

# Ambient air pollution associated with lower academic achievement among US children

## A nationwide panel study of school districts

Wenxin Lu<sup>a</sup>, Daniel A. Hackman<sup>b</sup>, Joel Schwartz<sup>a</sup>

**Background:** Ambient air pollution is an important environmental exposure and has been linked with impaired cognitive function. Few studies have investigated its impact on children's academic performance on a nationwide level. We hypothesize that higher ambient air pollution concentrations will be associated with lower average academic test scores.

**Methods:** We investigated three prevalent ambient air pollutants: PM<sub>2.5</sub>, NO<sub>2</sub> and ozone, and their associations with the average academic test scores, at the Geographic School District (GSD) level, of the third to eighth grade students in the United States from 2010 to 2016. We applied multivariate linear regression and controlled for urbanicity, socioeconomic status, student racial/ethnic compositions, and individual intercepts for each district-grade level and each year.

**Results:** We found that an interquartile range increase in PM<sub>2.5</sub> concentrations was associated with a 0.007 (95% confidence interval: 0.005, 0.009) SD lower average math test scores, and a 0.004 (95% confidence interval: 0.002, 0.005) SD lower average English language/arts test scores. Similar associations were observed for NO<sub>2</sub> and ozone on math, and for NO<sub>2</sub> on English language/arts. The magnitudes of these associations are equivalent to the effects of short-term reductions of thousands of dollars in district median household income. The reductions in test scores were larger for GSDs with higher socioeconomic status, though most associations remained negative at all socioeconomic levels.

**Conclusions:** Our results show that ambient air pollution within a GSD is associated with lower academic performance among children. Further improving air quality may benefit children's overall academic achievement and socioeconomic attainment across the lifespan.

## Introduction

Ambient air pollution has been associated with various adverse health effects, including impaired cognitive function.<sup>1</sup> Studies have associated air pollution exposure with neuroinflammation and neurodegeneration,<sup>2–6</sup> leading to increased risk of neurological disorders,<sup>7–11</sup> and accelerated cognitive decline.<sup>10</sup> Children are particularly vulnerable to neurotoxins because of on-going neurodevelopment processes such as myelination and synapse pruning.<sup>12</sup> Early childhood exposure to air pollution has

been linked with impaired performances in cognitive tests,<sup>13–17</sup> inattentiveness,<sup>18–20</sup> slower development of working memory,<sup>13,14,15,19–21</sup> deficits in gross and fine motor functions,<sup>20,22</sup> and worse academic performance.<sup>23,24</sup> Compromised learning ability and academic performance in childhood may have life-long impacts on socioeconomic status (SES), influencing higher education and expected income.<sup>25,26</sup>

Existing studies on air pollution and children's cognitive functions or academic performance mostly involved relatively small cohorts. Spanish studies found that exposure to traffic-related PM<sub>2.5</sub> (inhalable particles with diameters  $\leq 2.5 \mu\text{m}$ ) and NO<sub>2</sub> were associated with slower development of working memory among children.<sup>14,15</sup> A Chinese study compared the neurobehavioral testing results between two schools with different levels of traffic and NO<sub>2</sub> and found that children from the school with higher NO<sub>2</sub> levels performed worse on all nine tests.<sup>27</sup> In addition, an association between ozone exposure and cognitive decline has been found among older adults,<sup>28,29</sup> but has not been studied among children.

<sup>a</sup>Harvard T.H. Chan School of Public Health, Boston, Massachusetts; and

<sup>b</sup>University of Southern California Suzanne Dworak-Peck School of Social Work, Los Angeles, California

This work was supported by grant RD8358720 from the United States Environmental Protection Agency.

Result Replication: Exposure data are available upon reasonable request and approval from the corresponding author. Outcome data are maintained and published by the Stanford Center for Education Policy Analysis.

**SDC** Supplemental digital content is available through direct URL citations in the HTML and PDF versions of this article ([www.enviroepidem.com](http://www.enviroepidem.com)).

\*Corresponding Author. Address: Harvard T.H. Chan School of Public Health, Boston, MA. E-mail: [jschwartz@hsph.harvard.edu](mailto:jschwartz@hsph.harvard.edu) (J. Schwartz).

Copyright © 2021 The Authors. Published by Wolters Kluwer Health, Inc. on behalf of The Environmental Epidemiology. All rights reserved. This is an open-access article distributed under the terms of the Creative Commons Attribution-Non Commercial-No Derivatives License 4.0 (CCBY-NC-ND), where it is permissible to download and share the work provided it is properly cited. The work cannot be changed in any way or used commercially without permission from the journal.

Environmental Epidemiology (2021) 00:e174

Received: 24 July 2021; Accepted 28 September 2021

Published online 3 November 2021

DOI: 10.1097/EE9.000000000000174

## What this study adds

Ambient air pollution has been linked with various adverse health effects including impaired cognitive functions. Previous studies that investigated the associations between air pollution and children's cognitive development or academic performance mostly studied relatively small cohorts. We conducted a nationwide panel study in the United States that aggregated more than 250 million academic achievement tests from 10,921 school districts over 7 years. We found that ambient air pollution (PM<sub>2.5</sub>, NO<sub>2</sub>, and ozone) was associated with lower academic performance among children. These findings can have implications for air quality interventions, which may benefit children's educational and occupational attainment across the life course.

Moreover, there is limited evidence regarding the factors that may increase vulnerability to the effect of air pollution on achievement. SES and neighborhood factors, robust predictors of achievement,<sup>30–32</sup> have been shown to moderate the effect of lead exposure and air pollution on cognitive functions.<sup>33–35</sup> Effect measure modifications (EMMs) of the health impacts of air pollution by age and race/ethnicity have been found for respiratory outcomes and mortality,<sup>36,37</sup> but have not been studied for cognitive and academic outcomes.

We investigated the associations between ambient PM<sub>2.5</sub>, NO<sub>2</sub>, and ozone concentrations and the academic test scores of third to eighth grade students in the United States at the Geographic School District (GSD) level. We examined the potential EMM by age, racial/ethnic compositions, and SES.

## Methods

### Test score and covariates

Each US state is required by the No Child Left Behind Act (NCLB) of 2001 to conduct annual state-wide assessments of academic progress in math and ELA for all students of grades 3 through 8.<sup>38</sup> We retrieved these standardized state testing results from the Stanford Education Data Archive (SEDA) version 3.0, which included test data from 13,160 US GSDs.<sup>39</sup> We restricted to 10,921 GSDs with complete geographic information, covered at least one ZIP code centroid, and had standardized test score information for at least one grade-year-subject. Standardized test scores and covariates for grades 3 to 8 were available from 2010 to 2016. The final dataset was aggregated from 256,192,733 tests administered to 135,061,844 student-years (a student enrolled from grade 3 to 8 in the study period contributed to six student-years).

The SEDA dataset adjusted for differences in proficiency standards across states based on the National Assessment of Educational Progress (NAEP). The NAEP was administered annually at the same time on the same academic content to a representative sample of students across US states,<sup>40</sup> allowing for cross-state comparisons. The standardized test scores can be interpreted as the number of standard deviations (SDs) different from the average student performance, compared to a reference cohort (students in the fourth grade in 2009). For instance, the fifth grade students in a GSD with a 1.0 average standardized test score indicates that these students performed on average one SD higher than students in the reference cohort who were also in grade 5. The use of a reference cohort allows for comparison of student performances across school years.

The SEDA dataset included time-varying covariates derived from the 5-year estimates of the American Community Survey and the Common Core of Data.<sup>39</sup> We divided the covariates into four classes: (1) student racial/ethnic composition: proportion of native American, Asian, Hispanic/Latino, Black, and White students; (2) student-level SES: proportion of free lunch eligible students, reduced-price lunch eligible students, economically disadvantaged students and English language learners; (3) Urbanicity: urban, suburban, town or rural; and (4) GSD-level SES: log of median income, bachelor's degree rate, poverty rate, Supplemental Nutrition Assistance Program (SNAP) recipient rate, and single-mother household rate. Urbanicity and GSD-level SES vary by GSD and year. Student racial/ethnic composition and student-level SES vary by GSD, year, and grade.

### Ambient air pollution

The monthly ambient PM<sub>2.5</sub>, NO<sub>2</sub>, and O<sub>3</sub> levels at ZIP codes across the continental US were estimated using previously published hybrid models.<sup>41–43</sup> Briefly, these models combined satellite data, meteorological conditions, land-use variables, and chemical transport model simulations trained to measurements from ground-level monitors, with performance checked on held

out monitors. These estimates incorporated predictions from random forest, gradient boosting, and neural network to estimate daily ambient air pollution concentrations for 1 × 1 km grid cells. Grid cells whose centroids were inside of ZIP codes were averaged, and monthly means computed. The GSD-level monthly concentrations were calculated by averaging pollutant concentrations of ZIP codes whose centroids fall within the GSD, weighted by ZIP code populations in 2015.

We defined exposure in each school year as the average ambient pollutant concentrations during the 12-month period on and before the first month of the state testing window. The first months of the testing windows for each state-year were retrieved from state department of education websites, school district websites, public school websites and news articles, summarized in Table A1 of the Appendix; <http://links.lww.com/EE/A163>.

### Statistical analysis

We applied a generalized difference-in-difference (DID) analysis with two-way fixed effects models.<sup>44–46</sup> A cohort is defined as students in a specific grade in a specific GSD. The model takes the following form:

$$\text{Score}_{itg} = \beta_1 \text{Pollution}_{it} + \sum \beta \text{Covariates}_{itg} + \text{Cohort}_{ig} + \text{Year}_t + \varepsilon_{itg}$$

where  $i$  indexes GSD,  $t$  indexes school year, and  $g$  indexes grade.  $\text{Score}_{itg}$  is the average standardized test score of grade  $g$  students in GSD  $i$  in year  $t$ .  $\text{Pollution}_{it}$  is the air pollution concentrations in GSD  $i$  in the 12-month before testing in year  $t$ .  $\text{Covariates}_{itg}$  are covariates for grade  $g$  students in GSD  $i$  in year  $t$ .  $\text{Cohort}_{ig}$  and  $\text{Year}_t$  are cohort and year fixed effects, representing a binary indicator for each cohort and school year, respectively.  $\varepsilon_{itg}$  is the random errors. We conducted statistical analysis in R version 4.0.3 (package “plm”).

This two-way fixed effect (fixed effects for both cohorts and years) model is generalized from a traditional DID model by analyzing more than two time periods and investigating a continuous treatment variable instead of a binary one.<sup>44,45,47–50</sup> Similar methods have been applied in economics and policy analysis,<sup>51,52</sup> and for examining air pollution and mortality.<sup>46,53</sup> Consider two cohorts A and B over two consecutive time periods  $t$  and  $t + 1$ . Assume that the exposure level of cohort A remained constant, and the exposure level of cohort B increased by 1 unit from  $t$  to  $t + 1$ . In this scenario, cohort A is a negative control for cohort B: changes in the outcomes in cohort A can only be explained by variations in the same set of covariates as cohort B, not by variations of exposure levels. Table 1 presents the expected outcome levels, the estimated changes in outcome levels over the 2 years for both cohorts, and the DID estimate. Under the assumptions that  $\text{Covariates}_{itg}$  captured all other time-varying factors affecting the changing trends of the outcome, and the time fixed effects and cohort fixed effects do not have interactions,<sup>48</sup>  $\beta_1$  is a causal estimate of a 1-unit increase in the pollutant concentrations on the outcome.

Since the number of student enrollments in each cohort-year varied substantially, variations in average test scores and the amount of information contributed were also different. We accounted for these differences using weighted least squares, where the weights were the numbers of student enrollments in each cohort-year. We truncated the weights at the 5th (25 for Math and ELA) and 95th percentiles (1,177 for Math, 1,243 for ELA) to stabilize the weighting and avoid influential observations.

We explored potential EMM by grade, GSD racial/ethnic compositions, and GSD-level SES by adding an interaction term between the exposure and the modifier. For EMM by grade, the modifier is integer grade (3–8). For EMM by racial/ethnic compositions, we created binary variables flagging cohorts with Hispanic/Latino and Black students above the median levels.

**Table 1.** linear DID estimation with two-way fixed-effects model, illustrated with two cohorts over two consecutive time periods

	Cohort A (pollution remained constant)	Cohort B (pollution increased by 1 unit)
$T$	$\beta_1 \text{Pollution}_{At} + \sum \beta \text{Covariates}_{At} + \text{Cohort}_A + \text{Year}_t$	$\beta_1 \text{Pollution}_{Bt} + \sum \beta \text{Covariates}_{Bt} + \text{Cohort}_B + \text{Year}_t$
$t + 1$	$\beta_1 \text{Pollution}_{At} + \sum \beta \text{Covariates}_{A,t+1} + \text{Cohort}_A + \text{Year}_{t+1}$	$\beta_1 (\text{Pollution}_{Bt} + 1) + s \sum \beta \text{Covariates}_{B,t+1} + \text{Cohort}_B + \text{Year}_{t+1}$
$E$ (Difference)	$\sum \beta (\text{Covariates}_{A,t+1} - \text{Covariates}_{At}) + (\text{Year}_{t+1} - \text{Year}_t)$	$\beta_1 + \sum \beta (\text{Covariates}_{B,t+1} - \text{Covariates}_{Bt}) + (\text{Year}_{t+1} - \text{Year}_t)$
DID	$\beta_1 + \sum \beta ((\text{Covariates}_{B,t+1} - \text{Covariates}_{Bt}) - (\text{Covariates}_{A,t+1} - \text{Covariates}_{At}))$	

Pollution<sub>at</sub> is the air pollution concentrations for cohort A in the 12-month before testing in year *t*. Covariates<sub>at</sub> are covariates for students in cohort A in year *t*. Cohort<sub>A</sub> and Year<sub>t</sub> are cohort and year fixed effects, respectively.

For EMM by GSD-level SES, we used a binary indicator of positive SES composite. The SES composite is a variable created in the SEDA dataset that follows an approximately normal distribution.<sup>39,54</sup> Potential lag effects were explored by replacing the exposure in the base model with the exposure from the previous school year.

**Results**

**Summary statistics**

Table 2 presents the GSD-level summary statistics of exposure and covariates. Student-level covariates were averaged across grades and years; ambient air pollution and GSD-level covariates were averaged across years. The unpooled interquartile ranges (IQR) of the variables are also presented, and the regression results will be presented for each IQR increase in pollutant concentrations.

Table 3 presents the distributions of GSD-level ambient air pollution concentrations from 2010 to 2016. The average PM<sub>2.5</sub> concentrations had a decreasing trend. The average NO<sub>2</sub> concentrations first increased then decreased, while the 12-month maximum NO<sub>2</sub> concentrations decreased. The ozone concentrations fluctuated with no clear trend.

**Regression results**

The coefficients and 95% confidence intervals (CIs) of the associations between standardized test scores and the 12-month ambient air pollution levels are presented in Table 4. The results of the full model (column 3, later referred to as model 3) indicates that an IQR increase in PM<sub>2.5</sub> concentration was associated with a 0.007 (95% CI: 0.005, 0.009) SD lower average Math test score and a 0.004 (95% CI: 0.002, 0.005) SD lower average ELA test score; an IQR increase in NO<sub>2</sub> levels was associated with a 0.004 (95% CI: 0.002, 0.006) SD lower average Math test score and a 0.012 (95% CI: 0.010, 0.014) SD lower average ELA test score; an IQR increase in ozone concentrations was associated with a 0.005 (95% CI: 0.004, 0.006) SD lower average Math test scores, but a 0.002 (95% CI: 0.001, 0.003) SD higher average ELA test score. To put this in better context, the magnitude of the change in the Math test score associated with an IQR increase in ambient PM<sub>2.5</sub> (NO<sub>2</sub>/ozone) concentrations is the same as with a \$10,438 (\$6,422/\$8,289) decrease in GSD median income, a conservative estimate after adjusting for other SES covariates. The full regression results are summarized in Table A2 of the Appendix; <http://links.lww.com/EE/A163>.

To investigate whether the positive association between ozone and ELA was due to its negative correlation with the other two pollutants or an actual protective association, we fitted six

**Table 2.** Geographic school district level summary statistics in United States, averaged across grades 3–8 and school years 2010–2016

	Variable	Min	25th percentile	Median	Mean	75th percentile	Max	SD	Unpooled IQR	n
Test score	Standardized Math test score	-3.1	-0.2	0.0	0.0	0.2	1.3	0.4	0.5	10,908
	Standardized ELA test score	-2.0	-0.2	0.0	0.0	0.2	1.6	0.3	0.5	10,918
	No. enrolled students	10	46	109	328	271	72243	1231	230	10,908
Ambient air pollution	PM <sub>2.5</sub> (µg/m <sup>3</sup> )	0.8	7.0	8.7	8.3	9.8	15.8	2.1	2.8	10,898
	NO <sub>2</sub> (ppb)	1.9	8.9	11.5	13.2	15.8	42.8	6.3	7.3	10,898
	Ozone (ppm)	16.4	37.5	38.8	39.1	40.3	56.4	3.3	3.3	10,898
Student racial/ethnic composition	Native American (%)	0.0	0.1	0.3	2.6	0.7	100.0	10.4	0.7	10,908
	Asian (%)	0.0	0.2	0.7	2.1	1.7	74.7	4.9	2.0	10,908
	Hispanic/Latino (%)	0.0	1.8	4.7	13.3	14.4	99.9	20.1	11.6	10,908
	Black (%)	0.0	0.6	1.4	7.7	5.4	99.8	16.2	6.1	10,908
	White (%)	0.0	61.0	86.3	74.3	95.0	100.0	27.1	33.5	10,908
Student SES characteristics	Free lunch eligible (%)	0.6	25.2	38.8	40.0	53.4	97.7	20.2	29.9	10,908
	Reduced-price lunch eligible (%)	0.4	6.3	8.5	8.7	10.7	88.7	4.4	5.0	10,908
	Economically disadvantaged (%)	0.0	34.0	49.4	48.9	64.0	100.0	21.8	32.0	10,908
	English language learner (%)	0.0	0.2	1.0	4.4	4.3	81.4	8.6	4.0	10,886
Urbanicity	Urban (%)	6.0								10,878
	Suburb (%)	22.4								10,907
	Town (%)	20.2								10,907
	Rural (%)	51.4								10,907
GSD SES characteristics	SES composite	-4.2	-0.3	0.2	0.2	0.7	2.9	0.9	1.1	10,907
	Log of median income	9.9	10.6	10.8	10.8	11.0	12.3	0.3	0.4	10,878
	Bachelor's degree rate (%)	0.1	14.2	18.8	22.8	27.1	86.5	12.9	13.3	10,878
	Poverty rate (%)	0.1	9.9	15.1	15.7	20.3	54.3	8.0	11.8	10,878
	SNAP receipt rate (%)	0.3	6.3	9.9	10.9	14.5	49.0	6.2	8.7	10,878
	Single mom household rate (%)	0.3	11.2	14.2	15.2	17.9	55.8	5.9	7.1	10,878

Apart from unpooled IQR, all other measures were averaged across grades and school years. Student-level covariates were weighted on the number of enrolled students for each grade-year.

**Table 3.**  
Distribution of GSD-level ambient air pollution concentrations, 2010–2016

		2010	2011	2012	2013	2014	2015	2016
12-month PM <sub>2.5</sub> (µg/m <sup>3</sup> )	Min	0.0	0.0	0.0	0.2	0.0	0.0	0.0
	25th percentile	7.4	7.9	7.4	7.3	7.7	7.0	6.4
	Median	9.6	9.5	9.0	8.7	8.9	8.5	7.8
	Mean	9.1	9.1	8.6	8.4	8.6	8.2	7.5
	75th percentile	10.7	11.0	10.2	9.7	9.9	9.6	8.6
	Max	18.3	18.2	18.2	15.5	13.9	18.2	14.9
12-month NO <sub>2</sub> (ppb)	Min	0.0	0.0	0.0	1.2	0.0	0.0	0.0
	25th percentile	8.5	8.7	9.5	9.9	9.3	8.7	8.3
	Median	11.4	11.4	12.2	12.8	12.8	11.9	10.8
	Mean	13.2	13.4	14.1	14.1	14.0	13.0	12.2
	75th percentile	15.8	16.1	16.7	16.9	17.0	16.0	15.0
	Max	46.1	45.7	43.6	44.4	44.9	43.6	39.1
12-month Ozone (ppb)	Min	0.0	0.0	0.0	13.3	0.0	0.0	0.0
	25th percentile	35.7	37.8	37.4	38.8	37.7	36.7	37.5
	Median	37.3	39.5	38.9	40.1	38.9	37.9	38.8
	Mean	37.2	39.4	39.2	40.5	39.0	38.3	39.2
	75th percentile	38.8	41.3	40.9	42.2	39.9	39.3	40.1
	Max	58.6	55.6	54.9	56.2	55.6	57.7	56.5

single-pollutant models with the same covariates, fixed effects, and weights as model 3, with results illustrated in Figure 1. The association between ELA and ozone was slightly positive, but not statistically significant. Other associations remained negative.

**Effect measure modifications**

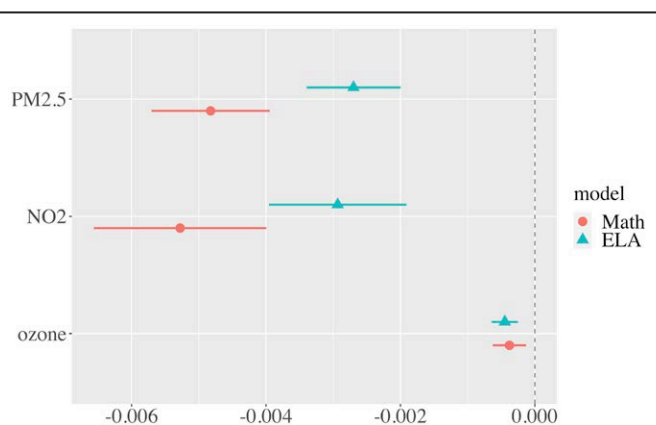
We tested for potential EMM by grades, Black and Hispanic/Latino student proportions and SES composite with interaction terms. Twenty-four models were fitted, all with the same covariates, fixed effects, and weights as model 3. The coefficients and 95% CIs for the interaction terms are presented in Figure 2.

The EMM by grades for the associations between test scores and all three pollutants were positive (less harmful at higher grades) except for the association between Math and NO<sub>2</sub>. The EMM by higher proportion of Black students was positive for the association between ELA and PM<sub>2.5</sub>, and negative for the association between Math and ozone. The EMM by higher proportion of Hispanic/Latino students were positive for the associations between Math and all three pollutants. The EMMs by

**Table 4.**  
Regression results of standardized test scores and 12-month ambient air pollution

	(1) β (95% CI)		(2) β (95% CI)		(3) β (95% CI)	
	<b>Math</b>					
PM <sub>2.5</sub> (IQR)	-0.011	(-0.013, -0.009)	-0.008	(-0.010, -0.006)	-0.007	(-0.009, -0.005)
NO <sub>2</sub> (IQR)	0.001	(-0.001, 0.003)	-0.001	(-0.003, 0.001)	-0.004	(-0.006, -0.002)
Ozone (IQR)	-0.006	(-0.007, -0.005)	-0.006	(-0.007, -0.004)	-0.005	(-0.006, -0.004)
Observations	361,852		348,119		347,468	
	<b>ELA</b>					
PM <sub>2.5</sub> (IQR)	-0.003	(-0.005, -0.001)	-0.004	(-0.006, -0.003)	-0.004	(-0.005, -0.002)
NO <sub>2</sub> (IQR)	-0.016	(-0.018, -0.014)	-0.011	(-0.013, -0.009)	-0.012	(-0.014, -0.010)
Ozone (IQR)	0.005	(0.004, 0.005)	0.002	(0.001, 0.003)	0.002	(0.001, 0.003)
Observations	383,121		367,958		367,285	

Model (1) is a crude model. Model (2) controlled for student racial/ethnic compositions and student-level SES. Model (3) controlled for student racial/ethnic compositions, student-level SES, urbanicity, and GSD-level SES.



**Figure 1.** Regression results and 95% confidence intervals of standardized Math/ELA test scores and 12-month ambient single air pollutant concentrations (IQR).

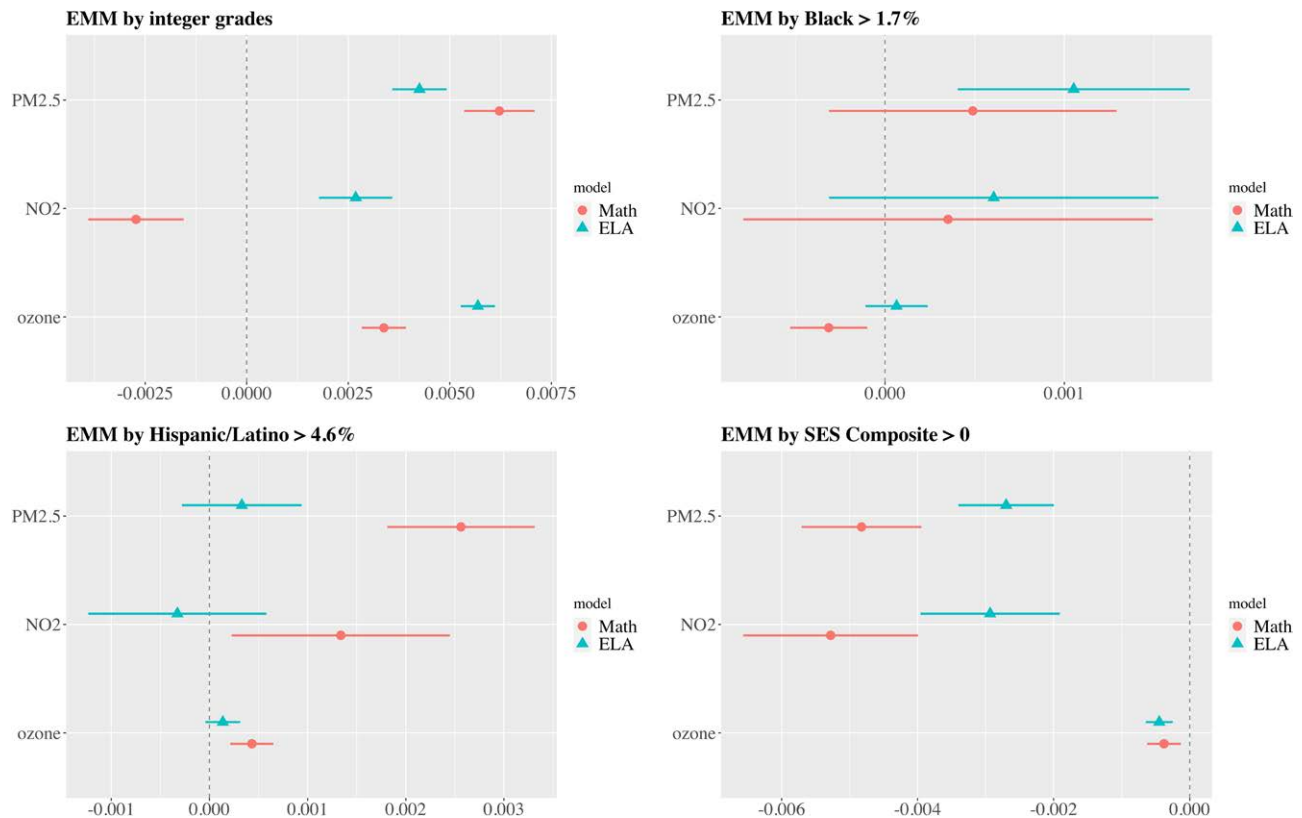
SES were negative for all six association pairs, suggesting that the association between air pollution and test scores were stronger for GSDs with higher SES. The main associations between air pollutant and test scores remained in the same directions as the results of model 3 for most strata of the modifiers. The coefficients for both main association terms for exposures and interaction terms are summarized in Table A3 of the Appendix; <http://links.lww.com/EE/A163>.

**Sensitivity analysis**

We compared model 3 to one-way fixed effects models nested in it and found that model 3 had significantly better fit. Detailed analysis is in the Appendix; <http://links.lww.com/EE/A163>. We investigated the associations of test scores and lagged air pollution from the previous school year. Compared with results of model 3, the coefficients of these lagged models are all in the same directions, and of similar magnitudes (ratios of unlagged and lagged coefficients ranged from 0.56 to 1.75).

**Discussion**

After controlling for covariates and two-way fixed effects, including GSD, grade, and year, we found that 12-month ambient PM<sub>2.5</sub>, NO<sub>2</sub>, and ozone levels were associated with lower average Math test scores; 12-month ambient PM<sub>2.5</sub> and NO<sub>2</sub>



**Figure 2.** Effect measure modifications of the associations between standardized Math/ELA test scores and 12-month ambient air pollution, tested with interaction terms between effect modifier and pollutant levels.

levels were associated with lower ELA test scores. An IQR-increase in ambient air pollution levels was associated with a 0.004 to 0.012 SD decrease in GSD average test scores. These results are of similar magnitude with a Chinese study that found a 0.014 SD decrease in examination scores associated with one SD of the difference between air pollution levels upwind and downwind of agricultural fires,<sup>55</sup> which was quantified as “decreases the probability of admission to an elite university by 0.027%” on the individual level. Also, as noted in the results, the magnitudes of these associations are equivalent to the impact of thousands of dollars per year decrease in GSD median household income, even after accounting for other aspects of GSD-level SES. Reductions in academic test scores among children can have life-long impacts on educational attainment, including dropping out of school, and lower future incomes.<sup>25,26</sup> These associations cannot be confounded by factors that vary across GSD because of the use of indicator variables for each GSD (and grade), eliminating a major source of potential confounding in air pollution studies. Common time trends were also controlled by indicator variables for year, and within-GSD differences in time trends due to time-varying covariates are also controlled. This greatly reduces the potential for confounding.

A positive association was found between ozone levels and ELA test scores in the three-pollutant model, but not in the single-pollutant model. This positive association appears to be due to the negative correlations between ozone and the other two pollutants, which could be due to chemical reactions such as the transformation of  $\text{NO}_2$  into ozone,<sup>56</sup> and the formation of  $\text{NO}_2$  from  $\text{NO}$  and ozone.<sup>57</sup> Overall, we did not find an association between ozone levels and ELA test scores.

The structure of the two-way fixed effects model resembles the DID analysis, as described in Table 1. Although the two-way fixed effects model has been proven to be equivalent to the DID estimator in the two groups and two time periods setting,<sup>58</sup> a recent study showed that in the two-group and multiple-period setting,

the DID estimator is equivalent to a weighted two-way fixed effects model and relies on an additional assumption of no interactions between the time and unit fixed effects.<sup>48</sup> In our model, since the treatment is continuous instead of two binary groups, the weights proposed by Imai and Kim<sup>48</sup> to adjust for mismatches of binary treatments do not apply, but the no interaction assumption should hold. The causal interpretations of the results rely on the no interaction assumption of the two-way fixed effects and the parallel trend assumption, which we were not able to test because we cannot observe the GSD-level test scores over a few years where the air pollution concentrations remained constant. Unable to test for these critical assumptions undercuts the validity of the causal interpretations. But even if causal interpretations are not warranted, the two-way fixed effects contribute to controlling for unmeasured confounders that are constant within a GSD-grade or common trends for all GSDs.

We found that the magnitudes of the associations vary by grades, racial/ethnic compositions, and SES. The decreases in test scores associated with higher air pollution concentrations were larger for younger children, except for the association between Math test scores and  $\text{NO}_2$  concentrations. This is generally consistent with the common belief that younger children are more vulnerable to neurotoxins.<sup>59</sup> The modification by racial/ethnic compositions may be due to complex social factors such as residential segregation. The associations of both Math and ELA test scores with all three air pollutants are stronger among GSDs with higher SES, which are in the opposite directions with other modifications found in studies on air pollution and other outcomes such as mortality, respiratory outcomes, and cardiovascular diseases.<sup>60,61</sup> One possible explanation is that compared with air pollution, SES factors are much stronger predictors of test scores. This is true in our study, as shown in Table A2 of the Appendix; <http://links.lww.com/EE/A163>, where several covariates have coefficients of much larger magnitudes compared with the coefficients of air pollutant concentrations. An additional

possibility is that lower-SES GSDs also may be associated with systematic and cumulative exposures to other environmental pollutants or additional stressors that render the difference in any one exposure less influential.<sup>62,63</sup> Thus, improving ambient air quality by 1 unit in a low-SES GSD may not be as beneficial as in a high-SES GSD. This is especially plausible when our results are interpreted causally. Another possibility is that the pollution concentrations mean different things. SES tends to be higher in suburban areas, where PM<sub>2.5</sub> has a larger component of secondary particles than inside of cities. These components may have different toxicities. Similarly, a higher fraction of NO<sub>2</sub> in suburbs may be transported, which may affect the concentrations and aging of other, unmeasured traffic exhaust components that NO<sub>2</sub> can serve as a surrogate for.

In the analyses for lagged associations, the results persisted in the same directions and of similar magnitudes. This suggests that the impact of air pollution on cognitive functions can be observed over several years, which were also found in other studies.<sup>5,14,19</sup> Another possibility is that the lagged associations were due to the positive correlation between the exposure variations across different years. This possible contamination of lag effects in two-way fixed effects model was described in a recent study.<sup>64</sup>

Our study has several limitations. First, we restricted to 10,921 of 13,160 GSDs. The results can only be generalized to GSDs with similar characteristics to the included GSDs, though study-specific interpretations cover the large majority of GSDs in the United States. Compared with the excluded GSDs, the included GSDs are less likely to be urban and have slightly lower bachelor's degree rate and median household income. Second, we cannot exclude residual confounding by time-varying covariates, such as the constructions of green spaces that may affect both air pollution levels and children's academic performances. Finally, this is an ecological study where exposures are matched to students on population-level based solely on geographic information of their residing school districts. Individual-level variations in air pollution exposures such as temporary migration and commuting across districts were not measured. These misclassifications of exposures are expected to be nondifferential and may shift the estimates toward the null.

In conclusion, we found negative associations between ambient air pollution levels and children's academic performance. Such associations were stronger among GSDs with higher SES. The lowering of both Math and ELA test scores may have life-long impacts on children. Further improving ambient air quality may benefit children's academic achievements and career in the long run.

### Conflict of interest statement

The authors declare that they have no conflicts of interest with regard to the content of this report.

### References

- Clifford A, Lang L, Chen R, Anstey KJ, Seaton A. Exposure to air pollution and cognitive functioning across the life course—a systematic literature review. *Environ Res*. 2016;147:383–398.
- Calderón-Garcidueñas L, Mora-Tiscareño A, Ontiveros E, et al. Air pollution, cognitive deficits and brain abnormalities: a pilot study with children and dogs. *Brain Cogn*. 2008;68:117–127.
- Block ML, Calderón-Garcidueñas L. Air pollution: mechanisms of neuroinflammation and CNS disease. *Trends Neurosci*. 2009;32:506–516.
- Levesque S, Taetzsch T, Lull ME, et al. Diesel exhaust activates and primes microglia: air pollution, neuroinflammation, and regulation of dopaminergic neurotoxicity. *Environ Health Perspect*. 2011;119:1149–1155.
- Calderón-Garcidueñas L, Solt AC, Henríquez-Roldán C, et al. Long-term air pollution exposure is associated with neuroinflammation, an altered innate immune response, disruption of the blood-brain barrier, ultrafine particulate deposition, and accumulation of amyloid beta-42 and alpha-synuclein in children and young adults. *Toxicol Pathol*. 2008;36:289–310.
- Calderón-Garcidueñas L, Azzarelli B, Acuna H, et al. Air pollution and brain damage. *Toxicol Pathol*. 2002;30:373–389.
- Calderón-Garcidueñas L, Herrera-Soto A, Jury N, et al. Reduced repressive epigenetic marks, increased DNA damage and Alzheimer's disease hallmarks in the brain of humans and mice exposed to particulate urban air pollution. *Environ Res*. 2020;183:109226.
- Calderón-Garcidueñas L, Reed W, Maronpot RR, et al. Brain inflammation and Alzheimer's-like pathology in individuals exposed to severe air pollution. *Toxicol Pathol*. 2004;32:650–658.
- Peters R, Ee N, Peters J, Booth A, Mudway I, Anstey KJ. Air pollution and dementia: a systematic review. *J Alzheimers Dis*. 2019;70(s1):S145–S163.
- Power MC, Adar SD, Yanosky JD, Weuve J. Exposure to air pollution as a potential contributor to cognitive function, cognitive decline, brain imaging, and dementia: a systematic review of epidemiologic research. *Neurotoxicology*. 2016;56:235–253.
- Oudin A, Forsberg B, Adolfsson AN, et al. Traffic-related air pollution and dementia incidence in Northern Sweden: a longitudinal study. *Environ Health Perspect*. 2016;124:306–312.
- Tierney AL, Nelson CA 3rd. Brain development and the role of experience in the early years. *Zero Three*. 2009;30:9–13.
- Sunyer J, Esnaola M, Alvarez-Pedrerol M, et al. Association between traffic-related air pollution in schools and cognitive development in primary school children: a prospective cohort study. *PLoS Med*. 2015;12:e1001792.
- Forns J, Dadvand P, Esnaola M, et al. Longitudinal association between air pollution exposure at school and cognitive development in school children over a period of 3.5 years. *Environ Res*. 2017;159:416–421.
- Alvarez-Pedrerol M, Rivas I, López-Vicente M, et al. Impact of commuting exposure to traffic-related air pollution on cognitive development in children walking to school. *Environ Pollut*. 2017;231(Pt 1):837–844.
- Calderón-Garcidueñas L, Engle R, Mora-Tiscareño A, et al. Exposure to severe urban air pollution influences cognitive outcomes, brain volume and systemic inflammation in clinically healthy children. *Brain Cogn*. 2011;77:345–355.
- Power MC, Weisskopf MG, Alexeeff SE, Coull BA, Spiro A 3rd, Schwartz J. Traffic-related air pollution and cognitive function in a cohort of older men. *Environ Health Perspect*. 2011;119:682–687.
- Sunyer J, Suades-González E, García-Esteban R, et al. Traffic-related air pollution and attention in primary school children: short-term association. *Epidemiology*. 2017;28:181–189.
- Rivas I, Basagaña X, Cirach M, et al. Association between early life exposure to air pollution and working memory and attention. *Environ Health Perspect*. 2019;127:57002.
- Lopuszanska U, Samardakiewicz M. The relationship between air pollution and cognitive functions in children and adolescents: a systematic review. *Cogn Behav Neurol*. 2020;33:157–178.
- Gui Z, Cai L, Zhang J, et al. Exposure to ambient air pollution and executive function among Chinese primary schoolchildren. *Int J Hyg Environ Health*. 2020;229:113583.
- Freire C, Ramos R, Puertas R, et al. Association of traffic-related air pollution with cognitive development in children. *J Epidemiol Community Health*. 2010;64:223–228.
- Mohai P, Kweon BS, Lee S, Ard K. Air pollution around schools is linked to poorer student health and academic performance. *Health Aff (Millwood)*. 2011;30:852–862.
- Grineski SE, Collins TW, Adkins DE. Hazardous air pollutants are associated with worse performance in reading, math, and science among US primary schoolchildren. *Environ Res*. 2020;181:108925.
- Maani SA, Kalb G. Academic performance, childhood economic resources, and the choice to leave school at age 16. *Econ Educ Rev*. 2007;26:361–374.
- Zax JS, Rees DL. IQ, academic performance, environment, and earnings. *Rev Econ Stat*. 2002;84:600–616.
- Wang S, Zhang J, Zeng X, Zeng Y, Wang S, Chen S. Association of traffic-related air pollution with children's neurobehavioral functions in Quanzhou, China. *Environ Health Perspect*. 2009;117:1612–1618.
- Cleary EG, Cifuentes M, Grinstein G, Brugge D, Shea TB. Association of low-level ozone with cognitive decline in older adults. *J Alzheimers Dis*. 2018;61:67–78.
- Lo YC, Lu YC, Chang YH, Kao S, Huang HB. Air pollution exposure and cognitive function in Taiwanese older adults: a repeated measurement study. *Int J Environ Res Public Health*. 2019;16:E2976.
- Duncan GJ, Morris PA, Rodrigues C. Does money really matter? Estimating impacts of family income on young children's achievement with data from random-assignment experiments. *Dev Psychol*. 2011;47:1263–1279.

31. Murnane RJ, Duncan GJ. *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*. Russel Sage Foundation Press; 2011.
32. Reardon SF. The widening academic achievement gap between the rich and the poor: new evidence and possible explanations. In: Duncan GJ, Murnane RJ, eds. *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances*. Russel Sage Foundation Press; 2011:91–115.
33. Ailshire J, Karraker A, Clarke P. Neighborhood social stressors, fine particulate matter air pollution, and cognitive function among older U.S. adults. *Soc Sci Med*. 2017;172:56–63.
34. Wang P, Tuvblad C, Younan D, et al. Socioeconomic disparities and sexual dimorphism in neurotoxic effects of ambient fine particles on youth IQ: a longitudinal analysis. *PLoS One*. 2017;12:e0188731.
35. Marshall AT, Betts S, Kan EC, McConnell R, Lanphear BP, Sowell ER. Association of lead-exposure risk and family income with childhood brain outcomes. *Nat Med*. 2020;26:91–97.
36. Braga AL, Saldiva PH, Pereira LA, et al. Health effects of air pollution exposure on children and adolescents in São Paulo, Brazil. *Pediatr Pulmonol*. 2001;31:106–113.
37. Wang B, Eum KD, Kazemiparkouhi F, et al. The impact of long-term PM2.5 exposure on specific causes of death: exposure-response curves and effect modification among 53 million U.S. Medicare beneficiaries. *Environ Health*. 2020;19:20.
38. US Department of Education. *Public Law print of PL 107-110, the No Child Left Behind Act of 2001*. Available at: <https://www2.ed.gov/policy/elsec/leg/esea02/index.html>. Accessed 20 January 2021.
39. Reardon SF, Ho AD, Shear BR, et al. *Stanford Education Data Archive (Version 3.0)*. Available at: <http://purl.stanford.edu/db586ns4974>. 30 ed. 2019. Accessed 24 June 2020.
40. National Center for Education Statistics. *About NAEP: A Common Measure of Student Achievement*. Available at: <https://nces.ed.gov/nationsreportcard/about/>. Accessed 20 January 2021.
41. Di Q, Amini H, Shi L, et al. An ensemble-based model of PM2.5 concentration across the contiguous United States with high spatiotemporal resolution. *Environ Int*. 2019;130:104909.
42. Di Q, Amini H, Shi L, et al. Assessing NO2 concentration and model uncertainty with high spatiotemporal resolution across the contiguous United States using ensemble model averaging. *Environ Sci Technol*. 2020;54:1372–1384.
43. Requia WJ, Di Q, Silvern R, et al. An ensemble learning approach for estimating high spatiotemporal resolution of ground-level ozone in the contiguous United States. *Environ Sci Technol*. 2020;54:11037–11047.
44. Gangl M. Causal inference in sociological research. *Annu Rev Sociol*. 2010;36:21–47.
45. Strumpf EC, Harper S, Kaufman JS. Fixed effects and difference-in-differences. In: Oakes JM, Kaufman JS, eds. *Methods in Social Epidemiology, 2nd Edition*. 2nd ed. Jossey-Bass & Pfeiffer Imprint, a Wiley brand; 2017.
46. Wang Y, Kloog I, Coull BA, Kosheleva A, Zanobetti A, Schwartz JD. Estimating causal effects of long-term PM2.5 exposure on mortality in New Jersey. *Environ Health Perspect*. 2016;124:1182–1188.
47. Callaway B, Karami S. Treatment effects in interactive fixed effects models. *arXiv*. 2020(2006.15780).
48. Imai K, Kim IS. On the use of two-way fixed effects regression models for causal inference with panel data. *Polit Anal*. 2020;29:1–11.
49. Wing C, Simon K, Bello-Gomez RA. Designing difference in difference studies: best practices for public health policy research. *Annu Rev Public Health*. 2018;39:453–469.
50. Callaway B, Sant'Anna PHC. Difference-in-differences with multiple time periods. *J Economet*. 2020; 225:200–230.
51. Menegaki AN, Ozturk I. Growth and energy nexus in Europe revisited: evidence from a fixed effects political economy model. *Energy Policy*. 2013;61:881–887.
52. Li Z, Huang Z, Zhang Y, Huang Z. Research on the economic growth for under-developed counties -- based on two-way fixed-effects model. *IPO Conference Series: Earth and Environmental Science*. Vol. 690. Beijing, China; 2021.
53. Schwartz J, Wei Y, Yitshak-Sade M, Di Q, Dominici F, Zanobetti A. A national difference in differences analysis of the effect of PM2.5 on annual death rates. *Environ Res*. 2021;194:110649.
54. Kuhfeld M, Domina T, Hanselman P. Validating the SEDA measures of district educational opportunities via a common assessment. *AERA Open*. 2019;5:1–18.
55. Zivin JG, Liu T, Song YQ, Tang Q, Zhang P. The unintended impacts of agricultural fires: human capital in China. *J Dev Econ*. 2020;147:102560.
56. Ghazali NA, Ramli NA, Yahaya AS, Yusof NF, Sansuddin N, Al Madhoun WA. Transformation of nitrogen dioxide into ozone and prediction of ozone concentrations using multiple linear regression techniques. *Environ Monit Assess*. 2010;165:475–489.
57. Innes WB. Effect of nitrogen oxide emissions on ozone levels in metropolitan regions. *Environ Sci Technol*. 1981;15:904–912.
58. Bertrand M, Duflo E, Mullainathan S. How much should we trust differences-in-differences estimates? *Q J Econ*. 2004;119:249–275.
59. Weiss B. Vulnerability of children and the developing brain to neurotoxic hazards. *Environ Health Perspect*. 2000;108(suppl 3):375–381.
60. O'Neill MS, Jerrett M, Kawachi I, et al.; Workshop on Air Pollution and Socioeconomic Conditions. Health, wealth, and air pollution: advancing theory and methods. *Environ Health Perspect*. 2003;111:1861–1870.
61. Laurent O, Bard D, Filleul L, Segala C. Effect of socioeconomic status on the relationship between atmospheric pollution and mortality. *J Epidemiol Community Health*. 2007;61:665–675.
62. Evans GW. The environment of childhood poverty. *Am Psychol*. 2004;59:77–92.
63. Hackman DA, Kraemer DJM. Socioeconomic disparities in achievement: insights on neurocognitive development and educational interventions. In: Thomas MSC, Mareschal D, Dumontheil I, eds. *Educational Neuroscience: Development Across the Life Span*. *Frontiers of Developmental Science*. Routledge Books; 2020:88–120.
64. Sun L, Abraham S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *J Economet*. 2020; 225:175–199.
65. US EPA. *NAOQS Table*. Available at: <https://www.epa.gov/criteria-air-pollutants/naaq-table>. Accessed 23 December 2021.