear and depend on the subject, pollutant concentration, and test score quantile. The theoretical reason for these differences is not clear nor explored in detail.

Additionally, as described in Table A1, several other common environmental pollutants and pollution sources are associated with detrimental health impacts in children, but studies have not previously examined them for their short- or long-term effects on academic achievement. While the effect of any individual pollutant on academic achievement may be small, communities facing the largest aggregate pollution burdens may be seeing an underappreciated level of learning loss due to chronic cognitive and physical impairments. The research that follows examines a broader range of pollution variables than found in existing studies and applies a fixed-effects panel regression model to capture the holistic impacts of pollution exposure throughout a child's life.

## 3. Data

I now turn to my own study and provide more information on the SEDA and CalEnviroScreen datasets used to establish my panel regression model, which I use to examine the relationship between test scores and pollution exposure in California.

*SEDA*

As a measure of standardized test performance, I use 2009-2018 test score data from 6th graders at California public schools obtained from the Stanford Education Data Archive (SEDA) (Reardon et al., 2021)[1]. SEDA includes test score data for 3rd through 8th graders, but I used 6th grade scores for my analysis since the dataset is missing California math scores for 7th and 8th graders for 2009-2014. Theoretically, the oldest possible students in the dataset would show the greatest amount of test score variation due to lifetime differences in pollution exposure, although acute cognitive impairment from short-run pollution exposure may not differ by age. SEDA uses standardized nationwide testing data from the National Assessment of Education Progress and tabulates scores for each school relative to a national reference cohort for each subject and grade (see technical documentation in Fahle et al., 2021). SEDA compiles this data with two different grading scales, denoted as the “cohort standardized” (CS) and “grade cohort standardized” (GCS) scales. The units for the CS scale are positive or negative standard deviations of difference relative to the national reference cohort, while the GCS scale indicates the grade level proficiency of the test results relative to the reference cohort (e.g., a score of 6 indicates the school or district is testing at a 6th grade level). The GCS scale also incorporates additional assumptions and thus is not a direct transform of the CS scale (Fahle et al., 2021). The GCS units are more readily interpretable for a broad audience and, since they are uniformly positive values, allow for taking the natural logarithm, which proved to be useful for my analysis. Hence, I use the GCS scale to present my primary findings in this paper. The SEDA dataset also includes estimates for several key school district qualities that I used as covariates in my model to control for potential confounding factors, such as race/ethnicity and socioeconomic status.

[1] SEDA includes data from 2009-2018, but is missing data from 2014. The omission of 2014 data from my model is a discrepancy worth noting but does not raise any immediate concerns for my findings.

### *CalEnviroScreen*

The environmental pollution data come from versions 2.0-4.0 of CalEnviroScreen (CES), a tool developed by the California Office of Environmental Health Hazard Assessment (OEHHA) that tabulates "scores" for each Census tract in California based on a variety of pollution, health, and demographic indicators (OEHHA, 2021)[2]. California lawmakers and regulators use CES data to inform mitigation efforts and prioritize investments of environmental program funds. CES Census tract pollution scores are transformations of raw data that include factors such as distance weighting meant to capture the true impact of a pollution variable on a Census tract. For CES indicators that measure a specific polluting compound, these transformations are straightforward with minimal methodological variation between CES versions. For a few select indicators that represent a collection of compounds or a pollution source rather than specific compounds, these transformations may be more subjective or may have had methodological adjustments that render them incomparable between CES versions. I examined the CES methodology for each pollution variable (as described in OEHHA, 2021) to assess whether they were sufficiently consistent across CES versions and whether the underlying data had enough variation to assemble a panel regression model across 2009-2018. I excluded six of the thirteen pollution variables from my analysis on these grounds (Table 1).

The collection of CES scores occurred over slightly different timeframes, ranging from 2009-2021 depending on the variable and the CES version. Each new release of CES uses more recent data, but the measurement timeframes do not perfectly match between variables given the different underlying datasets and methodologies. Additionally, the measurement of SEDA test score data occurred between 2009-2018, which does not perfectly overlap with the CES measurement timeframes. To assemble the data panel for my regression model, I mapped each of the three iterations of CES data to approximately three corresponding SEDA data years, depending on the measurement timeframe of each pollution

[2] CES version 1.0 assigned scores to zip codes rather than census tracts, and thus is not directly comparable with subsequent versions for the purposes of my analysis.

variable. These slight temporal discrepancies are worth noting but likely do not introduce any meaningful bias as the intent of this research is to estimate the holistic impacts of pollution exposure in students' living and learning environments rather than the precise impacts of pollution in a setting or time sequence. Studies that focus on specific settings, pollutants, and causal pathways necessitate more rigid assumptions and more precise time sequences than were available through SEDA and CES.

**Table 1:** Descriptive Statistics for All Variables

| **Dependent Variable** | **Units** | **Mean** | **Standard Deviation** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| Average Grade Level Achievement for 6th Graders | Natural log of district mean grade level scores, using the SEDA grade-cohort-standardized (GCS) scale | 5.36 | 1.52 | 0.33 | 12.32 |
| Average Grade Level Achievement for 6th Graders (math scores only) | Natural log of district mean grade level scores for math, using the SEDA grade-cohort-standardized (GCS) scale | 5.30 | 1.50 | 0.33 | 12.32 |
| Average Grade Level Achievement for 6th Graders (ELA scores only) | Natural log of district mean grade level scores for ELA, using the SEDA grade-cohort-standardized (GCS) scale | 5.43 | 1.54 | 0.33 | 11.33 |
| **Pollution Variables** | | | | | |
| PM 2.5 | Annual mean fine particulate matter (PM 2.5) concentration, micrograms per cubic meter (µg/m³) | 9.46 | 3.08 | 1.84 | 19.60 |
| Groundwater Threats | Sum of weighted number of selected sites from GeoTracker and CIWQS databases | 27.83 | 40.09 | 0.00 | 673.75 |
| Solid Waste Facilities | Sum of weighted number of solid waste sites and facilities | 3.34 | 4.47 | 0.00 | 35.75 |
| Hazardous Waste Facilities | Sum of weighted number of permitted hazardous waste generators, facilities, and chrome platers | 0.44 | 0.99 | 0.00 | 15.53 |
| Cleanup Sites | Sum of weighted number sites from Envirostor database | 8.10 | 11.81 | 0.00 | 158.7 |
| Traffic | Traffic volumes (vehicle-km per hour) divided by total road length (km) within 150 meters of each Census tract | 791.0 | 625.1 | 18.85 | 4358.4 |
| Impaired Water Bodies | Summed number of pollutants present in water bodies designated as impaired | 4.21 | 4.72 | 0.00 | 35.00 |
| **Control Variables** | | | | | |
| District Urban Status | Continuous variable with values from 0-1 | 0.17 | 0.33 | 0.00 | 1.00 |
| District Town Status | Continuous variable with values from 0-1 | 0.17 | 0.34 | 0.00 | 1.00 |
| District Rural Status | Continuous variable with values from 0-1 | 0.31 | 0.41 | 0.00 | 1.00 |
| Percent Native American | District percentage (0-1) | 0.02 | 0.05 | 0.00 | 1.00 |
| Percent Asian | District percentage (0-1) | 0.08 | 0.12 | 0.00 | 0.78 |
| Percent Hispanic | District percentage (0-1) | 0.48 | 0.29 | 0.00 | 1.00 |
| Percent Black | District percentage (0-1) | 0.04 | 0.06 | 0.00 | 0.70 |
| Percent Free and Reduced Lunch | District percentage (0-1) | 0.55 | 0.26 | 0.00 | 1.00 |
| Percent English Language Learners | District percentage (0-1) | 0.19 | 0.17 | 0.00 | 0.96 |
| Percent Special Education | District percentage (0-1) | 0.10 | 0.04 | 0.00 | 0.98 |
| Total Enrollment | District number of students | 682.1 | 2024 | 1.00 | 52693 |
| Median Income | District median income in inflation-adjusted US Dollars | 63,572 | 25,598 | 22,201 | 219,043 |
| Percent of Adults with at Least a Bachelor’s Degree | District percentage (0-1) | 0.26 | 0.17 | 0.00 | 0.84 |
| Unemployment Rate | District percentage (0-1) | 0.09 | 0.03 | 0.00 | 0.23 |
| Proportion of Single Mother Households | District percentage (0-1) | 0.17 | 0.05 | 0.01 | 0.36 |

Note: CES contains additional pollution variables that were not included in my regression model due to data limitations: Ozone, Diesel PM, Drinking Water Quality, Pesticides, Children’s Lead Risk from Housing, and Industrial Toxin Releases. The underlying data used to derive these variables in CES either had limited (or no) variation across panel years, or had major methodological or measurement changes that rendered them incomparable between CES versions. Each of these omitted variables has a theoretical connection to academic achievement and is worth exploring in future research.

## 4. Methodology and Empirical Framework

In this section, I offer the methodology behind my research and summarize the underlying theoretical relationship between standardized test performance as a dependent variable and a variety of determining factors, including pollution exposure.

### *Methodological Overview*

I apply a fixed-effects panel regression model to estimate the effect of Census-tract CES pollution scores on SEDA standardized test scores in geographically overlapping school districts. To connect CES scores to school districts, I used GIS mapping to match every California public school in the SEDA dataset to the corresponding Census tract, and then took the simple average of pollution scores for each school in a district. This approach serves as an appropriate proxy for students' holistic pollution exposure levels both at school and outside of it, since school districts cover a geographic area that encapsulates daily life for most students in the district. District averages reflect a less granular estimate of proximate pollution exposure at schools, but capture more of the cumulative effect of pollution exposure than targeted, quasi-experimental studies such as Amanzadeh et al. (2019), which only reflect the effect of short-run pollution exposure during the school day. Of course, a small percentage of students likely live or spend considerable time outside of the geographic area of their school district, but this effect is likely muted by the geographic enrollment restrictions of public-school districts and is not a likely source of omitted variable bias.

SEDA contains a wealth of information for each school district to control for confounding factors in a regression analysis, but is missing a few potentially relevant variables related to academic administration such as school funding, student-teacher ratio, administrative structure and practices, and extracurricular offerings. These factors often correlate with socioeconomic status, which the model includes, but do not necessarily do so. The inclusion of school district and year fixed effects in my model controls for district-level idiosyncrasies and produces regression coefficients that are more robust to omitted variable bias. The tradeoff of this more robust approach is that some time-invariant CES pollution variables are necessarily excluded from the panel model, as listed in Table 1.

*Theoretical Model*

The following equation represents a mathematical approximation of test score variance based on the data parameters included in my model:

**Mean district proficiency grade level for $6^{th}$ grade ELA, math, and overall test scores** = f(Environmental Pollution Effects, Demographic Effects, Socioeconomic Effects, Geographic Effects, Academic Effects, School District Fixed Effects, and Year Fixed Effects)

Where:

**Environmental Pollution effects** = f(school district prevalence of ambient fine particulate matter, vehicle traffic, toxic clean-up sites, impaired water bodies, groundwater threats, hazardous waste facilities, and solid waste facilities)

**Demographic effects** = f(district percentage Black, district percentage Hispanic, district percentage Asian, and district percentage Native American) [white is the omitted reference category]

**Socioeconomic effects** = f(median income, local unemployment, district free or reduced-price lunch percent, parents' educational attainment, percent of single-mother families)

**Geographic effects** = f(district characterization as urban, town, or rural) [suburb is the omitted reference category]

**Academic effects** = f(district enrollment, percent special education students, percent English language learners)

**School District Fixed Effects** = categorical control for California school districts such that idiosyncratic qualities of individual districts (such as administrative practices) do not bias other regression coefficients

**Year Fixed Effects** = categorical control for each year in the data panel such that idiosyncratic qualities of that year (such as macroeconomic conditions) do not bias other regression coefficients [2009 is the omitted reference year]

The model presented above aims to capture a wide range of factors known or suspected to influence student performance on standardized tests, which allows for isolating and estimating the impact of individual pollution variables. Of course, no number of controls in an observational study can perfectly eliminate potential correlation between the explanatory variables and the remaining error term. However, this model maximizes the number of relevant control variables available in the data and incorporates school district and year fixed effects to minimize this remaining error[3] and produce regression coefficients that are reasonably robust to potential omitted variable bias.

*Other Considerations*

**Multicollinearity**

Correlation between explanatory variables can potentially obscure statistical significance, and including all CES variables simultaneously in a regression trial appears to induce multicollinearity with either other CES variables or the SEDA school district control variables (Table A6). Correlation amongst the control variables also likely impacted their p-values, but this result is not of concern since I include these variables only to capture a holistic picture of test score variance and control for confounding effects. Hence, I adjusted the regression model to reduce collinearity amongst CES variables by using the natural log of test scores on the GCS scale as the dependent variable and by conducting regression trials with CES pollution variables input one at a time. This approach is consistent with earlier studies such as Ham et al. (2011) which found high correlations between explanatory pollution variables.

[3] Specifically, my panel regression model with school district and year fixed effects and all pollution and control variables included explains about 90% of the overall variation in test score data.

## Heteroskedasticity

A fixed effects panel regression design is susceptible to a heteroskedastic distribution with residual errors intercorrelated across different clusters such as school districts, counties, or other geographic designations. Existing studies on the connection between pollution exposure and academic performance typically only consider one level of error clustering: for example, Ham et al. (2011) cluster standard errors only at the school level while Gilraine (2022) clusters at only the district level. Heissel, Persico, & Simon (2019) test different clustering specifications as a measure of robustness for their findings, and present regression results with a combination of error clustering by individual student, school, and zip code. The ideal level of error clustering is not clear and thus testing multiple regression specifications with different clustering levels is appropriate. As described in a methodological paper on error clustering by Cameron and Miller (2015), clustering at "higher" (i.e., less granular) levels typically offers less bias but more variability, which in turn leads to larger standard errors and less statistical significance. Thus, in the absence of a clear theoretical imperative to do otherwise, a conservative approach favors error clustering at higher levels. The SEDA data allows for error clustering by "commute zone," which is decidedly less granular than school districts, zip codes, or counties (the dataset includes approximately 700 California school districts, 55 counties, and 16 commute zones). Thus, the favored regression results presented in the next section include error clustering by commute zone. However, as a measure of robustness, I also include results from lower clustering levels in Table A5.

## Interaction Effects

This theoretical model describes the "main effects" of the explanatory pollution variables (i.e., the simple linear effect of these variables across the test score distribution, while controlling for confounding factors). However, I also examine "interaction effects" between certain pollution variables and selected covariates representing key geographic and demographic characteristics, which may provide additional insight into the mechanisms linking pollution exposure to academic achievement. Specifically, I examine how the effect of certain pollutants varies based on a district's urban or rural status, the percent of students in a district that are Black or Hispanic, and a district's median income. These factors may influence the severity of incremental pollution impact because the particular chemical compounds associated with a given pollution variable are not homogenous (for example, fine particulate matter from a forest fire may contain different compounds than fine particulate matter from an industrial facility). Interaction effects with district urban or rural status may indicate whether particularly harmful pollution sources are located near population centers. Similarly, interaction effects with district percent Black or Hispanic may illustrate disparities in where these pollution sources were sited, or how pollution influences immigration patterns. Finally, interaction effects with income may show whether economic resources support personal pollution mitigation efforts, such as through household air or water filtration or proactive medical treatment for pollution-induced illness.

## 5. Results

This section presents the results of my analysis, which includes my primary regression specification and explores the different effects found for math and ELA scores, multiple robustness checks, effect size calculations, and the findings of my interaction effect tests.

### *Primary Specification*

Table 2 presents the results from the chosen specification of my fixed effects panel regression model. As described above, this regression specification includes the natural log of standardized test scores on the GCS scale as the dependent variable and inputs the pollution variables one at a time to limit multicollinearity, consistent with the methodological approach in prior studies. Since I used the natural log of test scores for all regression trials, I do not test non-linear functional forms for pollution variables. The chosen specification also clusters standard errors by commute zone to correct for heteroskedasticity, however I include results by different clustering levels as a robustness check in Table A5. As mentioned above, including all pollution variables included simultaneously (Table A6) appears to induce multicollinearity and obscure the effects of Groundwater Threats and Solid Waste Facilities, which are otherwise statistically significant when tested in isolation. Testing the pollution variables one at a time largely does not raise concerns about potential confounding effects from other pollutants, since the effects of most of the other pollution variables are themselves not statistically significant (whether tested simultaneously or individually) and the correlations between any two individual pollutants are relatively small (<0.5).

*Math vs ELA Scores*

The results of the chosen specification (Table 2) show that PM 2.5 has a statistically significant impact only on ELA scores and average scores, while Solid Waste Facilities has a statistically significant impact on only math scores and average scores. Groundwater Threats has a statistically significant impacts on math scores, ELA scores, and average scores. However, the results from the robustness tests (Tables A4 and A5) suggest that Groundwater Threats and Solid Waste facilities only have a statistically significant impact on math scores, and PM 2.5 only has a statistically significant impact on ELA scores.

**Table 2:** Regression Results from the Preferred Specification[a]. From top to bottom, each cell includes 1) elasticity at the mean, 2) the regression coefficient, and 3) the robust standard error. Results for the included control variables are found in Table A3. *** p<0.01, ** p<0.05, * p<0.1.

| **Significant Pollution Variables** | Average Scores | Math | ELA | Average Scores | Math | ELA | Average Scores | Math | ELA |
|---|---|---|---|---|---|---|---|---|---|
| PM 2.5 | -0.043<br>-0.00457**<br>(0.00213) | -0.0024<br>-0.000255<br>(0.00426) | -0.085<br>-0.00897***<br>(0.00247) | | | | | | |
| Groundwater Threats | | | | -0.0055<br>-0.000197**<br>(8.12e-05) | -0.0067<br>-0.000240**<br>(0.000100) | -0.0044<br>-0.000157*<br>(8.12e-05) | | | |
| Solid Waste Facilities | | | | | | | -0.011<br>-0.00338**<br>(0.00146) | -0.013<br>-0.00392**<br>(0.00164) | -0.0095<br>-0.00285<br>(0.00204) |
| Constant | 1.681***<br>(0.0640) | 1.581***<br>(0.0859) | 1.783***<br>(0.0635) | 1.637***<br>(0.0634) | 1.575***<br>(0.0775) | 1.703***<br>(0.0642) | 1.641***<br>(0.0631) | 1.579***<br>(0.0776) | 1.706***<br>(0.0641) |
| **Error Clustering Level** | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone |
| **Observations** | 10,964 | 5,486 | 5,478 | 11,554 | 5,782 | 5,772 | 11,554 | 5,782 | 5,772 |
| **N districts** | 712 | 710 | 711 | 723 | 720 | 722 | 723 | 720 | 722 |
| **$R^2$ (within districts; between district; overall)**[b] | 0.047; 0.490; 0.495 | 0.032; 0.536; 0.553 | 0.112; 0.299; 0.289 | 0.038; 0.511; 0.482 | 0.028; 0.569; 0.537 | 0.086; 0.301; 0.264 | 0.038; 0.497; 0.474 | 0.028; 0.552; 0.526 | 0.087; 0.301; 0.266 |

[a]For the Preferred specification, the dependent variable is natural log of grade levels (the GCS scale) and I inputted each pollution variable one at a time (i.e., each regression coefficient represents a separate regression trial). I did include four other pollution variables in my model (Traffic, Cleanup Sites, Hazardous Waste Facilities, and Impaired Water Bodies) but found they were not significant for either test subject and thus omitted them from this table.

[b]$R^2$ for the fixed effects panel regression trials is reported as the percent of variation in test scores either within or between school districts accounted for by the model inputs, with the "overall" $R^2$ calculated as the weighted average of the two. It does *not* represent the proportion of *total* test score variation across all observations accounted for by the suite of explanatory variables and fixed effects, which for all trials was approximately 0.9.

*Robustness*

I include two robustness checks to examine the consistency of my results under adjusted regression specifications. Table A4 uses standardized test scores with the natural log of the CS grade scale[4] as the dependent variable and shows that the SEDA assumptions used to derive the GCS grading scale had essentially no impact on my results. Table A5 uses the preferred regression specification and tests if the results are consistent across error clustering levels. As mentioned above, both robustness tests suggest that Groundwater Threats and Solid Waste Facilities only have a statistically significant impact on math scores. Regardless, all three pollution variables show a statistically significant impact on test scores for all clustering levels on both grading scales, with one exception: Groundwater Threats is not significant with errors clustered at the district level. The pollution data in my model vary by school district, but error clustering does not necessarily occur at this level. The best practices for error clustering denoted in Cameron and Miller (2015) favor the conservative approach of clustering at more aggregated levels (with the highest aggregation level in my dataset being commute zones). Thus, the anomalous result is worth noting but does not immediately undermine confidence in the results for Groundwater Threats, which is still significant in all other robustness trials. Additionally, clustering at the district level reveals a statistically significant effect on math scores from the Hazardous Waste Facilities variable, but this finding is not robust to any other error clustering levels.

*Effect Size*

Given that the CES pollution variables are each measured in different units and that the dependent variable in my preferred regression specification is the natural log of grade levels, I include the following calculations which allow for comparing the effects of pollution variables to each other and to similar results from prior studies. I find that a one standard deviation increase in a district's ambient PM 2.5 levels decreases ELA scores by 2.76%. I did not find a statistically significant effect of PM 2.5 on math scores. In contrast, I found a significant negative effect for Groundwater Threats on both math and

[4] Technically the CS grade scale with a constant added such that all values are positive, which preserves the distance between data points while allowing for taking the natural log.

ELA scores in the chosen specification, but per the robustness tests these variables may only have an impact on math scores. I find that a one standard deviation increase in a district's CES scores for Groundwater Threats and Solid Waste Facilities decreases math scores by 0.96% and 1.75%, respectively. The elasticities of these effects (the percent change in average test scores per percent change in the pollution variable from mean levels) were -0.085, -0.0067, and -0.013, respectively, for PM 2.5 on ELA scores, Groundwater Threats on math scores, and Solid Waste facilities on math scores.

*Interaction Effects*

Table 3a presents the results of regression trials that examine potential interactions between the three statistically significant pollution variables and selected covariates. I find that the effect of PM 2.5 on a district's ELA scores varies by Rural Status, Percent Black, and Percent Hispanic, while the effect of Groundwater Threats varies by Median Income and Percent Hispanic, and the effect of Solid Waste Facilities varies by Urban Status. Some of these interactions show that the effect of a pollutant changes considerably at certain levels of the selected covariate (Table 3b). However, interpreting the interaction effects is somewhat ambiguous as the inclusion of the interaction terms in some cases affected the statistical significance of the individual variable regression coefficients[5]. Furthermore, the directionality of these interactions was mixed (i.e., the effect of variable A may increase or decrease as variable B increases) in a manner that does not necessarily align with expectations, and some interactions were only statistically significant for a limited subset of covariate values (Table 3b). These interactions warrant careful interpretation and point to the multiple causal pathways that are likely at play for each pollution variable, which I discuss in further detail below.

[5] To some extent, these findings may be influenced by multicollinearity between the interaction term and the individual explanatory variables, as evident in high variance inflation factor (VIF) scores.

**Table 3a:** Interaction Effects. Linear regression coefficients that describe how the effect of pollution variables depends on the value of other explanatory variables. Cells with two values include coefficients for the pollutant and the selected covariate, respectively. *** p<0.01, ** p<0.05, * p<0.1.

| **Original Coefficients from Primary Regression Specification** | Urban Status | Rural Status | Percent Black | Percent Hispanic | Median Income |
|---|---|---|---|---|---|
| PM 2.5 (ELA scores)[a] | -0.00897***<br>-0.0392 | -0.00897***<br>-0.000487 | -0.00897***<br>-0.418** | -0.00897***<br>-0.0837 | -0.00897***<br>-1.33e-07 |
| Groundwater Threats (math scores) | -0.000240**<br>-0.0184 | -0.000240**<br>-0.0112 | -0.000240**<br>-0.353* | -0.000240**<br>-0.0245 | -0.000240**<br>5.28e-07 |
| Solid Waste Facilities (math scores) | -0.00392**<br>-0.0194 | -0.00392**<br>-0.0112 | -0.00392**<br>-0.362* | -0.00392**<br>-0.0263 | -0.00392**<br>4.70e-07 |
| **Updated Coefficients with Interaction Term Included** | | | | | |
| PM 2.5 (ELA scores) | -0.00894***<br>-0.0372 | -0.00484*<br>0.0862* | -0.00582[b]<br>0.474 | -0.0181***<br>-0.237*** | -0.00161<br>1.03e-06 |
| Groundwater Threats (math scores) | -0.000256**<br>-0.0238 | -0.000196<br>-0.000761 | -0.000286***<br>-0.477** | -0.000695***<br>-0.0508 | 0.000289<br>8.17e-07 |
| Solid Waste Facilities (math scores) | -0.00457**<br>-0.0335 | -0.00250<br>0.000280 | -0.00320<br>-0.249 | -0.00110<br>-0.00477 | -0.00703<br>2.91e-07 |
| **Interaction Coefficients**[c] | | | | | |
| PM 2.5 (ELA scores) | -0.000193 | -0.0101022* | -0.100515** | 0.0186714*** | -1.31e-07 |
| Groundwater Threats (math scores) | 0.0002013 | -0.0001327 | 0.0025524 | 0.000758*** | -9.16e-09* |
| Solid Waste Facilities (math scores) | 0.0097336* | -0.0032229 | -0.0487573 | -0.0046686 | 6.13e-08 |

[a]Test types selected for each pollution variable reflect the most robust linear effects found across error clustering levels per Table A5.
[b]p=0.102
[c]Note that some of the trials that produced statistically significant interaction effects did not simultaneously produce statistically significant effects for the individual interaction terms. Especially in cases where the terms themselves were significant prior to incorporating the interaction variable (for example, PM 2.5 and Percent Black), the change in standard errors for these terms may be due to collinearity with the interaction variable. Collinearity does not necessarily negate the observed interaction effect, but it is a caveat for assessing the validity of the result.

**Table 3b:** Marginal interactions. Linear regression coefficients that estimate the effect of pollution variables at a given level of other explanatory variables. *** p<0.01, ** p<0.05, * p<0.1.

| Respective Interaction Variable Level (Varies Between 0 to 1) | PM 2.5 and Rural Status | PM 2.5 and Percent Black | PM 2.5 and Percent Hispanic | Solid Waste Facilities and Urban Status | Groundwater Threats and Percent Hispanic | Groundwater Threats and Median Income by Decile |
|---|---|---|---|---|---|---|
| 0 | -.0048354* | -.0058198* | -.0181347*** | -0.00457** | -0.00069*** | 0.000289 |
| 0.1 | -.0058456** | -.0158719*** | -.0162675*** | -0.0036** | -0.00062*** | -0.0000579 |
| 0.2 | -.0068559*** | -.0259228*** | -.0144004*** | -0.00263* | -0.00054*** | -0.000105 |
| 0.3 | -.0078661*** | -.0359743*** | -.0125332*** | -0.00165 | -0.00047*** | -0.000153 |
| 0.4 | -.0088763*** | -.0460258*** | -.0106661*** | -0.00068 | -0.00039*** | -0.000197 |
| 0.5 | -.0098865*** | -.0560773*** | -.0088799*** | 0.000293 | -0.00032** | -0.000242* |
| 0.6 | -.0108968*** | -.0661288*** | -.0069318*** | 0.001266 | -0.00024* | -0.000291** |
| 0.7 | -.011907*** | -.0761804*** | -.0050647** | 0.00224 | -0.00016 | -0.000356*** |
| 0.8 | -.0129172*** | -.0862319*** | -.0031975 | 0.003213 | -8.9E-05 | -0.000450*** |
| 0.9 | -.0139274*** | -.0962834*** | -.0013304 | 0.004186 | -1.3E-05 | -0.000590*** |
| 1.0 | -.0149376*** | -.1063349*** | .0005368 | 0.00516 | 6.31E-05 | -0.00172** |

## 6. Discussion

Next, I interpret the regression results in comparison to prior studies, posit the theoretical basis for certain novel findings, use effect size calculations to assess possible policy responses, and lay the groundwork for future research needed to further understand the connection between pollution exposure and academic achievement.

### *Math vs ELA Scores*

Multiple prior studies similarly find a statistically significant impact of PM 2.5 on test scores in different contexts and with different methodologies (see Table A2). However, there are only limited studies examining the difference of the effect between math and ELA scores. Ham et al. (2011) use multiple measures for math and ELA scores—both raw scores and percent of students at least proficient—and show that PM 2.5 is statistically significant for both subjects, although the results are more robust for ELA scores (I only found the effect of PM 2.5 to be significant for ELA scores). Ham et al. (2011) also apply a quantile regression design and find that the marginal impact of PM 2.5 increases at higher math score levels. Conversely, Austin, Heutel, & Kreisman (2019) find that particulate matter emissions from diesel school buses only have a statistically significant impact on ELA scores, although particulate matter from diesel may contain different constituent compounds and particle sizes than general ambient PM 2.5.

I did not identify any other studies that differentiate air pollution impacts between math and ELA scores, and none of these studies offer a theoretical explanation as to why the effect would be different on different subjects (or why the effect would be non-linear in some cases). The causal relationship between pollution exposure and test scores is complex and occurs through multiple channels, and thus it is possible that the effects on ELA and math occur through different mechanisms. For example, perhaps impacts on ELA scores are mediated more by health issues that cause school absences, while math impacts occur more through acute cognitive impairment. Some studies have shown that math scores in general may be more sensitive to changes in exogenous factors (Trejo et al., 2021), but further research is needed to examine the different causal mechanisms by which pollution exposure affects math versus ELA scores.

*Error Clustering*

Existing studies do not appear to sufficiently engage with the potential effect of error clustering on pollution impacts. The only study identified that tested error clustering at different levels was Heissel, Persico, & Simon (2019), which determined that their results were robust at different clustering levels but did not test any "higher" level than zip code. Most other studies do not examine the issue at all and simply cluster errors by the frame of reference in question (typically the school or district level). Though largely consistent across trials, my regression results did vary somewhat between error cluster levels, with notable discrepancies for Groundwater Threats and Hazardous Waste Facilities when clustered at the district level (Table A5). Limiting error clustering to one level (without a clear empirical imperative to do so) may produce misleading results and future studies should engage with this issue more thoroughly.

*Groundwater Threats and Solid Waste Facilities*

Unlike my results for PM 2.5, which are supported by a number of previous studies, the statistically significant effect on test scores I find for the CES variables denoted as Groundwater Threats and Solid Waste Facilities appear to be largely novel findings. Since both of these variables represent pollution sources rather than direct pollutant measurements, the mechanisms through which they affect test scores are less immediately discernible. However, the significance and robustness of my findings warrant further exploration into the possible connections between the components of these variables and student performance on standardized tests.

To many, Solid Waste Facilities (mostly landfills, but also composting facilities, waste tire facilities, and scrap metal recyclers) are a public nuisance, with disruptive odors, air pollution from facility fires and landfill gas leaks/flares[6], soil and groundwater pollution from landfill leachate, frequent heavy truck traffic, and loud industrial machinery. A limited number of studies have found epidemiological impacts from landfills (Palmer et al., 2005; Vassiliadou et al., 2009; Mataloni et al.,

[6] EPA (2021) describes the public health and safety problems of solid waste facility fires from improperly disposed lithium-ion batteries (an increasingly common element in the waste stream).

2016) and a connection to academic achievement is certainly plausible. Future studies could take a more granular approach and use the distance between specific schools and these facilities as an explanatory variable or introduce a time component to see if students perform worse on days with facility fires or high odor levels.

The Groundwater Threats variable draws from two state databases[7] and consists of a variety of pollution sources deemed a threat to groundwater, such as leaking fuel storage tanks, oil and gas drilling ponds, dairy feedlots, sewage plants, and certain toxic cleanup sites not covered by the separate "Cleanup Sites" variable. CES highlights how various toxic compounds from these pollution sources, such as benzene, toluene, chlorinated solvents, lead, chromium, and arsenic can permeate groundwater and come into human contact through drinking water systems[8]. However, some of these volatile compounds could also reach people through evaporation or contact with contaminated soil or surfaces. While I was unable to incorporate the CES variable "Drinking Water Quality" into my model due to insufficient variation across panel years, a future study that incorporates direct drinking water quality data would be useful to help distinguish these causal paths.

*Negative Results*

I found a few negative (i.e., non-statistically significant) results for certain pollutants that warrant comparison to existing studies. Heissel, Persico, & Simon (2019) find a statistically significant impact of pollution from vehicle traffic on test scores. I find no such effect, whether by including traffic alongside PM 2.5 so that the variables do not confound each other (Table A6) or by testing traffic in isolation (Table 2). However, Heissel, Persico, & Simon (2019) find that the effects of traffic pollution are mediated by wind patterns, such that students that attend school downwind of major vehicle traffic show worse test

[7] GeoTracker and the California Integrated Water Quality System, both overseen by the California State Water Resources Control Board. Note that these pollution sources are common and not necessarily concentrated in urban or rural areas (OEHHA, 2021; Beckley et al., 2022).

[8] Nearly a million Californians currently have drinking water systems deemed unfit for human consumption, whether from dilapidated municipal infrastructure or contaminated wells (California State Auditor, 2022).

scores, higher absences, and more behavioral problems. My data maps high traffic levels only to geographically proximate school districts, and thus a negative finding for the traffic variable does not contradict the notion that wind patterns determine which schools bear the impact of traffic pollution. In contrast, my PM 2.5 variable reflects actual concentration measurements and thus its impact does not depend on wind patterns.

Separately, the mostly negative results for Cleanup Sites and Hazardous Waste Facilities are notable because these variables have some parallels in prior research. Rau, Urzua, and Reyes (2015) find a negative impact of toxic waste sites in Chile on the test scores and future earnings of students that attend the surrounding schools, and they estimate that each kilometer of distance from these sites improves math scores by 0.09 standard deviations. Other studies establish a connection between EPA Superfund sites (a primary component of the CES Cleanup Sites variable) and infant abnormalities, childhood lead exposure, and childhood cognitive and behavioral issues (Persico, Figlio, and Roth, 2020; Currie, Greenstone, and Moretti, 2011; Klemick, Mason, and Sullivan, 2020). These outcomes would theoretically have a negative impact on academic achievement, but I find no such effect. However, without access to actual pollution concentrations it is difficult to make a direct comparison. Perhaps in California these sites simply do not produce enough environmental pollution to have a detectable impact on local children, and studies in other locations would show otherwise.

The final pollution variable I examined—impaired water bodies—had the most tenuous theoretical support and likewise did not show a statistically significant effect on test scores. This negative finding suggests that pollution exposure from recreation in lakes and rivers or consuming wild-caught fish (which may contain high levels of mercury or other heavy metals) did not have a detectable negative impact on academic achievement in California from 2009-2018.

### *Effect Size Analysis*

Table A2 summarizes the effect size for PM 2.5 found in prior studies in order to contextualize my results. Prior studies establish a largely consistent framework for the effect of PM 2.5 on test scores over time: PM 2.5 levels *on test day alone* only produce 0.2-0.5x the effect of PM 2.5 levels throughout the school year, and air pollution mitigation largely reverses the effect. My analysis, which aimed to estimate the aggregate impact of pollution exposure throughout a student's life rather than over a limited timeframe[9], produced an effect size of approximately the same magnitude as studies that examine the effect of PM 2.5 on average test scores throughout the school year, which largely corroborates this existing understanding. Hence, the health and cognitive impacts of PM 2.5 appear largely contemporaneous rather than rooted in irreparable developmental harms, which is an encouraging finding for the potential benefits of policy intervention. Separately, the effect sizes I find for Groundwater Threats and Solid Waste Facilities are somewhat smaller than PM 2.5 but still non-trivial and worth further investigation, especially as the actual impact of poor drinking water quality may prove to be much greater than the indirect proxy offered by the collection of pollution sources denoted as Groundwater Threats.

*Interaction Effects*

The interaction effects I find in Table 3 provide additional context for the causal mechanisms supporting the impact of PM 2.5, Groundwater Threats, and Solid Waste Facilities on math or ELA test scores, although these interactions are complex and, in some cases, have ambiguous statistical validity (as noted in Table 3a). As a whole, my interaction tests support the notion that the constituent compounds of pollutants such as PM 2.5 are not homogenous, and that the incremental cognitive, physical, and academic effects of elevated pollution exposure may vary dramatically based on geography and demographics. For example, the magnitude of the interaction I found between PM 2.5 and Percent Black is particularly striking: for California school districts that are 70% Black (the highest value in my dataset), the effect of PM 2.5 on ELA scores is approximately 13-times the effect in districts that are 0% Black, and 8-time the average effect found across all districts (Table 3b). Similarly, Kodros et al. (2022) find that PM 2.5 in highly segregated U.S. counties contains 3-12 times the level of toxic heavy metals than PM in well-integrated counties, which may explain why the same concentration of PM 2.5 exposure appears to

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[9] One prior study—Ham et al. (2011)—takes a similarly holistic approach, but is not directly comparable since their measure for PM 2.5 is *percent of days above the regulatory standard*, which does not necessarily approximate actual PM 2.5 concentrations experienced throughout the year.

be more harmful in majority Black districts than majority White ones. Interestingly, I find an opposite (although less dramatic) effect for the interaction between PM 2.5 and Percent Hispanic: the effect of PM 2.5 on ELA scores is 3.6-times *lower* in districts that are 70% Hispanic versus districts that are 0% Hispanic, and 1.8x lower than the average effect found across all districts[10]. In California, the different effects of PM 2.5 in Black versus Hispanic districts may reflect historical patterns of land use and migration—perhaps discriminatory land use practices disproportionately sited the particularly harmful sources of PM 2.5 in Black neighborhoods, while, *ceteris paribus*, Latin American immigrants that arrived in California in more recent decades self-sorted away from these existing harms.

I also found evidence that the effect of the pollution variables depends somewhat on geography and income. The per-unit effect of PM 2.5 in fully rural districts is 1.7-times the effect of PM 2.5 in average districts, which, like with majority Black districts, suggests that heavily rural districts are exposed to more harmful particulate compounds. Likewise, the positive interaction between Solid Waste Facilities and urban status would suggest that perhaps the more toxic waste facilities are located away from major population centers, but this finding is likely irrelevant since the interaction was only significant for low values of urban status (Table 3b). Finally, I find that the effect of Groundwater Threats is more harmful as income *increases* above median levels. While I did not find a significant interaction between PM 2.5 and income, Mullen et al. (2020) found that the incremental effect of PM 2.5 was significantly more harmful in *high-income* schools, and the authors suggest that perhaps these schools are more sensitive to the effects of air pollution because they are less burdened by other socioeconomic disparities. Perhaps a similar mechanism supports the interaction I observed between Groundwater Threats and income, but further investigation is needed to corroborate and explain this finding. No other identified studies on the connection between pollution exposure and test scores examined these interactions, which should be given greater attention in future research.

[10] Note that these interactions of PM 2.5 and Percent Black or Percent Hispanic also include the same suite of control variables as all other regression trials (i.e., the effect of PM 2.5 varies by race/ethnicity *regardless of income and geography*)

*Policy Implications*

At least for PM 2.5, existing research suggests that the harms from continued exposure are mostly reversible, and that straightforward interventions may produce cost-effective academic benefits. Consider the finding in Gilraine (2020) that air purifiers installed in classrooms subsequently improved average student test scores by 0.2 standard deviations. While this result may appear to be somewhat higher than in similar studies (Table A2), it is not necessarily unreasonable given that indoor air quality may be worse than outdoor air quality (Chen & Zhao, 2011), and that commercially available air purifiers remove around 50-90+% of indoor particulates, though estimates vary (Gilraine, 2020; Maestas et al., 2019). This reduction in indoor PM 2.5 approximates a one-to-two-standard-deviation difference from the mean, and a potentially even greater reduction relative to (generally lower) ambient outdoor PM 2.5 levels. I found that a one standard deviation increase in district ambient PM 2.5 decreases ELA test scores by 0.12 standard deviations and average test scores by 0.066 standard deviations (since the effect of PM 2.5 on math scores appears to be minimal). Hypothetically, if 90% of ambient PM 2.5 in a mean district is eliminated (an unrealistic outcome for even the most aggressive regulatory standards), then that district would see a 0.12 standard deviation improvement in average test scores and a 0.21 standard deviation improvement in ELA scores. Thus, the finding from Gilraine (2020) is perhaps slightly high but appears reasonable. Hence, my results support the finding in Gilraine (2020) that air pollution mitigation has immediate benefits for academic achievement and that classroom air purifiers are a potentially cost-effect education intervention[11]. My findings also show that the per-unit impact of PM 2.5 in California is particularly severe in Black districts, and thus any policy mechanisms or funding to support indoor air filtration may produce outsize (and equitable) benefits by prioritizing these communities.

Separately, the policy implications of my results for Groundwater Threats and Solid Waste Facilities are less certain until further research is done to delineate the underlying causal mechanisms

[11]This finding is also supported by Stafford (2015), which found that school retrofits to improve ventilation increased test scores by 0.07-0.11 standard deviations, and that this educational benefit is more cost-effective than other common interventions such as class-size reductions.

(such as the extent to which these pollution sources are contaminating drinking water systems). Water quality and waste management systems are both thoroughly regulated in California, and the potential impacts of these variables on academic achievement warrant consideration in the cost-benefit analyses that support these regulations and associated mitigation efforts.

### *Remaining Questions and Future Research*

My findings corroborate and support a growing body of research pointing to significant negative impacts of PM 2.5 exposure on academic achievement, and present novel findings of a similar negative impact from a group of pollution sources denoted as Groundwater Threats and Solid Waste Facilities. For these latter two variables, I suggest additional research to replicate my findings and deduce the underlying causal mechanisms and mediating factors.

For PM 2.5, I also suggest additional research to understand the mechanisms and subcomponents of this variable that are driving the effect. "Particulate matter" is a catch-all term for several forms of small particles that accumulate in ambient air and can cause health problems through inhalation, where finer particles can penetrate further into the lungs[12] (Hassan et al., 2017). However, the constituents of particulate matter can vary based on the source and location. As described above, more toxic forms of PM 2.5 (such as heavy metal particulates from certain industrial sources) may be particularly concentrated and have disproportionate effects in Black communities. PM is also not entirely anthropogenic, as it also includes particles from wildfire smoke, pollen, sea spray, and other particulates arising from natural processes (Marcotte, 2017; Hassan et al., 2017). Coarse PM (PM 10) and PM from diesel exhaust are also known to have different constituents and effects than general PM 2.5 and are tracked separately in air toxics inventories (California Air Resources Board, n.d. -b). Thus, studies that estimate the impact of individual components of air pollution may also be picking up impacts from other highly correlated components. Fortunately, the collinearity of air pollution variables means that regulatory standards for pollution sources (such as vehicle exhaust) often affect multiple air pollutants simultaneously and

[12] PM 2.5 refers to particles of less than 2.5 microns in diameter, while PM 10 refers to particles of less than 10 microns in diameter (inclusive of PM 2.5).

differentiation is not necessary. However, the different components and particle sizes that comprise air pollution may still lead to different health (and educational) outcomes and warrant further study.

Finally, I recommend future research to examine the educational impact from other CES pollution variables that I was unable to incorporate into my panel regression model, such as pesticides, drinking water quality, industrial toxin releases, and lead exposure. Mohai et al. (2011) and Persico and Venator (2018) find a negative impact from industrial toxins on the test scores at surrounding schools, although Mohai et al. (2011) did not include controls for year, school, or district fixed effects. Many studies have examined the effect of lead poisoning on children's cognitive function and test performance (such as Trejo et al. (2021) which examined the Flint, Michigan lead crisis), but understanding the impact of sources of lead is difficult because many sources exist in the built environment and blood samples cannot differentiate them. CES 4.0 added a variable described as "children's lead risk from housing" that attempts to estimate lead exposure from lead-based paint typically found in older housing stock, while the CES variables for PM 2.5, drinking water quality, industrial toxin releases, and hazardous cleanup sites capture other sources of lead exposure. I was unable to incorporate three of these five CES variables in my data panel (Table 1), but a subsequent study focused on lead poisoning could gather enough panel data from relevant public datasets to differentiate the educational impacts of lead exposure from these various sources.

## 7. Conclusion

I find that California public school students have seen a small, but meaningful loss in standardized test score performance from exposure to certain forms of environmental pollution in their districts, including fine particulate matter in ambient air, landfills and other waste facilities, and water quality threats posed by a class of common contamination sources in the built environment. The effect sizes I find for each of these three pollution variables are substantial enough for policy consideration, especially as some paths to pollution mitigation (such as installing air filters in classrooms) may produce test score gains that are more cost-effective than other commonly prescribed educational interventions. Since pollution exposure often varies strongly by race, income, and geography, even untargeted mitigation has an equitable distribution of benefits. However, I also find that air pollution is particularly harmful in majority Black school districts and in heavily rural districts, and thus classroom air quality improvements would disproportionately benefit these communities.

Finally, I argue that all studies examining the connection between pollution and academic achievement (including my own) underestimate the true aggregate effect by not accounting for the endogenous effect of pollution on other determinants of educational outcomes, namely family income and socioeconomic status. Existing research clearly indicates that pollution exposure harms cognition and test performance, which in turn lowers expected lifetime incomes. Parents who themselves have experienced economic harm from undue pollution burdens are less enabled to foster academic success in their children. Thus, pollution mitigation provides both an immediate, direct benefit for current students and provides an indirect benefit for students in subsequent generations. And as such a profound correlation exists between race, income, pollution burden, public health, and academic achievement, these benefits would accrue disproportionately in disadvantaged communities and would work toward closing inequitable gaps in public health and educational outcomes.

## References


Aber, J. L., Grannis, K., Owen, S., & Sawhill, I. (2012). Middle childhood success and economic mobility. *Washington, DC: Centers on Children and Families at Brookings Institute*. https://www.brookings.edu/wp-content/uploads/2016/06/15-education-success-economic-mobility-aber-grannis-owen-sawhill.pdf

Akee, R. K., Copeland, W. E., Keeler, G., Angold, A., & Costello, E. J. (2010). Parents' incomes and children's outcomes: a quasi-experiment using transfer payments from casino profits. *American Economic Journal: Applied Economics*, *2*(1), 86-115. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2891175/?source=post_page

Allen, J. G., MacNaughton, P., Satish, U., Santanam, S., Vallarino, J., & Spengler, J. D. (2016). Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: a controlled exposure study of green and conventional office environments. *Environmental health perspectives*, *124*(6), 805-812. https://dash.harvard.edu/bitstream/handle/1/27662232/4892924.pdf?sequence=1

Amanzadeh, N., Vesal, M., & Ardestani, S. F. F. (2020). The impact of short-term exposure to ambient air pollution on test scores in Iran. *Population and Environment*, *41*(3), 253-285. https://link.springer.com/article/10.1007/s11111-019-00335-4

Anenberg, S. C., Henze, D. K., Tinney, V., Kinney, P. L., Raich, W., Fann, N., ... & Kuylenstierna, J. C. (2018). Estimates of the global burden of ambient PM 2.5, ozone, and NO2 on asthma incidence and emergency room visits. *Environmental health perspectives*, *126*(10), 107004. https://ehp.niehs.nih.gov/doi/10.1289/ehp3766

Archsmith, J., Heyes, A., & Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 827-863. https://www.journals.uchicago.edu/doi/full/10.1086/698728

Austin, W., Heutel, G., & Kreisman, D. (2019). School bus emissions, student health and academic performance. *Economics of Education Review*, *70*, 109-126. https://www.nber.org/system/files/working_papers/w25641/w25641.pdf

Ayotte, J. D., Nolan, B. T., & Gronberg, J. A. (2016). Predicting arsenic in drinking water wells of the Central Valley, California. *Environmental Science & Technology*, *50*(14), 7555-7563. https://pubs.acs.org/doi/pdf/10.1021/acs.est.6b01914

Baibergenova, A., Kudyakov, R., Zdeb, M., & Carpenter, D.O. (2003). Low birth weight and residential proximity to PCB-contaminated waste sites. *Environmental Health Perspectives* 111(10):1352-7. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.6053

Baibergenova, A., Kudyakov, R., Zdeb, M., & Carpenter, D.O. (2003). Low birth weight and residential proximity to PCB-contaminated waste sites. *Environmental Health Perspectives* 111(10):1352-7. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.6053

Bali, V. A., & Alvarez, R. M. (2003). Schools and educational outcomes: What causes the “race gap” in student test scores? *Social Science Quarterly*, *84*(3), 485-507. https://onlinelibrary.wiley.com/doi/pdf/10.1111/1540-6237.8403001?casa_token=UGfDmOzMqOAAAAAA:qoF2QHyijDwUIry1AdA4BoU-MeQMl_gntzt9K4QMtvIsvjhjBv0F86dTON86dho7jgiQwsPtiJAB6w

Beckley, L., McMasters, S., Cohen, M., Cordano, D., Rauch, S., & McHugh, T. (2022). The California GeoTracker Database: A Unique Public Resource for Understanding Contaminated Sites. *Groundwater Monitoring & Remediation*. https://ngwa.onlinelibrary.wiley.com/doi/epdf/10.1111/gwmr.12520

Been, V. (1994). Locally undesirable land uses in minority neighborhoods: Disproportionate siting or market dynamics? *Yale law journal*, 1383-1422. https://www.jstor.org/stable/797089

Beeson, W. L., Abbey, D. E., & Knutsen, S. F. (1998). Long-term concentrations of ambient air pollutants and incident lung cancer in California adults: results from the AHSMOG study.

Adventist Health Study on Smog. *Environmental health perspectives*, *106*(12), 813-823. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.106-1533247

OEHHA. (2021). CalEnviroScreen 4.0 Report. https://oehha.ca.gov/media/downloads/calenviroscreen/report/calenviroscreen40reportf2021.pdf

OEHHA. (2022). Uses of CalEnviroScreen. https://oehha.ca.gov/calenviroscreen/how-use

CalEPA. (2021a). SB 535 Disadvantaged Communities Map. https://experience.arcgis.com/experience/1c21c53da8de48f1b946f3402fbae55c/page/SB-535-Disadvantaged-Communities/

CalEPA. (2021b). Pollution and Prejudice. https://storymaps.arcgis.com/stories/f167b251809c43778a2f9f040f43d2f5

California Air Resources Board, n.d. -a. Inhalable Particulate Matter and Health. https://ww2.arb.ca.gov/resources/inhalable-particulate-matter-and-health

California Air Resources Board, n.d. -b. Criteria Pollutant Emissions Inventory Data. https://ww2.arb.ca.gov/criteria-pollutant-emission-inventory-data

California State Auditor. (2022, July 26). State Water Resources Control Board: It Lacks the Urgency Necessary to Ensure That Failing Water Systems Receive Needed Assistance in a Timely Manner. https://www.auditor.ca.gov/reports/2021-118/index.html#QL1

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317-372. http://cameron.econ.ucdavis.edu/research/Cameron_Miller_JHR_2015_February.pdf

Canfield, R.L., Henderson, C.R., Cory-Slechta, D.A., Cox, C., Jusko, T.A., & Lanphear, B.P. (2003). Intellectual Impairment in Children with Blood Lead Concentrations below 10 µg per Deciliter. *New England Journal of Medicine* 348(16):1517-26. https://www.nejm.org/doi/full/10.1056/NEJMoa022848

Chamberlain, G. E. (2013). Predictive effects of teachers and schools on test scores, college attendance, and earnings. *Proceedings of the National Academy of Sciences*, *110*(43), 17176-17182. https://www.pnas.org/doi/pdf/10.1073/pnas.1315746110

Chay, K. Y., & Greenstone, M. (2005). Does air quality matter? Evidence from the housing market. *Journal of political Economy*, *113*(2), 376-424. https://www.journals.uchicago.edu/doi/10.1086/427462

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *The Quarterly journal of economics*, *126*(4), 1593-1660. https://www.oecd.org/els/47789686.pdf

Chen, C., & Zhao, B. (2011). Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmospheric environment, 45*(2), 275-288. https://www.sciencedirect.com/science/article/abs/pii/S1352231010008241?via%3Dihub

Cho, H., Glewwe, P., & Whitler, M. (2012). Do reductions in class size raise students' test scores? Evidence from population variation in Minnesota's elementary schools. *Economics of Education Review*, *31*(3), 77-95. https://www.sciencedirect.com/science/article/abs/pii/S0272775712000180?via%3Dihub

Choi, H.S., Shim, Y.K., Kaye, W.E., & Ryan, P.B. (2006). Potential residential exposure to toxics release inventory chemicals during pregnancy and childhood brain cancer. *Environmental Health Perspectives* 114(7):1113- 8. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.9145

Conwell, J. A. (2021). Diverging disparities: race, parental income, and children's math scores, 1960 to 2009. *Sociology of Education*, *94*(2), 124-142. https://journals.sagepub.com/doi/abs/10.1177/0038040720963279

Currie, J., Greenstone, M., & Moretti, E. (2011). Superfund cleanups and infant health. *American Economic Review*, *101*(3), 435-41. https://www.nber.org/system/files/working_papers/w16844/w16844.pdf

Environmental Protection Agency. (2021). An Analysis of Lithium-Ion Battery Fires in Waste Management and Recycling. https://www.epa.gov/system/files/documents/2021-08/lithium-ion-battery-report-update-7.01_508.pdf

Eubig, P.A., Aguiar, A., & Schantz, S.L. (2010). Lead and PCBs as risk factors for attention deficit/hyperactivity disorder. *Environmental Health Perspectives* 118(12):1654-67. https://pubmed.ncbi.nlm.nih.gov/20829149/

Fahle, E. M., Chavez, B., Kalogrides, D., Shear, B. R., Reardon, S. F., & Ho, A. D. (2021). Stanford Education Data Archive: Technical Documentation (Version 4.1). http://purl.stanford.edu/db586ns4974.

Fram, M.S., Belitz, K. (2011). Probability of detecting perchlorate under natural conditions in deep groundwater in California and the southwestern United States. *Environmental Science and Technology* 45(4):1271-7. https://pubs.acs.org/doi/pdf/10.1021/es103103p

Gilraine, M. (2020). Air filters, pollution and student achievement. *Annenberg Institute at Brown University.* https://edworkingpapers.com/sites/default/files/Gilraine_AirFilters_1.pdf

Gilraine, M., & Zheng, A. (2022). *Air Pollution and Student Performance in the US* (No. w30061). National Bureau of Economic Research. https://www.nber.org/papers/w30061

Gonzalez, D. J., Nardone, A., Nguyen, A. V., Morello-Frosch, R., & Casey, J. A. (2022). Historic redlining and the siting of oil and gas wells in the United States. *Journal of Exposure Science & Environmental Epidemiology*, 1-8. https://www.nature.com/articles/s41370-022-00434-9

Gunier RB, Bradman A, Harley KG, Kogut K, Eskenazi B (2017). Prenatal residential proximity to agricultural pesticide use and IQ in 7-year-old children. *Environmental Health Perspectives* 125(5):057002. https://ehp.niehs.nih.gov/doi/full/10.1289/EHP504

Ha M, Kwon H-J, Lim M-H, Jee Y-K, Hong Y-C, Leem J-H, et al. (2009). Low blood levels of lead and mercury and symptoms of attention deficit hyperactivity in children: a report of the children's health and environment research (CHEER). *Neurotoxicology* 30(1):31-6. https://pubmed.ncbi.nlm.nih.gov/19100765/

Ham, J. C., Zweig, J. S., & Avol, E. L. (Revised 2011). Air pollution and academic performance: Evidence from California schools. *National Institute of Environmental Health Sciences*, *1*, 35. https://conference.iza.org/conference_files/TAM2012/ham_j1496.pdf

Hanna, B. G. (2007). House values, incomes, and industrial pollution. *Journal of Environmental Economics and Management*, *54*(1), 100-112. https://www.sciencedirect.com/science/article/abs/pii/S0095069607000204

Hassan, H., Abraham, M., Kumar, P., & Kakosimos, K. E. (2017). Sources and Emissions of Fugitive Particulate Matter. *Airborne Particles*, 21. https://www.researchgate.net/profile/Amela-Jericevic/publication/317012252_The_assessment_of_transboundary_and_regional_air_pollution_due_to_particles/links/5afede39a6fdcc722af54cc1/The-assessment-of-transboundary-and-regional-air-pollution-due-to-particles.pdf

Heissel, J. A., Persico, C., & Simon, D. (2022). Does pollution drive achievement? The effect of traffic pollution on academic performance. *Journal of Human Resources*, *57*(3), 747-776. https://docs.iza.org/dp12745.pdf

Heyes, A., Rivers, N., & Schaufele, B. (2019). Pollution and politician productivity: the effect of pm on mps. *Land Economics*, *95*(2), 157-173. https://muse.jhu.edu/article/721064/pdf

Houston, D., Wu, J., Ong, P., & Winer, A. (2004). Structural disparities of urban traffic in Southern California: implications for vehicle-related air pollution exposure in minority and high-poverty neighborhoods. *Journal of Urban Affairs*, *26*(5), 565-592. https://www.tandfonline.com/doi/abs/10.1111/j.0735-2166.2004.00215.x

Karas, D. (2015). Highway to inequity: the disparate impact of the interstate highway system on poor and minority communities in American cities. *New Visions for Public Affairs*, *7*, 9-21. https://www.ce.washington.edu/files/pdfs/about/Highway-to-inequity.pdf

Kim, Y., Kim, B. N., Hong, Y. C., Shin, M. S., Yoo, H. J., Kim, J. W., ... & Cho, S. C. (2009). Co-exposure to environmental lead and manganese affects the intelligence of school-aged children. *Neurotoxicology*, *30*(4), 564-571. https://www.sciencedirect.com/science/article/abs/pii/S0161813X09000758?via%3Dihub

Klemick, H., Mason, H., & Sullivan, K. (2020). Superfund cleanups and children's lead exposure. *Environmental Economics and Management* 100:102289. https://www.sciencedirect.com/science/article/pii/S0095069619303304

Kodros, J.K., Bell, M.L., Dominici, F. (2022). Unequal airborne exposure to toxic metals associated with race, ethnicity, and segregation in the USA. *Nature Communications* 13, 6329 (2022). https://doi.org/10.1038/s41467-022-33372-z

Kouznetsova, M., Huang, X., Ma, J., Lessner, L., & Carpenter, D.O. (2007). Increased rate of hospitalization for diabetes and residential proximity of hazardous waste sites. *Environmental Health Perspectives* 115(1):75-9. https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.9223

Künn, S., Palacios, J., & Pestel, N. (2019). The impact of indoor climate on human cognition: Evidence from chess tournaments. *IZA DP*, (12632). https://conference.iza.org/conference_files/environ_2019/palacios_j24419.pdf

Lane, H. M., Morello-Frosch, R., Marshall, J. D., & Apte, J. S. (2022). Historical redlining is associated with present-day air pollution disparities in US cities. *Environmental science & technology letters*, *9*(4), 345-350. https://pubs.acs.org/doi/full/10.1021/acs.estlett.1c01012

Lavy, V., Ebenstein, A., & Roth, S. (2014). *The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation* (No. w20648). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w20648/w20648.pdf

Leigh, A. (2010). Estimating teacher effectiveness from two-year changes in students' test scores. *Economics of Education Review*, *29*(3), 480-488. https://www.sciencedirect.com/science/article/abs/pii/S0272775709001289?via%3Dihub

Maestas, M. M., Brook, R. D., Ziemba, R. A., Li, F., Crane, R. C., Klaver, Z. M., Bard, R. L., Spino, C. A., Adar, S. D., & Morishita, M. (2019). Reduction of personal $PM_{2.5}$ exposure via indoor air filtration systems in Detroit: an intervention study. *Journal of exposure science & environmental epidemiology*, *29*(4), 484–490. https://doi.org/10.1038/s41370-018-0085-2

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: a review. *Frontiers in public health*, 14. https://www.frontiersin.org/articles/10.3389/fpubh.2020.00014/full

Marcotte, D. E. (2017). Something in the air? Air quality and children's educational outcomes. *Economics of Education Review*, *56*, 141-151. https://www.sciencedirect.com/science/article/abs/pii/S0272775716303703

Mataloni, F., Badaloni, C., Golini, M.N., Bolignano, A., Bucci, S., & Sozzi, R. (2016). Morbidity and mortality of people who live close to municipal waste landfills: a multisite cohort study. *International Journal of Epidemiology* 45(3):806-15. https://academic.oup.com/ije/article/45/3/806/2572780

Meyer, S., & Pagel, M. (2017). *Fresh air eases work–The effect of air quality on individual investor activity* (No. w24048). National Bureau of Economic Research. https://www.nber.org/papers/w24048

Mohai, P., & Saha, R. (2015). Which came first, people or pollution? Assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice. *Environmental Research Letters*, *10*(11), 115008. https://iopscience.iop.org/article/10.1088/1748-9326/10/11/115008/meta

Mohai, P., Kweon, B. S., Lee, S., & Ard, K. (2011). Air pollution around schools is linked to poorer student health and academic performance. *Health Affairs*, *30*(5), 852-862. https://www.healthaffairs.org/doi/10.1377/hlthaff.2011.0077

Mullen, C., Grineski, S. E., Collins, T. W., & Mendoza, D. L. (2020). Effects of PM2. 5 on third grade students' proficiency in math and English language arts. *International Journal of Environmental Research and Public Health*, *17*(18), 6931. https://www.mdpi.com/1660-4601/17/18/6931

Nuvolone, D., Petri, D., & Voller, F. (2018). The effects of ozone on human health. *Environmental Science and Pollution Research*, *25*(9), 8074-8088. https://link.springer.com/article/10.1007/s11356-017-9239-3

Palmer, S.R., Dunstan, F.D., Fielder, H., Fone, D.L., Higgs, G., & Senior, M.L. (2005). Risk of congenital anomalies after the opening of landfill sites. *Environmental Health Perspectives* 113(10):1362-5. https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.7487

Pastor Jr, M., Sadd, J. L., & Morello-Frosch, R. (2004). Reading, writing, and toxics: children's health, academic performance, and environmental justice in Los Angeles. *Environment and Planning C: Government and Policy*, *22*(2), 271-290. https://www.researchgate.net/publication/23542405_Reading_Writing_and_Toxics_Children's_Health_Academic_Performance_and_Environmental_Justice_in_Los_Angeles

Pastor, M., Sadd, J., & Hipp, J. (2001). Which came first? Toxic facilities, minority move-in, and environmental justice. *Journal of urban affairs*, *23*(1), 1-21. https://onlinelibrary.wiley.com/doi/epdf/10.1111/0735-2166.00072

Pellerin, C., and Booker, S.M. (2000). Reflections on hexavalent chromium: health hazards of an industrial heavyweight. *Environmental Health Perspectives* 108(9):A402-A7. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.108-a402

Persico, C., Figlio, D., & Roth, J. (2020). The developmental consequences of Superfund sites. *Journal of Labor Economics* 38(4):1055-97. https://www.journals.uchicago.edu/doi/10.1086/706807

Persico, C. L., & Venator, J. (2021). The effects of local industrial pollution on students and schools. *Journal of Human Resources*, *56*(2), 406-445. http://jhr.uwpress.org/content/56/2/406.short

Raanan R, Harley KG, Balmes JR, Bradman A, Lipsett M, Eskenazi B (2015). Early-life exposure to organophosphate pesticides and pediatric respiratory symptoms in the CHAMACOS cohort. *Environmental Health Perspectives* 123(2):179-85. https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.1408235

Rau, T., Urzúa, S., & Reyes, L. (2015). Early exposure to hazardous waste and academic achievement: Evidence from a case of environmental negligence. *Journal of the Association of Environmental and Resource Economists*, *2*(4), 527-563. https://www.journals.uchicago.edu/doi/full/10.1086/683112

Rauh, V.A., Perera, F.P., Horton, M.K., Whyatt, R.M., Bansal, R., and Hao, X. (2012). Brain anomalies in children exposed prenatally to a common organophosphate pesticide. *National Academy of Sciences* 109(20):7871- 6. https://www.pnas.org/doi/full/10.1073/pnas.1203396109

Reardon, S.F., Ho, A.D., Shear, B.R., Fahle, E. Kalogrides, D., Jang, H., and Chavez, B. (2021). "Stanford education data archive (version 4.1)." http://purl.stanford.edu/db586ns4974.

Sergeev, A.V., and Carpenter, D.O. (2005). Hospitalization rates for coronary heart disease in relation to residence near areas contaminated with persistent organic pollutants and other pollutants. Environmental Health Perspectives 113(6):756-61. https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.7595

Shilling, F., White, A., Lippert, L., & Lubell, M. (2010). Contaminated fish consumption in California's Central Valley Delta. *Environmental Research* 110(4):334-44. https://pubmed.ncbi.nlm.nih.gov/20176346/

Sivarajah, S., Smith, S. M., & Thomas, S. C. (2018). Tree cover and species composition effects on academic performance of primary school students. *PLoS One*, *13*(2), e0193254. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0193254

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management*, *70*, 34-50. https://www.sciencedirect.com/science/article/abs/pii/S0095069614001016

Steinmaus, C., Miller, M.D., & Smith, A.H. (2010). Perchlorate in drinking water during pregnancy and neonatal thyroid hormone levels in California. *Occupational Environmental Medicine* 52(12):1217-524. https://www.jstor.org/stable/pdf/45010163.pdf

Strayhorn, J.C., & Strayhorn, J. M. (2012). Lead exposure and the 2010 achievement test scores of children in New York counties. *Child and adolescent psychiatry and mental health*, *6*(1), 1-8. https://capmh.biomedcentral.com/articles/10.1186/1753-2000-6-4

Strayhorn, J.C., & Strayhorn, J. M. (2012). Lead exposure and the 2010 achievement test scores of children in New York counties. *Child and adolescent psychiatry and mental health*, *6*(1), 1-8. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3292821/

Surkan, P.J., Zhang, A., Trachtenberg, F., Daniel, D.B., McKinlay, S., & Bellinger, D.C. (2007). Neuropsychological function in children with blood lead levels < 10 μg/dL. *Neurotoxicology* 28(6):1170-7. https://pubmed.ncbi.nlm.nih.gov/17868887/

Taras, H. (2005). Nutrition and student performance at school. *Journal of school health*, *75*(6), 199-213. https://pubmed.ncbi.nlm.nih.gov/16014126/

Trejo, S., Yeomans-Maldonado, G., & Jacob, B. (2021). *The Psychosocial Effects of the Flint Water Crisis on School-Age Children* (No. w29341). National Bureau of Economic Research. https://www.nber.org/papers/w29341

United States Environmental Protection Agency. (2021). An Analysis of Lithium-ion Battery Firesin Waste Management and Recycling. https://www.epa.gov/system/files/documents/2021-08/lithium-ion-battery-report-update-7.01_508.pdf

Van Den Ham, A. K., & Heinze, A. (2018). Does the textbook matter? Longitudinal effects of textbook choice on primary school students' achievement in mathematics. *Studies in Educational Evaluation*, *59*, 133-140. https://www.sciencedirect.com/science/article/pii/S0191491X18301007

Vassiliadou, I., Papadopoulos, A., Costopoulou, D., Vasiliadou, S., Christoforou, S., & Leondiadis, L. (2009). Dioxin contamination after an accidental fire in the municipal landfill of Tagarades, Thessaloniki, Greece. Chemosphere 74(7):879-84. https://www.sciencedirect.com/science/article/pii/S0045653508014124

Wang, T., Zhao, B., Liou, K. N., Gu, Y., Jiang, Z., Song, K., ... & Zhu, Y. (2019). Mortality burdens in California due to air pollution attributable to local and nonlocal emissions. *Environment international*, 133, 105232. https://www.sciencedirect.com/science/article/pii/S016041201932447X

White, G. W., Stepney, C. T., Hatchimonji, D. R., Moceri, D. C., Linsky, A. V., Reyes-Portillo, J. A., & Elias, M. J. (2016). The increasing impact of socioeconomics and race on standardized academic test scores across elementary, middle, and high school. *American Journal of Orthopsychiatry*, *86*(1), 10. https://web.s.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=0&sid=78cff8f9-0ee5-4ae9-af7f-5551231bb0c7%40redis

Winchester P, Proctor C, Ying J (2016). County-level pesticide use and risk of shortened gestation and preterm birth. *Acta Paediatrica* 105(3):e107-e15. https://onlinelibrary.wiley.com/doi/pdf/10.1111/apa.13288

Zhang, Y., West, J. J., Mathur, R., Xing, J., Hogrefe, C., Roselle, S. J., ... & Wong, D. C. (2018). Long-term trends in the ambient PM 2.5-and O 3-related mortality burdens in the United States under emission reductions from 1990 to 2010. *Atmospheric chemistry and physics*, *18*(20), 15003-15016. https://acp.copernicus.org/articles/18/15003/2018/

## Appendix

**Table A1:** Sample of Relevant Literature Illustrating the Potential Effects of Pollution Exposure on Human Health and Cognition

| **Variable** | **Study** | **Findings and Methodology** |
|---|---|---|
| Particulate Matter (effect on health) | Beeson et al., 1998 | Elevated ambient PM 10 levels are associated with increased incidents of lung cancer in California; cohort study of California adults |
| | Anenberg et al., 2018 | 5-10 million global emergency room visits for asthma in 2015 were attributable to PM 2.5 emissions, 73% of which were from anthropogenic sources; log-lin regression using epidemiological health impact functions |
| | Wang et al., 2019 | Mortality from long-term PM 2.5 exposure in California was between 12,700-26,700 in 2012, of which 53% is attributable to in-state anthropogenic emissions; PM 2.5 atmospheric modelling with concentration response functions |
| Particulate Matter (effect on cognition) | Künn et al., 2019 | Chess players made more errors with elevated indoor PM 2.5 levels, exacerbated by time limitations; Fixed effects linear regression |
| | Archsmith et al., 2018 | Baseball umpires made more incorrect calls with elevated ambient PM 2.5 levels; Fixed effects linear regression |
| | Meyer & Pagel, 2017 | Stock traders were less productive at work on days with elevated ambient PM 2.5 levels; Fixed effects linear regression |
| | Heyes et al., 2019 | Canadian politicians made less complex speeches on days with elevated ambient PM 2.5 levels, and this effect was non-linear; Fixed effects kernel-weighted regression with text analysis |
| Toxic Cleanup Sites | Baibergenova et al., 2003 | New York zip codes with PCB-contaminated cleanup sites have increased rates of low birth weights; logistic regression |
| | Klemick et al., 2020 | EPA Superfund site mitigation decreased pediatric blood lead levels within 2km by 13-26%; quasi-experimental difference-in-difference fixed effects regression |
| | Persico et al., 2020 | Florida children born near EPA Superfund sites have more cognitive and behavioral problems and lower test scores than siblings born after remediation; quasi-experimental fixed effects regression with instrumental variable controls |
| Hazardous Waste Facilities | Kouznetsova et al., 2007 | New York zip codes with certain hazardous waste facilities have elevated diabetes hospitalizations; negative binomial regression |
| | Sergeev and Carpenter, 2005 | New York zip codes with certain hazardous waste facilities have elevated coronary heart disease hospitalizations; negative binomial regression |
| | Pellerin and Booker, 2000 | Hazardous waste facilities frequently handle compounds such as hexavalent chromium known to cause respiratory illness and cancer; literature review |
| Solid Waste Facilities | Palmer et al., 2005 | Welsh communities near new or recently expanded landfills saw an increased rate of birth defects; quasi-experimental logistic regression |
| | Mataloni et al., 2016 | Italian communities exposed to high levels of hydrogen sulfide from landfill gas saw an increase in respiratory illness and lung cancer; cohort study |
| | Vassiliadou et al., 2009 | Elevated toxic dioxin levels found in food in Greek community near a landfill fire; laboratory testing |
| Pesticides | Winchester et al., 2016 | California counties with elevated pesticide use have higher preterm births and lower birth weights; logistic regression |
| | Gunier et al., 2017 | Children in an agricultural area of California with high prenatal exposure to five groups of pesticides scored lower on IQ tests and other measures of cognitive function; linear regression |
| | Rauh et al., 2012 | Children with high chlorpyrifos exposure show increased brain abnormalities; cohort study with MRI examination |
| | Raanan et al., 2015 | Children with high early-life exposure to a group of pesticides saw elevated respiratory illness; cohort study |
| Soil and Water Contaminants | Fram and Belitz, 2011 | Groundwater systems in drier areas of California have elevated levels of perchlorate; logistic regression |
| | Steinmaus et al., 2010 | Elevated perchlorate in California water systems is associated with disrupted endocrine function; logistic regression |
| | Ayotte et al., 2016 | Areas in the California Central Valley have elevated risk of exposure to potentially toxic levels of arsenic and nitrates; logistic regression and boosted regression trees |
| | Shilling et al., 2010 | Subsistence fishing in California delta communities likely results in mercury consumption above EPA advisory limits; food frequency survey given to shore anglers |

**Table A2:** Effect Size Comparison for Studies that Examine the Impact of PM 2.5 Exposure on Test Scores

| **Study** | **Methods** | **Timeframe of Analysis** | **Findings** | **Effect Size Notes and Comparison** |
|---|---|---|---|---|
| Marcotte (2017) | Fixed effects panel OLS regression | Test day | Doubling PM 2.5 Air Quality Index scores on test day decreases ELA scores by 2% | This effect size is likely less than half the magnitude of the effect I find for aggregate PM 2.5 exposure on ELA scores alone |
| Heissel, Persico, & Simon (2019) | Quasi-experimental difference-in-difference regression | Test day and full academic year | Attending school downwind of a major highway lowers average test scores by 0.04 standard deviations | The effect of PM 2.5 throughout the school year is 2-4x greater than the effect on test day alone<br>The actual difference in PM 2.5 exposure concentrations between downwind and upwind schools is unknown, and thus comparison to other studies uncertain |
| Amanzadeh et al. (2019) | Quasi-experimental regression with visibility as an instrumental variable for air pollution exposure | Test day | One standard deviation increase in PM 2.5 on test day is associated with 0.029 of a standard deviation decrease in test scores | This estimate is consistent with the estimate in other studies that test-day exposure produces around 0.2-0.5x the effect of exposure throughout the year |
| Ham et al. (2011) | Fixed effects panel OLS regression | Observational, not time-dependent | One standard deviation increase in days of PM 2.5 above regulatory standard decreases reading scores by 0.006 standard deviations | This measure for PM 2.5 (percent of days above the regulatory standard) does not necessarily approximate actual PM 2.5 concentrations experienced throughout the year, and thus comparison to other studies is uncertain |
| Gilraine (2020) | Spatial discontinuity regression | 4 months | Air purifiers installed in classrooms for approximately 4 months subsequently improved average student test scores by 0.2 standard deviations | Air filtration likely decreased indoor PM levels by 50-90%, although actual pre- and post-treatment concentrations are unknown and thus comparison to other studies is uncertain |
| Gilraine (2022) | Quasi-experimental regression model with coal power plant operation as an instrumental variable for air pollution exposure | Academic year | One µg/m³ increase in ambient PM 2.5 decreases subsequent average test scores by 0.02 standard deviations | The effect of PM 2.5 throughout the school year is 2-5x greater than the effect on test day alone<br>By multiplying this per-unit effect by the standard deviation for ambient PM 2.5 in CES (3.08 µg/m³), this estimate is approximately equal to the effect I find for aggregate PM 2.5 exposure |
| Stafford (2015) | Quasi-experimental regression | One to two years after retrofits | School retrofits to improve ventilation increased average test scores by 0.07-0.11 standard deviations | The actual difference in PM 2.5 exposure concentrations between schools that did and did not receive ventilation retrofits is unknown, and thus comparison to other studies is infeasible |
| Lavy et al. (2014) | Fixed effects panel OLS regression | Test day | One standard deviation increase in PM 2.5 decreases scores on Israeli entrance exams by 0.028 standard deviations | This effect size closely matches Amanzadeh et al. (2019) and supports estimates that test-day exposure produces around 0.2-0.5x the effect of exposure throughout the year |

*Note*: my analysis (which estimates holistic effects rather than short-term effects) indicates that a one-standard-deviation increase in ambient PM 2.5 from mean levels decreases average test scores by 0.066 standard deviations

**Table A3**: Linear Regression Coefficients for Control Variables in Preferred Specification. Robust standard errors in parentheses. *Suburb Status*, *Percent White*, and *2009 Year* were omitted from the regression trials as the reference group. ***p<0.01, **p<0.05, *p<0.1.

| **Control Variables** | Average Scores | Math | ELA | Average Scores | Math | ELA | Average Scores | Math | ELA |
|---|---|---|---|---|---|---|---|---|---|
| Urban Status (0-1) | -0.0273 | -0.0163 | -0.0392 | -0.0296 | -0.0184 | -0.0415 | -0.0305 | -0.0194 | -0.0423 |
| | (0.0231) | (0.0275) | (0.0241) | (0.0227) | (0.0271) | (0.0246) | (0.0222) | (0.0265) | (0.0242) |
| Town Status (0-1) | 0.00235 | -0.00127 | 0.00507 | 0.000698 | -0.000799 | 0.00139 | 0.00198 | 0.000642 | 0.00251 |
| | (0.0137) | (0.0166) | (0.0162) | (0.0136) | (0.0175) | (0.0142) | (0.0143) | (0.0186) | (0.0144) |
| Rural Status (0-1) | -0.00781 | -0.0156 | -0.000487 | -0.00447 | -0.0112 | 0.00126 | -0.00454 | -0.0112 | 0.00115 |
| | (0.0137) | (0.0123) | (0.0197) | (0.0154) | (0.0144) | (0.0202) | (0.0154) | (0.0147) | (0.0202) |
| Percent Native American | -0.00169 | 0.0977 | -0.0956 | -0.0956 | -0.0545 | -0.137 | -0.0979 | -0.0577 | -0.139 |
| | (0.281) | (0.290) | (0.296) | (0.113) | (0.123) | (0.114) | (0.110) | (0.121) | (0.112) |
| Percent Asian | 0.121* | 0.235** | 0.00845 | 0.185** | 0.297*** | 0.0728 | 0.188** | 0.300*** | 0.0751 |
| | (0.0594) | (0.0917) | (0.0656) | (0.0700) | (0.101) | (0.0662) | (0.0697) | (0.0995) | (0.0666) |
| Percent Hispanic | -0.0711 | -0.0579 | -0.0837 | -0.0345 | -0.0245 | -0.0458 | -0.0356 | -0.0263 | -0.0465 |
| | (0.0708) | (0.0725) | (0.0741) | (0.0683) | (0.0664) | (0.0748) | (0.0684) | (0.0658) | (0.0752) |
| Percent Black | -0.418** | -0.408 | -0.418** | -0.409** | -0.353* | -0.453*** | -0.416** | -0.362* | -0.457*** |
| | (0.188) | (0.255) | (0.157) | (0.150) | (0.197) | (0.133) | (0.154) | (0.204) | (0.135) |
| Percent Free and Reduced | -0.0528 | -0.0562 | -0.0491 | -0.0713* | -0.0550 | -0.0884** | -0.0689* | -0.0519 | -0.0865** |
| Lunch | (0.0315) | (0.0432) | (0.0303) | (0.0381) | (0.0523) | (0.0337) | (0.0370) | (0.0517) | (0.0325) |
| Percent English Language | -0.0359 | -0.0682*** | -0.00397 | -0.0465*** | -0.0952*** | 0.00342 | -0.0471** | -0.0960*** | 0.00294 |
| Learners | (0.0230) | (0.0206) | (0.0395) | (0.0158) | (0.0238) | (0.0261) | (0.0161) | (0.0240) | (0.0265) |
| Percent Special Education | -0.103 | -0.140 | -0.0579 | -0.0726 | -0.106 | -0.0357 | -0.0728 | -0.106 | -0.0360 |
| | (0.0903) | (0.128) | (0.0897) | (0.0585) | (0.0948) | (0.0615) | (0.0565) | (0.0935) | (0.0601) |
| Total Enrollment | -8.82e-06 | -4.50e-06 | -1.31e-05 | -1.02e-05 | -4.35e-06 | -1.64e-05 | -1.11e-05 | -5.40e-06 | -1.71e-05 |
| | (9.23e-06) | (5.20e-06) | (1.39e-05) | (1.00e-05) | (5.78e-06) | (1.50e-05) | (9.96e-06) | (5.68e-06) | (1.50e-05) |
| Median Income ($) | 2.40e-07 | 5.69e-07 | -1.33e-07 | 2.04e-07 | 5.28e-07 | -1.64e-07 | 1.55e-07 | 4.70e-07 | -2.03e-07 |
| | (4.38e-07) | (5.55e-07) | (4.66e-07) | (4.76e-07) | (5.24e-07) | (5.50e-07) | (4.59e-07) | (5.08e-07) | (5.38e-07) |
| Percent of Adults with at | 0.216 | 0.335* | 0.0974 | 0.159 | 0.270 | 0.0548 | 0.159 | 0.271 | 0.0550 |
| Least a Bachelor's Degree | (0.142) | (0.159) | (0.159) | (0.136) | (0.157) | (0.160) | (0.135) | (0.156) | (0.160) |
| Unemployment Rate | 0.0925 | 0.295 | -0.112 | 0.204 | 0.445* | -0.0349 | 0.216 | 0.459* | -0.0251 |
| | (0.184) | (0.180) | (0.231) | (0.234) | (0.239) | (0.261) | (0.227) | (0.233) | (0.256) |
| Proportion of Single | -0.151 | -0.257 | -0.0531 | -0.125 | -0.261 | 0.000990 | -0.118 | -0.253 | 0.00762 |
| Mother Households | (0.130) | (0.152) | (0.123) | (0.154) | (0.168) | (0.149) | (0.156) | (0.167) | (0.155) |
| 2010.Year | 0.0179*** | 0.0221*** | 0.0137* | 0.0159** | 0.0198*** | 0.0121* | 0.0157** | 0.0194*** | 0.0119* |
| | (0.00602) | (0.00665) | (0.00647) | (0.00613) | (0.00641) | (0.00665) | (0.00598) | (0.00628) | (0.00649) |
| 2011.Year | 0.0296** | 0.0298*** | 0.0294* | 0.0228** | 0.0184* | 0.0278** | 0.0222** | 0.0177* | 0.0273** |
| | (0.0111) | (0.00976) | (0.0143) | (0.00904) | (0.00916) | (0.0110) | (0.00879) | (0.00894) | (0.0107) |
| 2012.Year | 0.0529*** | 0.0396*** | 0.0662*** | 0.0421*** | 0.0298* | 0.0543*** | 0.0414*** | 0.0290* | 0.0537*** |
| | (0.0119) | (0.0129) | (0.0122) | (0.0138) | (0.0142) | (0.0137) | (0.0133) | (0.0137) | (0.0133) |
| 2013.Year | 0.0662*** | 0.0416** | 0.0907*** | 0.0552*** | 0.0313** | 0.0787*** | 0.0543*** | 0.0302** | 0.0779*** |
| | (0.0160) | (0.0146) | (0.0192) | (0.0154) | (0.0147) | (0.0173) | (0.0148) | (0.0140) | (0.0168) |
| 2015.Year | 0.0373** | 0.0226 | 0.0522** | 0.0269 | 0.0154 | 0.0388* | 0.0327 | 0.0222 | 0.0435* |
| | (0.0170) | (0.0192) | (0.0195) | (0.0191) | (0.0214) | (0.0208) | (0.0191) | (0.0206) | (0.0215) |
| 2016.Year | 0.0557*** | 0.0274 | 0.0844*** | 0.0394* | 0.0160 | 0.0630*** | 0.0453** | 0.0230 | 0.0678*** |
| | (0.0147) | (0.0166) | (0.0175) | (0.0189) | (0.0224) | (0.0185) | (0.0190) | (0.0218) | (0.0193) |
| 2017.Year | 0.0816*** | 0.0469*** | 0.116*** | 0.0739*** | 0.0405** | 0.108*** | 0.0783*** | 0.0458*** | 0.111*** |
| | (0.0151) | (0.0148) | (0.0198) | (0.0145) | (0.0151) | (0.0188) | (0.0151) | (0.0153) | (0.0195) |
| 2018.Year | 0.0724*** | 0.0471*** | 0.0974*** | 0.0654*** | 0.0410** | 0.0898*** | 0.0701*** | 0.0465*** | 0.0937*** |
| | (0.0161) | (0.0135) | (0.0231) | (0.0155) | (0.0140) | (0.0219) | (0.0161) | (0.0142) | (0.0225) |
| Constant | 1.681*** | 1.581*** | 1.783*** | 1.637*** | 1.575*** | 1.703*** | 1.641*** | 1.579*** | 1.706*** |
| | (0.0640) | (0.0859) | (0.0635) | (0.0634) | (0.0775) | (0.0642) | (0.0631) | (0.0776) | (0.0641) |
| **Included Pollution Variable** | PM 2.5 | PM 2.5 | PM 2.5 | G.W. Threats | G.W. Threats | G.W. Threats | Solid Waste | Solid Waste | Solid Waste |
| **Error Clustering Level** | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone | Commute Zone |
| **Observations** | 10,964 | 5,486 | 5,478 | 11,554 | 5,782 | 5,772 | 11,554 | 5,782 | 5,772 |
| **N districts** | 712 | 710 | 711 | 723 | 720 | 722 | 723 | 720 | 722 |
| **$R^2$ (within districts; between districts; overall – see Table 2)** | 0.047; 0.490; 0.495 | 0.032; 0.536; 0.553 | 0.112; 0.299; 0.289 | 0.038; 0.511; 0.482 | 0.028; 0.569; 0.537 | 0.086; 0.301; 0.264 | 0.038; 0.497; 0.474 | 0.028; 0.552; 0.526 | 0.087; 0.301; 0.266 |

**Table A4**: Regression Results using the CS Grading Scale as a Robustness Test[a], with Different Error Clustering Levels

| **Test Subject** | Average | Math | ELA | Average | Math | ELA | Average | Math | ELA | Average | Math | ELA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PM 2.5 | -0.00376** (0.00166) | -0.000511 (0.00330) | -0.00709*** (0.00196) | -0.00376 (0.00233) | -0.000511 (0.00281) | -0.00709*** (0.00242) | -0.00376 (0.00256) | -0.000511 (0.00339) | -0.00709*** (0.00264) | -0.00361 (0.00270) | -4.01e-05 (0.00345) | -0.00722** (0.00283) |
| Groundwater Threats | -0.000129 (7.48e-05) | -0.000169* (8.27e-05) | -9.23e-05 (8.69e-05) | -0.000129 (0.000114) | -0.000169 (0.000142) | -9.23e-05 (0.000110) | -0.000129 (9.74e-05) | -0.000169** (8.13e-05) | -9.23e-05 (0.000119) | -0.000134 (0.000104) | -0.000170* (8.75e-05) | -9.88e-05 (0.000127) |
| Solid Waste | -0.00293** (0.00109) | -0.00347** (0.00145) | -0.00239* (0.00135) | -0.00293* (0.00168) | -0.00347** (0.00173) | -0.00239 (0.00215) | -0.00293* (0.00150) | -0.00347** (0.00150) | -0.00239 (0.00206) | -0.00318* (0.00159) | -0.00419** (0.00155) | -0.00216 (0.00211) |
| **Error Clustering Level** | Commute Zone | Commute Zone | Commute Zone | District | District | District | County | County | County | Metro Area | Metro Area | Metro Area |

[a]For this regression specification, the dependent variable is natural log of positive-transformed test scores on the CS scale and each pollution variable was input one at a time (i.e., each regression coefficient represents a separate regression trial). Robust standard errors in parentheses. Control variables and constants omitted. *** p<0.01, ** p<0.05, * p<0.1.

**Table A5**: Regression Results from the Preferred Specification[a], with Error Clustering at Different Levels as a Robustness Test.

| **Test Subject** | Average | Math | ELA | Average | Math | ELA | Average | Math | ELA |
|---|---|---|---|---|---|---|---|---|---|
| PM 2.5 | -0.00457 (0.00299) | -0.000255 (0.00358) | -0.00897*** (0.00314) | -0.00457 (0.00321) | -0.000255 (0.00427) | -0.00897*** (0.00327) | -0.00433 (0.00339) | 0.000455 (0.00434) | -0.00916** (0.00353) |
| Groundwater Threats | -0.000197 (0.000165) | -0.000240 (0.000198) | -0.000157 (0.000162) | -0.000197 (0.000130) | -0.000240** (0.000107) | -0.000157 (0.000159) | -0.000202 (0.000139) | -0.000242** (0.000114) | -0.000165 (0.000170) |
| Solid Waste | -0.00338 (0.00226) | -0.00392* (0.00226) | -0.00285 (0.00289) | -0.00338 (0.00203) | -0.00392** (0.00187) | -0.00285 (0.00282) | -0.00361 (0.00215) | -0.00480** (0.00193) | -0.00240 (0.00285) |
| Hazardous Waste | 0.00806 (0.00579) | 0.0103* (0.00546) | 0.00564 (0.00770) | 0.00806 (0.00704) | 0.0103 (0.00859) | 0.00564 (0.00633) | 0.00860 (0.00700) | 0.0102 (0.00870) | 0.00672 (0.00611) |
| Impaired Water Bodies | 2.23e-06 (0.00292) | 0.00336 (0.00314) | -0.00353 (0.00353) | 2.23e-06 (0.00264) | 0.00336 (0.00289) | -0.00353 (0.00336) | 0.000295 (0.00264) | 0.00383 (0.00309) | -0.00341 (0.00312) |
| Cleanup Sites | 8.44e-06 (0.00128) | -5.87e-05 (0.00157) | -9.35e-06 (0.00132) | 8.44e-06 (0.00123) | -5.87e-05 (0.00155) | -9.35e-06 (0.00128) | 0.000471 (0.00122) | 0.000360 (0.00161) | 0.000513 (0.00125) |
| Traffic | -1.16e-05 (1.16e-05) | -1.98e-05 (1.62e-05) | -3.76e-06 (1.27e-05) | -1.16e-05 (1.01e-05) | -1.98e-05 (1.52e-05) | -3.76e-06 (1.13e-05) | -1.18e-05 (1.23e-05) | -2.05e-05 (1.72e-05) | -3.55e-06 (1.22e-05) |
| **Error Clustering Level** | District | District | District | County | County | County | Metro Area | Metro Area | Metro Area |

[a]For the Preferred specification, the dependent variable is natural log of grade levels (on the GCS scale) and each pollution variable was input one at a time (i.e., each regression coefficient represents a separate regression trial). Robust standard errors in parentheses. Control variables and constants omitted. *** p<0.01, ** p<0.05, * p<0.1.

**Table A6**: Regression Results with All Pollution Variables Included Simultaneously[a] and with Different Error Clustering Levels

| **Test Subject** | Average | Math | ELA | Average | Math | ELA | Average | Math | ELA | Average | Math | ELA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PM 2.5 | -0.00494**<br>(0.00211) | -0.000895<br>(0.00414) | -0.00907***<br>(0.00255) | -0.00494*<br>(0.00291) | -0.000895<br>(0.00350) | -0.00907***<br>(0.00304) | -0.00494<br>(0.00319) | -0.000895<br>(0.00418) | -0.00907***<br>(0.00331) | -0.00475<br>(0.00334) | -0.000331<br>(0.00420) | -0.00921**<br>(0.00358) |
| Groundwater Threats | -3.90e-05<br>(0.000150) | -5.83e-05<br>(0.000144) | -2.75e-05<br>(0.000158) | -3.90e-05<br>(0.000138) | -5.83e-05<br>(0.000188) | -2.75e-05<br>(0.000127) | -3.90e-05<br>(0.000131) | -5.83e-05<br>(0.000121) | -2.75e-05<br>(0.000146) | -3.99e-05<br>(0.000142) | -5.05e-05<br>(0.000135) | -3.54e-05<br>(0.000157) |
| Solid Waste | -0.00330<br>(0.00208) | -0.00350<br>(0.00208) | -0.00311<br>(0.00285) | -0.00330<br>(0.00250) | -0.00350<br>(0.00240) | -0.00311<br>(0.00328) | -0.00330<br>(0.00263) | -0.00350<br>(0.00241) | -0.00311<br>(0.00343) | -0.00344<br>(0.00280) | -0.00445*<br>(0.00254) | -0.00243<br>(0.00344) |
| Traffic | -8.76e-06<br>(9.03e-06) | -1.41e-05<br>(1.52e-05) | -3.83e-06<br>(7.38e-06) | -8.76e-06<br>(1.15e-05) | -1.41e-05<br>(1.54e-05) | -3.83e-06<br>(1.21e-05) | -8.76e-06<br>(9.99e-06) | -1.41e-05<br>(1.50e-05) | -3.83e-06<br>(1.00e-05) | -9.24e-06<br>(1.23e-05) | -1.50e-05<br>(1.71e-05) | -4.00e-06<br>(1.11e-05) |
| Cleanup Sites | -0.000127<br>(0.00114) | -2.86e-06<br>(0.00138) | -0.000308<br>(0.000939) | -0.000127<br>(0.00125) | -2.86e-06<br>(0.00156) | -0.000308<br>(0.00125) | -0.000127<br>(0.00115) | -2.86e-06<br>(0.00141) | -0.000308<br>(0.00123) | 0.000345<br>(0.00111) | 0.000420<br>(0.00143) | 0.000228<br>(0.00117) |
| Hazardous Waste | 0.00722<br>(0.00605) | 0.00956<br>(0.00762) | 0.00478<br>(0.00557) | 0.00722<br>(0.00593) | 0.00956*<br>(0.00533) | 0.00478<br>(0.00806) | 0.00722<br>(0.00705) | 0.00956<br>(0.00857) | 0.00478<br>(0.00640) | 0.00746<br>(0.00697) | 0.00915<br>(0.00871) | 0.00563<br>(0.00607) |
| Impaired Water Bodies | 0.000684<br>(0.00248) | 0.00370<br>(0.00332) | -0.00248<br>(0.00290) | 0.000684<br>(0.00286) | 0.00370<br>(0.00305) | -0.00248<br>(0.00342) | 0.000684<br>(0.00242) | 0.00370<br>(0.00279) | -0.00248<br>(0.00297) | 0.000991<br>(0.00259) | 0.00420<br>(0.00303) | -0.00237<br>(0.00300) |
| **Error Clustering Level** | Commute Zone | Commute Zone | Commute Zone | District | District | District | County | County | County | Metro Area | Metro Area | Metro Area |

[a]For this regression specification, the dependent variable is natural log grade levels (on the GCS scale) and each pollution variable was input simultaneously (i.e., in the same regression trial). Robust standard errors in parentheses. Control variables and constants omitted.
*** p<0.01, ** p<0.05, * p<0.1.