

Children's Health and Air Pollution Study: STandardized Assessments, Attention and Cognition in California Kids (CHAPS: STACK)

FINAL REPORT

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Abstract

Air pollution has been linked to impaired cognitive outcomes and lower academic performance in children. While the risks of criteria pollutants are recognized, data remain limited regarding how standardized academic metrics correlate with neurobehavioral instruments.

We conducted a systematic literature review of air pollution and standardized test performance to identify research gaps and relevant covariates for our analyses. We conducted a secondary analysis, at the school level, of publicly available data from the California Department of Education (CDE) from 2014 to 2019 for 3rd through 11th grades. Linear mixed effect models assessed the relationship between air pollutants and standardized test scores, using all available years of data for each exam at each grade level. We also utilized newly collected data from the Children's Health and Air Pollution Study (CHAPS) in Fresno, California (n=193, ages 7-18). Daily prenatal and first-year exposures to seven air pollutants were estimated using spatio-temporal models and compared with tests and biomarkers of cognition. Last, using data from these analyses, we used g-estimation to estimate how much standardized test performance could change if California air pollutant exposures were decreased.

In a statewide analysis, increased air pollution exposure was associated with lower standardized test scores. The highest associations were found for PM_{2.5} and O₃ two years prior; and in younger children. In the CHAPS cohort, third-grade SBAC scores demonstrated robust correlations with the NIH Toolbox total and crystallized cognition composites and a moderate correlation with serum BDNF. First-trimester exposure to traffic-related air pollutants was associated with elevated childhood aggressive and rule-breaking behavior. First-year of life exposure across all seven pollutants was consistently associated with depressed BDNF.

These findings add to a growing body of evidence that air pollution exposure affects not only children's physical health but also their cognitive development.

Project Background and Scientific Executive Summary

Performance

Title

Children's Health and Air Pollution Study: Standardized Assessments, Attention and Cognition in California Kids

Issue(s)

Air pollution has been linked to impaired cognitive outcomes and lower academic performance in children. Children are uniquely vulnerable to ambient air pollution due to physiological factors that increase their effective dose during critical developmental windows. While the risks of criteria pollutants are recognized, data remain limited regarding how modern standardized academic metrics correlate with intensive neurobehavioral instruments, and looking at non-criteria pollutants—such as polycyclic aromatic hydrocarbons (PAHs) and black carbon (BC). In addition, there is a gap in California-specific research.

Main Question

Does air pollution exposure in early life play a meaningful role in shaping children's academic outcomes?

Key Research Findings

- From our literature review we found limited data and inconclusive findings, which underscores the imperative for continued research using individual-level outcome data and with non-criteria pollutants.
- Higher PM_{2.5}, O₃, NO₂, and Diesel PM were associated with a lower percent of students meeting state standards for ELA and Math at the school level, with findings most pronounced for PM_{2.5} and O₃ exposures two years prior to testing.
- In the CHAPS study population, third-grade SBAC scores demonstrated robust correlations with the NIH Toolbox total and crystallized cognition composites ($r \sim 0.55-0.60$) and a moderate correlation with serum BDNF ($r=0.35$).

Conclusions

These findings add to a growing body of evidence that air pollution exposure affects not only children's physical health but also their cognitive development. By leveraging both school and home exposures, our study uniquely captured the majority of air pollution exposures children experience daily, strengthening the case for targeted interventions. These results can inform policies that promote efforts to reduce air pollution overall and prevent new school buildings in high pollution areas. They also underscore the need for resource allocation in communities disproportionately burdened by air pollution to reduce the burden of exposure at a child's home and mitigate its impact on academic outcomes.

More Information

The Children's Health and Air Pollution Study: STandardized Assessments, Attention and Cognition in California Kids (CHAPS: STACK) study, sponsored by the California Air Resources Board (CARB), analyzed publicly available California standardized testing data, and also collected both standardized test data and in-depth neurobehavioral assessments from children enrolled in the larger CHAPS study. It was led by Elizabeth Noth, Nina Holland and Stephanie Holm. The full report is available on the CARB website, and more information can be obtained from Hnin-Hnin Aung at CARB.

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Executive Summary

Background

Air pollution has been linked to impaired cognitive outcomes and lower academic performance in children. Children are uniquely vulnerable to ambient air pollution due to physiological factors that increase their effective dose during critical developmental windows. While the risks of criteria pollutants are recognized, data remain limited regarding how modern standardized academic metrics correlate with intensive neurobehavioral instruments, and looking at non-criteria pollutants—such as polycyclic aromatic hydrocarbons (PAHs) and black carbon (BC). In addition, there is a gap in California-specific research.

Objectives and methods.

Objective 1: Identify research gaps on standardized testing of California children and identify key variables to account for as confounders in our analyses.

Method: Conduct a systematic literature review of peer-reviewed literature with air pollutant concentrations as the exposure and standardized test scores as the outcome variable, limiting to studies in the US that have individual outcome data.

Objective 2: Address the gap in California-based analysis of the relationship between standardized testing and air pollution exposure, the research team examined associations between average annual air pollutant concentrations at school site (PM_{2.5}, NO₂, O₃, Diesel PM, and traffic exposures) and average performance on standardized tests in the following year (including English/Language Arts (ELA), mathematics, and science) at California public schools from 2014 to 2019.

Method: We conducted a secondary analysis, at the school level, of publicly available data from the California Department of Education (CDE) from 2014 to 2019 for 3rd through 11th grades. Linear mixed effect models assessed the relationship between air pollutants and standardized test scores, using all available years of data for each exam at each grade level.

Objective 3: Address the gap in research on the cognitive effects air pollution of non-criteria pollutants—pollutants not monitored and regulated by the EPA, such as PAHs and black carbon (BC)—especially for exposure in the prenatal period. PAHs are carcinogenic, 18–20 toxic air contaminants that are co-emitted with regulated gaseous and particulate combustion products (PM, NO_x, CO) from common sources, such as motor vehicles and biomass burning.

Method: Utilizing data from the Children's Health and Air Pollution Study (CHAPS) in Fresno, California (n=193, ages 7–18). Daily prenatal and first-year exposures to PM_{2.5}, PM₁₀, O₃, NO₂, NO_x, PAH₄₅₆ and elemental carbon (EC) were estimated using spatio-temporal models. Outcome measures

included the NIH Toolbox Cognition Battery, the Child Behavior Checklist (CBCL), California Smarter Balanced Assessments (SBAC) standardized test scores, and serum brain-derived neurotrophic factor (BDNF) and urinary 8-hydroxy-2-deoxyguanosine (8-OHdG) biomarkers. Linear and distributed lag models (DLM) were applied.

Objective 4: Estimate how much standardized test performance could change if California air pollutant exposures were decreased.

Method: A dataset of California elementary school students ($n=1230000$) was simulated, assuming means and correlations based on known statewide data. G-computation was performed both using estimates derived from earlier chapters, in combination with different hypothetical interventions to estimate impact on test performance for California students.

Results

Our systematic review uncovered evidence that children and adolescents exposed to elevated concentrations of air pollution, particularly PAHs and some air toxics, during prenatal and early life stages may exhibit lower scores on standardized tests compared to those with lower exposures. We also found need for future research in this domain to employ improved temporal and spatial exposure assessments (especially of non-criteria pollutants).

Higher PM_{2.5}, O₃, NO₂, and Diesel PM were associated with a lower percent of students meeting state standards for ELA and Math at the school level, with findings most pronounced for PM_{2.5} and O₃ exposures two years prior to testing. A 2.43 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} was associated with 4.35% fewer elementary school students achieving state standards (95% CI -4.81%, -3.90%), and a 3.36 ppm increase in ozone was associated with 3.61% fewer elementary students meeting state standards (95% CI -4.43%, -2.78%). Findings clustered based on grade levels with stronger associations for younger grade levels.

In the CHAPS study populations, we found that math standardized test scores were negatively associated with increased exposure to O₃ and PM_{2.5}, but not NO₂. A one part per billion (ppb) increase in O₃ was associated with a -0.078 (95% CI: -0.145 to -0.010) standard deviation decrease in test scores and a one microgram per meter cubed ($\mu\text{g}/\text{m}^3$) increase in PM_{2.5} was associated with a -0.074 standard deviation decrease in test score (95% CI: -0.120 to -0.032). There was also a weak negative association between English Language Arts and both O₃ and PM_{2.5}, however, the confidence intervals for these associations overlapped the null.

In the CHAPS study population, third-grade SBAC scores demonstrated robust correlations with the NIH Toolbox total and crystallized cognition composites ($r \sim 0.55$ - 0.60) and a moderate correlation with serum BDNF ($r=0.35$). Linear models revealed that first-trimester exposure to traffic-related air pollutants (PM_{2.5} and PAH₄₅₆) were associated with elevated childhood z-scores for aggressive and rule-breaking behavior. First-year of life exposure across all seven pollutants was

consistently associated with depressed serum BDNF levels; DLM analysis identified a critical susceptibility window around 5 to 6 months of life, which mirrored a corresponding localized dip in NIH Toolbox total cognition scores.

Calculations estimating impact of air pollution reduction intervention impacts suggest that bringing the PM_{2.5} concentration in highly exposed areas down to 9 µg/m³ (the current National Ambient Air Quality Standard) would have a modest benefit for California elementary school students, by increasing the average students' standardized test scores 1-2 years later by 5 to 20 points, depending on the exact assumed effect size.

Conclusions

The association between air pollutant exposure at home and school and student standardized test scores emphasizes the neurocognitive impact of air pollution on a measure available for nearly all California children.

In the statewide analysis, at the school level, of publicly available data from the California Department of Education (CDE) from 2014 to 2019 for 3rd through 11th grades, we found that increased air pollution exposure is associated with lower standardized test scores for children in California schools. The most pronounced associations were found for PM_{2.5} and O₃ two years prior; and in younger children. Given that insults to brain growth and development have the potential for lifelong effects on the California population and economy, this analysis provides detailed estimates for a pressing problem needing policy interventions.

In the small, but well-characterized CHAPS cohort, both O₃ and PM_{2.5} exposures were negatively associated with standardized math test performance. There was also a strong relationship between the NIH Toolbox Cognition Battery scores (the detailed neurocognitive assessment completed by our participants) and 3rd grade SBAC testing scores.

Results from the g-computation analysis imply the potential for a school achievement benefit for California students 1-2 years after a potential air pollution intervention, which could shift the overall score distribution as much as a quarter of a standard deviation. The exact degree of the change is dependent on both how much an intervention would decrease pollutant concentrations, and which estimated effect size is used.

These findings add to a growing body of evidence that air pollution exposure affects not only children's physical health but also their cognitive development. By leveraging both school and home exposures, our study uniquely captured the majority of air pollution exposures children experience daily, strengthening the case for targeted interventions. These results can inform policies that promote efforts to reduce air pollution overall and prevent new school buildings in high pollution areas. They also underscore the need for resource allocation in communities disproportionately burdened by air pollution to reduce the burden of exposure at a child's home and mitigate its impact on academic outcomes.

Chapter 1: Systematic Review of Childhood Air Pollution Exposure and Child/Adolescent Standardized Test

PM_{2.5}, NO₂, and PAH have been identified as air pollutants contributing to the neurodevelopmental health of children (U.S. EPA Office of Air and Radiation, 2023). Standardized testing data provide a unique and widely used source of information on the cognitive performance of children in the U.S.. For this task, Dr. Stephanie Holm (UCSF) and Ms. Iran Torres Aleman (UCB Graduate Student Researcher) completed a systematic review of air pollution exposure during the prenatal and childhood periods and effects on standardized test performance in children and adolescents. The systematic review is included in Appendix A.

The systematic review included papers with air pollutant concentrations as the exposure and standardized test scores as the outcome variable, limiting to studies in the U.S. that have individual outcome data. The introduction of this systematic review presented a variety of factors that have previously been shown to relate to children's academic performance. These factors include noise, Attention-deficit/hyperactivity disorder (ADHD) symptoms, traffic-related air pollution, socioeconomic status (SES), neighborhood access to green spaces and temperature (Alvarez-Pedrerol et al 2017, Kioumourtzoglou et al 2016, Kulick et al 2020, Schikowski et al 2020, Medrano et al 2022, Ha et al 2021).

Dr. Holm and Ms. Aleman searched PubMed, Web of Science, and Scopus databases. Articles were independently reviewed for inclusion by both authors and bias assessments were performed independently (using Risk of Bias 2.0 (RoB2) for any trials, and Risk of Bias Tool for Non-randomized Studies (ROBINS-I) for observational studies). Dr. Holm and Ms. Aleman pre-registered the systematic review protocol with PROSPERO (the International Prospective Register of Systematic Reviews) and followed the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (Page et al 2021) for conducting and reporting systematic reviews.

For this systematic review, 10,968 articles were screened, however, only 29 full-text articles were reviewed. Only studies meeting the inclusion criteria were included in the systemic review. In total 5 articles met the inclusion criteria and are summarized in Appendix A. Notably, only 3 different datasets were represented across the 5 studies included in the review.

In summary, children exposed to increased levels of combustion related pollutants and air toxics during prenatal and early life stages may exhibit lower scores on standardized tests compared to those with lower exposures. The studied pollutants included polycyclic aromatic hydrocarbons (PAHs) and Diesel PM, and air toxics such as isophorone, trichloroethylene, and manganese compounds. However, the systematic review indicated that this association was weak, and inconsistent across studies. Estimates for the association between increasing combustion related pollutants and standardized test scores (e.g. Z-scores) ranged

from -0.13 to 0.03, with most study estimates having confidence intervals that crossed the null. There was a similar pattern of association with the air toxics; point estimates for association with standardized testing results ranged from -0.05 to 0.04, again with most confidence intervals crossing the null. Among the two studies reporting raw math scores, exposure to high concentrations of air toxics (compared to low) was associated with decreases of 1.6 to decreases of 1.3 points. A standardized bias assessment completed by the research team found that all five included studies also had a very high risk of bias, further emphasizing the need for caution when interpreting or legislating based on these results. Details of pollutant intervals, the reviewed studies and findings can be found in Appendix A. This systematic review also underscored the need for additional research on children's individual test score outcomes in relation to air pollution exposure, given that so few articles in the literature include individual data.

Furthermore, this systematic review was included in the project to identify key variables to account for as confounders in the later analyses. SES was identified as a key confounder to control for in analyses, and the studies used multiple metrics for doing so. Based on findings from Stingone et al. 2016 (in which fewer of the study results had confidence intervals crossing the null), school district funding and a metric for student absences should be included in the analysis. The research team had hoped to use the extant literature to determine best ways to account for the effect of greenspace on children's learning; after completing the systematic review, the researchers found this work has not been done previously with individual student data. Available information for green spaces included parks within a radius, park accessibility and tree coverage.

Thus, the systematic review found an expected association between air pollutant exposure and standardized testing results, but most notable was how few studies used individual test scores, as the research team subsequently did in chapter 3.

Chapter 2: Statewide Association between PM_{2.5}, NO₂, O₃, and Traffic Exposures and Standardized Test Performance

As mentioned in Chapter 1, there are few studies assessing air pollutant exposures and standardized test or learning outcomes using individual data. There are, however, many analyses of the association between air pollutant exposures and standardized test or learning outcomes associated with ecologic data. Most such ecologic studies have found a decrease in student academic performance associated with higher nearby pollutant exposure, even when controlling for SES (Stenson et al 2021). Yet, a comprehensive ecological analysis had not previously been performed on modern California testing data.

To address the gap in California-based analysis, the research team examined associations between average annual air pollutant concentrations at school site (PM_{2.5}, NO₂, O₃, Diesel PM, and traffic exposures) and average performance on standardized tests in the following year (including English/Language Arts, mathematics, and science) at California public schools from 2014 to 2019. These used sophisticated exposure models that had previously been developed under CARB Contract 19RD004. Annual average school exposure to PM_{2.5} was 9.5 µg/m³ (IQR: 2.43), to ozone was 38.8 ppb (IQR: 3.36), and to NO₂ was 10.0 ppb (IQR: 5.19) between 2013 and 2018; on average there were 3.1 tons of diesel PM per year (IQR: 5.49) and 947.6 vehicles per hour near schools (IQR 739.4). The percentage of students eligible for free and reduced-price meals (FRPM) was used as a proxy for SES, and district funding and student absenteeism were also included, given information gleaned from the systematic review in chapter 1. The scientific paper documenting these methods and analyses is included in Appendix B.

Negative associations were observed between all individual air pollutants and meeting Standardized Balanced Assessments for California (SBAC) ELA and Math standards (Figure B1). Across all pollutants, and for both ELA and math, these associations demonstrated larger effect sizes at younger grade levels. For example, in third graders, an IQR increase in PM_{2.5} exposure (2.43 µg/m³) is associated with 5.02% (95% CI: -5.35, -4.70) fewer students meeting SBAC ELA state standards at a school, accounting for covariates. Meanwhile, for eighth graders, an IQR increase in PM_{2.5} exposure is only associated with 2.49% (95% CI: -4.06, -1.10) fewer students meeting SBAC ELA state standards.

The results of the 127 models completed under the contract for this project (1 year lag of 5 pollutants [PM_{2.5}, O₃, NO₂, Diesel PM, Traffic], related to 7 grade levels, 2 tests and 2 subjects; plus 5 pollutants and 3 grade levels for the other test) are

Table 2.1 Summary Concentration-Response Functions for Different School Levels. Outcome is the % decrease in students meeting grade level standards related to one IQR increase in pollutant exposure.

Pollutant	Pooled Point Estimate Related to prior year exposure (estimate and CI)	Pooled Point Estimate Related to exposure two years prior (estimate and CI)
Elementary School		
PM _{2.5}	-0.21 (-0.32,-0.1)	-4.35 (-4.81,-3.9)
O ₃	-2.15 (-2.95,-1.35)	-3.61 (-4.43,-2.78)
NO ₂	-4.22 (-4.95,-3.49)	-3.56 (-4.15,-2.97)
Diesel PM	-2.63 (-2.98,-2.29)	
Traffic	1.64 (1.5,1.79)	
Middle School		
PM _{2.5}	-0.08 (-0.36,0.21)	-3.38 (-3.8,-2.96)
O ₃	-1.84 (-2.34,-1.34)	-3.21 (-3.83,-2.6)
NO ₂	-3.5 (-3.85,-3.15)	-2.74 (-3.17,-2.31)
Diesel PM	-2.14 (-2.75,-1.54)	
Traffic	1.59 (1.44,1.74)	
High School		
PM _{2.5}	-0.38 (-1.24,0.48)	-1.83 (-2.93,-0.72)
O ₃	1.18 (-0.37,2.72)	0.28 (-1.06,1.62)
NO ₂	-2 (-3.24,-0.76)	-1.16 (-2.38,0.06)
Diesel PM	-0.72 (-1.5,0.05)	
Traffic	1.62 (0.48,2.75)	

listed in table B.2 and supplemental tables S.B2 and S.B3. (This is 28 models short of the 155 initially

anticipated in the

contract. The 28

models not calculated are 7 models each for the California Alternate Assessment (CAA) English and math tests associated with Diesel and traffic. Because of the small number of schools with sufficient students taking the CAA to report the results, the confidence intervals on the CAA-specific pollutant estimates are very wide. It was determined prior to completing diesel or traffic models that these would be of little utility and these were not performed). However, all the models using individual pollutants (3 pollutants [PM_{2.5}, O₃ and NO₂], related to 7 grade levels, and 2 subjects; 42 models) were actually completed a second time, using a 2-year lag.

The reported associations are

relationships across schools. Attempts to calculate within school estimates (i.e. how the relationship between pollutants and test scores varies within a school) were unsuccessful, due to an inability of the statistical models to converge. This is because of heterogeneity in the underlying data and too few observations for each school, given that the maximum possible was 5 observations per school within the five years of testing data.

The pattern of associations seemed to cluster within different school types (elementary, middle and high schools). Thus, the research team has calculated summary concentration response functions between air pollutant exposures and for each school level/type. Results were pooled using the random effect method for meta-analysis across English language and math results to provide a single summary estimate for each school type (since both subjects followed similar patterns). The only high school grade in which the California SBAC tests were completed was 11th grade, so the high school summary estimate derives from the data using this grade only. The elementary school summary estimate is based on the estimates from grades 3-5, and the middle school summary estimate is based on the estimates from grades 6-8. Notably, models calculated within the subgroup of male students and the subgroup of female students were very similar to the overall findings. Analyses were also performed within common racial/ethnic groups. The research team strongly cautions to not over-interpret apparent differences in these because the sample sizes are wildly different. There is geographic clustering in the presence of data for different subgroups. This suggests that differences may be more a function of selection bias of the schools reporting data for different subgroups, rather than true differences in the relationship between air pollution and test outcomes.

As discussed at length in appendix B, the general pattern of results is that a one unit change in a specific given pollutant was associated with fewer students meeting grade level standards. These effects were largest in the youngest grades, and largest for 2-year prior PM_{2.5} exposures, followed by ozone exposures at one or two year lags. Notably, the association with nearby traffic shows a different pattern than those with specific pollutants. The research team posits that this represents bias due to differential exposure misclassification in this metric-with prevailing wind direction, and whether a school is downwind or upwind from the majority of traffic being a key factor that is not captured by this exposure metric. Without that differentiation, the traffic measure may be serving as a proxy for urban areas. Urban schools often have more resources available (Jones 2024), which could be why traffic density is showing a positive association with outcome scores, contrary to the associations seen with specific pollutants. An additional limitation with both the traffic measure and the DPM metric are that these are not estimated exposures in the same way in which air pollution concentrations are the direct exposure of interest. For both traffic and DPM, the metrics use emissions or traffic counts to describe, quantitatively, an exposure that is a proxy for a group of air pollutants.

These analyses raise a few key points for consideration by California regulators. First, outdoor air pollutant exposures are associated with lower standardized test

scores at California schools, making factors affecting air pollutants at schools a prime target for interventions. (These are based on data from students taking the usual assessments, not including those who take the alternative assessments. Those estimates had too much variability to be informative.) Though the associations seem of small magnitude, as of the 24-25 school year, California has 5.8 million students, so 0.2-2% fewer meeting standards could be as many as 11,600 to 116,000 students. Not only that, but this analysis provides estimates for practical changes in pollutants, meaning that the percent of affected students would be expected to be higher in areas with worse air pollution. Two, for interventions that could make a similar magnitude change in pollutants, one might expect the largest benefit from interventions targeting PM_{2.5} or NO₂ exposures. Finally, these results suggest that traffic density alone is likely an inadequate metric to capture air pollutant exposures relevant for neurodevelopment, and more specific measures should be utilized.

Chapter 3: Lifetime Exposure to Multiple Air Pollutants, Cognition and Attention, in the SJV

The Children's Health and Air Pollution Study (CHAPS) is a long-running cohort of children in the San Joaquin Valley, who were enrolled either prenatally or as young elementary school students. They have been followed for multiple visits over the last 5-10 years, and the research team has detailed health, residential and school histories for the children in the cohort. This is a lower income, predominantly Latinx cohort living in one of the country's most polluted regions. As described in detail in appendices C and D, 193 members of the CHAPS cohort (ages 7-18) successfully returned for a visit that included a neurodevelopmental assessment as part of the CHAPS-Stack study. These assessments included blood and urine sampling for biomarkers, completion of an iPad based cognitive assessment (the NIH Toolbox Cognition Battery), completion of surveys by the parent and older youth regarding social/emotional health, and collection of prior school standardized test scores from the parents (using the schools' online portals). This chapter contains summaries of these works, but the complete scientific papers documenting these methods and analyses are included in Appendices C and D.

Task 3 of this project included two parts utilizing this CHAPS cohort data: (a) assessing the relationship between air pollutant exposure and standardized test performance using individual student data and (b) assessing longer exposures to air pollution for these same individuals in association with more complex neurocognitive outcomes. Longer exposures may be particularly biologically relevant, and the ability to assess individuals directly avoids ecologic biases. These tasks were informed by those described in chapters 1 and 2. From those chapters, the researchers determined that there are not clear indicators of which measure of green spaces is important for students. The hypotheses to be tested in this set of analyses included that (3a) air pollution exposure at home and school might be related to individual standardized test scores, and that (3b) multi-year exposures to air pollution might be related to results on in-depth neurocognitive testing.

3a. Individual test scores in the CHAPS cohort and association with air pollution

Ninety-seven children provided test scores from the Smarter Balanced Assessments for California (SBAC) standardized tests, taken between 2015 and 2022. These were performed as part of the students' usual schooling, and thus available only for those age-eligible for testing, and whose parents were able to provide test results. Test scores were analyzed in a repeated measures analysis associating them with pollutant exposure (NO_2 , O_3 , and $\text{PM}_{2.5}$) based on high-resolution land use regression-based models matched to the home and school addresses in the year prior to testing. A full scientific paper describing this analysis is included in appendix C. Most reported scores were from elementary and

middle school years rather than high school, because of the age of the cohort. Results for the SBAC math test included that a one ppb increase in O_3 was associated with a -0.078 (95% CI: -0.145, -0.010) standard deviation decrease in test scores and a one $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ was associated with a -0.074 standard deviation decrease in test score (95% CI: -0.120, -0.032). These correspond to approximately a -7.8 and -7.4 point decrease in raw test scores respectively. There was also a weak (and statistically insignificant) relationship between $\text{PM}_{2.5}$, O_3 and SBAC English test scores.

Notably, these results generally align with the pattern seen in the statewide

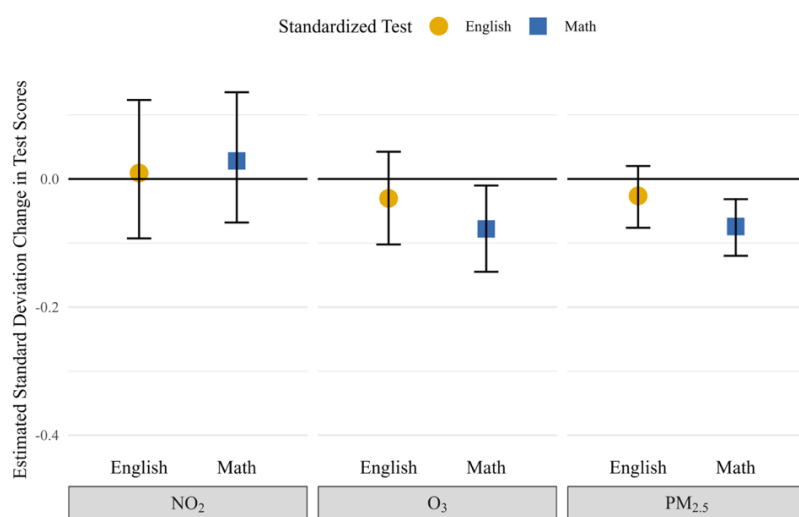


Figure 3.1
Estimated standard deviation change in standardized test score associated with a one unit change in exposure concentration, from the repeated measures model in the CHAPS participants.

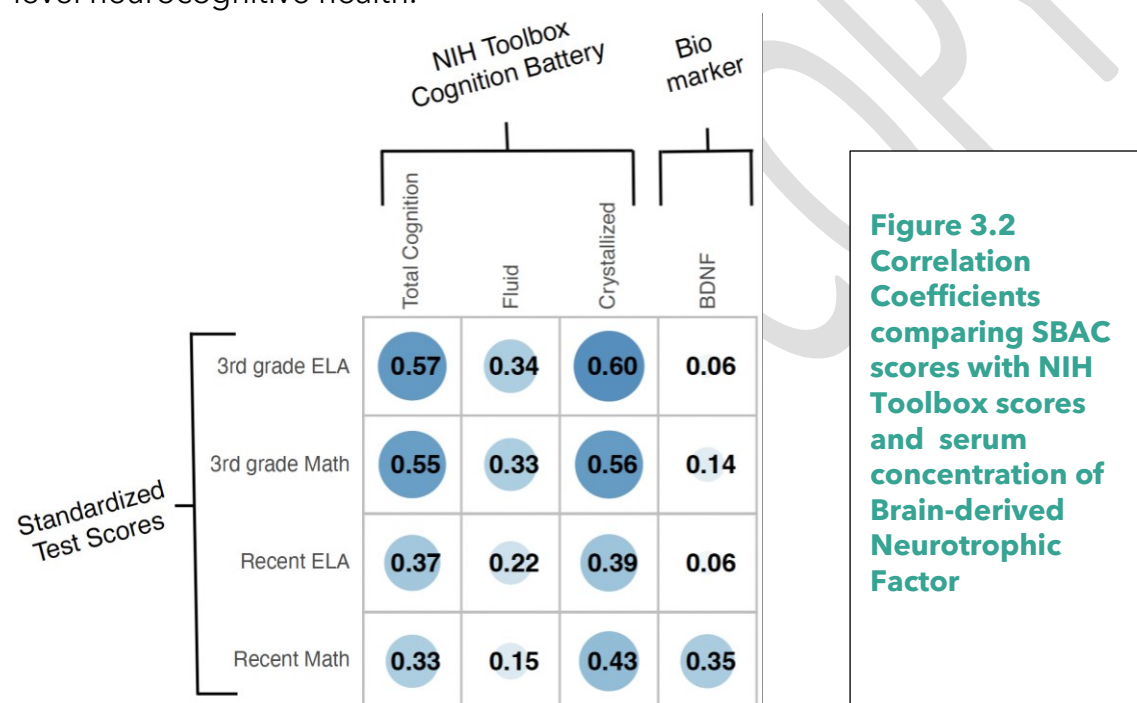
analysis (described in chapter 2 and appendix B). In both the individual estimates seen in these analyses and the statewide analyses using school data, increases in $\text{PM}_{2.5}$ or O_3 were associated with decreases in standardized test scores, with larger estimated effects for math scores compared to English scores. While this is a small population of students, they are from a particularly vulnerable group—one that is both more highly exposed and known to have lower test scores than the state average. This alignment of the individual and statewide pattern suggests that, at least among the most exposed students, school-level changes are a good indicator of individual changes.

3b. Early Life and prenatal exposures to air pollution and associations with more complex measures of neurodevelopment

These analyses include estimated pregnancy and first year of life exposures to both criteria and non-criteria pollutants, including $\text{PM}_{2.5}$, NO_2 , polycyclic aromatic hydrocarbons (PAH_{456}), and black carbon (BC). A full description of the study is included in Appendix D.

A pivotal hypothesis of this research was that California's Smarter Balanced Assessments (SBAC) might be an effective proxy for pediatric environmental neurotoxicity. Comprehensive, resource-intensive clinical tools for assessing neurocognition, like the National Institutes of Health Toolbox Cognition Battery

(NIH Toolbox), are logistically impractical to implement on a macro policy scale. Yet, this study demonstrated that third-grade standardized SBAC math and English Language Arts (ELA) scores correlate robustly with the NIH Toolbox total and crystallized cognition composite scores ($r \sim 0.55\text{--}0.60$), as well as moderately with concentrations of a biomarker for brain development: serum brain-derived neurotrophic factor (BDNF, $r=0.35$). Correlation coefficients are listed quantitatively in Figure 3.2, and also depicted visually with blue representing positive correlations and circles that are larger and darker representing larger correlation coefficients. Because state-mandated standardized testing data are universally collected, they both are representative of the population and capture massive sample sizes, making them an invaluable policy resource. These findings establish that school-level academic metrics might reliably reflect underlying population-level neurocognitive health.



Looking at exposure-outcome relationships, the assessments completed at the study visit revealed that first-trimester exposure to traffic-related air pollutants ($PM_{2.5}$ and PAH_{456}) was significantly associated with elevated childhood z-scores for aggressive and rule-breaking behaviors. Furthermore, first-year postnatal exposure across all seven studied pollutants was consistently linked to lower levels of serum brain-derived neurotrophic factor (BDNF), a vital biomarker for neurogenesis. Utilizing distributed lag models to identify particularly vulnerable windows of exposure, the research team identified a highly specific window of vulnerability around 5 to 6 months of age, where peak pollution exposure directly mirrored localized drops in both serum BDNF levels and total cognition scores on the NIH Toolbox Cognition Battery. For example, as pictured below, at 6 months of life, a 1 ppb increase in NO_2 is associated with a -0.6 decrease in the BDNF serum concentration (95% CI -1, -0.2) and a -1.3 NIH Toolbox Total Cognition

score (95% CI -2.7, 0.07). These associations are particularly impressive, given that, on average, the exposure is from 13-14 years prior to the outcome assessment.

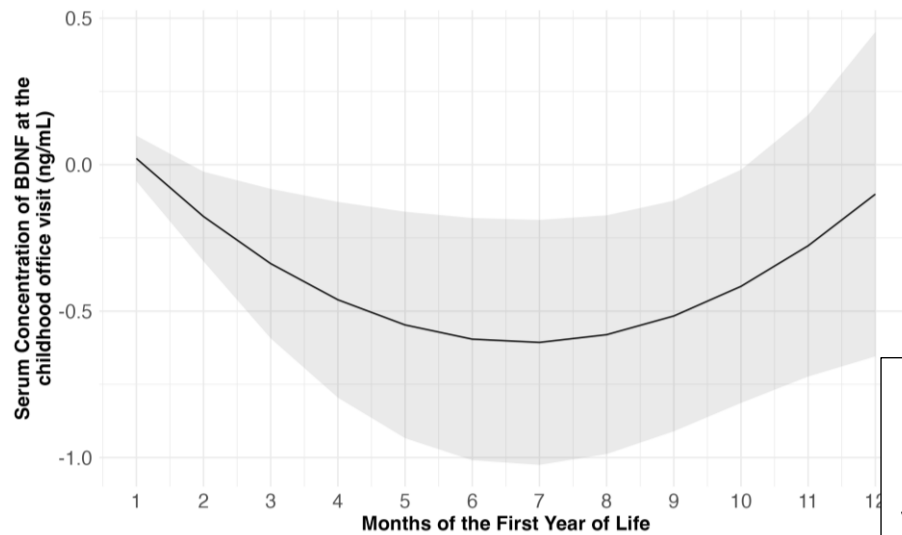


Figure 3.3
Key Exposure Window for Brain-Derived Neurotrophic Factor Serum Concentration associated with NO₂ exposure

Notably, initial linear models associating pregnancy exposure in our small Fresno cohort yielded a highly counterintuitive result: prenatal pollution exposure appeared to associate with *high* scores. However, a post-hoc sensitivity analysis revealed this to be artifactual, driven by seasonal pollution patterns confounding age milestones. Because traffic pollution in Fresno peaks during the summer months, prenatal exposure levels are inherently dictated by a child's birth date, which simultaneously determines whether they enter kindergarten as a biologically older or younger student. When the research team stratified the data by kindergarten start age, the positive correlation inverted, emphasizing the seasonal nature of the effect. For regulatory bodies, this finding emphasizes that impact assessments should integrate complex spatio-temporal exposure modeling with institutional calendars to ensure mitigation strategies are accurately targeted and evaluated.

In conclusion, the analyses from task three tie together some key strands. Because the findings of the ecological study (3a) hold true at the individual level, this suggests that interventions to decrease air pollution in communities could benefit individual students, in addition to potential positive changes at a school level. And because the individual test scores are strongly associated with cognition measured with the NIH Toolbox cognition scores (3b), the (ecologic) school-level findings may even be useful as a representation of individual cognition, not just individual school test scores. Thus, policy analysts could utilize fluctuations in school-administered standardized test scores as a scalable, real-world metric to evaluate the success or failure of localized air quality interventions and regulatory clean-air mandates, if they consider long enough exposure windows to obscure seasonal variations.

Chapter 4: Projected Economic Benefit to California of Decreasing Air Pollutant Effects on Cognition

Using g-computation and input from the analyses described in earlier chapters, the research team estimated how much standardized test performance could change if California air pollutant exposures were decreased. This was contracted as a limited follow up analysis, resulting in one paragraph or more summary, thus there is no appendix for this chapter. The assumed intervention is such that high pollutant exposures would be brought down to a specific target concentration, with no change to exposure for those below the target concentration.

Method: This analysis was performed in R (v 4.5.3). A dataset of California elementary school students ($n=1230000$) was simulated, assuming means and correlations based on known statewide data. $PM_{2.5}$ exposure for California elementary school children was simulated to be $10.15 \text{ microgram}/\text{m}^3$ (based on the CalEnviroScreen (CES) 4.0¹ statewide average), with 31.34% of the population in poverty (based on CES and Healthy Places Index (HPI) statewide averages²), and 77% having access to a park within a half mile of their home (HPI). Data were simulated to approximate the 2021-2022 school year SBAC results: a 3rd grade mean scaled score of 2409, 2050 for 4th grade, 2091 for 5th grade and a standard deviation of 105 (see technical report³). G-computation⁴ was performed both using estimates derived from earlier chapters, in combination with different hypothetical interventions. Results were bootstrapped with 100 iterations to produce confidence intervals. Because no relationships between NIH Toolbox and air pollutant exposures reached significance, this estimate was not performed using the Toolbox scores.

Grosse and Zhou⁵ previously reported that a 0.066 SD increase in IQ is associated with an increase in lifetime earnings of \$10,600- 13,100 USD. Because NIH Toolbox has been strongly associated with IQ, the research team had proposed using this to estimate the monetary value of additional NIH Toolbox points.

Results: These calculations suggest that bringing the $PM_{2.5}$ concentration in highly exposed areas down to $9 \text{ }\mu\text{g}/\text{m}^3$ (the current National Ambient Air Quality Standard) would have a modest benefit for California elementary school students, by increasing the average students' standardized test scores 1-2 years later by 5 to 20 points, depending on the exact assumed effect size. These were also calculated assuming more extreme interventions (see Table 4.1). This analysis suggests that if an extreme intervention was performed which brought all exposures in the state to $7 \text{ }\mu\text{g}/\text{m}^3$ or below, there could be as much as a 22.6 point increase in elementary SBAC scores.

Dollar valuation was estimated as described in the contract. However, this is more speculative than initially intended, because there are no known studies directly linking SBAC scores with IQ. While the research team suggests *extreme caution* in interpreting this, *if* SBAC results were to follow a similar pattern in association with lifetime earnings as IQ, then an average SBAC score improvement

of 9.71 points (= 0.092 SD) might be associated with an average increase of $(0.045) * (10600/0.066) = \$14,852$ in lifetime earnings, based on 2016 USD.⁵

PM _{2.5} Lowered to ($\mu\text{g}/\text{m}^3$)	Assuming -3 per 1 $\mu\text{g}/\text{m}^3$ (using the estimated mean change for elementary age, from Ch. 2)	Assuming -7 per 1 $\mu\text{g}/\text{m}^3$ (using the estimated maximum within individual change, from Ch. 3a)
≤ 9	4.73 (4.72, 4.74)	11.01 (10.98, 11.03)
≤ 8	7.05 (7.04, 7.06)	16.42 (16.39, 16.44)
≤ 7	9.71 (9.70, 9.73)	22.61 (22.58, 22.64)

Table 4.1 G-computation Results for Putative Air Pollution Interventions, Showing the Average Improvement in the Mean SBAC Score

Score

Conclusions: The use of g-computation allows for a calculation of effects assuming feasible real-world changes (i.e., rather than decreasing all exposures by $1 \mu\text{g}/\text{m}^3$, the use of g-computation allowed for estimation of the effect if targeted interventions decreased the pollutant concentrations only in those areas with existing PM_{2.5} concentrations above the target). Results from the g-computation analysis imply the potential for a school achievement benefit for California students 1-2 years after a potential air pollution intervention, which could shift the overall score distribution as much as a quarter of a standard deviation. The exact degree of the change is dependent on both how much an intervention would decrease pollutant concentrations, and which estimated effect size is used.

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Chapter 5: Outreach and Reporting

5.1. Reporting C-R functions to the academic community

We have published one peer-reviewed journal article on the STACK project:

Loomis S, Lutzker L, Holland M, Tyner T, Hammond SK, Balmes J, Su J, Noth E, Holm S. Characterizing the relationship between air pollution and childhood cognition in the Children's health and air pollution study, 2026 Environmental Research 302(124590). doi.org/10.1016/j.envres.2026.124590.

A second paper has been submitted to a journal, and a third paper is in preparation and will be submitted within the quarter:

Holm SM, Holland N, Balmes JR, Loomis S and Noth E. Statewide Association between PM2.5, NO2, O3, and Traffic Exposures and Standardized Test Performance, *Under review*.

Holm SM, Holland N, Balmes JR, Tyner T, Guo W, Garza A, Manzo D, Vasquez-Vasquez B, Loomis S, Noth EM. Neurobehavioral Assessments in a Highly Air-Pollution-Exposed Population. *Under preparation*.

We have presented our findings to the academic community through a local San Joaquin Valley conference in October 2024 in Merced, Air Quality and Health:

Anabelle Garza, Oral Presentation, "Children's Health and Air Pollution Study: Standardized Assessments, Attention and Cognition in California Kids (CHAPS: STACK) "

5.2. Outreach to the CHAPS Community

We utilized the existing San Joaquin Valley Environmental Justice Steering committee meeting as an appropriate place to introduce the aims of STACK and to gain feedback about community concerns. The SJV Environmental Justice Steering Committee is a coalition of 18 environmental justice organizations working across the SJV. Drs. Holm and Noth presented the STACK study at the July 2, 2024, meeting of the SJV EJ Steering Committee.

5.3. Community Outreach efforts

Community Outreach efforts were taken to provide materials to the study participants and to the general public.

For study participants: the Research Team and CCAC informed current CHAPS cohorts about the added neurodevelopmental components in detail during a reconsent process. CCAC staff briefly explained to current CHAPS cohort families that we were continuing the CHAPS study with additional study visits to conduct additional studies. If the participant families were interested, they administered a

brief eligibility questionnaire to assess whether the participant still lives in the study area. If the participant met the eligibility criteria, then they were scheduled for return visits and reconsent.

For the return of findings to the study participants, we had two different stages. The first stage was during the study. At the conclusion of the office visits, we provided participants with their anthropometric and biometric measures for weight, height, and blood pressure.

CCAC and Drs. Holm and Noth worked to produce the Public Outreach Document after the end of the data collection and study analyses (Appendix E). This document will be shared by CCAC as a newsletter article and also on their website. The more engaging version for the website is also in Appendix E. These materials are currently being translated into Spanish.

For the general public:

The Public Outreach Document will be posted on the CCAC website. Additionally, CCAC staff will present the findings to relevant San Joaquin Valley Community Steering Committees in late summer through fall 2026 using the slide deck in Appendix E. The community committees targeted for presentations are Fresno, Shafter, Arvin/Lamont and Stockton.

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Note to the reader: These are the references used in the main body of the report. Each Appendix includes its own set of references.

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Glossary of Terms, Abbreviations, and Symbols

PM _{2.5}	Particulate Matter
NO ₂	Nitrogen Dioxide
O ₃	Ozone
CAB	Community Advisory Board
CHAPS: STACK	Children's Health and Air Pollution Study: STandardized Assessments, Attention and Cognition in California Kids
CHAPS	Children's Health and Air Pollution Study
CCAC	Central California Asthma Collaborative
SBAC	Smarter Balanced Assessments for California

Appendix A: Research Paper: Relationship of Air Pollution Exposures and Individual Children's Standardized Test Scores: Systematic Review of US Studies

Abstract

Assessing the critical impact of air pollution on cognitive function in childhood is imperative for understanding the breadth of air pollution-related health outcomes. Because standardized testing data are a uniquely widely available source of cognitive data in US children, our objective was to conduct a systematic review of literature on the relationship between air pollution exposure and standardized test scores among children in the United States, focusing on studies with individual-level test data. Searches were performed in October 2023, across PubMed, Web of Science, Scopus, and PsycINFO databases. Articles selected for inclusion had individual-level standardized test scores, direct concentrations (non-surrogate measures) of air pollution exposure and were published research articles in the US with publication dates of 2003 or later. Out of 10,968 articles screened, 29 full-text articles were reviewed, with 5 meeting inclusion criteria. Notably, only 3 different datasets were represented across the 5 studies included in this review. Despite some estimated effects hovering around the null, a trend of small decreases in standardized test scores with higher air pollution exposure emerged in our analyses, though findings were inconsistent. Polycyclic aromatic hydrocarbons (PAHs) and air toxic exposures such as isophorone, trichloroethylene, and manganese compounds exhibited more consistent patterns compared to those for other pollutants. Literature not included in the review further underscored the variability of associations between air pollution and academic performance, even in ecologic data. Overall, the limited data and inconclusive findings underscore the imperative for continued research using individual-level outcome data and with non-criteria pollutants.

Key words: systematic review, air pollution, standardized test scores, academic testing

Introduction

Although combined emissions of criteria and precursor pollutants have dropped by 78% since the 1970 Clean Air Act, assessing the effects of air pollution on cognitive function throughout the life course remains important.¹⁻⁵ The details of these relationships may be complex, with research in this area showing a mixture of results.⁶⁻⁹

Studying air pollution effects on the neurocognitive development of children is imperative due to the profound impact that learning and brain growth have on both individual well-being and societal prosperity. Cognitive ability in children has been positively associated with economic productivity in adulthood, and gains in economic output are expected from interventions designed to improve cognitive ability.¹⁰ Though there are known limitations with this measure, earlier research shows that a one-point increase in IQ is associated with a 4% increase in welfare growth for the average country and that national IQ is an important determinant of the differences in economic activity across different countries.¹¹ Because lead exposure also affects children's cognitive function, a study in 2009 found that for every dollar spent on lead paint hazard control in the U.S., a return of \$17- \$221 was seen, suggesting the potential economic value of improving environmental exposures and in turn, cognitive function.¹⁰

Combustion-related pollutants, those produced and released into the air through the burning of various fuels, may be particularly problematic for children's cognitive development due to their ubiquity in the environment.¹² Project TENDR (Targeting Environmental Neurodevelopmental Risks), a multidisciplinary group of U.S. experts in children's environmental and neurodevelopmental health, has identified three combustion-related air pollutants (particulate matter with an aerodynamic diameter less than 2.5 microns (PM_{2.5}), nitrogen dioxide (NO₂), and polycyclic aromatic hydrocarbons (PAH) as particularly detrimental to the neurodevelopmental health of children.¹³ Increased (or High) exposure to PAHs in childhood has been associated with decreases in cognition, decreases in attention, and increases in mood symptoms.¹³ Increased (or High) exposure to traffic-related air pollution, including PM_{2.5}, and NO₂, have also been associated with memory issues, in addition to cognition.¹³ Ultrafine particles, the component of PM_{2.5} that is particles smaller than 1 micron in diameter, have also been studied as potential neurotoxins, in part because of their ability to travel directly into the central nervous system.¹⁴ While there is general support for the association between combustion-related pollutants and neurodevelopment, many details still need to be better understood.⁹ These include details of the mechanisms for neurodevelopmental effects, vital information on the critical time periods of exposure, the role of different PM sources and their components, and the effects on populations that are especially vulnerable (such as infants and young children), highly exposed (such as racial and ethnic minorities) or understudied areas (such as non-urban populations).

Though less ubiquitous, air toxics may also contribute to adverse neurodevelopmental effects. The Clean Air Act defines air toxics as pollutants that cause adverse effects on the environment or serious health effects such as birth

defects, reproductive effects, and cancer.¹⁵ There are 188 air toxics that EPA is required to monitor and control, including perchloroethylene (PCE) and isophorone.¹⁵ Perchloroethylene (PCE) is a colorless solvent that is commonly used in dry-cleaning and in industrial settings, as a component of products like degreasers, water repellents, and paint removers.¹⁶ Isophorone is another widely used solvent, including in the printing and metal coating industries.¹⁷ Though there has been substantial attention to PCE-contaminated drinking water and potential neurocognitive effects, very little work has focused on air toxics and cognitive development in children.^{18,19} Even less research has assessed the effects of combinations of air pollution exposures on cognitive function in children and the mechanisms behind these interactions.

Cognition and neurodevelopmental growth are complicated constructs that, by necessity, are assessed in simplified and incomplete ways. There are testing techniques that assess general cognitive abilities as well as ones that assess specific cognitive domains such as attention, language, and memory.²⁰ These can be advantageous in their ability to measure detailed components of a child's cognition, but often involve time and resource-intensive assessments, which are completed only with a limited group of children. In contrast, standardized testing is completed by most American children through their schooling. Standardized test scores thus capture a more representative population in comparison to assessments performed only as part of research studies.²¹ Though school standardized testing is known to demonstrate racial biases, this is unfortunately true for other, more complex neurocognitive assessment methods as well, so using standardized test scores can overcome the issue of limited representation even though the tests themselves continue to be flawed.²² Finally, most of the extant work in the literature is susceptible to the ecologic fallacy; wherein analyses made at the school or district level are assumed to represent the relationship between air pollution and cognition outcomes for an individual student. Though there is less published work at the individual level, it is critical to understand the extant literature that is based on individual data.

Previous work has shown that there are a variety of other factors that relate to both children's test scores and air pollution exposures, and thus should be considered in discussions of this relationship. Noise has been associated with impaired test scores, Attention-deficit/ hyperactivity disorder (ADHD) symptoms, and higher traffic-related air pollution (TRAP).²³⁻²⁵ Individuals with low socioeconomic status (SES) and certain ethnic minority groups tend to experience higher air pollution exposures and more structural disadvantages, and both factors are independently associated with academic performance.^{26,27} Geographic location is also linked to both exposure and outcome in a variety of ways, leading to injustice in both the burden of air pollutant exposures and the allocation of resources to schools.²⁸ Recent research has also demonstrated a link between increased neighborhood access to green space and higher academic achievement while areas with more green space tend to be associated with lower TRAP concentrations.²⁹ Finally, indoor and outdoor temperature is associated with both changes in air quality and academic performance.³⁰

This paper will systematically review what is already known about the relationship between air pollution exposures and standardized test scores in US children, specifically from work that uses individual test score data, rather than group-level data. This review will serve as background for future needed work that should assess at the individual-level the relationships between air pollution exposures, school standardized test scores and detailed cognitive function testing.

Methods

The Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) Protocols 2015 Checklist was used when conducting this systematic review. The protocol for this review was registered with PROSPERO on October 12, 2023 (CRD42023472121), and *available online*. On November 28, 2023, an amendment was submitted noting that a second database importation had been conducted.

On October 10, 2023, we searched PubMed, Web of Science, Scopus, and PsycINFO, using the following search terms: ("Air Pollution"[Mesh] OR "Air Pollutants"[Mesh] OR "ambient pollution" OR "outdoor air pollution" OR "air quality" OR "particles" OR "Particulate Matter"[Mesh] OR "Nitrogen Dioxide"[Mesh] OR "pm2.5" OR "pm2,5" OR "pm 2.5" OR "pm10" OR "pm 10" OR "no2" OR "nox" OR "black carbon" OR "Soot"[Mesh] OR "elemental carbon" OR "Carbon"[Mesh] OR "Ozone"[Mesh] OR "diesel exhaust" OR "Vehicle Emissions"[Mesh] OR "gasses" OR "gaseous pollution" OR "gaseous pollutant" OR "ultrafine particle" OR "aromatic hydrocarbons" OR "Polycyclic Aromatic Hydrocarbons"[Mesh] OR "PAH" OR "Sulfur Dioxide"[Mesh] OR "Volatile Organic Compounds"[Mesh] OR "VOC") AND ("standardized test scores" OR "standardized tests" OR "academic test scores" OR "academic test performance" OR "Academic Performance"[Mesh] OR "academic testing" OR "Academic Success"[Mesh] OR "Learning"[Mesh] OR "school performance" OR "College Admission Test"[Mesh] OR "Computerized Adaptive Testing"[Mesh]). We filtered to articles with publication dates of 2003 or later, written in English or Spanish, with human populations, in the United States. We included published research articles, excluding books, reviews, or unpublished literature. On October 14, 2023, the search was repeated in three of the databases (Web of Science, Scopus, and PsycINFO). This search was identical with one exception: the removal of "mesh" from the search terms, as these three databases did not recognize the term Medical Subject Headings (mesh) and thus limited our results.

("Air Pollution" OR "Air Pollutants" OR "ambient pollution" OR "outdoor air pollution" OR "air quality" OR "particles" OR "Particulate Matter" OR "Nitrogen Dioxide" OR "pm2.5" OR "pm2,5" OR "pm 2.5" OR "pm10" OR "pm 10" OR "no2" OR "nox" OR "black carbon" OR "Soot" OR "elemental carbon" OR "Carbon" OR "Ozone" OR "diesel exhaust" OR "Vehicle Emissions" OR "gasses" OR "gaseous pollution" OR "gaseous pollutant" OR "ultrafine particle" OR "aromatic hydrocarbons" OR "Polycyclic Aromatic Hydrocarbons" OR "PAH" OR "Sulfur

Dioxide" OR "Volatile Organic Compounds" OR "VOC") AND ("standardized test scores" OR "standardized tests" OR "academic test scores" OR "academic test performance" OR "Academic Performance" OR "academic testing" OR "Academic Success" OR "Learning" OR "school performance" OR "College Admission Test" OR "Computerized Adaptive Testing")

We imported all references into Covidence, an online platform used to manage systematic reviews. We used Covidence to screen the papers by title and abstract during the first stage, by full-text review during the second stage, and to manage records and data throughout the review.

Screening of abstracts was performed independently for inclusion by two of the authors (I.T.A., referred to as Reviewer A and S.M.H, mentioned below as Reviewer B), with initial blinding to each other's decisions. Any disagreements between the individual assessments were resolved through discussion. To be included, an article must have had a population of children in the US (no participants over 18 years of age). Studies had to include an exposure to specific individual pollutants (could be measured or modeled). Articles using only traffic surrogates, e.g. using distance to roads and freeways, or surrogates for ventilation status of indoor spaces were excluded. Only studies with standardized test scores reported at the individual level were included. Studies using GPA, academic achievement or neurological/neurocognitive testing were excluded. After screening and full-text review, a total of 5 articles were included in this review. Upon full-text review, Reviewer A created and completed a data extraction template within Covidence (in discussion with and confirmed by Reviewer B).

The Covidence template for extraction included data summarizing the study design, the study population, air pollution measurements, outcome assessments, confounders, and modeling strategies. Summary measures were described as reported (ORs, risk differences, etc.). Lastly, we extracted information on data completeness and how missing data were handled.

Risk of bias was assessed using the Cochrane Review Risk of Bias in Non-Randomized Studies- of Exposure (ROBINS-E). Bias Assessment was performed independently for inclusion by A and B Reviewers, with initial blinding to each other's decisions. Due to the small sample size, we have compiled the findings across inherent groupings found within the data; and have visualized the data through forest plots, listed the outcomes in a table and described them in the text, but have refrained from doing any statistical analyses or quantitative summary of the findings. Additionally, due to the small number of included studies, we did not use any quantitative methods to assess risk of bias arising from reporting biases or to assess certainty in the body of evidence for an outcome. All results and conclusions were discussed and agreed upon by all co-authors.

Results

After removal of duplicates, the search yielded a total of 10,968 papers. For title and abstract screening, Reviewers A and B had a 99.7% agreement with a Cohen's Kappa of 0.57748. After initial screening, 29 studies were moved forward for a full-text article review. For full text review, reviewers A and B had a 75.9% agreement with a Cohen's Kappa of 0.21622, all disagreements were easily resolved in discussion between the reviewers. Half the articles excluded during full text review (12 studies) assessed the wrong outcomes (Figure A1); specifically, three of those studies had group-level standardized test score data rather than individual data.³¹⁻³³ Nine of the studies used other measures of neurocognitive development or achievement such as grade point average (GPA) or more in-depth neurocognitive testing.³³⁻⁴¹ After the full text review, five studies met the inclusion criteria in our systematic review (Figure A1).

The five studies used a cohort study design (Table A1) and only three different datasets were analyzed. Balalian et al. 2022⁴² and Stingone et al. 2016⁴³ used data from the New York City Longitudinal Study of Early Development (LSED). Stingone et al. 2017⁴⁴ and Lett et al. 2017⁴⁵ used the Early Childhood Longitudinal Study Birth cohort (ECLS-B, a nationally representative birth cohort born in 2001). Finally, Margolis et al. 2021⁴⁶ utilized data from the Mothers and Newborns prospective birth cohort (MaNPBC, also based in New York City). In the LSED cohort participants were tested in third grade, those in the ECLS-B were tested in kindergarten; and those in MaNPBC were adolescent participants within the 13-15 age range. All five studies included math scores as an outcome while only three studies investigated English language arts (ELA) scores. While none of the papers adjusted for all the confounders that we had pre-specified as potentially important (such as temperature, noise, and green space), all studies adjusted for socioeconomic status and race/ ethnicity. All papers except Margolis et al. 2021 adjusted for factors associated with the geographic location where participants lived.

Exposure across the five studies can be categorized into two groups: combustion and air toxics (such as isophorone, trichloroethylene, and manganese compounds) (see Table A1). Three of the studies measured exposure prenatally while the other two studies measured early-life exposures. In Balalian et al. 2022, PAH exposure was measured as the log transformed sum of eight carcinogenic PAHs collected using air monitoring backpacks worn for 48 hours during the third trimester of pregnancy. For all other papers, both air toxics and diesel PM were estimated from the EPA's National Air Toxics Assessment (NATA) from 1996 and 2002. These models combine stationary and mobile emissions data with dispersion modelling and population-data to estimate the hazard that an individual would be exposed to for a specific pollutant.

The estimated relationships between the standardized test scores and air pollutant exposure were generally similar, regardless of whether combustion-related pollutants or air toxics were being considered. Among children in the LSED cohort, prenatal diesel particulate matter (PM) exposure did not have a large effect on third-grade English and language arts standardized test scores (Figure A2a).

Point estimates were very close to the null, and varied in which direction they were relative to the null depending on which subset of the data was being analyzed, suggesting that some of the variability in the relationship may be due to chance or reporting of only a subset of the performed analyses. Surprisingly, the children with higher exposure to diesel PM appeared to have slightly higher test scores for English and language arts compared to children with the baseline exposure, but among the children most highly exposed to diesel PM, those who were at the 75th percentile for English demonstrated a higher effect of diesel exposure compared to the children with baseline exposure. The relationship is more consistent for math test scores: children in the LSED cohort with high exposure to diesel PM had substantially lower math scores across all learning groups, and regardless of what their baseline math skills were (Figure A2a). The same patterns were seen in the LSED cohort with exposure to perchloroethylene- the associations between prenatal perchloroethylene exposure and English/language arts scores varied depending on which subsets of the data were assessed (Figure A3a), while higher perchloroethylene exposure was consistently associated with decreased math scores (Figure A3a).

While there was a different exposure-outcome relationship between math and English skills in the LSED cohort, Margolis et al. (2021)⁴⁶ found that the relationship between exposure to PAHs and standardized test scores was similar for both math and English skills in the MaNPBC cohort. Prenatal exposure to log-transformed airborne PAHs in adolescents showed a negative relationship with both math and English Language Art (ELA) test scores (Figure A2b). Although both confidence intervals cross the null, the bulk of the probability density is below zero, suggesting that there may be a decrease in standardized test scores associated with increased PAH exposure.

Among the kindergarteners in the ECLS-B, who were tested in math only, there was a consistent relationship between prenatal air toxic exposures and math test score outcomes (Figure A3b). Children exposed to isophorone, trichloroethylene, and manganese compounds all tended to have lower test scores in math when compared to children with baseline exposures.

Using the structured Risk of Bias Assessment in Non-Randomized Studies of Exposure tool (ROBINS-E), all five studies obtained an overall Very High Risk of bias (Figure A4). Particular domains of high risk for bias across all papers were those assessing measurement of the exposure, handling of missing data, and selection of the reported result. Potential biases from the exposure measurement are largely due to the use of a single temporal measure of air pollution to represent a larger duration of exposure, rather than an identified time period that occurred before the outcome. All five studies also had substantial missingness in some of their data. Though some mitigated this potential bias with multiple imputation, others relied on a complete case analysis. Finally, none of the studies included a prespecified analysis plan and as a result, received a high risk of bias in the selection of reported results.

Discussion

We systematically reviewed and summarized existing peer-reviewed publications regarding the relationship between air pollution exposures and individual standardized test scores in children within the US. While our review focuses on five specific studies, it is noteworthy that the findings are derived from only three distinct cohorts, and that the whole set of studies may be at high risk of bias. In general, the studies show small decreases in standardized test scores with air pollution exposure (though some of the estimated effects crossed the null). It is difficult to extrapolate any broad conclusions based on the limited and potentially biased literature. Inconsistent patterns of association between air pollutants and student academic performance are present in published ecologic studies (those with group-level data such as that reported by district or by school), which may be related to high risks for bias as well as heterogeneity in study designs and locations.⁴⁷ For example, studies that took place in El Paso, Texas, USA found that exposure to diesel PM was negatively associated with GPA among fourth and fifth grade students.^{33,35} A different study looking at the effects of diesel PM from school bus emissions reported that diesel particulate filters and diesel oxidation catalysts had a positive and consistent effect on both ELA and math test scores.⁴⁸

When considering the subject matter of the assessment, the findings among the studies analyzed for this review suggest a stronger relationship between air pollution exposure and math scores compared to ELA scores, including within studies that evaluated both testing domains. Other studies (ones not included in this review, such as ecologic studies, or studies with less specific exposure or outcome measures) show mixed results in terms of which domain is more affected by air pollution: math or verbal abilities. Multiple studies that have found relationships between increased air pollution exposure and worsened academic performance in focused areas (such as within a specific city or state) have found similar magnitudes of effect for math and verbal outcomes.^{39-41, 49-51} Among studies that looked at a broader, more nationally representative set of US school data, those that focused on wildfire smoke and hazardous air pollutants also found effects of similar magnitude for math and English skills, while a study that assessed annual ambient exposures to criteria pollutants found a stronger effect for math, as we did in this review.^{32, 41, 50} It is possible that there are true variations in the relationships between air pollutants and educational outcomes across different locations—such as if highly exposed students are more likely to receive early interventions in a particular area. Results from one study even suggest that exposure at home versus at school may affect math and English competencies differently, which may further complicate the interpretation of a literature that includes a mix of these exposures.⁵²

There are multiple mechanisms by which air pollution is thought to affect neurocognitive outcomes. The first is that air pollution increases permeability of the blood-brain barrier, in both animal models and humans.^{53, 54} A study investigating whether residency in cities with high air pollution would lead to neuroinflammation and neurodegeneration found that exposure to air pollution was linked to disruption of the blood-brain barrier among healthy children and young adults who died suddenly, which the authors ascribed to air pollution.⁵³ An

intact blood-barrier is necessary to maintain CNS homeostasis, including through the regulation of leukocyte migration and preventing the leakage of blood through the tight junctions in cerebral vasculature.⁵⁴ Further studies have demonstrated that exposure to air pollution, such as diesel exhaust particulate matter can directly induce dopaminergic neuron dysfunction.⁵⁵ Further evidence of direct effects on neurons is demonstrated by a study examining the relationship between prenatal exposure to PM_{2.5} in children and decreased size of the corpus callosum, thought to result from changes in the number or size of axons connecting the two hemispheres.⁵⁶ Finally, pollutant exposure has been linked to systemic inflammation which can then lead to neuroinflammation.^{53, 57-59}

Among the studies reviewed for this paper, the most consistent patterns were seen between test scores, PAHs, and the following air toxic exposures: isophorone, trichloroethylene, and manganese compounds. The collective findings from these studies suggest that elevated exposures to PAHs and some air toxics may be associated with a decrease in test scores, especially when viewed against the backdrop of the other neurodevelopmental literature as described in the introduction. Despite using a fairly small study group (n=200), Margolis et al. 2021⁴⁶ demonstrated a small but consistent decrease in math and English test scores associated with increased PAH exposure. This aligns with their team's previous findings that increased PAH exposure in the same cohort was associated with a lower cognitive development at age 3.⁶⁰ A similar relationship was also found in a Polish cohort; the prevalence of depressed verbal IQ index (DepVIQ) was significantly higher in children with higher exposure to prenatal PAH as measured by cord blood PAH-DNA adducts.⁶¹ There is also prior literature implicating exposure to manganese with cognitive outcomes, though not specific to airborne manganese. South Korean children with higher manganese concentrations in the blood showed lower scores in thinking, reading, calculations, and a higher commission error.⁶² In East Liverpool, Ohio, IQ scores for children aged 7-9 were negatively associated with higher manganese concentrations in hair.⁶³ Given the mechanistic evidence for air pollution effects on the brain, and findings from other studies looking at PAH and selected air toxics, it is possible that the individual-level studies reviewed here could be hinting at an association that gets obscured in ecologic studies.

The existing body of literature concerning air pollution exposures and their impact on test score outcomes in children is limited, particularly in terms of individual-level data. This underscores the importance of our rigorous systematic review, with a pre-registered protocol, strict adherence to PRISMA guidelines and focus on individual-level data.

Yet, the small number of studies, representing only three datasets, limits our inferences and the external validity. The small number of studies that have been published may be related to the difficulty of obtaining individual-level educational data, and potentially also because of some publication bias, where studies with nonsignificant findings are less likely to be published. Additionally, the measurement of non-criteria pollutant exposures is rare, especially for PAHs, perchloroethylene, and other toxic air contaminants. For the studies that assessed

multiple pollutants, many of the pollutants had similar point estimates. Similar estimates between each pollutant and test score outcomes may be due to high correlations among pollutants. Finer spatial and temporal resolution for exposure assessments may be able to elucidate these relationships further.

Conclusions

In summary, our review uncovered evidence that children and adolescents exposed to elevated concentrations of air pollution, particularly PAHs and some air toxics, during prenatal and early life stages may exhibit lower scores on standardized tests compared to those with lower exposures. However, the available published evidence was deemed weak, primarily attributed to suboptimal exposure assessment and handling of missing data. This review underscores the need for future research in this domain to employ improved temporal and spatial exposure assessments (especially of non-criteria pollutants) to minimize the risk of exposure misclassification, the need for prespecified analysis plans that include handling of missing data, and the significance of studying this relationship at the individual level rather than relying solely on ecologic approaches.

Figure A1. PRISMA Diagram, demonstrating the articles eliminated/included at each step of the review process

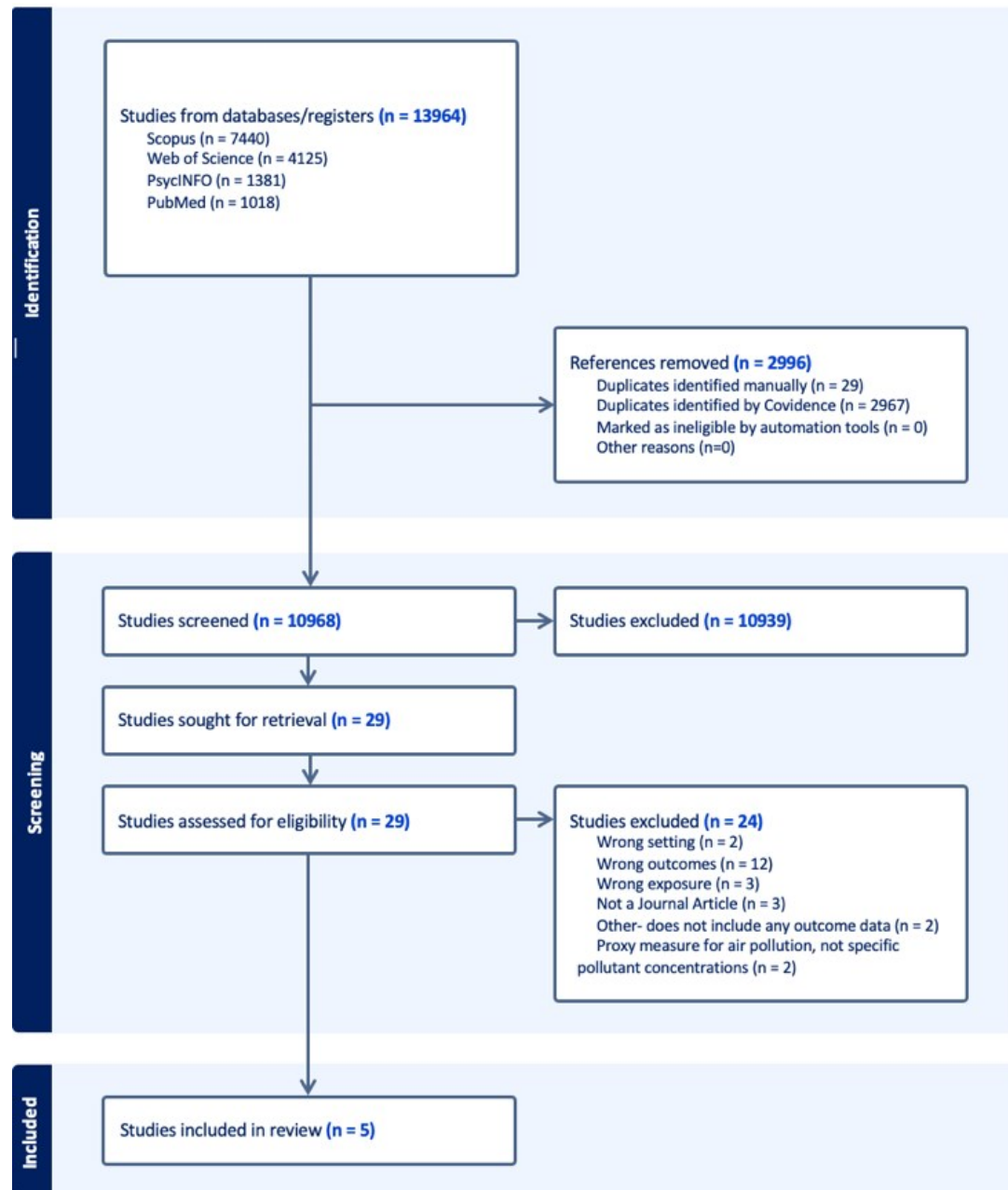
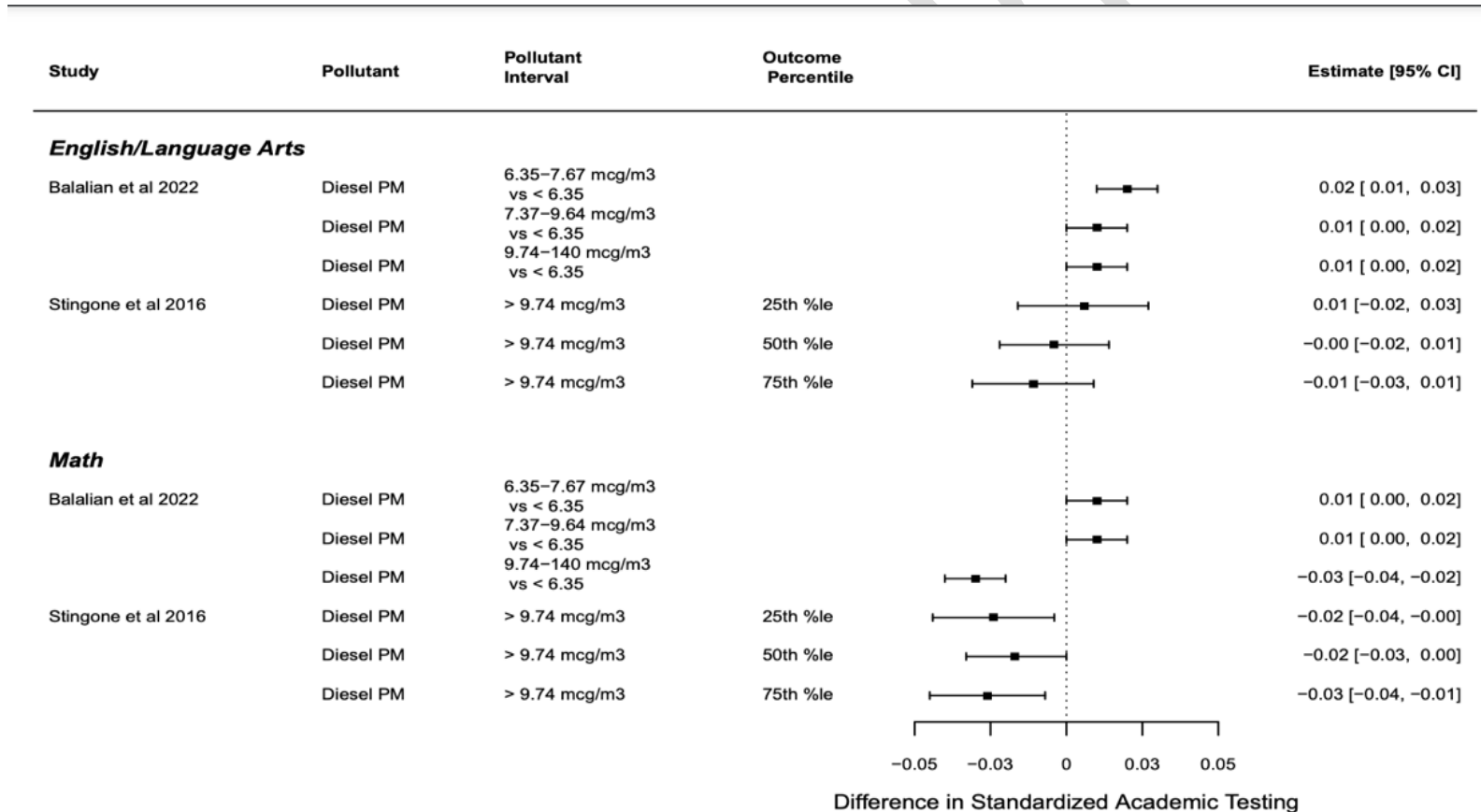
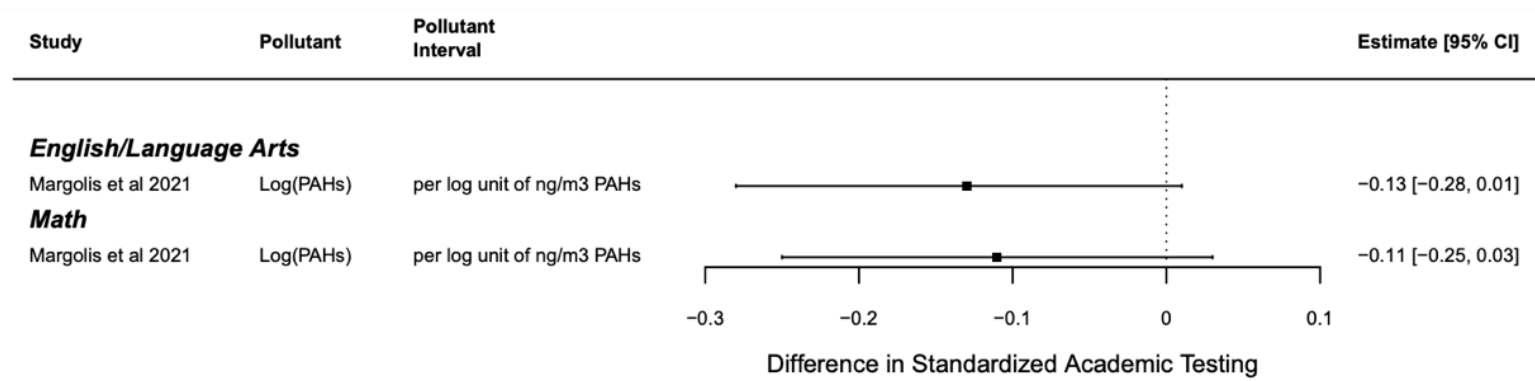


Figure A2. Forest plots showing estimated differences in Standardized test scores associated with exposures to combustion-related air pollutants, including (a) studies reporting the association between prenatal Diesel PM exposure and third grade test scores and (b) studies reporting the association between early-life PAH exposure and adolescent testing outcomes.

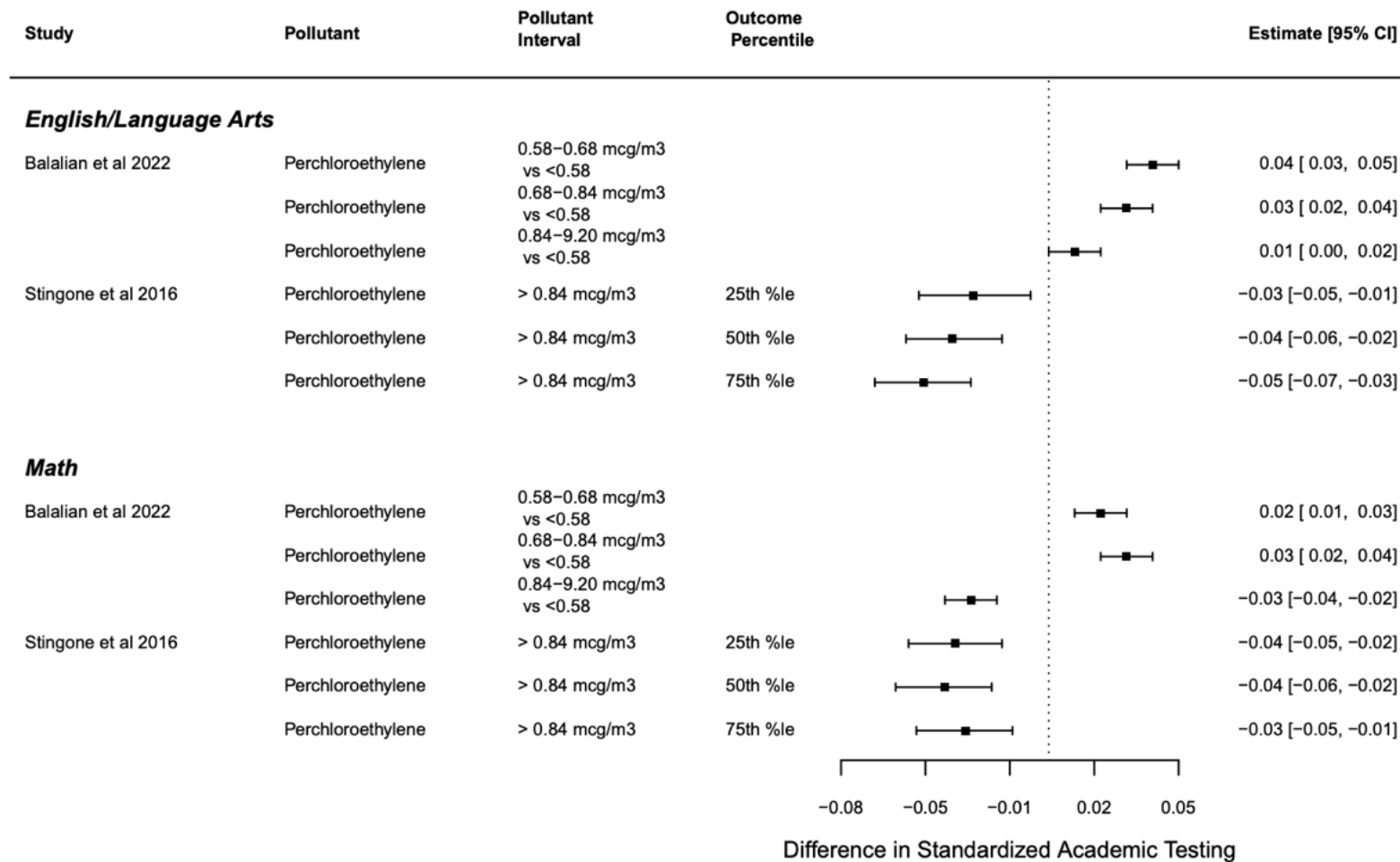


(a)

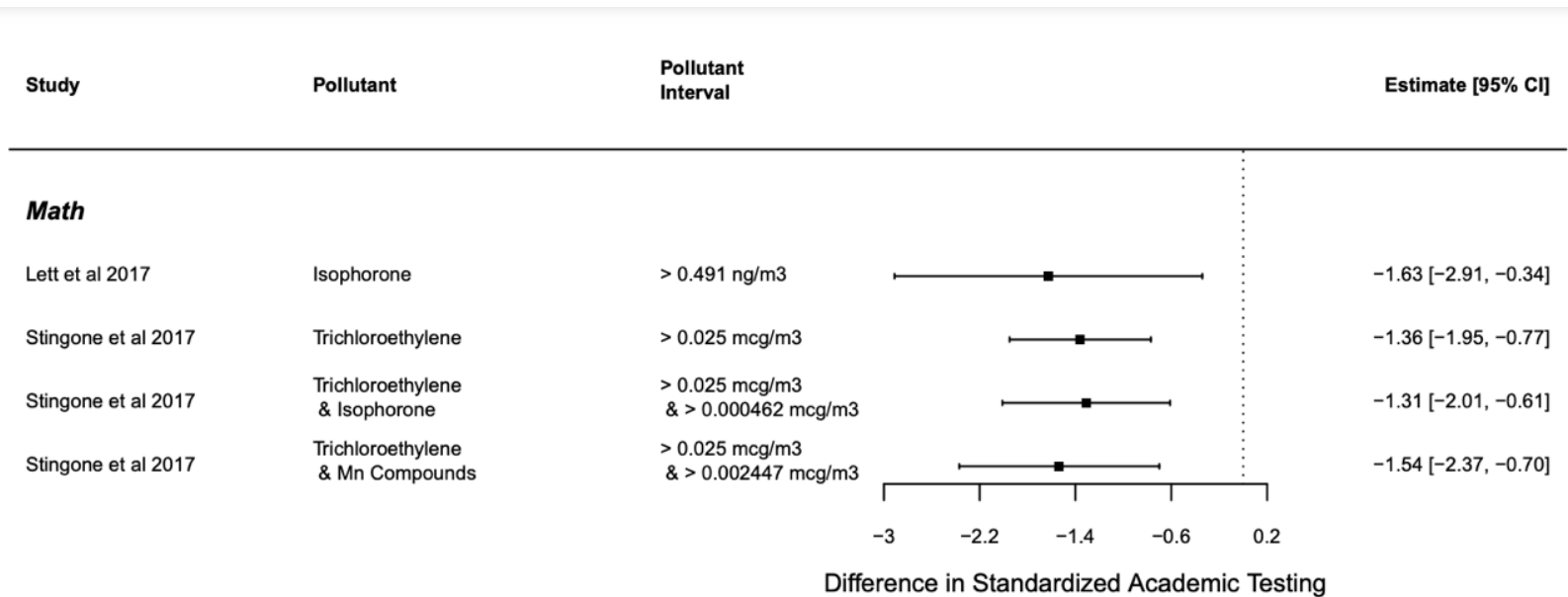


(b)

Figure A3. Forest plots showing estimated differences in standardized test scores associated with exposures to air toxics, including (a) studies reporting the association between prenatal perchloroethylene exposure and third grade test scores and (b) studies reporting the association between early-life toxics exposure and testing outcomes at kindergarten entrance.



(a)



(b)

Figure A4. Risk of Bias Assessment results, using the ROBINS-E methodology

	Risk of bias domains							Overall
	D1	D2	D3	D4	D5	D6	D7	
Balalian et al 2022	-	!	X	+	-	+	X	!
Stingone et al 2016	X	!	X	+	-	+	X	!
Margolis et al 2021	-	!	X	+	-	+	X	!
Lett et al 2017	-	!	X	+	!	+	X	!
Stingone et al 2017	-	!	X	+	!	+	X	!

Study

Domains:
D1: Bias due to confounding.
D2: Bias arising from measurement of the exposure.
D3: Bias in selection of participants into the study (or into the analysis).
D4: Bias due to post-exposure interventions.
D5: Bias due to missing data.
D6: Bias arising from measurement of the outcome.
D7: Bias in selection of the reported result.

Judgement
! Very high
X High
- Some concerns
+ Low

Citation	N	Location & Cohort	Exposure	Type of Exposure	Exposure Window	Outcome	Test	Covariates	Age/ Grade Level	Model
Balalian et al. 2022	187401	New York City (LSED)	Diesel PM & Perchloroethylene	Categorical	Prenatal	Standardized Math & Language Z-scores	New York State ELA & Math Test	Maternal Race; NDI; Maternal Education; Child's highest venous lead level; Maternal occupation status; Maternal marital status	Third Grade	Linear Model
Lett et al. 2017	4050	Urban US (ECLS-B)	Isophorone	Categorical	Early-life	Math score	A 58-item mathematics assessment	Child Race; NDI; SES; Maternal age at childbirth; Maternal marital; Primary language spoken at home	Kindergarten	Multiple Linear Regression
Margolis et al. 2021	200	New York City (MaNPBC)	Log-PAH	Continuous	Prenatal	Basic Reading Index Score; Passage Comprehension; Spelling; Broad Math Index	Woodcock-Johnson Tests of Achievement-III	Ethnicity; Maternal years of education; Maternal country of birth; Language of prenatal interview; Maternal marital status; Material hardship; Quality of home caregiving at age 3; Early life stress; Sex; NEPSY-II Inhibition subtest	13-15 years	Linear Regression

Stingo ne et al. 2016	2015 59	New York City (LSED)	Diesel PM & Perchlo- roethyle ne	Categori cal	Prenat al	Meeting ELA & Math Third grade standard	New York State ELA & Math Test	Maternal Race; NDI; Maternal educational attainment; Maternal insurance status; Child's eligibility for school lunch programs; Child's number of days absent from third grade; Maternal age; Maternal marital status; Maternal nativity; Maternal use of tobacco or alcohol during pregnancy; Maximum childhood blood lead level	Third Grade	Quantile Regressio n
Stingo ne et al. 2017	6800	US (ECLS- B)	Ambient Air Toxics	Categori cal	Early- life	Math scores	A 58-item mathematics assessment	Child Race; Urbanicity; NDI; SES; Maternal age at childbirth; Maternal marital status; Primary language spoken at home	Kindergar ten	Multi- Variable Linear Regressio n

Table A1. Summary Data Extraction Table

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Appendix B: Research Paper: Statewide Association between PM_{2.5}, NO₂, O₃, and Traffic Exposures and Standardized Test Performance

Abstract

Assessing the impact of air pollution on cognitive function, particularly in childhood, is critical to understanding the full scope of air pollution-health-related outcomes. Our objective was to conduct an ecologic analysis to examine associations between annual air pollutant exposures (PM_{2.5}, NO₂, O₃, Diesel PM, and traffic exposures) and school-level performance on standardized tests (including ELA, mathematics, and science) in California public schools between 2014 to 2019. Higher PM_{2.5}, O₃, NO₂, and Diesel PM were associated with a lower percent of students meeting state standards for ELA and Math at the school level, with findings most pronounced for PM_{2.5} and O₃ exposures two years prior to testing. A 2.43 ug/m³ increase in PM_{2.5} was associated with 4.35% fewer elementary school students achieving state standards (95% CI -4.81%, -3.90%), and a 3.36 ppm increase in ozone was associated with 3.61% fewer elementary students meeting state standards (95% CI -4.43%, -2.78%). Findings clustered based on grade levels with stronger associations for younger grade levels. Because this analysis draws on data from nearly 4 million students, summarized at the school level, these estimates are particularly relevant for policymaking, especially in California.

Background/Context

Air pollution is a substantial contributor to many adverse human health outcomes.¹ Much less is known about the effects of air pollution on neurocognitive function, yet the literature that exists has linked air pollution to memory issues and cognitive impairments.²

Air pollution effects on cognitive development in childhood may be especially important as this period is characterized by rapid brain growth and foundational learning. Children are particularly vulnerable to air pollution due to developing immune systems, higher breathing rates, and nasal passages that are less efficient at filtering out pollutants than adults.³ Cognitive ability in childhood is also linked to long-term well-being, with research showing that individuals who exhibit higher cognitive abilities early in life tend to experience greater annual and lifetime earnings as adults.⁴ Similar associations can be found at a national level; previous research found a statistically significant association between country-level IQ and economic growth for the average country.⁵ These factors highlight the importance of focusing research on the effects of air pollution on cognition during childhood and focusing on settings where children spend time, such as schools.

School environments often have elevated concentrations of traffic-related pollutants released by vehicle exhaust into the air. Many California public schools reside close to major roads and heavily-trafficked highways, especially schools with a disproportionate number of nonwhite and economically disadvantaged students.^{6,7} Children at schools near these busy roads face long-term exposure to harmful pollutants like PM_{2.5} (fine particles with a diameter of 2.5 micrometers or smaller), diesel-specific particulate matter, and nitrogen dioxide (NO₂),⁸ which are emitted from vehicle exhaust and other sources.^{9,10}

Beyond traffic-related pollutants, exposure to ground-level ozone at school remains a concern. Ozone (O₃) is created by chemical reactions involving NO_x and volatile organic compounds (VOC) in the presence of heat and sunlight.¹¹ Exposure to ozone in schools remains high and has been associated with increased school absences (largely attributed to respiratory illnesses) and higher district costs.¹² Outdoor ozone concentrations are greater than those found indoors,¹³ meaning children may be highly exposed during high physical activity, such as PE and recess.

Multiple studies have shown that when comparing schools with higher roadway pollution exposure to those with lower, students in lower pollution exposure schools perform better on cognitive testing even when controlling for SES.^{14,15} Despite this, a recent systematic review of TRAP and academic performance concluded that the confidence in the overall body of evidence for the TRAP-academic performance association is low due to the potential for bias in many existing studies.¹⁶

These exposures are especially important in California, which includes some of the most polluted places to live in the US.¹⁷ Over 90% of Californians are exposed to unhealthy levels of one or more air pollutants at various times throughout the year.¹⁸ For this reason, a California-wide study fills an important gap in understanding by decreasing the selection bias of which school sites and students are able to be assessed and including school sites across a wide range of exposure concentrations.

To address these gaps in the literature, we examined associations between annual air pollutants (PM_{2.5}, NO₂, O₃, Diesel PM, and traffic exposures) and average performance on

standardized tests (including English/language arts (ELA), mathematics, and science) at California public school sites from 2014 to 2019.

Methods

We conducted a secondary analysis, at the school level, of publicly available data from the California Department of Education (CDE) from 2014 to 2019 for 3rd through 11th grades. Schools with at least 3 years of outcome data for the school years between 2014 and 2019 (Supplementary Figure 1) were included in the sample. This period was selected because California began using the Smarter Balanced testing system in 2014. We chose the cut-off year as 2019– pre-COVID-19 pandemic– because testing was inconsistently completed across districts in the following years, and various other pandemic-related factors substantially changed educational outcomes in unusual ways. The study sample consisted of 9,320 schools, roughly 84% of all public schools in California (Supplementary Figure 1); those schools serve 96% of California students.

Exposures

The exposures of interest in this study were PM_{2.5}, NO₂, O₃, Diesel PM, and traffic density. We estimated exposures for each school site using statewide models for PM_{2.5}, NO₂, and O₃, developed for all of California.¹⁹ These models are sophisticated land-use regression models that create daily surfaces for California from 2012-2019, with a spatial resolution of 100 meters. The models incorporate statewide daily traffic data on highways, daily remote sensing data, daily weather data, parcel-level land use, detailed land cover data, every two-week vegetation index, and tree canopy data. They were validated using the Deletion/Subtraction/Addition machine learning algorithm. The high resolution of 100 meters allowed us to assign individual daily PM_{2.5} (µg/m³), NO₂ (ppb), and O₃ (ppb) concentrations to each public school in California from 2013 to 2019, which fully covers the time period of the testing data (2014-2019).

We created school-based annual estimates by averaging daily values. Because exact testing dates are not reported, we paired the outcome data with the exposure data from the previous year, or two years prior, in order to ensure that exposures occurred prior to the testing. For example, SBAC math test outcomes from 2015 (school year 2014-2015) were linked to exposure estimates from January-December of 2014 (the 'prior year' models) or January-December of 2013 (the 'two years prior' models).

Finally, exposure to Diesel PM and traffic density were estimated using CalEnviroscreen (CES), developed by the California Environmental Protection Agency Office of Environmental Health Hazard Assessment (OEHHA). For the census tract in which each school was located, the data include annual diesel PM in tons per year and traffic density, measured as vehicles per hour within 150m of the census tract. Data relevant for this study are those from CalEnviroscreen 3.0 and 4.0, which draw on data from 2015 and 2019. These CalEnviroscreen variables were matched with the first (2014-15) and last (2018-2019) years

of available testing data, as an approximation of what the equivalent metrics would have been in 2014 and 2018; there is no CES data for a two-year lag.

Outcomes

Outcome data came from the California Department of Education (CDE) at the school level. The CDE serves roughly 4,000,000 children in over 10,000 schools and collects student, school, and district data.²⁰

This study looked at results from 3 different standardized tests- the Smarter Balanced Assessment Consortium (SBAC) test (English/ Language Arts, ELA and Mathematics), which is given to the majority of California students, the California Alternate Assessment (CAA ELA and Math), for those needing an alternative assessment because of disabilities, and the California Science Test (CAST). The Smarter Balanced Assessment System was created in 2010 by a consortium of states to help educators and school districts develop a comprehensive assessment system for K-12.²¹ Scoring for these exams is based on the Common Core State Standards (CCSS), with content experts and CCSS authors review all testing content.²² The ELA and math tests used in this analysis were completed by California students in grades 3 through 8 (every year) and 11. The science exam was administered in fifth and eighth grade and once in high school. California began testing students in this framework in the 2014-2015 school year, and there is an uninterrupted period of five years (through the 2018-2019 school year, the year prior to the COVID-19 pandemic), when students were consistently assessed using these exams.

This study had five primary outcomes of interest: percent of students meeting SBAC ELA state standards, percent of students meeting SBAC Math state standards, percent of students meeting CAA ELA Level 3 ("Understanding"), percent of students meeting CAA Math Level 3, and percent of students meeting CAST Science state standards. These tests had data available for one year (the science exam), four years (CAA), or five years (SBAC) for each school within the 2014-2019 period. Schools that do not serve students in the relevant testing grades, or where 10 or fewer students were tested in a grade level do not report results.

Covariates

All models controlled for SES, percent of English language learners, school district funding, and chronic absenteeism. Covariates were also collected from publicly accessible CDE data. The percent of students at each school eligible for free and reduced-price meals (FRPM) was used as a proxy for socioeconomic status. The percentage of English language learners was used directly from CDS (calculated as the percentage of students identified in the California Longitudinal Pupil Achievement Data System (CALPADS) as English learners on Census Day). Finally, chronic absenteeism was defined as the proportion of chronically absent students at a school. Students were chronically absent if they were absent for 10% or more of the days they were expected to attend. The CDE reports data these variables annually and at the school level.

To adjust for annual district funding, we used district expenditures reported by CDE (amount of money spent by the district per student per year) and assigned that to each school based on their district membership.

Statistical Analysis

Data analyses were performed using R using a prespecified data analysis plan posted to the Open Science Framework (<https://osf.io/e4jgv/overview>).

Linear mixed effect models assessed the relationship between air pollutants and standardized test scores, using all available years of data for each exam at each grade level. Standard assumptions were checked. Each school was allowed a random intercept that estimated between-school differences in baseline test scores. Models that included a random slope to allow the effect of air pollution on test performance to vary by school were consistently unable to converge, likely due to the limited number of data points per school (1-5). Thus, the only random term used in the models was a random intercept. All models controlled for SES, district funding, school absenteeism, and demographic composition of the school. Robust confidence intervals were estimated using bootstrapping. The initial plan was to assess the relationship between testing scores and pollutant exposure in the prior year only, but an early coding error led to both prior year and two-year prior models being run; as such both are being reported.

Data missingness for Chronic absenteeism was greater than 10% because data for 2014-15 and 2015-16 were not collected or reported (as confirmed with the analytics team from the CDE). We explored the variability within our data (2016-2019) and found that the variability in chronic absenteeism year to year is minimal. Thus, we used a fixed covariate-the average of chronic absenteeism rates per school from the years the data are available. Data missingness was minimal for all other exposure and covariate variables.

To determine the effect of air pollution on average standardized test performance in California public schools, our main analysis includes a total of 115 linear mixed effects models assessing percent of students meeting standards for each combination of test subject, exposure, and grade level (Supplementary Tables S.B1 and S.B2), and 15 linear models (Supplementary Table S.B3) (no random effect because there is only one year of data) for the science test models with each exposure and grade combination. No mathematical corrections were applied for multiple comparisons, though the results are interpreted in groups, rather than considering each individual model. Subgroup Analyses were performed for each population subgroup that had data reported for at least 10% of California schools (Supplemental Table S.B4); this included male and female students and students in the following racial/ethnic categories: Asian, Black or African American, Hispanic or Latino (Latinx), and White. Post-hoc sensitivity analyses were also performed to look at the main analysis for ELA, math, and science using scaled test scores rather than percentage (Supplemental Tables S.B1-S.B3).

We intentionally completed a summarization of the analysis to assist with the policy - relevance of the results. We calculated pooled estimates to summarize this complex set of results down, with that pooling driven by the pattern of results of the individual models. Pooling was done using random effects maximum likelihood meta-analysis; models would have been simplified to fixed effects were that appropriate given the I^2 measures of variability.

Results

From the 9829 California schools with any reported testing data in the studied interval, the final analytic sample included 9320 schools, which were distributed across 887 unique school districts, and served a total of 3.825 million pupils (Table B1, Supplemental Figure S.B1). An average of 8888 schools were included per test year. In an average school, 41.2% of students met SBAC state standards, 11.1% met CAA Level 3, and 28.0% met CAAST state standards. Relative consistency in scores for SBAC, CAA, and CAST scores was seen over time, with slight increases across the years (Table B1).

Annual average school exposure to $PM_{2.5}$ was $9.5 \mu g/m^3$ (IQR: 2.43), to ozone was 38.8 ppb (IQR: 3.36), and to NO_2 was 10.0 ppb (IQR: 5.19) between 2013 and 2018; concentrations that are near ($PM_{2.5}$) or well below (ozone and NO_2) the national ambient air quality standards.²⁶ On average there were 3.1 tons of diesel PM per year (IQR: 5.49) and 947.6 vehicles per hour near schools (IQR 739.4). Aggregate air pollution exposure for all pollutants decreased slightly across the test years (Table B1), with larger decreases seen in NO_2 and diesel PM. Pollutants showed only minimal to moderate correlations with each other (Pearson correlation coefficients range -0.05 to 0.4, Supplemental Table S.B5). Ozone concentrations across the years were highly correlated with each other (Pearson correlation coefficients 0.967-0.991), and NO_2 concentrations were also highly correlated with each other (Pearson correlation coefficients 0.989-0.998). $PM_{2.5}$ concentrations were somewhat more variable with correlation coefficients ranging 0.896 to 0.961 amongst most years, and with the 2018 pollutant data having much lower correlations with the others (Pearson correlation coefficients 0.649 to 0.797).

Higher exposures to NO_2 , O_3 , and Diesel PM in the prior year were associated with fewer students meeting SBAC ELA and Math standards (Figures 1 a and b, Figure 2a, Table B2, Supplemental Table S.B1). For example, schools with annual ozone concentrations that were one IQR higher (3.36 ppb) had 3.23 percent fewer 6th graders meeting the SBAC Math standard (95% CI -3.65, -2.82). Associations with $PM_{2.5}$ had confidence intervals spanning zero or were very small. Estimates for the relationship between meeting the standard and the summary traffic-related exposure metric were slightly positive (e.g. % of third graders meeting the SBAC ELA standard was 1.59% higher; 95% CI 1.34, 1.85). Thus, though $PM_{2.5}$, NO_2 , and Diesel PM are traffic-related pollutants, their associations with test performance differ from the associations we calculated for traffic density (often used elsewhere in the literature as a proxy measure for air pollutant exposure).

Looking at associations between meeting the state standards and exposures *two years prior*, negative associations were observed between each individual air pollutant (PM_{2.5}, O₃, and NO₂) and meeting SBAC ELA and Math standards (Figure B1 a and b, Table B2, Supplemental Table S.B1). Test results were similarly associated with ozone over a one- or two-year lag. But a larger decrease in percent of students meeting standards was associated with NO₂ and PM_{2.5} exposures two years prior, compared to exposure in the prior year. For example, among fifth graders, an IQR increase in PM_{2.5} in the year prior to testing was associated with 0.35 percent fewer students meeting the standard (95% CI: -0.57, -0.10), whereas an IQR increase in PM_{2.5} two years prior to testing was associated with 3.86 percent fewer students meeting the standard (95% CI: -4.18, -3.55).

For the two-year lag—when the most pollutants were associated with testing results—the pollutant-test performance associations were strongest in magnitude for PM_{2.5}, followed by O₃, NO₂, and Diesel PM (Figure B1 a and b, Table B2, Supplemental Table S.B1). For instance, when comparing associations for third graders across all pollutants, an IQR increase in PM_{2.5} exposure is associated with 4.67 percent fewer students meeting SBAC math state standards (95% CI: -5.05, -4.36), while O₃ is associated with 3.10 fewer (95% CI: -3.51, -2.75), and NO₂ with 3.75 fewer (95% CI: -4.18, -3.28).

Across models, associations indicated a larger effect at lower grade levels. For example, in third graders, PM_{2.5} exposure that is one IQR higher two years prior to testing is associated with 5.02 (95% CI: -5.35, -4.70) percent fewer students meeting SBAC ELA state standards, accounting for covariates. Meanwhile, for eighth graders, an IQR more PM_{2.5} exposure two years prior to testing is only associated with 2.78 (95% CI: -3.24, -2.36) percent fewer students meeting SBAC ELA state standards, holding covariates constant. 11th-grade results seem to be less affected by air pollution, and estimates were much more variable.

Results were quite similar between the SBAC ELA and Mathematics exams (Figure 1 a and b, Table B2, Supplemental Table S.B1), suggesting similar relationships with air pollutant exposure for both subjects. Subgroup analyses stratified by sex demonstrated very similar relationships between pollutants and test scores across all pollutants and age groups (Figure B2, Supplementary Figure S.B2), with minor differences in ELA performance related to NO₂ between sex strata. Subgroup analyses were also performed within California's most common racial ethnic groups (Asian, Black, Latinx and White; Supplemental Table S4 and Supplemental Figures S.B3 and S.B4); these show some variability in the patterns of association, but sample sizes for the different groups are very variable since testing results are suppressed for groups that don't have 10 or more students within that group in a grade level at a particular school. As an example, looking at 3rd grade ELA models, there are 1,408 schools with data for Asian students, 1,084 schools with data for Black students, 5,190 schools with data for Latinx students and 3,305 schools with data for White students.

A post-hoc sensitivity analysis using mean scaled scores on the exams (Supplemental Figure S.B5, Supplemental Table S.B1), rather than percent meeting the standards, showed a similar pattern of results to that main analysis. For example, schools with an exposure of 1

IQR higher PM_{2.5} had estimated decreases in SBAC scores ranging from -3.5 to -8.5 points depending on the grade level. Associations were generally stronger for the individual pollutants and positive for traffic, with stronger effects estimated for younger grade levels. However, the effect sizes for NO₂ are shifted upwards when using scaled scores rather than percentages meeting the standards, showing some instability in the NO₂ results related to the outcome metric chosen.

For the California Alternative Assessment, given to students with learning differences, most estimates were close to zero and had wide confidence intervals- likely due to substantially smaller sample sizes (Figure B1 c and d, Supplementary Table S.B2). For example, among third graders the association between PM_{2.5} and the percent of students achieving “understanding” (Level 3) on the ELA CAA was based on only 51 schools and had a confidence interval spanning from 1.59 to 9.76. No estimates were generated for Diesel PM or traffic-related exposures (models were unable to converge) due to small sample sizes and given that data on Diesel PM and traffic exposures were only available for two years.

Slight negative associations were observed between PM_{2.5}, O₃, and meeting CAST Science standards (Figure B1e, Supplementary Table S.B3), with slight positive associations found between NO₂, traffic, and meeting CAST Science standards. Confidence intervals for associations with diesel PM are so wide as to be uninformative (e.g., among 5th graders an IQR increase in diesel PM was associated with 5.90 percent *more* students meeting the standard (95% CI 1.22, 10.58)). These results come from models having only one year of data for CAST science outcomes, since this test was only recently implemented.

Based on the observed patterns in the data (similar among adjacent grade levels, and similar effects between ELA and math), and real-world knowledge of how California schools are structured, estimates were pooled at the school level and combining the effects for English and math (Figure B3, Table B3). Elementary estimates included those based on grades 3-5, middle school estimates are based on those for grades 6-8 and high school estimates come from only the grade 11 estimates. These clearly demonstrate the same basic pattern as described above; fewer students meeting state standards in elementary and middle school if exposed to higher pollutant concentrations, particularly pollutants two years prior to testing, but minimal effect at the high school level. I squared values suggest that the chosen random effects pooling methods were appropriate.

Discussion/Interpretation

In this study, we aimed to investigate the relationship between air pollution and standardized test performance using school-level data on California public schools from 2014 to 2019. We found that increased exposure to PM_{2.5}, O₃, NO₂, and Diesel PM was associated with a decrease in meeting standards on the primary state standardized tests (SBAC ELA and SBAC Math). Findings tended to cluster based on grade levels, with elementary-aged students most affected. Associations were strongest for PM_{2.5} and O₃ exposures two years prior, with similar patterns seen in male and female students. Most of the results were similar regardless of lag time use (prior year versus two year prior); which

may either reflect a long-term exposure effect that doesn't vary much or may simply be reflective of the very high correlation between pollutant exposures year to year at a single school site. Notably, PM_{2.5} concentrations were the most variable year to year, and it was the only pollutant to have obviously different estimated effects at the different lags.

Though higher NO₂ was also associated with a decrease in standardized test performance, these results seemed to vary the most in sensitivity analyses (e.g. when using scaled score rather than percent meeting the standard) and have the most variability between adjacent grade levels. This suggests some instability in these estimated effects, and we are thus cautious about interpreting the relationship between NO₂ and test performance.

This paper fills a critical gap by including not only PM_{2.5} and NO₂^{2,16} –the two pollutants that have been most studied relating to children's neurocognitive development—but also including ozone and two of the proxy measures that are often used to represent traffic-related pollution in the absence of detailed pollutant data: census-tract estimates of Diesel PM and nearby traffic density. As we've demonstrated here, use of such a proxy measure can produce very different results, possibly due to exposure misclassification. Because these measures do not account for wind direction and other atmospheric conditions, they may be serving as a measure of urbanicity rather than being specific to traffic-related pollution. Analyses which use only measures of nearby traffic may thus miss important existing relationships.

The results from the alternative (CAA) exams represent such a small subset of California schools that selection bias is likely at play, with schools that serve a large number of special needs students being potentially different than those that serve special needs students within mainstream classrooms. Because of the small sample size and this potential for selection bias in this analysis, we would not advise consideration of special needs students differently based on these results.

The results from the science exam are provocative and hint that science performance may not be as affected by air pollutant exposure as English and math performance. However, the single year of science testing data means that this may reflect residual confounding that is handled by the random intercept in the SBAC models, rather than a true difference, and is worthy of further study.

Our findings align with most studies that had a similar structure to ours— a US cohort, school-based annual exposures, large sample sizes, looking specifically at standardized testing.²³⁻²⁵ Though much of the literature is ecologic, assessing outcomes at a school, district or county level, there are a few studies that have been able to assess individual data. Exposure to diesel PM around the time of the child's birth has been associated with lower ELA and math testing results at third grade.²⁶ Exposure to hazardous air pollutants in childhood among a nationally representative cohort of K-3 students was associated with lower reading, math and science scores, assessed longitudinally.²⁴ A recent analysis by members of our group showed lower individual student standardized test scores across the full testing range,

among a small cohort of students on the same SBAC tests analyzed here. Scores were associated with ozone and PM_{2.5}, with decreases in mean scaled scores of around 7 points per unit of pollutant.²¹ These findings are incredibly similar to those individual-level findings, suggesting that the data presented here may be—cautiously—interpreted to perhaps reflect associations that occur at the individual level, minimizing the chance of an ecologic bias.

Though this has focused on standardized testing data as a measure of cognition, studies with a more diverse set of outcomes have also found adverse effects on childhood cognition with air pollution exposure. Children aged 7-10 years from highly polluted schools in Barcelona had smaller cognitive growth (assessed with repeated testing over a year) compared to children from matched, less polluted schools.¹⁴ New York children with higher prenatal airborne polycyclic aromatic hydrocarbons (PAHs) exposures had worse spelling skills, worse reading comprehension, and math skills in adolescence.³² A recent systematic review of prenatal and early-life exposures and neurodevelopmental skills in preschool and school-aged children found PM_{2.5}, NO₂, and PAH to most consistently represent the greatest risk, with associations seen with attention and learning outcomes.²⁷ Structural changes have even been documented in the brains of children exposed to higher PM_{2.5} concentrations.^{28,29}

Not all studies have found decreases in cognition associated with air pollutant exposure including some looking at different specific outcomes, such as visuoconstruction abilities³⁴ or cognitive flexibility³⁰ or those using a different ecologic unit of study (such as the 2010-2016 nationwide US study using district-level test data that found only O₃ was associated with math scores³⁵). A recent systematic review of air pollution effects on broadly-defined student performance found that though most studies showed some relationship between TRAP and student performance, no consistent relationships were found for specific pollutants, academic subjects or age groups, and the authors noted a high risk for bias in many of the studies.³¹ Thus, despite many analyses demonstrating some associations between TRAP and student academic achievement, studies such as this—which build off a large amount of data between different ages and subjects—remain valuable.

There are multiple mechanisms by which air pollution can affect cognition. The first is that exposure to air pollutants promotes neuroinflammation and oxidative stress.^{32,33} Experimental animal models show that exposure to PM_{2.5} leads to the release of proinflammatory cytokines and impaired myelin repair.³⁴ Furthermore, air pollutants can damage and penetrate the blood brain barrier and cause systemic inflammation and neuronal and white matter injuries, which adversely impacts an already developing nervous system.³⁴⁻³⁶ Larger effects of air pollution on the brains of younger children could be explained by differences in brain plasticity—while periods of widespread structural and functional changes in brain plasticity occur throughout our childhood and adolescence, the most changes occur from infancy to age 6, followed by ages 6-10, and lesser changes during adolescence.^{37,38}

The greatest strength of our study is that it uses data from a large, state-wide, and truly representative population. Using standardized test scores for our outcome nearly eliminates

selection bias in the SBAC models as these tests are taken by almost all students in California public schools. This also allows for direct comparisons in effect sizes across age groups, whereas much of the prior age group comparisons come from systematic reviews.^{27,31} We also had quantitative estimates of air pollutant exposures, for decreased exposure misclassification compared to many studies in the literature.²⁷

Nonetheless, our findings have several limitations. The small sample size for CAA and only one year of CAST test scores may have affected our ability to determine associations for these. CAA test scores may also not be as generalizable or informative as using SBAC test scores because the CAA is intended for longitudinal tracking of individual students on an independent educational plan, without a specific benchmark expected for all students. Importantly, standardized test scores present an opportunity to use a large, representative analytic sample, they are not the best measure of cognitive ability. Test scores can reflect the quality of education or limited socioeconomic resources, and there are known biases in standardized exams that can affect performance on standardized exams in different racial groups, reflecting differences in shared culture rather than intelligence or neurodevelopmental growth.³⁹ In addition, the analyses using data from racial and ethnic subgroups come from samples of schools that range over nearly an order of magnitude in the number of schools, meaning that these should not be directly compared because of the potential for selection biases.

In conclusion, our study found that air pollution is associated with lower standardized test scores for children in California schools. The most pronounced associations were found for PM_{2.5} and O₃ two years prior; and in younger children. Given that insults to brain growth and development have the potential for lifelong effects on the California population and economy, this analysis provides detailed estimates for a pressing problem needing policy interventions.

Table B1. Characteristics for schools stratified by test year (schools included if they have outcome data for at least 3 years)

		Overall	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
n (schools)		9320	8811	8878	8879	8910	8960
SBAC Percentage Standard Met and ELA Percentage Standard Met		41.23 (21.99)	36.90 (21.69)	40.62 (22.21)	41.27 (21.85)	43.04 (21.84)	44.25 (21.67)
Math Percentage Standard Met		45.79 (20.94)	41.19 (21.16)	45.40 (21.24)	45.62 (20.87)	47.74 (20.49)	48.90 (20.13)
Percentage Met Level 3		36.68 (22.08)	32.61 (21.36)	35.83 (22.12)	36.92 (21.94)	38.33 (22.12)	39.59 (22.16)
ELA Percent Met Level 3		11.15 (15.73)	NA	7.37 (12.70)	12.36 (17.50)	12.45 (15.19)	12.15 (16.42)
Math Percent Met Level 3		14.55 (17.42)	NA	10.06 (14.56)	17.07 (20.01)	16.84 (16.91)	13.94 (16.81)
CAAST Percentage Standard Met		7.76 (12.99)	NA	4.70 (9.85)	7.72 (13.07)	8.08 (11.74)	10.34 (15.84)
Percentage Eligible for Free or Reduced Price Meals (FRPM)		27.99 (18.88)	NA	NA	NA	NA	27.99 (18.88)
Percentage identified as English Learners		61.31 (28.11)	60.76 (28.65)	61.19 (28.53)	60.34 (28.45)	62.38 (27.55)	61.75 (27.47)
Chronic Absenteeism Rate		24.59 (19.22)	26.08 (20.31)	25.94 (20.03)	25.06 (19.39)	24.04 (18.68)	22.34 (17.63)
Yearly PM2.5		9.80 (6.62)	9.80 (6.43)	9.85 (6.66)	9.80 (6.57)	9.78 (6.66)	9.78 (6.75)
The year prior to the testing year	Yearly O3	9.52 (2.02)	9.42 (1.78)	9.43 (1.94)	9.24 (1.84)	9.13 (1.74)	10.24 (2.40)
	Yearly NO2	38.74 (2.48)	39.43 (2.49)	38.92 (2.25)	38.31 (2.46)	38.30 (2.42)	38.76 (2.56)
	Diesel PM	9.74 (3.40)	10.42 (3.50)	10.10 (3.45)	9.67 (3.63)	9.24 (3.18)	9.39 (3.13)
	Traffic	3.11 (5.08)	6.71 (5.85)	NA	NA	NA	0.20 (0.30)
Two years prior to testing year		947.63 (780.65)	854.34 (723.27)	NA	NA	NA	1022.98 (816.35)
Two years prior to testing year	Yearly PM2.5	9.50 (1.87)	10.35 (1.81)	9.42 (1.78)	9.43 (1.94)	9.24 (1.85)	9.14 (1.74)
	Yearly O3	38.75 (2.46)	38.89 (2.48)	39.43 (2.50)	38.92 (2.24)	38.30 (2.46)	38.31 (2.42)
	Yearly NO2	10.13 (3.56)	11.40 (3.74)	10.44 (3.49)	10.10 (3.45)	9.66 (3.63)	9.26 (3.17)

Values listed are mean (SD).

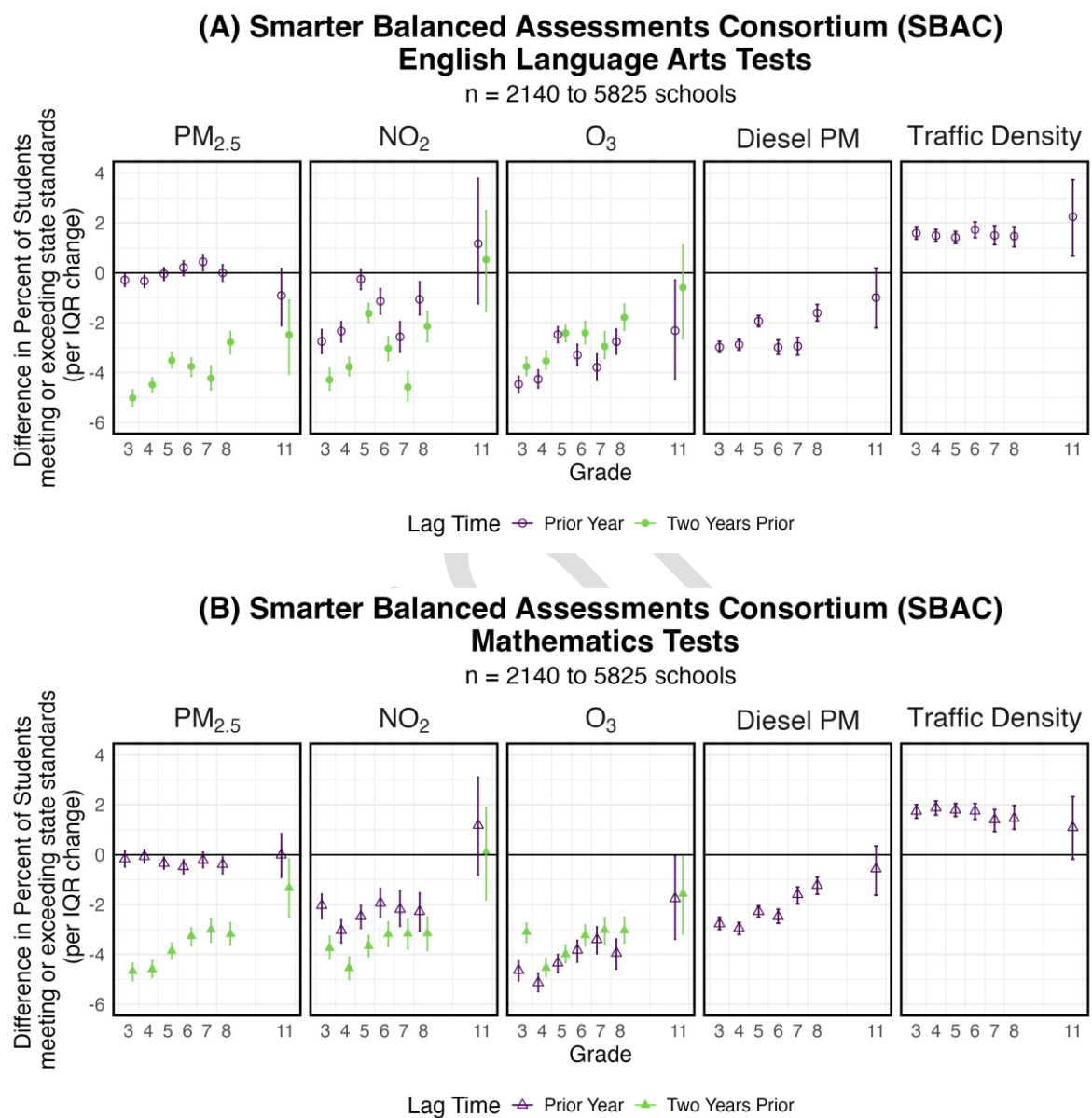
Table B2. Estimates of the effect on percentage of students at a school meeting or exceeding the state standards on the Smarter Balanced Assessment Consortium Exams in California, per IQR change in pollutant. Coefficients come from linear mixed models that controlled for percent of students at a school who qualify for free and reduced priced meals, percent for whom English was their second language, percent of students chronically absent at the school, and district level funding; and included a random intercept for each school location because 5 years of data contributed to the model. (IQR changes: 2.43 $\mu\text{g}/\text{m}^3$ PM_{2.5}, 3.36 ppm O₃, 5.19 ppm NO₂, 5.49 tons per year Diesel PM, 739.4 vehicles per hour of Traffic Density)

Exposure	Subject	Grade	Number of Schools	Associated with pollution 1 year prior				Associated with pollution 2 years prior			
				Effect Estimate	Standard Error	Bootstrapped Confidence Intervals		Effect Estimate	Standard Error	Bootstrapped Confidence Intervals	
						Lower Limit	Upper Limit			Lower Limit	Upper Limit
Annual PM _{2.5}	ELA	3	5796	-0.29	0.13	-0.54	-0.03	-5.02	0.16	-5.35	-4.70
		4	5795	-0.33	0.13	-0.59	-0.10	-4.49	0.16	-4.77	-4.21
		5	5825	-0.04	0.12	-0.30	0.20	-3.51	0.15	-3.80	-3.19
		6	4329	0.21	0.15	-0.11	0.47	-3.76	0.18	-4.15	-3.42
		7	2734	0.44	0.17	0.09	0.73	-4.23	0.23	-4.69	-3.73
		8	2742	0.00	0.17	-0.33	0.32	-2.78	0.22	-3.24	-2.36
		11	2140	-0.91	0.60	-2.12	0.17	-2.49	0.77	-4.06	-1.10
	Math	3	5795	-0.17	0.14	-0.49	0.14	-4.67	0.17	-5.05	-4.36
		4	5793	-0.07	0.13	-0.33	0.17	-4.60	0.17	-4.92	-4.25
		5	5825	-0.35	0.13	-0.57	-0.10	-3.86	0.16	-4.18	-3.55
		6	4330	-0.48	0.14	-0.76	-0.20	-3.27	0.19	-3.64	-2.94
		7	2736	-0.22	0.16	-0.52	0.10	-3.01	0.22	-3.51	-2.57
		8	2741	-0.39	0.18	-0.76	-0.09	-3.19	0.24	-3.62	-2.74
		11	2137	-0.01	0.46	-0.91	0.84	-1.34	0.62	-2.49	-0.17
Annual O ₃	ELA	3	5796	-4.47	0.19	-4.81	-4.15	-3.76	0.18	-4.10	-3.39
		4	5795	-4.27	0.18	-4.62	-3.90	-3.53	0.17	-3.85	-3.14
		5	5825	-2.48	0.17	-2.80	-2.17	-2.42	0.17	-2.75	-2.11
		6	4329	-3.30	0.21	-3.71	-2.87	-2.41	0.21	-2.84	-1.94
		7	2734	-3.79	0.27	-4.31	-3.26	-2.95	0.27	-3.43	-2.37
		8	2742	-2.76	0.27	-3.26	-2.26	-1.79	0.26	-2.31	-1.27
		11	2140	-2.32	0.97	-4.29	-0.29	-0.59	0.96	-2.64	1.10
	Math	3	5795	-4.64	0.20	-5.06	-4.27	-3.10	0.19	-3.51	-2.75
		4	5793	-5.14	0.19	-5.49	-4.75	-4.54	0.19	-4.87	-4.16
		5	5825	-4.35	0.19	-4.73	-4.00	-4.00	0.18	-4.33	-3.62
		6	4330	-3.83	0.22	-4.31	-3.44	-3.23	0.22	-3.65	-2.82
		7	2736	-3.41	0.27	-3.97	-2.90	-3.03	0.27	-3.59	-2.52
		8	2741	-3.95	0.30	-4.59	-3.39	-3.04	0.29	-3.55	-2.51
		11	2137	-1.76	0.83	-3.40	-0.05	-1.57	0.82	-3.18	-0.06
Annual NO ₂	ELA	3	5796	-2.75	0.22	-3.23	-2.28	-4.29	0.20	-4.70	-3.84
		4	5795	-2.34	0.22	-2.77	-1.96	-3.77	0.20	-4.12	-3.40
		5	5825	-0.25	0.20	-0.67	0.15	-1.63	0.18	-1.98	-1.23
		6	4329	-1.14	0.26	-1.65	-0.64	-3.03	0.23	-3.51	-2.57
		7	2734	-2.57	0.34	-3.18	-1.96	-4.58	0.31	-5.13	-3.96
		8	2742	-1.06	0.33	-1.68	-0.36	-2.15	0.30	-2.75	-1.55
		11	2140	1.17	1.19	-1.24	3.79	0.53	1.05	-1.55	2.48
	Math	3	5795	-2.04	0.24	-2.56	-1.59	-3.75	0.22	-4.18	-3.28
		4	5793	-3.04	0.24	-3.54	-2.62	-4.55	0.22	-5.00	-4.11
		5	5825	-2.48	0.23	-2.95	-2.03	-3.67	0.21	-4.08	-3.25
		6	4330	-1.94	0.27	-2.49	-1.36	-3.19	0.24	-3.67	-2.70
		7	2736	-2.19	0.36	-2.87	-1.45	-3.17	0.31	-3.77	-2.58
		8	2741	-2.28	0.38	-3.06	-1.54	-3.16	0.33	-3.84	-2.50
		11	2137	1.18	1.06	-0.81	3.11	0.09	0.90	-1.81	1.88
Diesel PM	ELA	3	5796	-2.98	0.12	-3.19	-2.75				
		4	5795	-2.88	0.11	-3.10	-2.67				
		5	5825	-1.94	0.11	-2.16	-1.71				
		6	4329	-2.99	0.14	-3.27	-2.69				
		7	2734	-2.94	0.18	-3.30	-2.59				
		8	2742	-1.61	0.17	-1.93	-1.27				
		11	2140	-0.99	0.65	-2.21	0.19				
	Math	3	5795	-2.77	0.12	-3.00	-2.51				
		4	5793	-2.95	0.12	-3.20	-2.72				
		5	5825	-2.28	0.12	-2.51	-2.05				
		6	4330	-2.48	0.14	-2.75	-2.19				
		7	2736	-1.60	0.17	-1.97	-1.30				
		8	2741	-1.23	0.18	-1.59	-0.90				
		11	2137	-0.57	0.49	-1.63	0.35				
Traffic Density	ELA	3	5796	1.59	0.13	1.35	1.85				
		4	5795	1.49	0.13	1.25	1.74				
		5	5825	1.42	0.12	1.18	1.66				
		6	4329	1.73	0.16	1.41	2.04				
		7	2734	1.50	0.21	1.13	1.89				
		8	2742	1.47	0.20	1.05	1.85				
		11	2140	2.25	0.80	0.67	3.74				
	Math	3	5795	1.74	0.14	1.46	2.01				
		4	5793	1.88	0.14	1.59	2.15				
		5	5825	1.79	0.14	1.53	2.05				
		6	4330	1.75	0.16	1.42	2.05				
		7	2736	1.40	0.21	0.93	1.81				
		8	2741	1.46	0.23	1.02	1.97				
		11	2137	1.09	0.72	-0.18	2.32				

Table B3. Pooled Estimates of the effect of pollutants on percentage of students at a school meeting or exceeding the state standards on the Smarter Balanced Assessment Consortium Exams in California, per IQR change in pollutant. Pooled estimates come from random effects meta-analyses, based on linear mixed models that controlled for percent of students at a school who qualify for free and reduced priced meals, percent for whom English was their second language, percent of students chronically absent at the school, and district level funding; and included a random intercept for each school location.

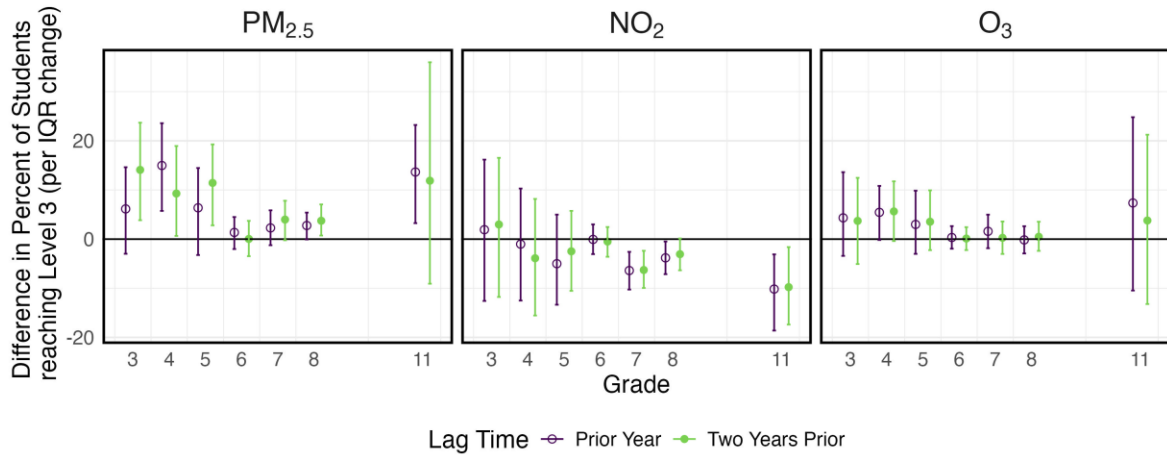
Exposure	School Level	Pollutant IQR	Associated with pollution 1 year prior				Associated with pollution 2 years prior			
			Effect Estimate per IQR of pollutant	Confidence Intervals (per IQR)		Pooled I ² Value (heterogeneity among pooled estimates)	Effect Estimate per IQR of pollutant	Confidence Intervals (per IQR)		Pooled I ² Value (heterogeneity among pooled estimates)
				Lower Limit	Upper Limit			Lower Limit	Upper Limit	
Annual PM _{2.5}	Elementary	2.43	-0.21	-0.32	-0.10	13.96	-4.35	-4.81	-3.90	91.80
	Middle		-0.08	-0.36	0.21	79.29	-3.38	-3.80	-2.96	83.87
	High		-0.38	-1.24	0.48	28.38	-1.83	-2.93	-0.72	24.66
Annual O ₃	Elementary	3.36	-2.15	-2.95	-1.35	94.96	-3.61	-4.43	-2.78	96.14
	Middle		-1.84	-2.34	-1.34	74.48	-3.21	-3.83	-2.60	86.51
	High		1.18	-0.37	2.72	0.00	0.28	-1.06	1.62	0.00
Annual NO ₂	Elementary	5.19	-4.22	-4.95	-3.49	95.91	-3.56	-4.15	-2.97	93.96
	Middle		-3.50	-3.85	-3.15	65.78	-2.74	-3.17	-2.31	78.60
	High		-2.00	-3.24	-0.76	0.00	-1.16	-2.38	0.06	0.00
Diesel PM	Elementary	5.49	-2.63	-2.98	-2.29	92.47				
	Middle		-2.14	-2.75	-1.54	95.49				
	High		-0.72	-1.50	0.05	0.00				
Traffic Density	Elementary	739.4	1.64	1.50	1.79	45.34				
	Middle		1.59	1.44	1.74	0.00				
	High		1.62	0.48	2.75	14.11				

Figure. B1 Plots showing fixed effects for exposure to air pollutants on percent meeting standards for (a-b) the Standard Balanced Assessment Consortium English/Language Arts and Mathematics Examinations (c-d) the California Alternate Assessment English/Language Arts and Mathematics Examinations (e) the California Science Test



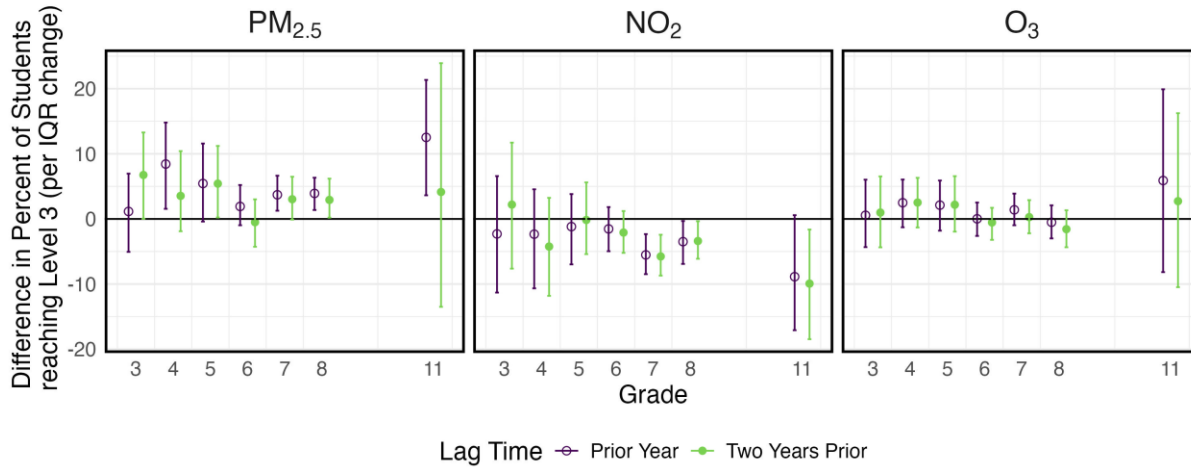
(C) California Alternate Assessment (CAA) English Language Arts Tests

n = 49 to 169 schools



(D) California Alternate Assessment (CAA) Mathematics Tests

n = 49 to 169 schools



(E) California Science Test (CAST)

n = 1172 to 5625 schools

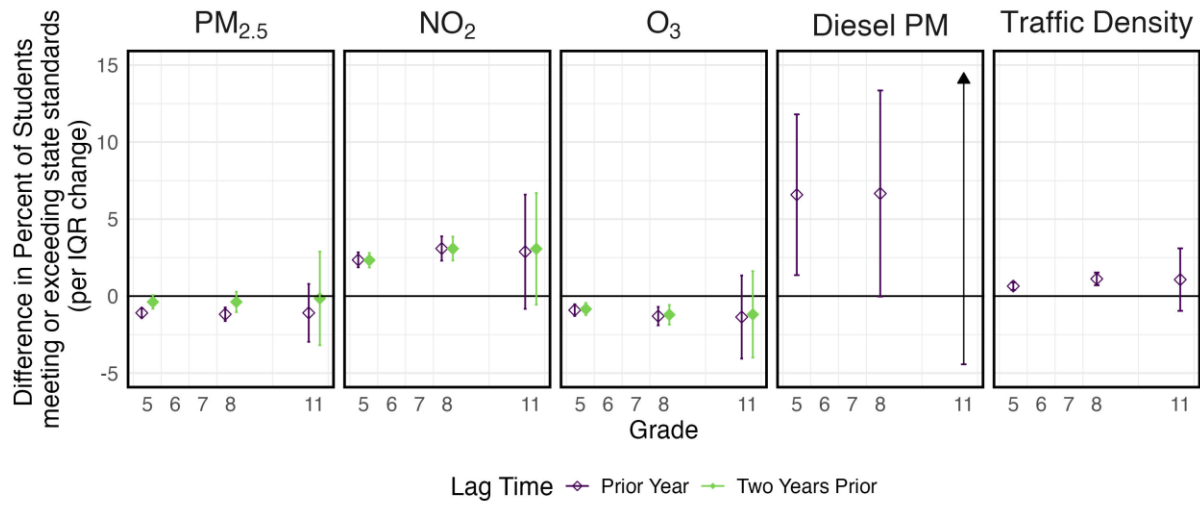


Figure. B2 Plots showing fixed effects for exposure to air pollutants two years prior on percent meeting standards for the Standard Balanced Assessment Consortium English/Language Arts and Mathematics Examinations among (a) male students only and (b) female students only

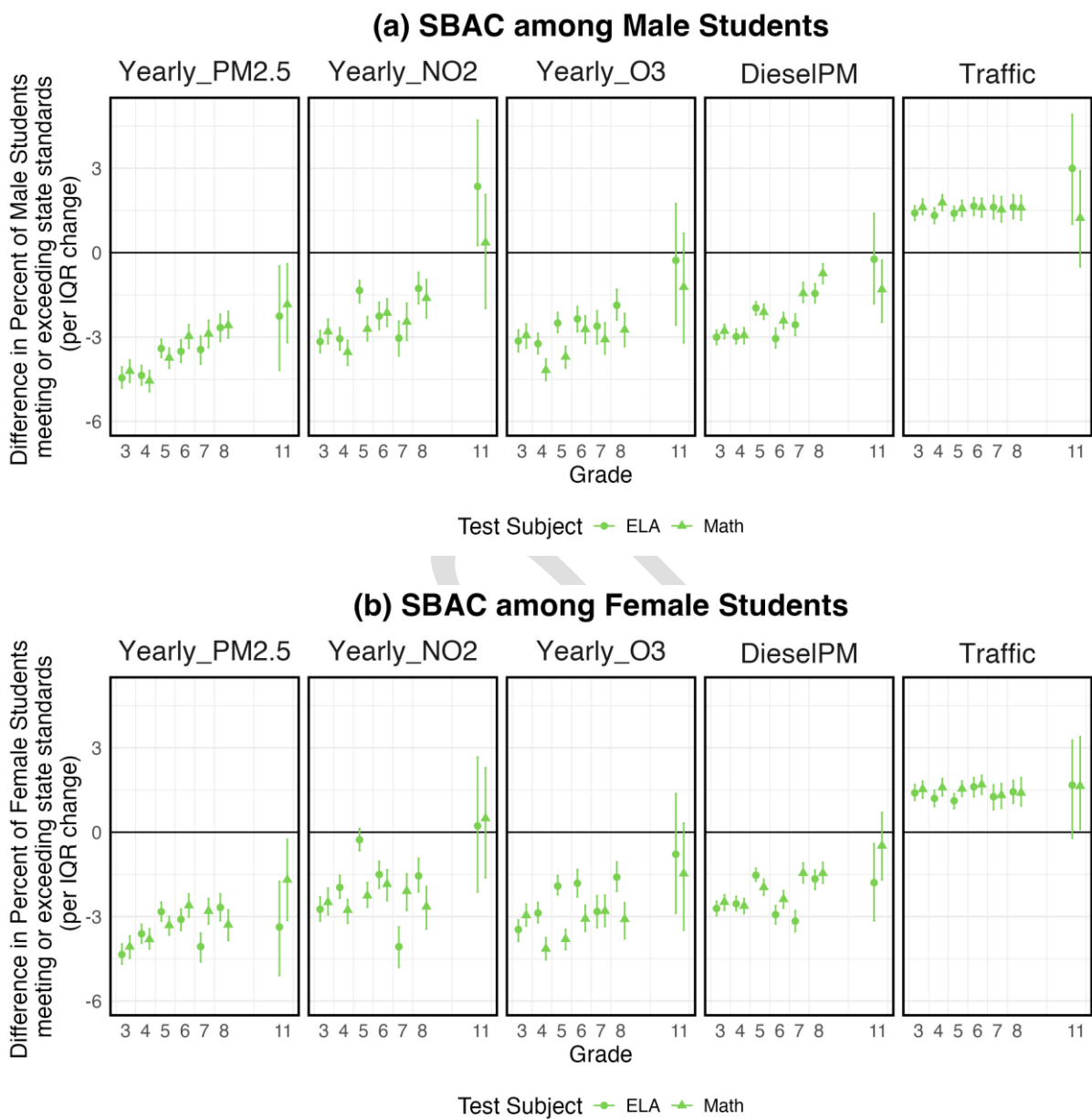
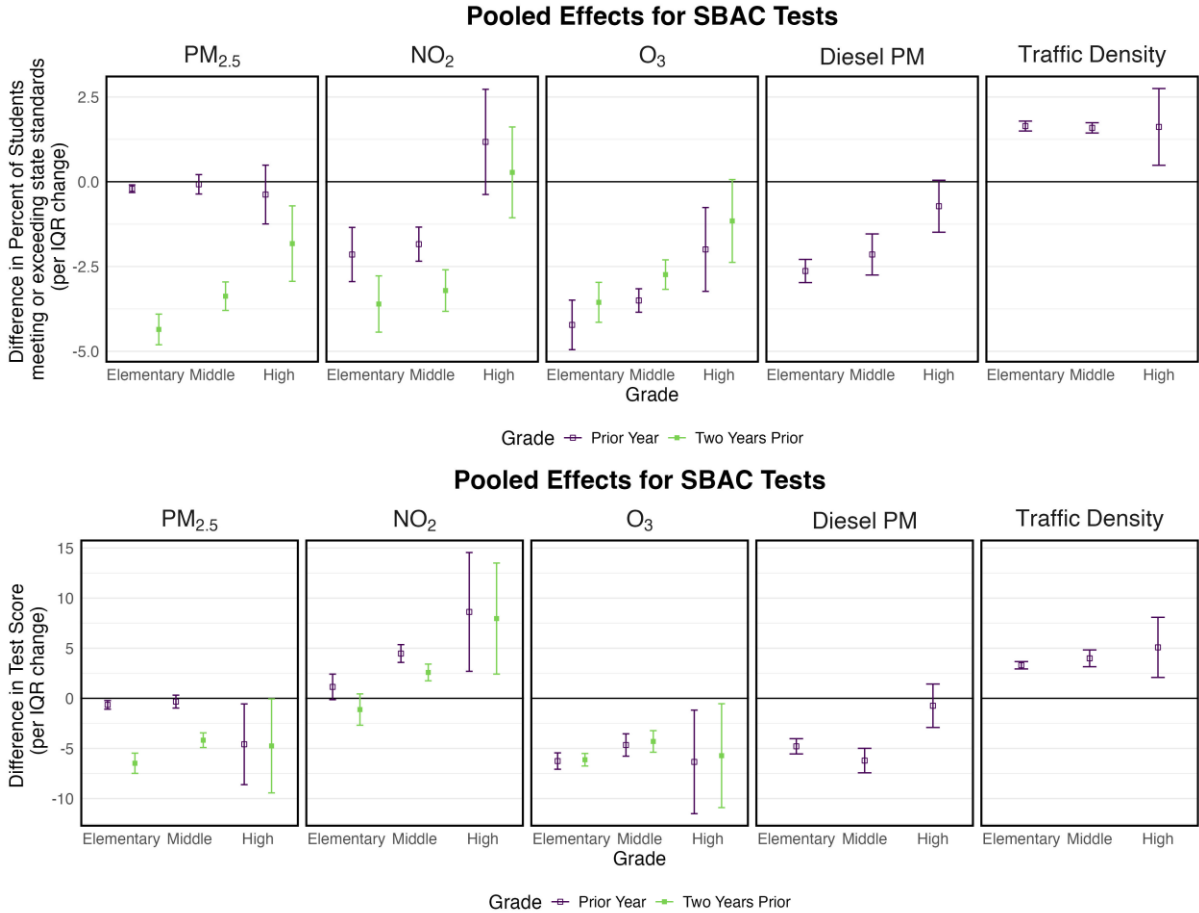
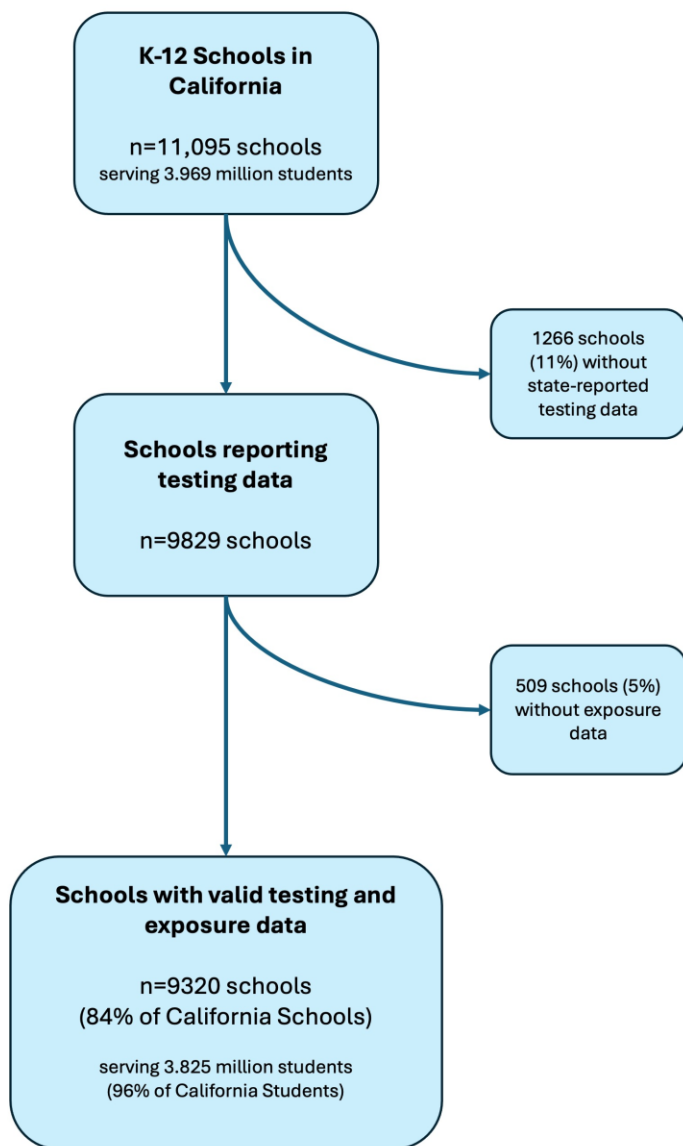


Figure. B3 Plots showing pooled effects for exposure to air pollutants on percent meeting standards for the Smarter Balanced Assessment Consortium Test at each school level. These have been pooled across grades and subjects using a random effects meta-analysis.



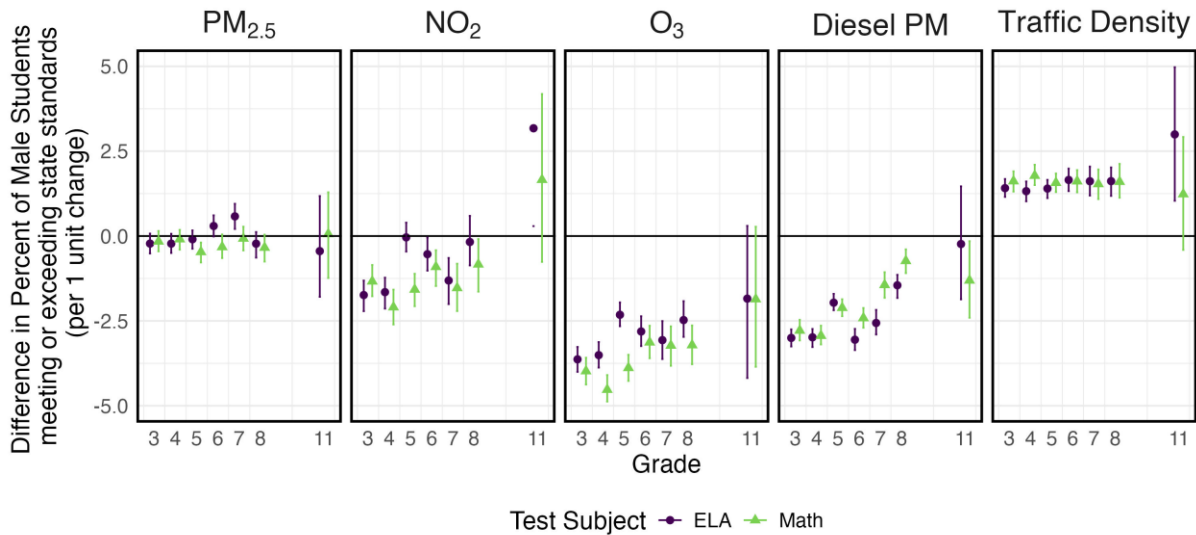
Supplementary Tables and Figures

Supplementary Figure S.B1. Flowchart diagramming included schools

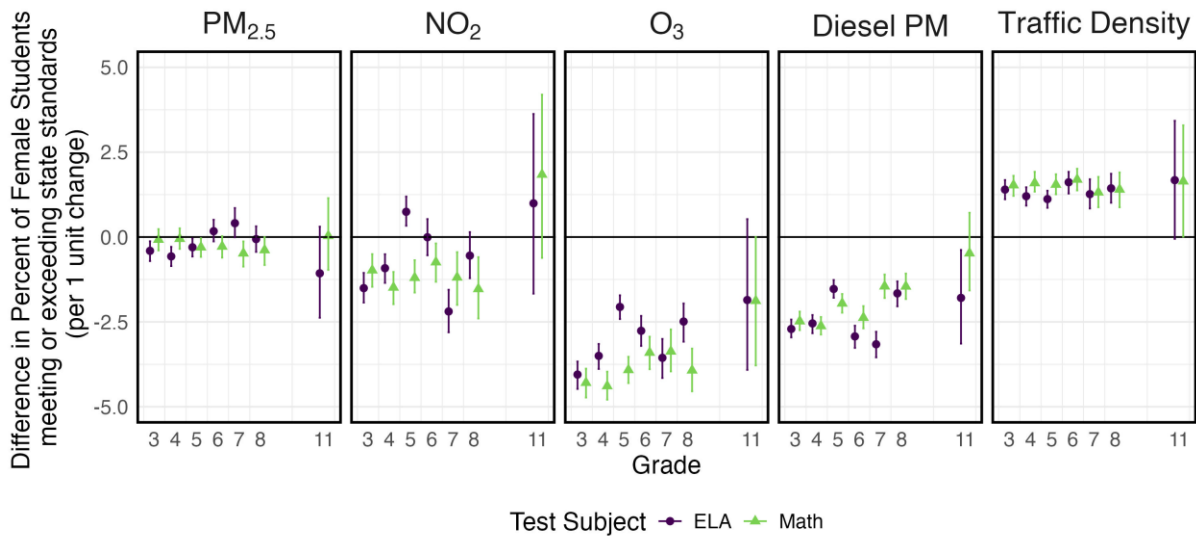


Supplementary Figure S.B2. Main results stratified by reported student sex, prior year exposures

(a) SBAC among Male Students

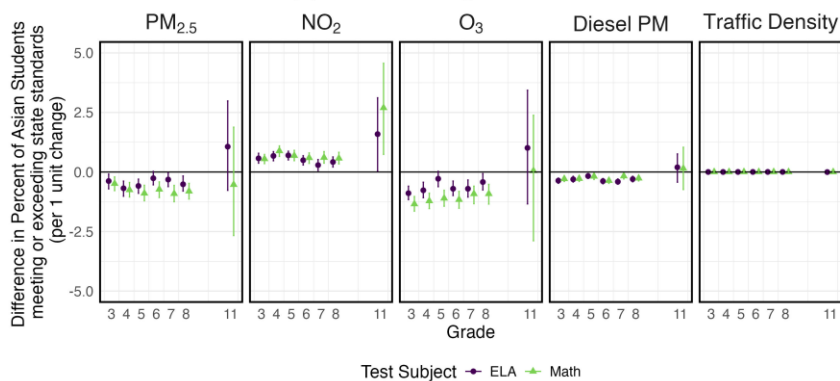


(b) SBAC among Female Students

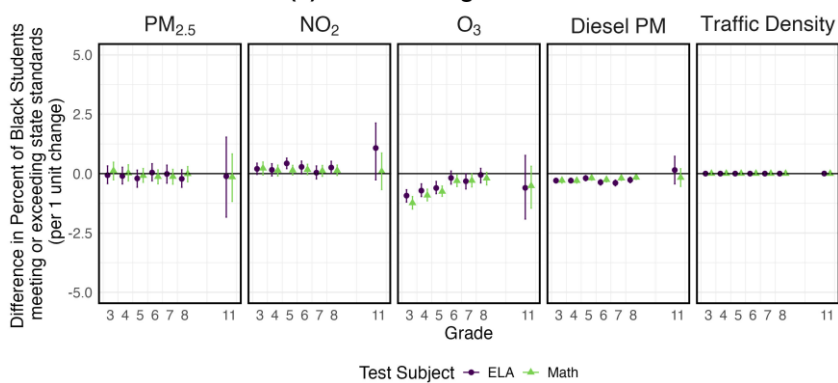


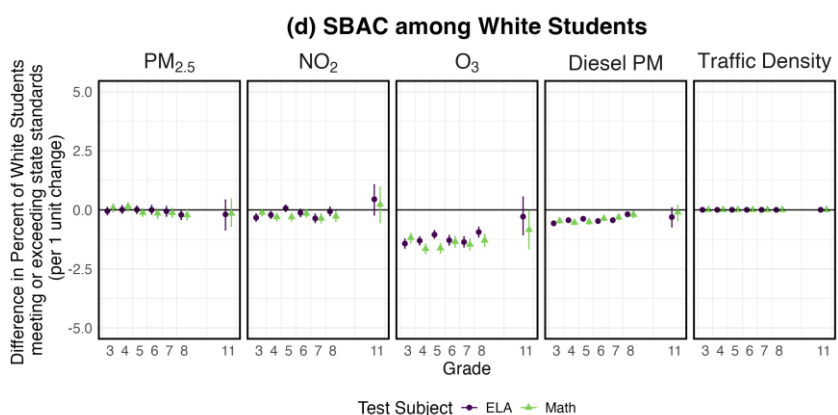
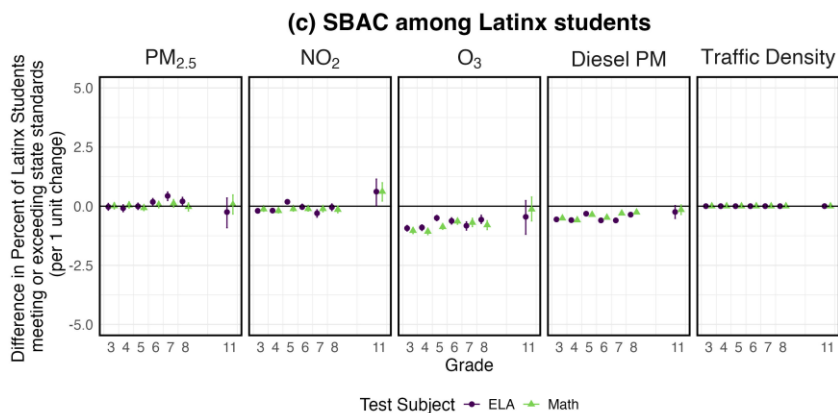
Supplementary Figure S.B3. Main results stratified by reported student race/ethnicity, prior year exposures *(sample sizes among these analyses are very different. See Table S4)*

(a) SBAC among Asian Students

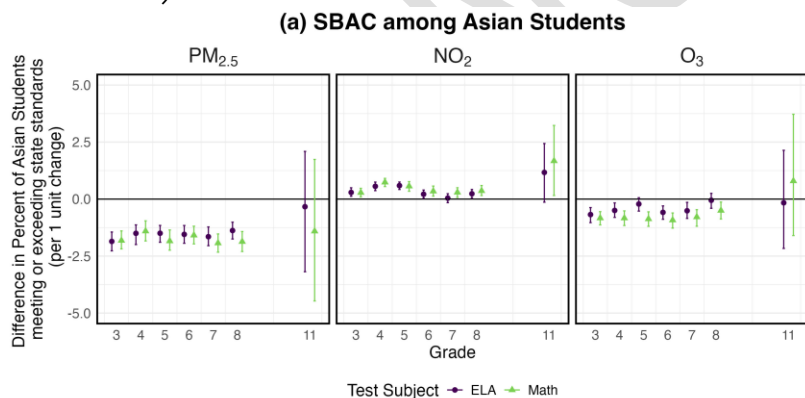


(b) SBAC among Black Students

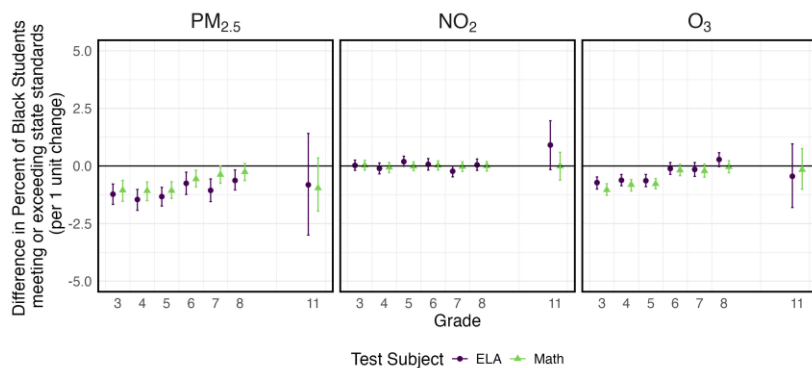




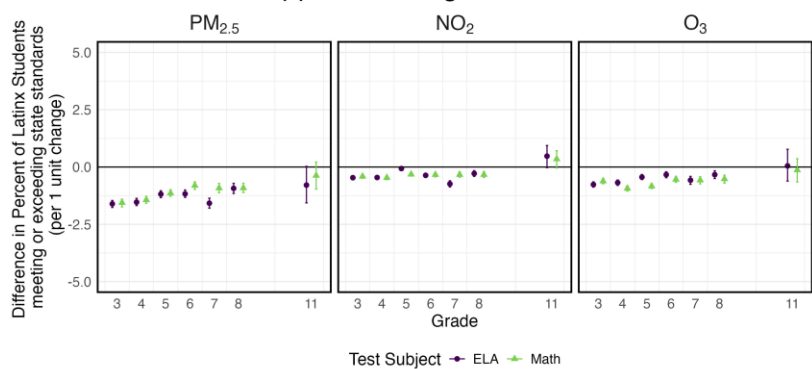
Supplementary Figure S.B4. Main results stratified by reported student race/ethnicity, two years prior exposures (*sample sizes among these analyses are very different. See Table S.B4*)



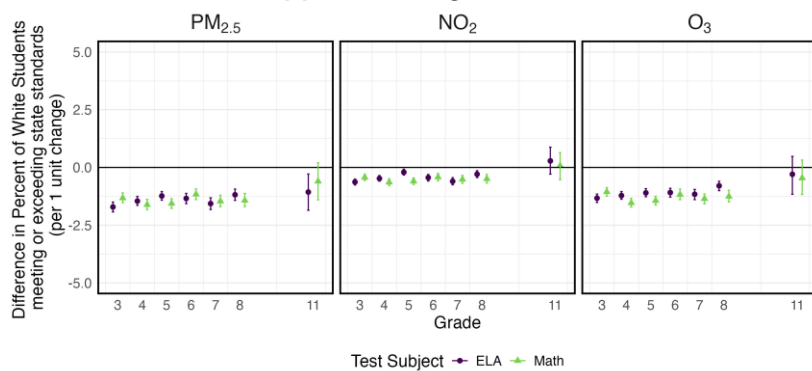
(b) SBAC among Black Students



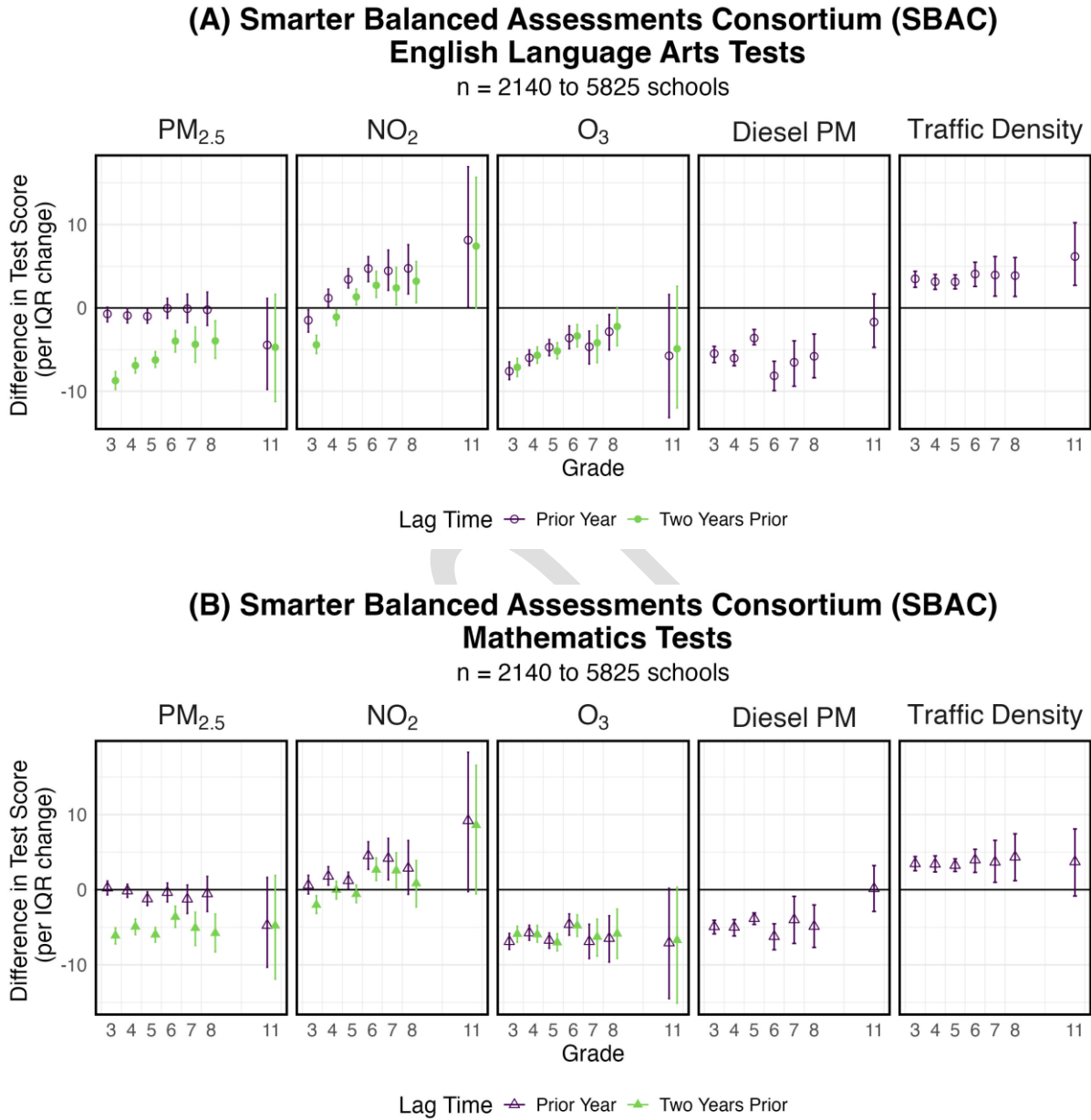
(c) SBAC among Latinx students



(d) SBAC among White Students



Supplementary Figure S.B5. Main results using mean scaled test score, rather than percentage of students meeting the state standards.



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Appendix C: Research Paper: Characterizing the Relationship Between Air Pollution and Childhood Cognition in the Children's Health and Air Pollution Study

Note: this paper has already been published and is available here:

Loomis S, Lutzker L, Holland M, Tyner T, Katharine Hammond S, Balmes J, Su J, Noth E, Holm S. Characterizing the relationship between air pollution and childhood cognition in the Children's health and air pollution study. Environ Res. 2026 Aug 1;302:124590. doi: 10.1016/j.envres.2026.124590. Epub 2026 Apr 30. PMID: 42069109.

DO NOT COPY

Abstract

Air pollution has been linked to impaired cognitive outcomes and lower academic performance in children. The Children's Health and Air Pollution Study (CHAPS) is a longitudinal cohort study following children who live in the Fresno metropolitan area of California, where air pollution is notoriously high. In this study, we investigated the relationship between three high-priority air pollutants ($PM_{2.5}$, NO_2 , and O_3) modeled using sophisticated land use regression models and multiple years of standardized test scores from children in the CHAPS cohort. We analyzed data from 97 children who had reported at least three years of standardized testing between 2015 and 2022. To model the relationship between pollution and testing performance over multiple time points, we ran six mixed effects linear regression models differentiated by pollutant ($PM_{2.5}$, NO_2 , and O_3), and standardized tests (English Language Arts or math). Math standardized test scores were negatively associated with O_3 and $PM_{2.5}$, but not NO_2 . A one part per billion (ppb) increase in O_3 was associated with a -0.078 (95% CI: -0.145 to -0.010) standard deviation decrease in test scores and a one microgram per meter cubed ($\mu g/m^3$) increase in $PM_{2.5}$ was associated with a -0.074 standard deviation decrease in test score (95% CI: -0.120 to -0.032). There was also a weak negative association between English Language Arts and both O_3 and $PM_{2.5}$, however, the confidence intervals for these associations overlapped the null. This association between air pollutant exposure at home and school and student standardized test scores emphasizes the neurocognitive impact of air pollution on a measure available for nearly all California children.

Keywords: Air Pollution, Academic achievement, Standardized test scores, Children

Introduction

Air pollution is a widespread but modifiable hazard, making it a critical target for public health interventions. Historically, most epidemiological studies on air pollution have focused on physical health. However, emerging evidence in the past 20 years suggests a critical role for air pollution in cognitive health.^{36,50,59} Exposure to high levels of air pollution are associated with cognitive dysfunction in children and with neurodegenerative disorders such as Alzheimer's in adults.⁶⁰ In 2015, a group of scientists and medical experts - concerned about rising rates of neurocognitive delays - issued a call to action to reduce toxic chemical exposures in children.⁶¹ These guidelines noted the importance of regulating traffic-related air pollutants: specifically nitrogen dioxide (NO₂) and particulate matter with an aerodynamic diameter less than 2.5 micrometers (PM_{2.5}). Reducing air pollution exposures in children is particularly important because children undergo rapid brain development, spend more time outside, and breathe more air per unit body mass compared to adults.⁶² Furthermore, cognitive delays in childhood can impact a child's life trajectory - a one-unit increase in intelligence quotient (IQ) measured in childhood is associated with a 1 percent increase in adult earnings.¹⁶ In order to create targeted interventions, it is essential to parse out the effects of different pollutants on cognition, considering the timing, length and modes of exposure.

For comparing the effects of different pollutants on childhood cognition, standardized test results are widely available and are consistent across geography and time. Thus, they have high external validity. Further, they are highly correlated with cognitive abilities and are predictive of later life career outcomes.^{63,64} While there are a number of benefits to using standardized tests in research, standardized tests arise from institutionally racist practices and, as a result, racial gaps persist in standardized test performance independent of cognitive abilities.⁶⁵⁻⁶⁷ Despite this known limitation, the present analysis will utilize standardized test performance from this cohort to parallel a statewide ecological analysis also being conducted by our research group. The following sections briefly review the literature on the relationship between NO₂, ozone (O₃), and PM_{2.5}, and academic performance in children.

All three pollutants have been negatively associated with childhood cognition in some capacity; however, specific results vary depending on the type of exposure assessment, population, and measure of cognition. In one ecological analysis in the US, both reading and math scores were negatively associated with higher NO₂ and PM_{2.5} concentrations at schools, but only math scores were negatively associated with higher O₃ concentrations.⁶⁸ At the individual level, cumulative O₃ and PM_{2.5} exposures were negatively associated with math and reading standardized test scores in 3rd grade students.⁴⁴ Larger scale studies have found negative associations between O₃ and PM_{2.5} exposures and grade point average in 9th graders in Denmark,⁶⁹ and annual O₃ exposure and exam performance in high school students in Brazil.⁷⁰ On the other hand, multiple studies in Europe found no association between NO₂ exposure^{6,71,72} and cognitive functioning, nor between short-term O₃ or PM_{2.5} exposure and standardized test performance.^{48,73} Study conclusions are highly impacted by

the type of exposure assessment and the geographical region in question, making it important to study the relationship between pollutants and cognitive outcomes among specific, vulnerable populations.

To understand the impact of NO₂, O₃, and PM_{2.5} exposures on academic performance in a highly exposed population, this study analyzes the relationship between all three pollutants and standardized test performance in the Children's Health and Air Pollution Study (CHAPS) cohort. For a decade, CHAPS researchers have been following a cohort of mostly low-income children of color from Fresno in the San Joaquin Valley (SJV) of California to characterize the local pollution exposures using high-resolution land use regression models and to research the effects of air pollution on children's health. Fresno has some of the worst air pollution in the United States and consistently fails to meet U.S. Environmental Protection Agency health standards for O₃ and PM_{2.5}.³ Fresno also has fewer students meeting grade-level math and science standards compared to the rest of California.⁷⁴

Differing methods of exposure assessment and confounding control have led to variability in conclusions from previous studies considering the effects of NO₂, O₃, and PM_{2.5} exposure on standardized test performance. While several studies have looked at air pollution exposures and standardized test performance, few have been conducted at the individual level, and only a few have quantified exposures at both the school and the home.^{73,48,75,76} Of the studies that estimated both school and home exposures, only one uses a land use regression model of high spatiotemporal resolution.⁴⁸ The high burden of exposure, the poor academic outcomes in the SJV, and the availability of this highly-resolved, individual-level data on test scores, make the CHAPS cohort important for leveraging to assess how NO₂, O₃, and PM_{2.5} exposures are affecting children's academic performance. We hypothesized that all three pollutants would be negatively associated with both ELA and math standardized test scores.

Materials and Methods

Study population and recruitment

Participants in the CHAPS cohort were recruited from first and second grade classes in Fresno and Clovis public schools between 2015 and 2016 (n = 299, ages 6-8). They were seen for follow-up between 2017 and 2019 with a 73 percent retention rate (n = 218, ages 8 - 10). Standardized test performance was assessed under the CHAPS Standardized Assessments, Attention and Cognition in California Kids (CHAPS-STACK) protocol at either the third (ages 12-15, 2021-2023) or fourth (ages 13-17, 2023-2025) study visit. In total, 129 participants were seen for a CHAPS-STACK visit (Supplemental Figure S.C1). At recruitment, the cohort was 80 percent Latinx, 11 percent Black, and predominantly low income. The CHAPS project is approved by the University of California Berkeley Institutional Review Board. Written informed consent and permission was received from each accompanying parent and written assent was received from all children.

Air Pollution Modeling

In brief, daily concentrations of NO₂, O₃, and PM_{2.5} between 2012 and 2022 (the last year of testing data) were modeled using a high-resolution land use regression model.^{77,78} Daily pollutant concentrations were modeled at a 100-meter resolution using a single model framework machine learning algorithm to adjust for factors such as land use, surface type, and vehicular density.^{41,77} Pollutant measurements were extracted from mobile monitoring sources, government monitoring sites, and fixed-site saturation monitoring. Pollutant measurements were combined with data on daily traffic density, meteorological conditions, and multiple types of land-use (vegetation, impervious surfaces, etc.) to model daily pollution concentrations across the state of California using a v-fold, out-of-sample, cross-validation machine learning algorithm.

Exposure Assignment

At the first study visit, the child's parent or guardian reported residential and school histories from the child's birth through the current residence. At subsequent visits, residential and school histories were reported from the last reported residence and school through the current residence and school, with additional review and collection for missing data (Supplemental Figure S.C1). Thus, a lifetime residential history was compiled for each participant, cataloguing all prior places of residence and their corresponding dates. Parent-reported residential and publicly-available school addresses were geocoded using the ArcGIS World Geocoder from the ArcGIS Esri Software.⁷⁹ Location data were merged with the temporally and spatially resolved air pollution data to create a lifetime exposure history for each participant. To create individual, daily (24-hour) average exposures from 24-hour concentrations at each location, residential and school concentrations were weighted by the hours a participant was assumed to be in school for each exposure day (8 hours a day for weekdays during the school year, 0 hours a day for weekends, holidays, and breaks). Finally, we aggregated daily averages to annual averages (January - December) for each year of pollutant exposure. Exact testing dates were unavailable but occurred in the spring of each school year. Thus, annual averages in the year prior to standardized testing were used as the exposures in the final model, to ensure the appropriate temporality of exposures prior to the outcome measure.

Covariate Measurements

Child-specific covariates used in this analysis were collected at the child's first and second study visits. At both visits, the child's parent or guardian was interviewed using an in-depth questionnaire offered in either English or Spanish. At the first study visit, the interview assessed demographic characteristics about the child including gender, age, and race. Age was incorporated into the model as age at third grade, to account for age differences among participants without introducing potential collinearity into the model. Race was not included in the statistical model (as a proxy of institutional racism) as there was little variability in the race variable itself, and the race variable was highly collinear with the

interview language variable. Furthermore, based on our *a priori* directed acyclic graph, confounding by race was accounted for by an adjustment of language. At both visits, parents or guardians were asked about their household income, their home ownership status, their income needs, and their education. Reported household incomes were categorized into “above the poverty line” or “below the poverty line” based on the nationwide poverty line for an average household in 2015 (\$24,250). Home ownership was categorized into “Rent”, “Own”, “Other arrangements”, “Don’t know” or “Refused”. Income needs was a subjective measurement of how well the family’s income met their needs and was categorized as “More than enough”, “Just enough”, “Not enough”, “Don’t know”, “Refused”. Maternal education was reported and categorized in the model as follows: “less than 8th grade”, “some high school”, “high school or GED”, “some college”, “complete college”, “advanced degree”. Parents or guardians were further interviewed about smoking in the child’s home, and whether the child lived with a smoker was categorized as “yes” or “no”.

Census tract neighborhood income values were extracted from the 5-year American Community Survey collected between 2010 and 2014, so as to use the data from immediately prior to the testing interval.⁸⁰ Median neighborhood incomes were classified into “above the poverty line” or “below the poverty line” based on the poverty line for an average household in 2015. Census tract park access and tree canopy were extracted from the California Healthy Places Index (HPI).⁸¹ Park access is defined by the HPI as the percent in decimal form of people in a neighborhood within half a mile of a park, beach or open space. Tree canopy is classified by the HPI as the percent in decimal form of tree canopy in a neighborhood. Both park access and tree canopy were modeled as continuous variables. Neighborhood income, park access as a metric of greenspace, and tree canopy were spatially merged to the address reported for each child in the year before their standardized test date, and averages were calculated based on the address(es) at which the child lived.

Outcome measurement

In 2015, California began using an updated form of statewide standardized testing for English Language Arts (ELA) and math called the Smarter Balanced Assessments (SBAC).⁸² The SBAC tests are administered in 3rd - 8th grade and in 11th grade. Testing is done in the spring semester of every school year, although the exact test dates are not publicly available for each school. This analysis focuses on tests administered between 2015 and 2022 (and reported to our team during their 3rd or 4th study visits): from the start of SBAC testing to the end of the available exposure data. For the state of California, SBAC scores for 3rd - 8th graders range from 2114 - 2769 for ELA and 2189 - 2802 for math with higher scores indicating better performance.⁸³ Scores at the statewide level fluctuate slightly by year and grade based on the test characteristics and statewide period effects (such as COVID-19) in a given year. To adjust for these differences, we standardized the test scores in our sample to z-scores using the statewide averages and standard deviations for a given grade and year.

Test data were collected for all participants at the time of their CHAPS-STACK study visit. Test scores were available to parents in online school district portals. Test scores were extracted from these portals (with assistance by study staff) at the time of the visit, rather than requiring recall by the parent or participant during reporting.

Statistical Analysis

Descriptive statistics were calculated using R Version 4.4.0. All analyses were prespecified in a detailed statistical analysis plan (SAP) available on Open Science Framework. Changes to the analysis plan were updated prior to performing additional analyses ([SAP](https://osf.io/d9yhj/overview?view_only=922f5d9afb8845e296c270ba0646958b), URL: https://osf.io/d9yhj/overview?view_only=922f5d9afb8845e296c270ba0646958b)

We applied a time-nested, mixed effects linear model to quantify the relationship between air pollution and individual-level standardized test performance over multiple years in the CHAPS cohort. We restricted the main analysis to individuals with three years of standardized testing to balance maximizing both our sample size and the number of tests available for each participant. For each participant in the study, we used a random intercept to account for non-independence of test scores over repeated years of testing. Air pollution concentrations were modeled as time varying exposure. All other model variables were treated as fixed effects and were measured at baseline.

In our primary model we selected covariates a priori based on domain knowledge with the aid of a directed acyclic graph (see the SAP, linked above). Covariates selected included potential confounders related to both the exposure and the outcome as well as variables thought to be highly correlated with the outcome only.⁸⁴ We ran six different mixed effects models differentiated by pollutant (NO₂, O₃, or PM_{2.5}) and test subject (ELA or math). Our primary models were adjusted for school district, income level, interview language, living with a smoker, park access, neighborhood income, and age at 3rd grade as shown in the equation below:

(1)

$$y_{ij} \text{ (test z-score)} = \beta_0 + \beta_1(\text{pollution}) + \beta_2(\text{household income}) + \beta_3(\text{smoking in home}) + \beta_4(\text{school district}) + \beta_5(\text{language}) + \beta_6(\text{age}) + \beta_7(\text{neighborhood income}) + \beta_8(\text{neighborhood park access}) + u_i(\text{random intercept})$$

For each model, we calculated point estimates and bootstrapped confidence intervals using the lme4 package in R designed for linear mixed model estimations.⁸⁵

Sensitivity Analyses

We ran multiple sensitivity analyses to assess the robustness of our results to changes in exposure assessments, years of testing modeled, and covariate selection. In sensitivity analysis 1, we ran our mixed effects model over only two years of testing, and over four years of testing to determine the impact of years of testing on our results. In sensitivity analysis 2, we included an adjustment for the testing year in our model to determine the likelihood of residual confounding by year in our model. In sensitivity analysis 3, we assessed the impacts of using school only or residential only exposures on our results. In Sensitivity analysis 4, we ran multiple versions of our model to assess how susceptible our results were to changes in our covariate adjustments. To assess the sensitivity of our results to using the household income variable as a marker of socioeconomic status, we adjusted one by one for maternal education, home ownership, and income needs. We also performed a sensitivity analysis to assess tree canopy as measured by the Healthy Places Index as an indicator of neighborhood greenspace compared to park access. Finally, in sensitivity analysis 5, we analyzed whether or not the results of our single pollutant models changed with adjustment for either of the other pollutants (for example adjusting for O₃ or PM_{2.5} in our NO₂ exposure model).

Finally, we assessed the potential risk of bias due to loss to follow-up by comparing the exposure and covariate distributions of individuals lost between study visit 2 and their CHAPS-STACK visit where standardized test scores were collected, individuals not included in the analysis due to missing standardized test scores or covariates, and individuals included in our analysis (Supplemental Figure 3.1). We restricted the exposure analysis to before 2018, as we did not have exposure information on individuals who were lost to follow-up after 2018.

Results

Of the 129 participants seen for a CHAPS-STACK visit, 107 (83.0 %) reported at least one year of standardized testing, 105 (81.4 %) reported at least two years of testing, and 100 (77.5 %) reported at least three years of testing. The remaining 22 (17.1 %) participants reported no testing because they either took an alternative form of the test or attended schools that did not perform standardized testing. Three individuals did not have complete covariate data and were excluded from the analysis. The final sample size in this analysis was 97 individuals who reported three or more years of standardized testing and had complete data on study covariates (Supplemental Figure S.C1). Average annual air pollution concentrations were 14.08 µg/m³ for PM_{2.5}, 8.70 ppb for NO₂, and 41.24 ppb for O₃ (Table C2). Forty-nine (50.5 %) participants had a household income below the poverty line, and 37 (38.1 %) participants lived in a neighborhood where the median household income was below the poverty line. The majority of study participants self-identified as Hispanic (89.7 %), and roughly one third of participants (35.1 %) preferred Spanish as an interview language compared to English (Table C1).

Mean test scores for ELA ranged from 2411 (standard deviation (SD) = 83.6) in 3rd grade to 2478 (SD = 90.3) in 5th grade corresponding to a z-score of -0.105 and -0.241 below the statewide average respectively. Mean math test scores ranged from 2424 (SD = 68.4) in 3rd grade to 2484 (SD = 76.8) in 5th graders, corresponding to a z-score of -0.048 and -0.122 below the statewide average respectively. Raw scores on these standardized tests in the CHAPS cohort were consistently lower than statewide averages, though like the statewide scores, they increased slightly from 3rd grade to 5th grade (Table C3).

Math standardized test scores were negatively associated with O_3 and $PM_{2.5}$, but not NO_2 exposures. A one ppb increase in O_3 was associated with a -0.078 (95% CI: -0.145, -0.010) standard deviation decrease in test scores and a one $\mu g/m^3$ increase in $PM_{2.5}$ was associated with a -0.074 standard deviation decrease in test score (95% CI: -0.120, -0.032). These correspond to approximately a -7.8 and -7.4 point decrease in raw test scores respectively. There was a weak negative association between ELA and both O_3 and $PM_{2.5}$ exposures, however, the confidence intervals for these associations overlapped the null (Figure 3.1).

Sensitivity Analyses

A sensitivity analysis examining different numbers of testing years showed the relationships between math test scores and pollutant exposures were the same but stronger when modeled over four years of testing, and the same but weaker when modeled over two years of testing. As expected, confidence intervals in the two-year model were larger compared to the three year model because there were fewer points to use to account for within-individual variability. The relationship between pollutant exposures and ELA test scores was slightly more susceptible to changes in the number of years modeled compared to those looking at math test scores, but all associations remained null (Figure 3.2).

Standardization of the test scores using yearly mean and standard deviations should eliminate a relationship between which year a child was tested and their outcome score. To evaluate our assumption that standardizing to the statewide average eliminates the relationship between year and test scores, we chose to adjust for the test year in a sensitivity analysis. After including an adjustment for the testing year, we saw similar patterns for O_3 and NO_2 , but not $PM_{2.5}$. The adjustment for the testing year greatly increased the variability in estimates, and the confidence intervals for all estimates overlapped with zero (Supplemental Figure S.C2).

The results were generally robust to changes in the parameterization of the exposure and covariates. A sensitivity analysis for the type of exposure assessment revealed nearly identical model outputs when using residential only exposure, but somewhat different results when using school only exposures (Supplemental Figure S.C3). For example, the negative relationship between O_3 exposure and math scores seen in the main model (adjusting for residence and school) was essentially zero when only adjusting for school. Sensitivity analyses for covariates did not change the results of the main model (Supplemental Figure S.C4). Finally, sensitivity analyses for the strength of our single

pollutant models to other pollutant adjustments were robust, only our conclusions for the O₃ exposure model when adjusted for PM_{2.5} differed from the main analysis. The negative relationship between O₃ and math scores becomes null when adjusted for PM_{2.5} (Supplemental Figure S.C5).

Finally, the exposure distributions for participants lost to follow-up prior to a CHAPS-STACK visit (N = 95), individuals with CHAPS-STACK visits who were excluded from our analysis (N = 31) and individuals who were included in the analysis (N = 97) did not differ substantially between any pollutants (Supplemental Table S.C1). However, covariates – household income and race in particular – differed between groups. The Loss to Follow-up group had a higher proportion of participants below the poverty line (72.6%) and a higher proportion of Black participants (12.6 %) while the Not Analyzed group had a lower proportion of participants below the poverty line (41.9 %) and higher proportion of Black participants (12.9%) compared to the Analyzed group (50.5 % below the poverty line, 1 % Black).

Discussion

In the present study, we examined the association between three criteria air pollutants and standardized test performance in the CHAPS cohort. In our fully adjusted models, we found that PM_{2.5} concentrations were associated with small but detectable decreases in math standardized test scores. A sensitivity analysis adjusting for the number of testing years included in our model revealed that including four years in the model (as opposed to three years) marginally strengthened the associations between O₃ and PM_{2.5} concentrations and math scores, while including only two years in the model weakened the associations and increased the variability in the estimator. In the main analysis, there were also weak negative correlations between O₃ and PM_{2.5} concentrations and ELA test scores, but the 95% confidence intervals for these associations overlapped the null.

The results of this analysis suggest that exposure to certain pollutants may decrease math test scores, and to a lesser extent reading test scores. Previous research found that both annual school-level O₃ concentrations and annual individual-level O₃ exposure were negatively associated with math scores but not English test scores.^{44,68} There is perhaps more evidence that pollutants are negatively associated with both math and reading scores. For example, cumulative O₃ and PM_{2.5} exposures were negatively associated with math and reading standardized test scores in 3rd grade students, PM_{2.5} exposure was negatively associated with math and ELA test scores in sixth graders, and NO₂ exposure was negatively associated with all standardized test scores in high schoolers.^{44,48,86} This suggests that an association between pollutants and ELA scores may be present but too weak to detect with the current analysis. Indeed, our analysis was performed in a cohort where *all students* are experiencing high concentrations of air pollution exposure compared to the general population. Therefore, even small associations seen in this analysis could indicate much larger associations when comparing this high exposure population to a low exposure population. We also found that including more years of test scores in our analyses

strengthened the observed associations, while including fewer years of test scores weakened the associations. This suggests that there may be a stronger association between longer term exposure and test performance in this population.

These results must be considered in light of several limitations. In this cohort, there is a high likelihood that the standardized test scores were impacted by period effects year-to-year – such as COVID-19. To account for this confounding by year, we standardized student test scores to the California statewide averages for each year and grade. We believe that this standardization accounted for variability between years, as the Fresno County averages fluctuated in a pattern consistent with the statewide averages over the course of the study period, making residual confounding by year on the standardized scores unlikely. Furthermore, variability in our estimator increased substantially with an adjustment for the testing year (Supplemental Figure S.C2). This increase in variability indicates potential collinearity between the testing year adjustment and other variables already accounted for in the model. While we remain cautious about overinterpreting our results, we believe that the robustness of our findings to sensitivity analyses suggests a true association exists between pollution and test performance in this cohort.

The CHAPS cohort has seen a significant amount of loss to follow up throughout the course of the longitudinal study, particularly during the COVID-19 pandemic. To better understand the risk of bias due to loss to follow up, we examined the exposure and covariate distributions from individuals lost to follow up, those seen at the CHAPS-STACK visit but excluded from this analysis, and included in the analysis. Overall, the exposure distributions (2014 - 2018) between groups were nearly identical. On the other hand, the covariate distributions of household income, home ownership, and maternal education did differ substantially between groups (Supplemental Table S.C1). Despite the differences in covariate distributions, the similar exposure distributions between groups give us moderate confidence that the loss to follow up was not related to exposure status. Therefore, bias due to loss to follow up would likely be, if anything, non-differential, and therefore bias our results towards the null.

This is one of the few studies on air pollution and academic performance conducted using a well-characterized longitudinal cohort. Many other studies in the field use cross-sectional analyses or are performed at the ecological level. In addition, the limited range of SES among the participants in this cohort decreases the risk of residual confounding of the relationship by SES. CHAPS researchers have also collected biomarkers of cognition as well as a battery of neurocognitive tests in this cohort. Therefore, upcoming CHAPS analyses will be able to compare the standardized test outcomes with more in-depth assessments of cognition. The CHAPS Cohort Study is also one of the only cohort studies to assess air pollution exposures at both the school and the home, and our sensitivity analysis demonstrates that using exposure just from the school or home can change study findings (Supplemental Figure S.C3). This cohort's detailed information on residential and school histories collected over a 10-year period enabled a more accurate representation of each participant's exposure histories. Furthermore, we used a high resolution land use

regression model to determine pollutant concentrations.⁷⁷ For longitudinal studies, complex models such as the one used in this analysis have a lower risk of exposure misclassification compared to other commonly used methods such as inverse distance weighting or census-tract air quality measurements.^{36,41,87} The high-resolution models as well as the inclusion of both school and home exposures decreased the risk of exposure misclassification bias in this analysis.

Conclusion

In this small, but well-characterized cohort, both O_3 and $PM_{2.5}$ exposures were negatively associated with standardized math test performance. These findings add to a growing body of evidence that air pollution exposure affects not only children's physical health but also their cognitive development. By leveraging both school and home exposures, our study uniquely captured the majority of air pollution exposures children experience daily, strengthening the case for targeted interventions. These results can inform policies that promote efforts to reduce air pollution overall and prevent new school buildings in high pollution areas. They also underscore the need for resource allocation in communities disproportionately burdened by air pollution to reduce the burden of exposure at a child's home and mitigate its impact on academic outcomes.

Table C1. Descriptive statistics of the CHAPS cohort members included in this analysis.

COHORT CHARACTERISTICS

(N = 97 STUDENTS)

AGE AT 3RD GRADE (SD)	8.29 (0.38)
NEIGHBORHOOD PARK ACCESS PERCENTILE FROM HEALTHY PLACES INDEX (SD)	0.37 (0.25)
NEIGHBORHOOD TREE CANOPY PERCENTILE FROM HEALTHY PLACES INDEX (SD)	0.42 (0.19)
HOUSEHOLD INCOME (%)	
BELOW POVERTY LINE	49 (50.5 %)
ABOVE POVERTY LINE	48 (49.5 %)
NEIGHBORHOOD INCOME (%)	
BELOW POVERTY LINE	37 (38.1 %)
ABOVE POVERTY LINE	60 (61.8 %)
INCOME NEEDS (%)	
NOT ENOUGH	17 (17.5 %)
JUST ENOUGH	76 (78.4 %)
MORE THAN NEEDED	4 (4.1 %)
HOME OWNERSHIP	
RENT / OTHER	64 (66.0 %)
OWN	33 (34.0 %)
MATERNAL EDUCATION (%)	
LESS THAN 8TH GRADE	17 (17.5 %)
	18 (18.6 %)

SOME HIGH SCHOOL	18 (18.6 %)
HIGH SCHOOL OR GED	21 (21.6 %)
SOME COLLEGE	17 (17.5 %)
COMPLETE COLLEGE	6 (6.2 %)
ADVANCED DEGREE	
GENDER	50 (51.5 %)
GIRL	47 (48.5 %)
BOY	
PREFERRED LANGUAGE (%)	34 (35.1 %)
SPANISH	63 (64.9 %)
ENGLISH	
LIVE WITH A SMOKER (%)	14 (14.4 %)
YES	83 (85.6 %)
NO	
SCHOOL DISTRICT (%)	92 (94.8 %)
FRESNO	5 (5.2 %)
OTHER	

Descriptive statistics for the 97 study participants who had three or more years of standardized testing data available. All covariates were fixed across the three years included and were extracted from data collected at the closest timepoint prior to standardized testing.

SD = Standard deviation.

Table C2. Average air pollution exposures (mean and standard deviation) for CHAPS cohort member included in the analysis (N = 97).

YEAR	NO ₂	O ₃	PM _{2.5}
Overall	8.70 (1.19)	41.24 (1.11)	14.08 (2.37)
2014	10.06 (1.09)	40.62 (0.83)	13.34 (0.57)
2015	9.58 (1.08)	42.20 (1.49)	12.84 (0.58)
2016	9.17 (0.88)	41.03 (0.40)	13.68 (0.27)
2017	8.36 (0.86)	40.39 (0.39)	12.65 (0.26)
2018	8.08 (0.87)	40.13 (0.38)	12.85 (0.28)
2019	8.73 (0.92)	41.85 (0.40)	13.84 (0.40)
2020	7.83 (0.93)	40.67 (0.40)	11.40 (0.28)
2021	8.55 (0.96)	41.90 (1.27)	19.31 (1.00)
2022	8.00 (0.98)	42.37 (0.45)	16.77 (0.63)

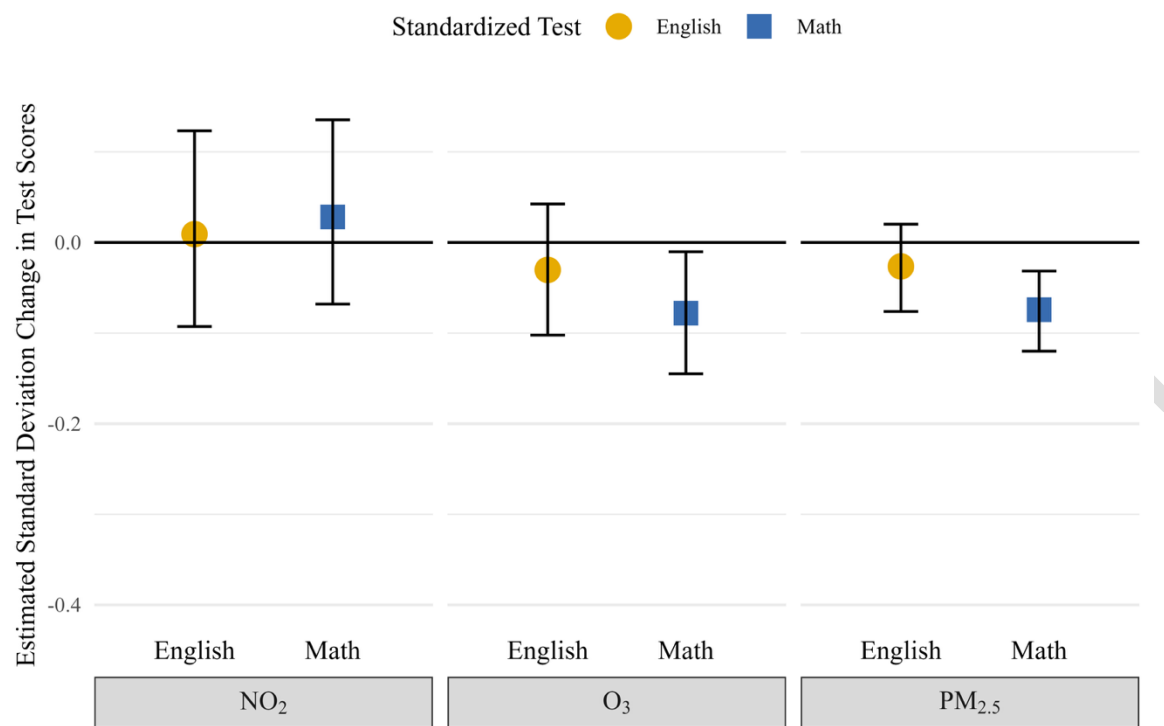
Air pollution exposures for each year of exposure available were averaged over study participants. Overall air pollution exposures were averaged over all timepoints. NO₂ and O₃ concentrations are in parts per billion. PM_{2.5} concentrations are in micrograms / meter cubed.

Table C3. Comparison of standardized test scores in the CHAPS cohort (N = 97) to the California statewide level.

GRADE	CHAPS COHORT AVERAGE	CALIFORNIA STATE AVERAGE	CHAPS SCORE	Z-
3RD GRADE				
ELA	2411 (83.6)	2418 (90.4)	-0.105	
MATH	2424 (68.4)	2428 (82.4)	-0.048	
4TH GRADE				
ELA	2457 (83.6)	2466 (96.9)	-0.075	
MATH	2462 (73.2)	2471 (86.3)	-0.082	
5TH GRADE				
ELA	2478 (90.3)	2504 (98.6)	-0.241	
MATH	2484 (76.8)	2498 (95.7)	-0.122	

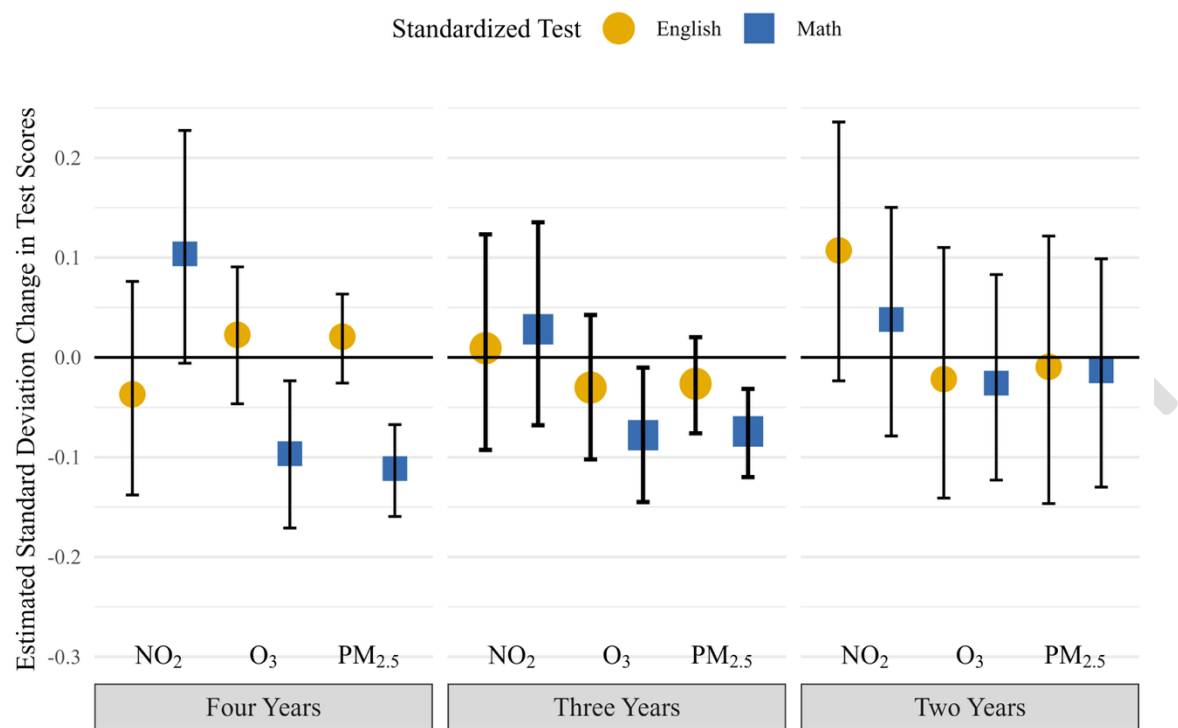
Standardized test scores in the CHAPS cohort shown here were averaged over the three most common grades of study data included in the analysis. For descriptive purposes, the California statewide averages shown here were from 2017 (3rd grade), 2018 (4th grade), and 2019 (5th grade) respectively. Z-scores were calculated based on a given grade and year and averaged over each grade in the CHAPS cohort. Additional test score averages can be found in supplemental table S.C2.

Figure C. 1. Estimated standard deviation change in test score associated with a one unit change in exposure concentration.



All models were adjusted for household income, smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, and neighborhood park access. Test scores were standardized to the statewide average for a given year and grade. Confidence intervals were calculated using bootstrapping due to a small sample size (n = 97).

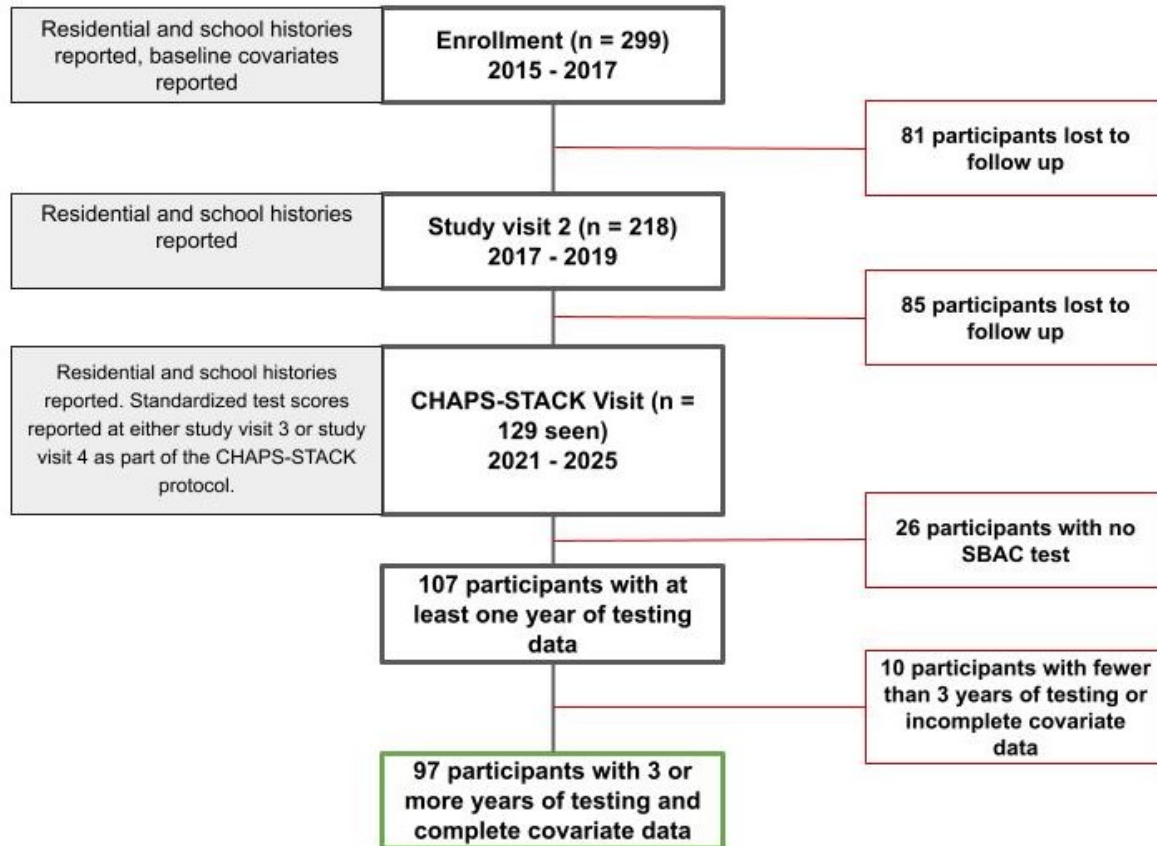
Figure C. 2. Sensitivity analysis for the number of years included in the model.



Associations between pollutants and test scores were modeled over four, three (main model) and two years of testing. As before, all models were adjusted for household income, smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, and neighborhood park access, and test scores were standardized to the statewide averages.

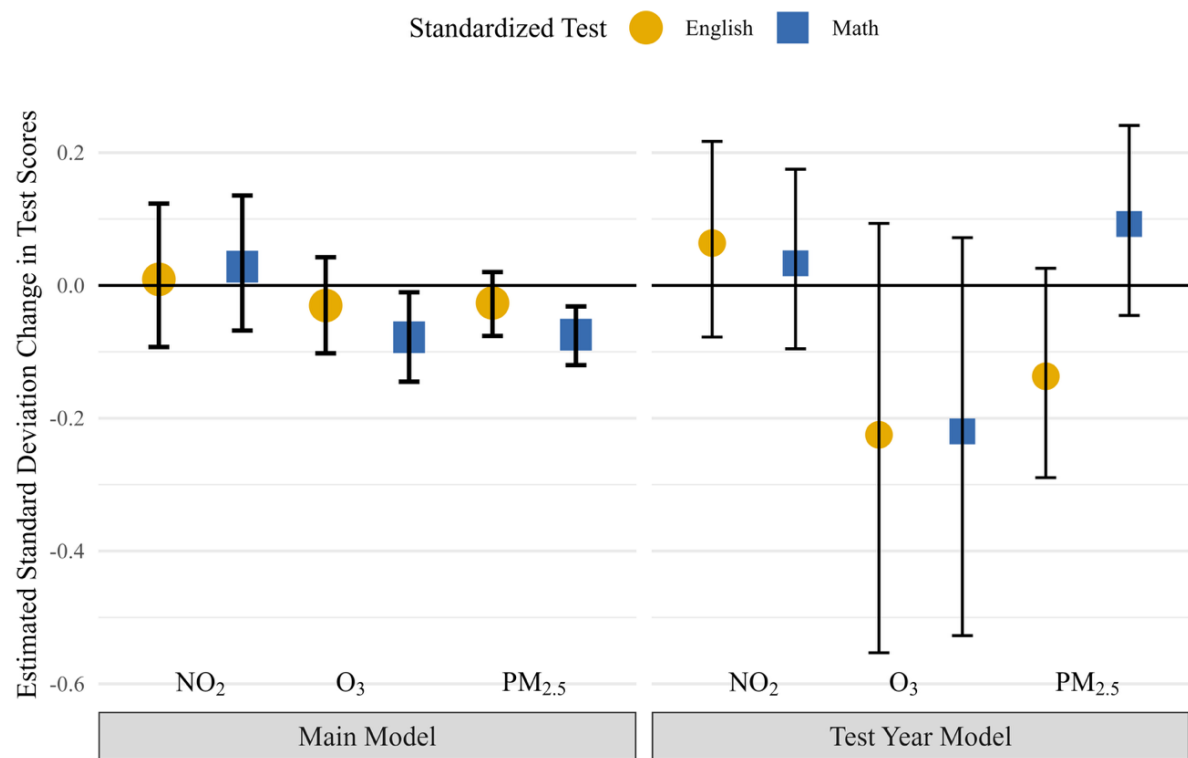
Supplementary Tables and Figures

Supplementary Figure S.C1. CHAPS Study Flowchart



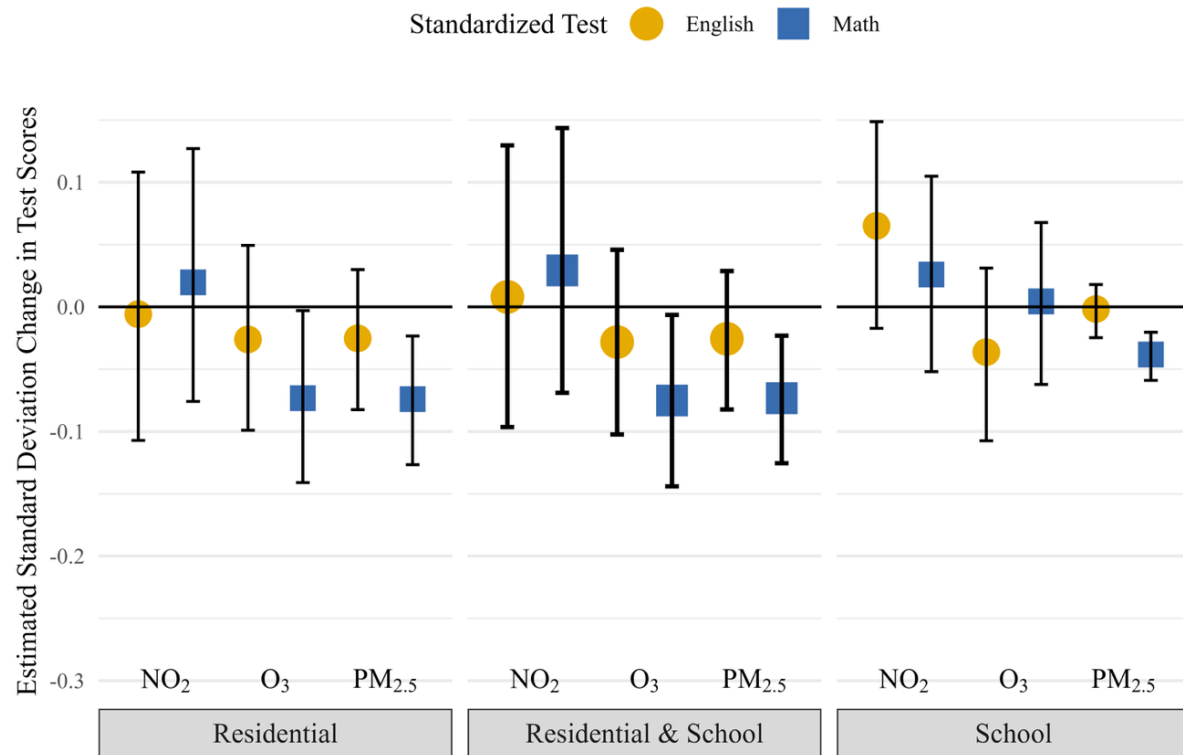
Study visit flowchart. Bolded boxes indicate enrollment numbers at each stage of CHAPS visits. Red boxes indicate individuals who are not eligible for this analysis. Grey boxes describe information collected at each visit.

Supplementary Figure S.C2. Sensitivity Analysis for the inclusion of test year



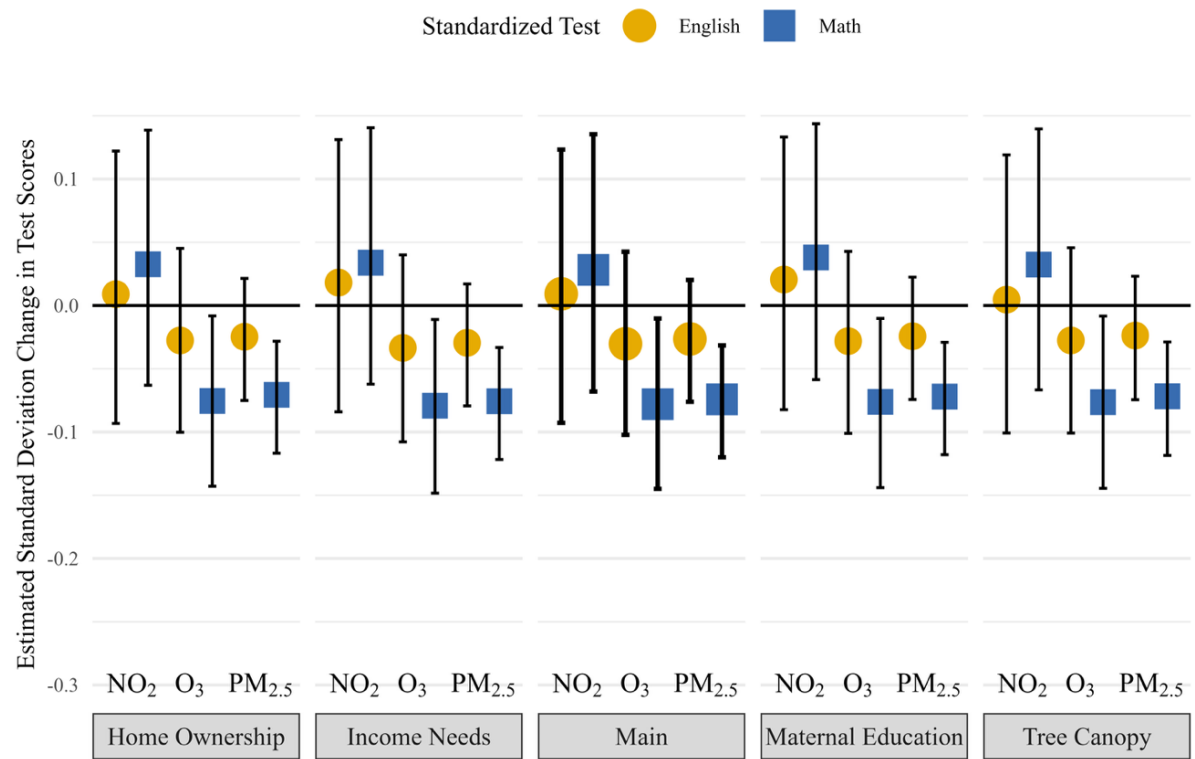
All models were adjusted for household income, smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, and neighborhood park access, and test scores were standardized to the statewide averages. The Test Year model was additionally adjusted for test year.

Supplementary Figure S.C3. Sensitivity analysis for differing methods of exposure assessment



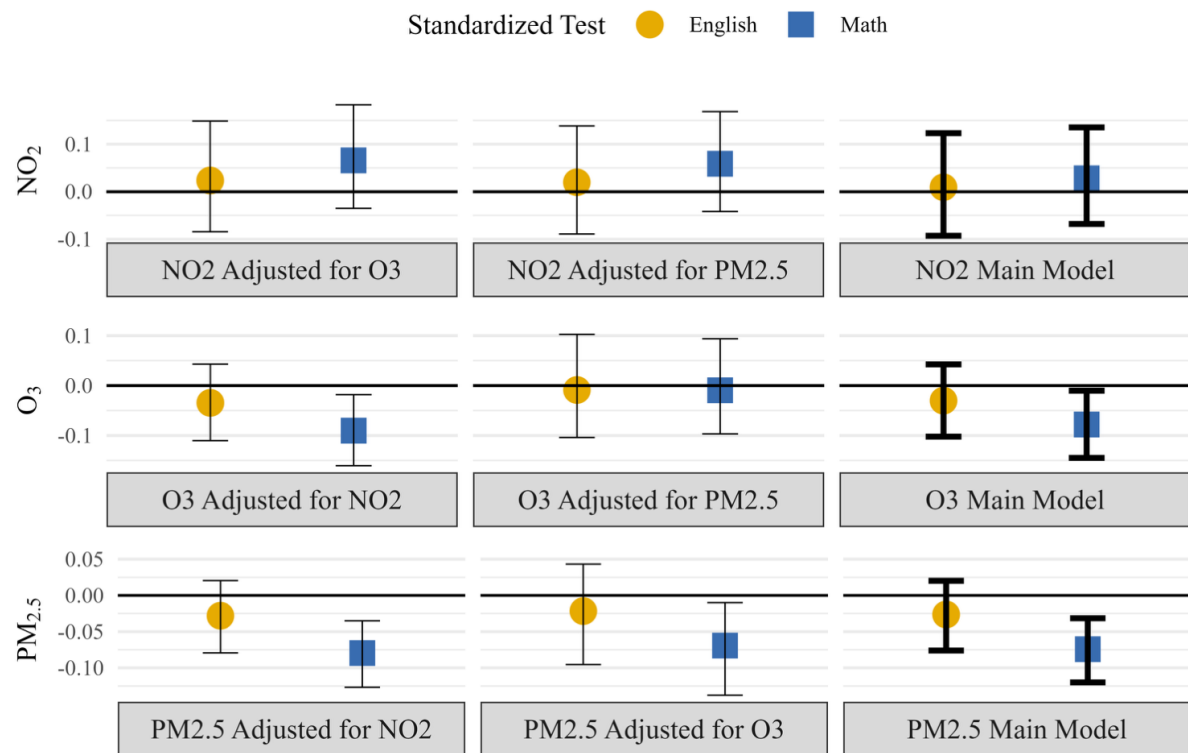
All models were adjusted for household income, smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, and neighborhood park access, and test scores were standardized to the statewide averages. In the residential, school, and residential and school models, the residence only, the school only, or both the residence and school were included in the exposure assessment respectively.

Supplementary Figure S.C4. Sensitivity analysis for changes in measurements of household income and neighborhood greenspace.



All models were adjusted for smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, measurements of household socioeconomic status, and neighborhood greenspace. Test scores were standardized to the statewide averages. The Home Ownership, Income Needs and Maternal Education models substituted indicators of home ownership, income needs, and maternal education for household income respectively. The Tree canopy model substituted the percent of tree canopy in a neighborhood for the percent of park access in a neighborhood.

Supplementary Figure S.C5. Sensitivity analysis for multi-pollutant adjustments



All models were adjusted for household income, smoking in the home, school district, preferred language, age at 3rd grade, neighborhood income, and neighborhood park access, and test scores were standardized to the statewide averages. The bolded models were adjusted for one pollutant only and are the models used in the main analysis. In the top row, the NO_2 models were adjusted for O_3 and $\text{PM}_{2.5}$ respectively. In the middle row, the O_3 models were adjusted for NO_2 and $\text{PM}_{2.5}$ respectively. In the bottom row, the $\text{PM}_{2.5}$ models were adjusted for NO_2 and O_3 respectively.

Supplementary Table S.C1. Loss to Follow up Comparison

	LOSS FOLLOW-UP SINCE VISIT (N = 95)	TO LAST (N = 31)	NOT ANALYZED (N = 97)
AVERAGE PM2.5 (MEAN, SD)	13.00 (0.76)	13.02 (0.64)	13.07 (0.56)
AVERAGE NO2 (MEAN, SD)	9.07 (1.36)	8.86 (1.18)	9.05 (1.21)
AVERAGE O3 (MEAN, SD)	40.93 (1.11)	40.97 (1.19)	40.87 (1.09)
HOUSEHOLD INCOME (%)			
BELOW POVERTY LINE	69 (72.6 %)	13 (41.9 %)	49 (50.5 %)
ABOVE POVERTY LINE	23 (24.2 %)	16 (51.6 %)	48 (49.5 %)
INCOME NEEDS (%)			
NOT ENOUGH	18 (18.9 %)	3 (9.7 %)	17 (17.5 %)
JUST ENOUGH	69 (72.6 %)	24 (77.4 %)	76 (78.4 %)
MORE THAN NEEDED	5 (5.3 %)	2 (6.5 %)	4 (4.1 %)
HOME OWNERSHIP			
RENT / OTHER	77 (81.1 %)	14 (45.2 %)	64 (66.0 %)
OWN	18 (18.9 %)	17 (54.8 %)	33 (34.0 %)
MATERNAL EDUCATION (%)			
LESS THAN 8TH GRADE	10 (10.5 %)	1 (3.2 %)	17 (17.5 %)
SOME HIGH SCHOOL	17 (17.9 %)	2 (6.5 %)	18 (18.6 %)
HIGH SCHOOL OR GED	27 (28.4 %)	9 (29.0 %)	18 (18.6 %)
SOME COLLEGE	24 (25.3 %)	11 (35.5 %)	21 (21.6 %)
COMPLETE COLLEGE	15 (15.8 %)	3 (9.7 %)	17 (17.5 %)

ADVANCED DEGREE	1 (1.1 %)	5 (16.1 %)	6 (6.2 %)
GENDER			
GIRL	42 (44.2 %)	12 (38.7 %)	50 (51.5 %)
BOY	53 (55.8 %)	19 (61.3 %)	47 (48.5 %)
PREFERRED LANGUAGE (%)			
SPANISH	20 (21.1 %)	7 (22.6 %)	34 (35.1 %)
ENGLISH	75 (78.9 %)	24 (77.4 %)	63 (64.9 %)
RACE / ETHNICITY			
HISPANIC	72 (75.8 %)	24 (77.4 %)	87 (89.7 %)
BLACK	12 (12.6 %)	4 (12.9 %)	1 (1 %)
WHITE	8 (8.4 %)	1 (3.2 %)	7 (7.2 %)
ASIAN OR PACIFIC ISLANDER	3 (3.2 %)	2 (6.5 %)	2 (2.1 %)
LIVE WITH A SMOKER (%)			
YES	21 (22.1 %)	7 (22.6 %)	14 (14.4 %)
NO	74 (77.9 %)	24 (77.4 %)	83 (85.6 %)

Descriptive analysis of covariates for CHAPS cohort members who were included in the analysis compared to those not included in the analysis. Column 1 is cohort members who were lost to follow up between the last study visit in 2019 and the current study visit (N = 95). Column 2 is cohort members who were seen at the most recent visit, but who were not analyzed (N = 31) because they 1) did not have available test scores, or 2) did not have available covariates. Column 3 is participants who were included in the analysis (N = 97). Average exposure concentrations were averaged over 2014 - 2018, because these years were available for all three groups.

Supplementary Table S.C2. Comparison of Average Standardized Test scores

	CHAPS Cohort Average	Fresno Average	California State Average
3rd Grade (2016)			
ELA	2382 (75.0)	2404 (Unknown)	2420 (88.9)
Math	2399 (58.1)	2417 (Unknown)	2429 (81.3)
4th Grade (2017)			
ELA	2426 (83.9)	2445 (Unknown)	2460 (95.1)
Math	2437 (66.1)	2453 (Unknown)	2468 (85.4)
5th Grade (2018)			
ELA	2469 (90.2)	2483 (Unknown)	2500 (98.4)
Math	2471 (61.2)	2481 (Unknown)	2495 (94.6)
3rd Grade (2017)			
ELA	2418 (91.5)	2408 (Unknown)	2418 (90.4)
Math	2433 (79.7)	2421 (Unknown)	2428 (82.4)
4th Grade (2018)			
ELA	2460 (86.3)	2453 (Unknown)	2466 (96.9)
Math	2469 (84.5)	2459 (Unknown)	2471 (86.3)
5th Grade (2019)			

ELA	2486 (91.8)	2489 (Unknown)	2504 (98.6)
Math	2495 (85.9)	2486 (Unknown)	2498 (95.7)
3rd Grade (2018)			
ELA	2440 (69.9)	2420 (Unknown)	2425 (90.6)
Math	2422 (47.6)	2428 (Unknown)	2433 (84.7)
4th Grade (2019)			
ELA	2500 (59.4)	2458 (Unknown)	2468 (97.2)
Math	2490 (44.2)	2467 (Unknown)	2474 (86.7)
7th Grade (2022)			
ELA	2549 (97.1)	2533 (Unknown)	2528 (96.6)
Math	2497 (76.3)	2494 (Unknown)	2516 (105.7)

Average standardized test scores (and standard deviations) for the CHAPS cohort, Fresno County, and California for sample grades and years which were included in the CHAPS analysis. CHAPS cohort averages were calculated from study data. Fresno and California averages were extracted from publicly available data. No standard deviations for Fresno County were found online.

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Appendix D: Neurobehavioral Assessments in a Highly Air-Pollution-Exposed Population

Abstract

Background: Children are uniquely vulnerable to ambient air pollution due to physiological factors that increase their effective dose during critical developmental windows. While the risks of criteria pollutants are recognized, data remain limited regarding how standardized academic metrics correlate with neurobehavioral outcomes measured by more in-depth testing, and how neurobehavioral outcomes are associated with non-criteria pollutants—such as polycyclic aromatic hydrocarbons (PAHs) and black carbon (BC).

Methods: Utilizing data from the Children's Health and Air Pollution Study (CHAPS) in Fresno, California, we evaluated neurobehavioral outcomes in a highly exposed, lower-income, predominantly Hispanic cohort (n=193, ages 7–18). Prenatal and year of life one exposures to PM_{2.5}, PM₁₀, O₃, NO₂, NO_x, PAH₄₅₆ and elemental carbon (EC) were estimated daily using spatio-temporal models. Outcome measures included the NIH Toolbox Cognition Battery, the Child Behavior Checklist (CBCL), California Smarter Balanced Assessments (SBAC) standardized test scores, and serum brain-derived neurotrophic factor (BDNF) and urinary 8-hydroxy-2-deoxyguanosine (8-OHdG) biomarkers. Correlations between the various outcomes were assessed, and linear and distributed lag models (DLM) were used to associated the outcomes with pollutant exposures.

Results: Third-grade SBAC scores demonstrated robust correlations with the NIH Toolbox total and crystallized cognition composites ($r \sim 0.55\text{--}0.60$) and a moderate correlation with serum BDNF ($r=0.35$). Linear models revealed that first-trimester exposure to traffic-related air pollutants (PM_{2.5} and PAH₄₅₆) were associated with elevated childhood z-scores for aggressive and rule-breaking behavior. First-year of life exposure across all seven pollutants was consistently associated with depressed serum BDNF levels; DLM analysis identified a critical susceptibility window around 5 to 6 months of life, which mirrored a corresponding localized dip in NIH Toolbox total cognition scores.

Conclusion: Early-life exposure to ambient air pollution induces persistent neurocognitive and behavioral alterations extending into adolescence. Furthermore, the strong concordance between school-administered standardized test scores and resource-intensive neurobehavioral tools indicates that population-level academic datasets may be able to serve as valid proxy endpoints for assessing environmental neurotoxicity and guiding air quality policy.

Background/Context

Children are especially vulnerable to ambient environmental hazards because differences in their activity levels and physiology mean that they are exposed to a higher effective dose of air pollution.¹ Because childhood is characterized by rapid change and development, oxidative insults during childhood can disrupt growth patterns and may have life-long consequences.¹⁻⁴ There are many known adverse health effects of air pollutants, including mounting evidence for neuro-developmental effects in childhood.¹

In addition to the neurodevelopmental effects of air pollution exposure throughout childhood and adolescence, exposure during the prenatal period (when there is rapid growth of brain structures) may also have substantial and long-term effects. Functional connectivity of the human fetal brain increases substantially in the second half of pregnancy.^{5,6} Higher prenatal fine particulate matter (PM_{2.5}) exposure levels have been associated with lower cognitive functioning in early childhood (ages 1-6),⁷⁻¹⁰ as has prenatal exposure to larger PM (ages 2-6),^{11,12} to polycyclic aromatic hydrocarbons (PAHs; aged 5),¹³ to nitrogen dioxide (NO₂; age 7),¹⁴ and to roadway proximity (age 7-8).^{14,15} Though a large re-analysis of multiple European birth cohorts did not find any relationship between *in-utero* PM_{2.5} and cognitive function,¹⁶ exposure misclassification may have obscured a relationship (air pollutant data used were collected many years after the presumed exposure). An association was recently demonstrated between prenatal PM_{2.5} exposure and intelligence quotient (IQ) in 10-11-year-olds, the oldest cohort in which prenatal exposure—based on air pollutant data collected at the time of the presumed exposure—has been associated with cognition.¹⁷

Notably, there are very few studies that have examined the cognitive effects of non-criteria pollutants—pollutants not monitored and regulated by the EPA, such as PAHs and black carbon (BC)—especially for exposure in the prenatal period. PAHs are carcinogenic,¹⁸⁻²⁰ toxic air contaminants²¹ that are co-emitted with regulated gaseous and particulate combustion products (PM, NO_x, CO) from common sources, such as motor vehicles and biomass burning.²²⁻²⁵ Human exposure to PAHs is associated with significant adverse health outcomes, but the extent and trends in environmental concentrations are poorly understood, as no state or national agency requires routine monitoring of PAHs.²⁶⁻²⁹ PAHs are also classified as Persistent Organic Pollutants,³⁰ meaning that they remain present in the environment for long periods, which makes it even more crucial that we understand what the effects of our PAHs will be on this and future generations. Yet, all the known relationships between prenatal PAH exposure and childhood neurodevelopment come from only two cohorts, both of which used a single snapshot of PAH exposure during pregnancy (either a 48-hour personal monitor³¹⁻³³ or umbilical cord DNA adducts¹³) to estimate exposure for the full prenatal period. PAH exposures can vary by more than an order of magnitude throughout pregnancy,²⁷ so single measurements are unlikely to capture the full variation in exposure. Furthermore, researchers generally report only particle-phase dominant PAH concentrations.³¹⁻³³ But excluding vapor-phase PAHs underestimates total PAH exposure by up to 80%³⁴ and also emphasizes the exposure to the larger, less volatile PAHs. Existing research on BC—which is often used as a tracer for ultrafine, diesel exhaust particles— and cognition is relatively mixed. Some studies have demonstrated decreased cognition in childhood with either total lifetime or recent BC exposures,³⁵⁻³⁷ yet a few studies have found

no relationship,^{15,38,39} potentially because of inadequate exposure estimates during critical windows of development or crude spatial resolutions for their exposure.³⁹

Cognition and neurodevelopmental growth are complicated constructs that can be assessed in a variety of ways, including those that assess general cognitive abilities as well as ones that assess specific cognitive domains such as attention, language, and memory.⁴⁰ A recent systematic review (2022) looking at traffic-related air pollutant (TRAP) exposure,⁴¹ either prenatally or postnatally, and neurodevelopmental outcomes in children focused on these detailed metrics such as IQ, executive functioning, learning and memory domains, and motor skills. Those authors concluded that there was a negative effect of PAH, PM_{2.5} and NO₂ on children's cognitive functioning, particularly attention and executive functioning, as well as overall intelligence. Yet limited numbers of children complete such detailed cognitive assessments, because they are time and resource intensive. In contrast, though it is not designed to assess broad cognitive growth, standardized testing is completed by most American children through their schooling, and multiple recent studies have in fact demonstrated relationships between air pollution and school⁴² or district^{43,44} level academic outcomes. A 2021 systematic review of TRAP exposure and academic outcomes (including standardized testing results) found evidence of a negative association between TRAP and test scores, though the authors noted that the overall quality of the evidence was low.⁴⁵ Thus, there is a need for work that combines both standardized testing outcomes and more detailed neurobehavioral assessments in children highly exposed to air pollution to tie together these disparate portions of the literature, and to help us understand whether standardized testing—the more widely available endpoint—could be used as a potential proxy for other cognitive outcomes.

Assessment of neurologically relevant biomarkers can also inform the biological processes that may underpin air pollutant-cognitive function relationships. Commonly measured biomarkers of effect include 8-hydroxy-2-deoxyguanosine (8-OHdG), a marker of oxidative stress^{46,47} and Brain-Derived Neurotrophic Factor (BDNF) a biomarker of neurogenesis. 8-OHdG is produced by hydroxylation of guanine—a type of DNA oxidative damage— and has been associated with a variety of health outcomes including psychiatric disorders.^{48,49} 8-OHdG^{50–54} has been specifically associated with exposure to pollutants like ozone, PM and PAH in children and adults, including with seasonal variability.^{50,51,55} BDNF is a growth factor that regulates neuron plasticity and differentiation and may be particularly important for cognition and learning.^{56,57} BDNF has been considered as an informative biomarker for cognition and neurodegeneration in adults and has been used in research of neurotoxicity from other environmental toxicants,^{58–60} but not yet with air pollution.

Because adverse neurobehavioral affects are likely to be most severe in highly exposed children, there is a particular need to assess these relationships among populations with high air pollutant exposures. Compared to the rest of the US, the Fresno metropolitan area (the largest city in California's San Joaquin Valley) has both extraordinarily high ozone and particle pollution and fewer students meeting grade-level standards. These disparities are particularly stark when comparing math and science results; in 2018-2019 (the last year with complete testing data prior to the COVID-19 pandemic), 18% of Fresno students met or exceeded state math standards, and only 16% of students met or exceeded science standards in Fresno.⁶¹ Given that Fresno has some of the most socioeconomically vulnerable

communities in California⁶² and that childhood cognitive growth is known to be associated with future earnings,⁶³ any contribution of air pollutant-associated changes in neurodevelopment and associated cognition would be expected to have substantial lifetime impacts for members of this community.

Because our research team has worked extensively in the Fresno area, we are able to estimate daily exposures to PM_{2.5}, PM₁₀, O₃, NO₂, NO_x, 4-, 5- and 6- ringed Polycyclic Aromatic Hydrocarbons (PAH₄₅₆), and BC—many of which are traffic related—including during the critical prenatal and early-life exposure windows, in this particularly exposed population. This analysis combines those robust exposure data with the following outcomes measured in childhood or adolescence: detailed neurobehavioral assessments, biomarkers and standardized testing results. The hypotheses were that higher air pollutant exposure would be associated with worse neurobehavioral outcomes and that the various ways of measuring neurocognition could be correlated with each other.

Methods:

Study population and recruitment

The Children's Health and Air Pollution Study (CHAPS) includes two pediatric environmental health cohorts that were assembled in the San Joaquin Valley of California and have been followed for multiple years. The CHAPS1 cohort children were recruited from a local medical center where the parent was receiving prenatal care at 18-25 weeks in utero between 2015- 2017 (original n=225), and were seen at roughly 12 months, 24 months, 7.5 years and 8.5 years of age. The CHAPS2 cohort children (original n=299) were recruited at ages six-eight from 2015 to 2016 from first and second grade classes in the Fresno area and seen at roughly 7 years, 9 years, 15 years and 16 years. Historically roughly 70% of CHAPS cohorts were retained between contact periods, though retention was lower during the COVID-19 pandemic. Notably, the loss reflects an inability to reach prior participants, consistent with this being a lower-income, highly mobile cohort, rather than participation refusal (e.g., at the CHAPS 2 13–16-year visits, 41% of participants returned after the COVID pandemic, 53% of participants were unreachable, and only 6% chose to withdraw when reached). As reported in a prior paper, those lost to follow up were more likely to be below the poverty line, and to self-identify as Black, but had generally similar air pollutant exposure distributions when compared to those who remained in the study.⁶⁴

This paper reports on neurobehavioral assessments that were added onto the study as part of the Children's Health and Air Pollution Study-Standardized Assessments and Cognition in Kids (CHAPS-STACK). 193 participants completed a CHAPS-STACK visit between 2024 and 2025 at the field office site at Central California Asthma Collaborative in Fresno, CA (at one of the participants' last two CHAPS visits, see Figure 1). The CHAPS project is approved by the University of California Berkeley Institutional Review Board. Written informed consent and permission was received from each accompanying parent, and written assent was received from all children.

Air Pollution Modeling

A combination of field monitoring and predictive modeling was used to estimate exposures for each of the participants for the entirety of their gestational period and their first year of life (births occurred between 2006 and 2016). PM_{2.5}, PM₁₀, and O₃ data were interpolated from the EPA's Air Quality System (AQS) ambient data using inverse-distance-squared weighting. The model used up to four sites, with the maximum allowed radius from each address being 50 km. Linear regression air pollution exposure modeling was used to develop a daily spatial-temporal model for NO₂ and the sum of 4-, 5-, and 6-ring PAH compounds (PAH456) using field monitoring data from Fresno and Clovis, as described in prior papers from our team.^{27,65} Exposure regression model covariates included aggregated particle phase-PAH and NO₂ measured continuously at fixed sites, relative humidity, temperature, wind speed, atmospheric stability, distance to nearest freeway, Caline4 dispersion model estimates of concentrations from local traffic, distance to nearest rail lines, and amount of rail yard, urban, and open space land use within 1 km radius circular buffers. Linear regression models with sampling location and sampling date as random effects were used to simultaneously model the temporal and spatial components. The inclusion criteria for covariates were their statistical significance and percentage of covariance explained (i.e., improvement in explanatory power). Further information about exposure models can be found in a previous paper.⁶⁵

Exposure Assignment

During their visits to the study center for health outcome measurements, parents/guardians were asked to report the street address, city, and state of all residences where the pregnant parent resided during the gestational period, and the dates they were at each. Each address was geocoded using ArcGIS (ESRI, Redlands, CA) to create a residential history throughout the pregnancy.

For the CHAPS1 cohort, pregnancy addresses were ascertained during pregnancy or in the first year of life, with addresses reviewed and any gaps in address history filled at later visits. For the CHAPS2 cohort pregnancy addresses were reported by the parent retrospectively at child or adolescent visits. Daily ambient (i.e., outdoor) residential pollutant concentrations for each day were estimated using the residential location (parental residence during pregnancy or child residence during the first year of life) on the day of interest and the corresponding modeled daily value of each pollutant for that location. Concentrations were aggregated for each participant for each trimester of the gestational period, and each month during the first year of life. Daily ambient concentrations were averaged to create an estimate across the whole pregnancy and across the entire first year of life.

Covariate Measurements

Child-specific covariates used in this analysis were collected at the child's two recent study visits. At both visits, the child's parent or guardian was interviewed using an in-depth questionnaire offered in either English or Spanish. Older youth (>10 years) were also asked privately about their own potential smoking behavior.

Race was self-reported by participants, choosing between "White", "Black or African American", "Hispanic or Latino", "Asian", "Native American or Other Pacific Islander", "American Indian or Alaskan Native", "Mexican", "Middle Eastern or Arab", "Some other group", and "I don't understand this question". Due to the low number of participants in other groups, these were further summarized as Hispanic, non-Hispanic white or non-Hispanic other, as has been done previously in this cohort.^{64,65} At both visits, parents or guardians were asked about their household income, their home ownership status, their income needs, and their education. Reported household incomes were categorized into "above or below \$30,000". Parents or guardians were further interviewed about smoking in the child's home and the cars in which the child frequently rode, and whether the child was exposed to smoking was categorized as "yes" or "no".

Two covariates were used to represent the timing of the office visits. These included which season the visit occurred in and the age of the youth on the visit date (calculated from their parent-reported date of birth). Consistent with weather patterns in Fresno, visit season was described as either the hot season (April through October) or the cool season (November through March).

Outcome measurement

At recent CHAPS visits, participants had anthropometrics and blood pressure measured, biospecimen samples collected (urine, blood, hair, nails, saliva), and performed lung function testing (spirometry). At the CHAPS-STACK visit, the youth additionally completed several neurobehavioral assessments, which are used for these analyses.

The NIH Toolbox Cognition Battery, a validated and widely used set of measures that allow for continuity of cognitive assessment across a wide variety of ages (7-85 years),⁶⁶ was administered in the office via an iPad app. It consists of seven standard but adaptive computerized instruments, and study staff were trained in the use of this tool by a pediatrician and a neurodevelopmental psychometrist, per the guidance in the administration manual.⁶⁷ Per the technical manual, the cognition battery composite scores have excellent empirical liability with change sensitive scores in pediatric populations of 0.98-0.99, and a correlation coefficient of 0.64 when comparing to full scale IQ testing.⁶⁸ The participants completed 7 tasks (list sorting working memory, oral reading recognition, picture vocabulary, flanker inhibitory control and attention, dimensional change card sort, pattern comparison processing speed, and picture sequence memory). Collectively, these tasks assess executive function, attention, working memory, language, processing speed, and episodic memory. If the participant was able to complete the full set of tasks required for each composite score, the software calculated three composite cognition scores: fluid cognition, crystallized cognition and total cognition. The fluid cognition component is intended to represent cognitive processes, whereas crystallized cognition is a measure of knowledge. A higher score on these composites indicates better cognitive functioning. In the validation sample for this battery of tests, fluid and crystallized cognition are moderately correlated with a correlation coefficient of 0.35; total cognition is highly correlated with both individual domains (total to fluid $R=0.86$, total to crystallized $R=0.78$).

For all participants, the parent also completed the multiple-choice portion of the Child Behavior Checklist (CBCL),⁶⁹ a widely used assessment of behavioral and emotional issues. Children over age eleven also completed a companion survey, the Brief Problem

Monitor(BPM). The software calculates 8 standardized syndrome scales from the CBCL based on a factor analysis derived from the validation sample (Anxious/Depressed, Depressed, Somatic Complaints, Stress Problems, Thought Problems, Attention Problems, Rule-breaking behavior, and Aggressive behavior) and 3 from the BPM (Internalizing Problems, Externalizing Problems, Total Problems). A higher score on these scales indicates more problems with the specific domain. In the normative sample for these tests, test-retest reliabilities for the CBC syndrome scales used range 0.82-0.9. As recommended in the manual for these forms, raw values were standardized within 6-11- and 12-18-year age groups, and these standardized scores were used for analysis.

Two biological markers relevant to brain growth and development were also assessed from the biospecimens collected at these visits: serum brain derived neurotrophic factor (BDNF) and urine 8-Oxo-2'-deoxyguanosine (8-OHdG). Both BDNF and 8-OHdG were measured using Enzyme-Linked Immunosorbent Assay (ELISA) kits according to protocols from their respective manufacturers (ABCAM and Invitrogen-ThermoFisher Scientific) and as previously described.^{52,70,71} All samples were run in duplicate; QA/QC samples included method blanks, coded repeat samples, and internal controls. All ELISA plates were read on the SpectraMax plate reader at 450nm (Molecular Devices, San Jose, CA) and analyzed using SoftMax Pro 7.1.2. To achieve reliable and accurate results, repeated runs were performed for samples with higher coefficients of variation (COV) or for sample concentrations outside of the calibration range by changing dilution factors. All calibration curves had an $R^2 > 0.99$. For BDNF, the limit of detection (LOD) was 0.0024 ng/mL, and the mean COV was 2.9%. For 8-OHdG, the LOD was 0.94 ng/mL, and the mean COV was 7.1%.

In 2015, California began using an updated form of statewide standardized testing for English Language Arts (ELA) and math called the Smarter Balanced Assessments (SBAC).⁶¹ The SBAC tests are administered in 3rd - 8th grade and in 11th grade. Testing is done in the spring semester of every school year. For the state of California, SBAC scores for 3rd - 8th graders range from 2114 - 2769 for ELA and 2189 - 2802 for math with higher scores indicating better performance. For any participants who previously completed California standardized tests, CCAC staff worked with parents to obtain prior testing results, most commonly by helping them navigate their online portal for download or copying from the parent's own records. SBAC scores were available from third grade testing for 104 participants (68% of those far enough in school to have completed any standardized testing), and within the current or prior 2 school years for 52 participants (51% of those who were in grades that would be expected to have had testing results). Scores at the statewide level fluctuate slightly by year and grade based on the test characteristics and statewide period effects (such as COVID-19) each year. To adjust for these differences, we standardized the test scores in our sample to z-scores using the statewide averages and standard deviations for a given grade and year.

Statistical Analysis

R version 4.5.3 ("Reassured Reassurer")⁷² was used for modeling, using the packages `corrplot`,⁷³ `dlm`,⁷⁴ `kableExtra`,⁷⁵ `MASS`,⁷⁶ `mice`,⁷⁷ `openxlsx`,⁷⁸ `tableone`,⁷⁹ and the `tidyverse`.⁸⁰ We selected covariates a priori based on domain knowledge with the aid of a directed acyclic graph (supplemental figure S.D1). Covariates selected included potential confounders related

to both the exposure and the outcome as well as variables thought to be highly correlated with the outcome only.⁸¹

The main analyses were done using linear regressions. The standard assumptions of linear models (linearity of the relationship, normally distributed residuals, and non-heteroskedasticity) were assessed with fitted v. residual and Q-Q plots. For the main analysis, 630 separate linear models were run: one for each of the 18 outcomes (3 from the NIH Toolbox, 8 from CBCL, 3 from BPM, 2 biomarkers, 2 SBAC) with each of the seven air pollutants (NO₂, NO_x, EC, PAH₄₅₆, PM_{2.5}, PM₁₀, O₃), and each of 5 time points (trimester 1, trimester 2, trimester 3, the whole pregnancy, the first year of life).

The secondary analyses were done using distributed lag models (DLM), which allowed us to include monthly averages of exposure during the complete first year of life in a single analysis, thereby controlling for exposure at all other times within the year.^{74,82,83} Models were unable to converge if the relationship was allowed to be flexible in both directions. Thus, we assumed that the relationship between each pollutant and neurodevelopmental outcome was linear across our range of pollutant concentrations, but we allowed the shape of the time-lag dimension to vary flexibly. We examined multiple options for smoothing functions (including allowing non-linearity in the exposure dimension) and examined the Akaike Information Criteria (AIC).⁸³ The model specification with the best model fit (lowest AIC) used b-splines for the smoothing functions.

We did not calculate or report p-values and thus did not adjust for multiple comparisons in our models. Instead, we interpret the results of pollutant-specific models in the context of larger patterns.

Because effects of prenatal exposure on standardized testing scores showed effects that were quite different from the relationships with any of the other outcomes, a *post-hoc* sensitivity analysis was run incorporating the kindergarten cutoff date. Because of seasonality in pollution, the fact that pregnancies are less than a year, and that there are strong effects on educational attainment related to age at school entry, it would be possible for seasonal effects to confound the pollutant-outcome relationship for school-based outcomes. Children born between March 1 and the kindergarten entry date (that date ranged Sept 1- Dec 2 depending on the child's year of birth) were considered 'young' at kindergarten start and those born between December 3 and February 29 were considered 'old' at kindergarten start.

2.4 Missing Data

To minimize bias resulting from missing data, we used multiple imputations to generate missing exposures and covariates. Imputation was done with version 3.19.0 of the "mice" package in R. Of the 195 participants, 7 were known to live out of the Fresno area during the exposure periods. Given that these participants would thus have had exposures that were not well represented by those in our dataset, exposure values could not be imputed for these. Of the remaining 188 participants, one or more summary measures (trimester averages, pregnancy average or first year of life average) had to be imputed for NO₂, NO_x, and PAH concentrations for 24% of participants, EC for 48% of participants, PM_{2.5} for 19% of participants, PM₁₀ for 22%, and O₃ for 19% of participants. Across all participants, 4105 out of

15708 exposure-months (26%) were imputed. Most commonly data were missing for the first or last months of year one of life.

Results

In total, 193 youth (mean age 13.97 years, range 7-18; Table D1) completed a CHAPS: STACK visit. 48% of the cohort was male and 85% was Hispanic. This was a low-income population, with only 58% of households having an annual income above \$30,000, and half of families receiving government assistance. 12 percent of the youth were exposed to cigarette smoke in their home or family car. Though 20% of the youth themselves reported having tried smoking or vaping at some point, only 6% reported vaping in the last month, and 2% smoked in the last month.

These youth had a mean PM_{2.5} exposure of 16.6 µg/m³ during their prenatal window and 15.2 µg/m³ during their first year of life, above the current air quality standards, consistent with living in the Fresno area 7-18 years ago. The mean pollutant exposures for each trimester, the whole pregnancy and the first year of life are presented in Table D2. During both the pregnancy and first year of life exposure windows, the NO₂ and NO_x concentrations were very highly correlated ($r=0.95$ - 0.95 , Figure D2) and PM_{2.5} was highly correlated with NO_x and NO₂ ($r=0.61$ - 0.68). During the first year of life, EC was very highly correlated with O₃ ($r=0.94$), but they were only moderately correlated during pregnancy ($r=0.56$). Comparing across the time periods, both ozone and EC during pregnancy were highly correlated with their own concentration during the first year of life ($r=0.92$ - 0.93).

We were able to obtain near complete data for the tasks performed at our study visit. 191 youth (99%) had complete CBCL data and 134 youths completed the brief problem monitor (100% of the participants that were age-eligible). 187 completed sufficient tasks on the NIH Toolbox Cognition battery such that they had crystallized cognition composite scores (97%), and 174 (90%) had fluid and total cognition scores. We obtained a sufficient blood sample for BDNF analysis in 164 participants (85%) and were able to measure 8-OHdG in urinary samples from all 193 participants. Of the 153 participants old enough to take standardized testing at school, 93 were able to locate SBAC scores from their 3rd grade school year (61%), and 52 (34%) had recent SBAC scores (within the last 2 years).

The various measures within each set of outcomes correlated well with each other (Figure D3). The total cognition composite score was strongly correlated with both the fluid and crystallized composites ($r\sim0.8$), and the fluid and crystallized components were somewhat associated with each other ($r=0.34$), all of which were very similar to the correlations reported in the validation samples for those tests. The different components within the child behavior checklist were highly correlated (most $r > 0.5$). The SBAC math and ELA scores taken at the same time were well correlated ($r\sim0.6$).

When comparing across outcomes (Figure D3), the problems captured on the child behavior checklist (completed by the parent) had a moderate correlation with the brief problem monitor completed by the youth themselves; most correlation coefficients were in the 0.3-0.4 range. The child behavior checklist problems were weakly to moderately (and consistently) inversely associated with both the performance on the NIH toolbox and on the recent standardized testing results. The youth's own report of their problems did not show a relationship with the NIH Toolbox nor standardized testing. 8-OHdG, the biomarker of oxidative stress, did not show a relationship with any of the other outcomes, but BDNF was

moderately correlated with the youth's performance on recent standardized math testing ($r=0.35$). SBAC performance at third grade (on both subjects) was strongly correlated with both crystallized and total cognition as assessed by the NIH Toolbox (all r 0.55-0.6) and moderately correlated with fluid cognition ($r \sim 0.35$).

Using linear models to assess the relationship between NIH toolbox scores and mean pollutant exposures during pregnancy and the first year of life did not show any clear patterns with most time period-outcome pairings having a variety of pollutant effect estimates that clustered around the null (Figure D4).

Exposure to multiple pollutants during the first trimester was associated with later rule-breaking behavior and aggressive behavior; the most pronounced effects were the associations with $PM_{2.5}$ and PAH_{456} (Figure D5). One $\mu g/m^3$ higher $PM_{2.5}$ in the first trimester was associated with a 0.024 higher z score for aggressive behavior (95% CI 0.004, 0.044) and a 1 $\mu g/m^3$ higher PAH_{456} exposure during the first trimester was associated with a 0.043 higher z score for aggressive behavior (95% CI 0.008, 0.078). For rule-breaking behavior, 1 $\mu g/m^3$ higher first trimester $PM_{2.5}$ was associated with a 0.022 higher z score for aggressive behavior (95% CI 0.004, 0.039) and 1 $\mu g/m^3$ higher PAH_{456} with a 0.034 higher z score (95% CI 0.002, 0.065). There were no clear relationships with any of the other parent-reported scales, and no clear relationship between pollutant exposures during pregnancy or the first year of life and socio-behavioral problems reported by the youth (Figure D6).

Exposure to all seven of the pollutants during the first year of life seemed to be associated with decreased levels of BDNF (Figure D7). All seven relationships had negative estimated effects, many of which do not cross the null. For example, a 1 ppb increase in NO_2 is associated with a -0.43 ng/mL decrease in serum BDNF concentration (95% CI -0.75, -0.10). Exposure during pregnancy did not show a clear pattern of relationships with serum BDNF concentrations. 8-OHdG concentrations were not as widely associated with pregnancy and early-life exposure (Figure D8), but exposure specifically to 1 ppb higher average ozone during both the entire pregnancy and the first year of life is associated with increased 8-OHdG (1.01 ng/mL higher with pregnancy exposure, 95% CI -0.023, 2.035 ; 2.77 ng/mL higher with first year exposure, 95% CI 0.72, 4.82).

Air pollutant exposures during the first year of life did not show clear relationships with standardized testing at grade three (Figure D9). Unexpectedly, higher pollutant exposure during pregnancy-and particularly higher pollution in the second trimester-was consistently associated with higher SBAC scores. Excluding ozone, exposure to all six other pollutants during first trimester, second trimester, and for the whole pregnancy was associated with higher SBAC scores, with effect sizes ranging from 0.001 to 0.09. For example, 1 ppb higher second trimester NO_2 was associated with a 0.040-point increase in SBAC ELA (95% CI 0.00, 0.080) and a 0.044-point increase in SBAC math score (95% CI 0.010, 0.077). Ozone showed the inverse relationship, with 1 ppb higher ozone in the second trimester associated with -0.010 points lower SBAC ELA (95% CI -0.020, 0.001) and -0.008 lower SBAC math scores (95% CI -0.017, 0.000). However, a *post-hoc* sensitivity analysis that stratified children based on whether their birthdate was before or after the kindergarten entry date demonstrated that these relationships between air pollution exposure in pregnancy and third grade standardized test scores were very different within birthdate strata (Figure D10). Using the same example as above, among the 29 children who were

“old” at the time they started kindergarten (meaning they had turned five sometime after the prior year’s kindergarten cutoff but before March 1) 1 ppb higher second trimester NO₂ was associated with a -0.025 point lower SBAC ELA (95% CI -0.17, 0.12) and a -0.042 point difference in SBAC math score (95% CI -0.149, 0.066). Whereas for the 50 children who were young at the time they started kindergarten (meaning they had turned five sometime between March 1 and the fall of that year) 1 ppb higher second trimester NO₂ was associated with a 0.040 point increase in SBAC ELA (95% CI 0.00, 0.080) and a 0.044 point increase in SBAC math score (95% CI 0.010, 0.077). The ozone relationship also inverted, with a negative relationship with ozone remaining during the second trimester in those who started school young, but a positive correlation between ozone and scores among those who started school when they were older. The first trimester, third trimester, whole pregnancy and first year pollutant associations were generally null and very similar within strata. These sensitivity analyses suggested that the initial finding of a positive association between air pollution exposure and SBAC scores was confounded.

Distributed lag models were used to assess particularly susceptible periods of exposure during the first year of life. For most outcomes, when controlling for exposures at all other months of the first year of life, no clear patterns were seen in which months were particularly important for exposure; point estimates hovered near the null and confidence bands widely spanned both sides of the null. However, for BDNF concentrations, exposure to NO₂, NO_x, particles, EC, and PAH all seemed to show a pattern of having the strongest negative relationships in the middle portion of the first year of life, with confidence intervals that did not cross the null for some time points for NO_x and NO₂ and that were clearly asymmetric at the most affected time points for all of these pollutants. For example, a 1 ppb increase in NO₂ during the child’s fifth month of life was associated with a -0.55 ng/mL difference in BDNF concentration (95% CI -0.93, -0.16) (Figure D11a depicts the BDNF NO₂ as an example of this set of results, due to the need for these graphs to be larger for the reader to interpret, compared to those that create a single estimate).

Though an overall effect had not been seen in the linear models assessing average first year of life exposure and NIH Cognition Toolbox scores, in the DLM models the middle months of the first year of life seemed to also be potentially important for decreases in NIH Cognition Toolbox scores. The pattern of effect estimates relating NO₂, NO_x and PM_{2.5} to cognition showed a very similar bowl shape with a minimum around the middle of the first year of life to those with the BDNF concentrations. For example, a 1 ppb increase in NO₂ during the child’s fifth month of life was associated with a -1.33 change in total cognition score (95% CI -2.64, -0.022) (Figure D11b).

Discussion/Interpretation

The findings of this study can have an impact much larger than might be expected for a study of this size. While there were no clear relationships seen between pregnancy/early-life pollutant exposures and the detailed cognitive assessment, that is perhaps unsurprising given the small sample size (<200 subjects) and the long duration between exposure and the measured outcome. Yet, this analysis demonstrated key relationships between the California state standardized testing scores that our participants reported from their school-based testing, and more in-depth neurobehavioral assessments performed at our field office. Most notably, there was a strong relationship between 3rd grade SBAC testing scores and NIH

Toolbox Cognition Battery scores. Because the NIH Toolbox is intended as an age-agnostic assessment tool, utilizing the 3rd grade testing scores in this study (rather than restricting to participants with recent school standardized testing) allowed for the largest possible sample size and would be expected to relate well to Toolbox scores, even though the NIH Cognition Toolbox was completed at a wider variety of ages. For those that had recent testing, there were also moderate relationships between *recent* SBAC scores and the NIH Toolbox scores, as well as recent SBAC scores and parent-reported social or behavioral problems. Finally, there was also a moderate correlation between serum BDNF and recent SBAC scores. These relationships suggest that SBAC scores—a much more easily ascertained measure, and one that is available for nearly all California students—could be used as a proxy outcome. While imperfect, these results suggest that SBAC scores are highly related to other cognitive, social and behavioral outcomes, and suggest that interventions aimed at improvements in SBAC scores related to air pollutant exposures may have benefits for these other measures as well.

A recent study from our group demonstrated that when assessed using all repeated measures available from this cohort, an individual participant's SBAC scores were significantly and inversely associated with exposure to PM_{2.5} in the year prior to testing, with a stronger effect for math than for English/language arts.⁶⁴ A one µg/m³ increase in prior year PM_{2.5}, considering their exposures at home and school, was associated with 7 to 8 point lower raw SBAC scores— a sizeable amount given that the difference between the grade level means is roughly 20 points in middle school and 35 points in elementary school. In a different analysis (using statewide data from thousands of California schools and millions of students), fewer students meeting state standards for SBAC scores (per school) were associated with pollutant concentrations at each school, particularly with those two years prior (see Appendix B).⁸⁴ Taken together, these studies suggest some important possibilities. This seems to be an instance where ecologic data are a good reflection of effects at the individual level; air pollutant exposures were related both to lower individual student SBAC scores and fewer students at a given school meeting the standards. Plus, from this analysis the individual SBAC scores are strongly related to more in-depth neurocognitive testing. This combination of findings suggests that school-level standardized testing results might be a potentially useful metric for evaluating effects of air pollutant policy changes for California children. Changes in SBAC test scores could be both a target of interventions, and because the data are widely available, they could also potentially be used for future impact assessments. Because of the large sample size in state standardized test result datasets, small effects are more likely to be captured, and even small changes in neurobehavioral functioning may be important when considering the population distribution.

Even though we did not find a relationship between average pregnancy or early-life exposures and results from NIH toolbox testing, there were some relationships with child behavior checklist items. While we are cautious to not overinterpret individual confidence intervals that avoid the null—given the large number of parameters studied—there are two parent-reported behavior concerns that seem to show general patterns of increase in association with pollutant exposures in pregnancy. First trimester exposure to traffic-related air pollutants (nitrogen oxides, particulates, PAH) may be a contributor to rule-breaking and aggressive behavior in childhood and adolescence.

Associations between first year of life pollutant exposures and SBAC scores were generally null, and not noteworthy, even though prior analyses had found relationships with more recent pollutant exposure. There was a pattern of associations found with pregnancy exposures and SBAC test scores. However, subgroup sensitivity analyses demonstrated that age at kindergarten entry may be an important confounder of that relationship. Pollutant exposure in Fresno has a strong seasonal pattern, with traffic-related pollutants being the highest between November and February, and ozone being the highest in June through September. Thus, because pregnancy covers only a portion of the year, the pregnancy concentrations are strongly related to when the child was born, and thus, when they started school. It is well established that, in general, children within the same grade who are older than their peers have higher educational achievement.⁸⁵ Thus, amongst the full cohort, the high traffic related air pollutant exposures and lower ozone exposures that occur during the winter may be serving as a proxy for being an older student, manifesting in what looks like higher test scores associated with higher pollutant exposures.

When comparing the younger students to the older students, not only does the traffic related air pollutant-SBAC score relationship invert, but so does the association with ozone. Because of (1) inverted associations between children born ~ half a year apart, and (2) the ozone relationship consistently opposing the relationship with the other pollutants, this pattern of results is consistent with the pollutant exposures serving as a marker for a seasonal pattern. Within each strata, the older children have an academic advantage, but the pollutant exposure pattern consistent with being older *within* each stratum is in the opposite direction and manifests as opposite associations. Thus, in total, we did not find noteworthy relationships between SBAC scores in third grade and pregnancy or first year of life air pollution exposure.

Lower BDNF serum concentrations in childhood and adolescence were associated with exposure to all seven pollutants during the first year of life. Distributed lag analysis allowed for assessment of the most critical windows for exposure, demonstrating the strongest effect size around age 6 to 7 months. The importance of this time window could result from a combination of factors including that the first 6-8 months are a period of the most rapid synapse formation in the brain⁸⁶ and that by age 6 months, more babies may be spending time in less controlled environments and being exposed to more air pollution. While this is not sufficiently supported by this study, the similar pattern of traffic-related air pollution associations with BDNF and NIH Toolbox scores raises the provocative possibility that changes in BDNF could be mediating later cognitive effects.

Recent studies on the demonstrated effects of PM_{2.5} on neurodevelopment using laboratory and animal data provide a strong mechanistic basis for a causal link between air pollutant exposure and neurodevelopment in children.⁸⁷ For example, PM is directly toxic to human neurons,⁸⁸ can change neuron gene expression,^{89,90} and may also have a role in central nervous system myelination.⁹¹ These direct effects are problematic given that particulate matter (especially the ultrafine particulate fraction in EC, those less than 0.1 microns in diameter) can enter the systemic circulation, can cross the blood-brain barrier, and have been found in the brain tissue.^{87,92} In addition to the direct effects of pollutants, the induction of reactive oxygen species and oxidative stress leading to inflammation⁹³ is known to contribute to the pathogenesis of respiratory disease, cardiovascular disease, and cancers. Oxidative

stress has been implicated in neurodegenerative disorders^{94,95} and is also thought to be a potential key contributor to difficulties in learning and cognition.^{96,97} Rodents have demonstrated increased neuroinflammation following exposure to fine particles, including prenatal exposure.^{98–100} In people, exposure to prenatal diesel exhaust, which has a large PM component,⁹⁷ induced long-term changes in the microglia, the resident immune cells in the brain, into adulthood,⁹⁸ mirroring the animal studies. Nitrogen oxides and ozone directly induce oxidative stress in their original state or can decompose to free radicals, while pollutants like PM and PAH create oxidative stress through tissue inflammation and/or damage in biological systems. Free radicals contribute to damage of several cellular and subcellular structures, including lipid membranes and DNA.⁹⁶ Youth with asthma are particularly susceptible; air pollution can trigger symptoms, driven by airway inflammation¹⁰¹ that also affects the systemic circulation.

A major strength of this analysis is the inclusion of a wide array of different neurobehavioral outcomes in a population of youths who are highly exposed to air pollution. The strong associations demonstrated between the different outcomes are important for considering the potential use of standardized testing as a proxy outcome that can be targeted for air pollution interventions. Though this study is of a smaller sample size, which may have limited the ability to find associations between pregnancy and early-life air pollutant exposures and neurobehavioral outcomes, this small sample comes from some of the most impacted youth in California.

Air pollution effects on childhood social-emotional, behavioral and cognitive development have a strong basis in pathophysiology and have been identified in several studies. The key contributions of this study are that California SBAC testing is correlated with intensive cognitive testing in youths, a biomarker of neurogenesis, and parental reports of emotional and behavioral difficulties; and exposure to air pollutants in pregnancy and during the first year of life are associated with neurocognitive and behavioral effects that extend into late childhood and adolescence.

Funding

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Table D1. Demographic Characteristics of the Cohort

	Mean	SD	Count	Percent
n			193	100 %
Study Visit during the Hot Season			100	51.8 %
Age	13.97	3.68		
Current Grade at School				
Up to 2nd Grade			22	12.6 %
3rd to 10th Grade			102	58.3 %
11th to 12th Grade			51	29.1 %
Sex at Birth				
Male			92	47.9 %
Female			100	52.1 %
Gender (Parent reported)				
boy			93	48.2 %
girl			99	51.3 %
transgender boy			1	0.5 %
Race/Ethnicity (Parent reported)				
Hispanic			163	84.9 %
Non-Hispanic White			9	4.7 %
Non-Hispanic Other Race			20	10.4 %
Annual Household Income				
More than \$30,000 (%)			111	57.8 %
Smoking				
Smoking in the Home or Car in the Last Month			24	12.4 %
Kid reports ever smoking or vaping			38	20.1 %
Kid smoked a cigarette in the last month			3	1.6 %
Kid vaped in the last month			12	6.2 %

Table D2. Summary Pollutant Concentrations during the Relevant Time Intervals (Means and Standard Deviations)

	Trimester 1	Trimester 2	Trimester 3	Whole Pregnancy	First Year of Life
NO₂ (ppb)	9.2 (3.8)	9.8 (5.2)	9.4 (4.3)	9.11(4.1)	9.4 (2.6)
NO_x (ppb)	21.7 (8.9)	22.3 (11.9)	22.0 (10.1)	21.5 (9.0)	21.8 (6.5)
EC (ng/m ³)	1.2 (0.7)	1.2 (0.8)	1.2 (0.6)	1.2 (0.8)	1.2 (0.6)
PAH₄₅₆ (µg/m ³)	9.4 (3.3)	9.3 (4.3)	9.6 (4.1)	9.5 (4.1)	9.4 (1.7)
PM_{2.5} (µg/m ³)	16.4 (5.8)	17.1 (8.0)	16.6 (6.6)	16.3 (6.7)	16.6 (3.2)

PM₁₀ (µg/m ³)	33.8 (6.6)	34.6 (8.1)	34.1 (8.1)	32.4 (7.6)	33.8 (4.2)
O₃ (ppb)*	39.3 (16.5)	39.7 (17.7)	38.5 (19.1)	39.6 (19.9)	39.1 (12.9)

*ozone is the average of the 8-hour daily maximum averages as reported in the regulatory networks, unlike the other pollutants that are averages of the entire daily concentrations.

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Figure D1. CHAPS Study Diagram and Neurodevelopmental ("STACK") Visits

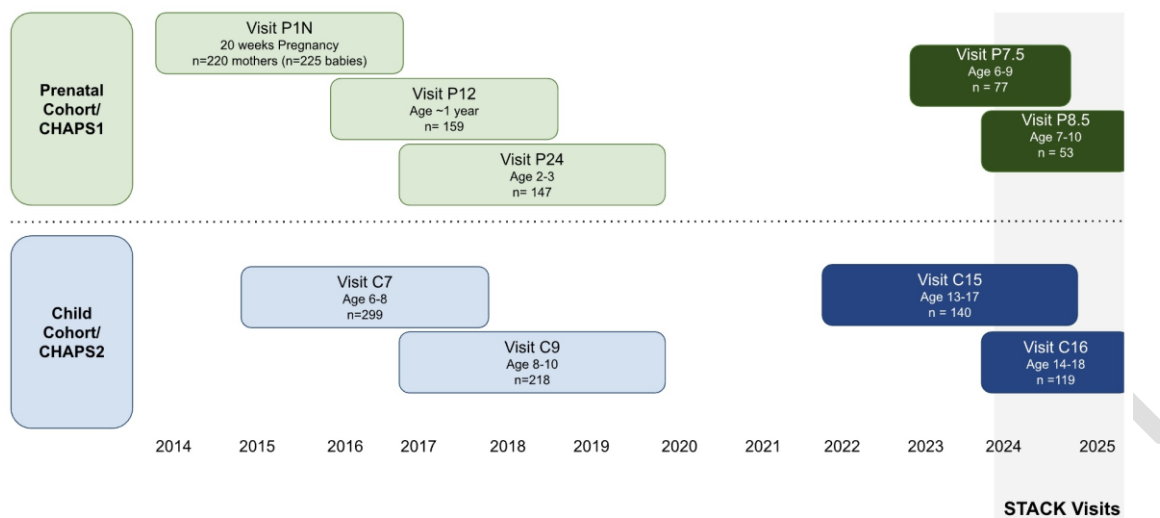
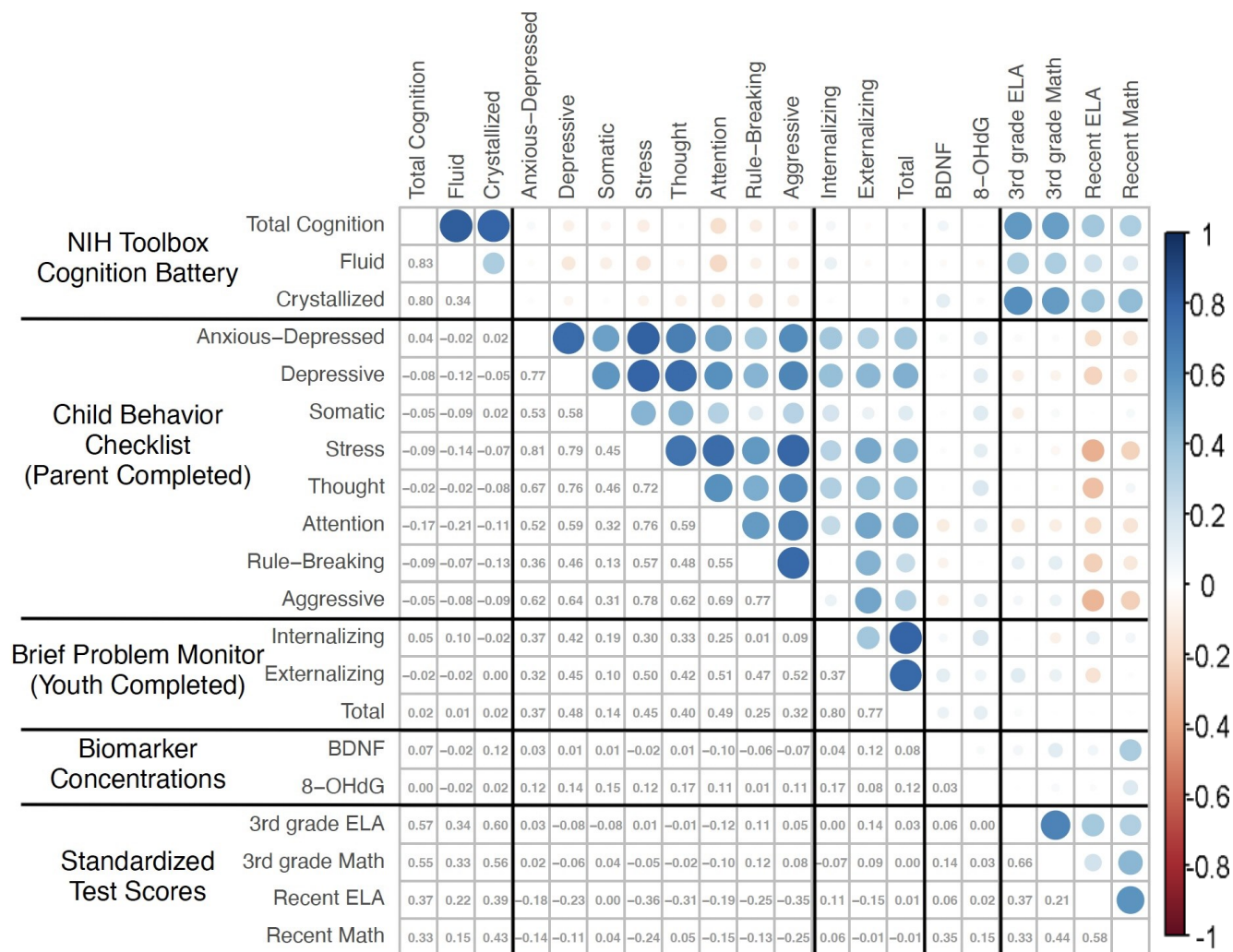


Figure D2. Correlations between Different Pollutants



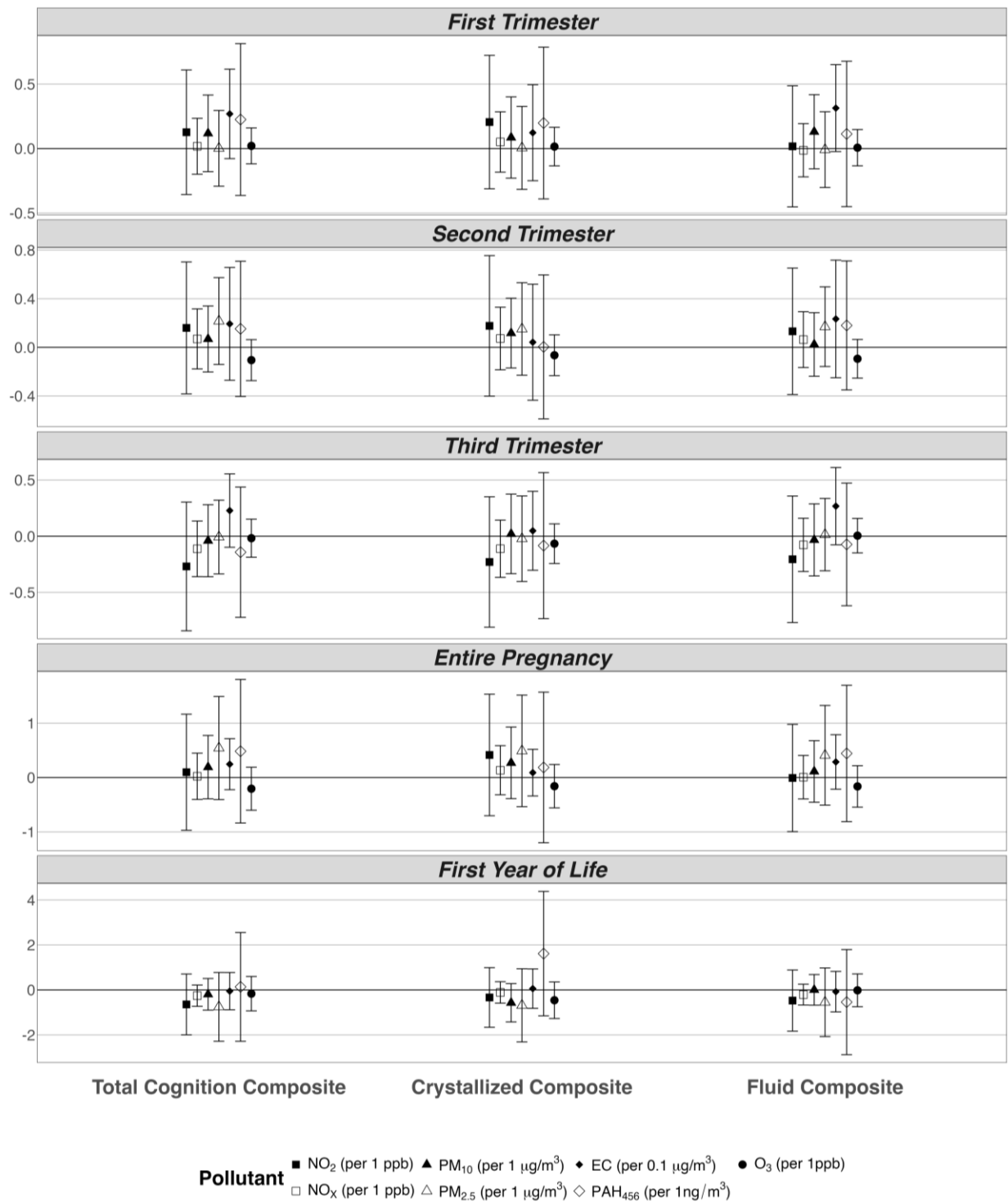
Acronyms used in the figure: EC - elemental carbon; NO₂- nitrogen dioxide; NO_x - nitrogen oxides; O₃ - ozone, PAH₄₅₆ - polycyclic aromatic hydrocarbons with 4,5 or 6 rings; PM_{2.5} - fine particulate matter; PM₁₀ - coarse particulate matter

Figure D3. Correlations between Different Neurobehavioral Outcomes



Acronyms used in the figure: 8-OHdG – eight hydroxy two deoxy guanosine; BDNF – brain derived neurotrophic factor; ELA- English/Language Arts; NIH – National Institutes of Health

Figure D4. Estimated Change in NIH Toolbox Cognition Battery Scores associated with Pollutant Exposures during Different Time Frames using Linear Models



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Figure D5. Estimated Change in Child Behavior Checklist Scaled Scores associated with Pollutant Exposures during Different Time Frames using Linear Models

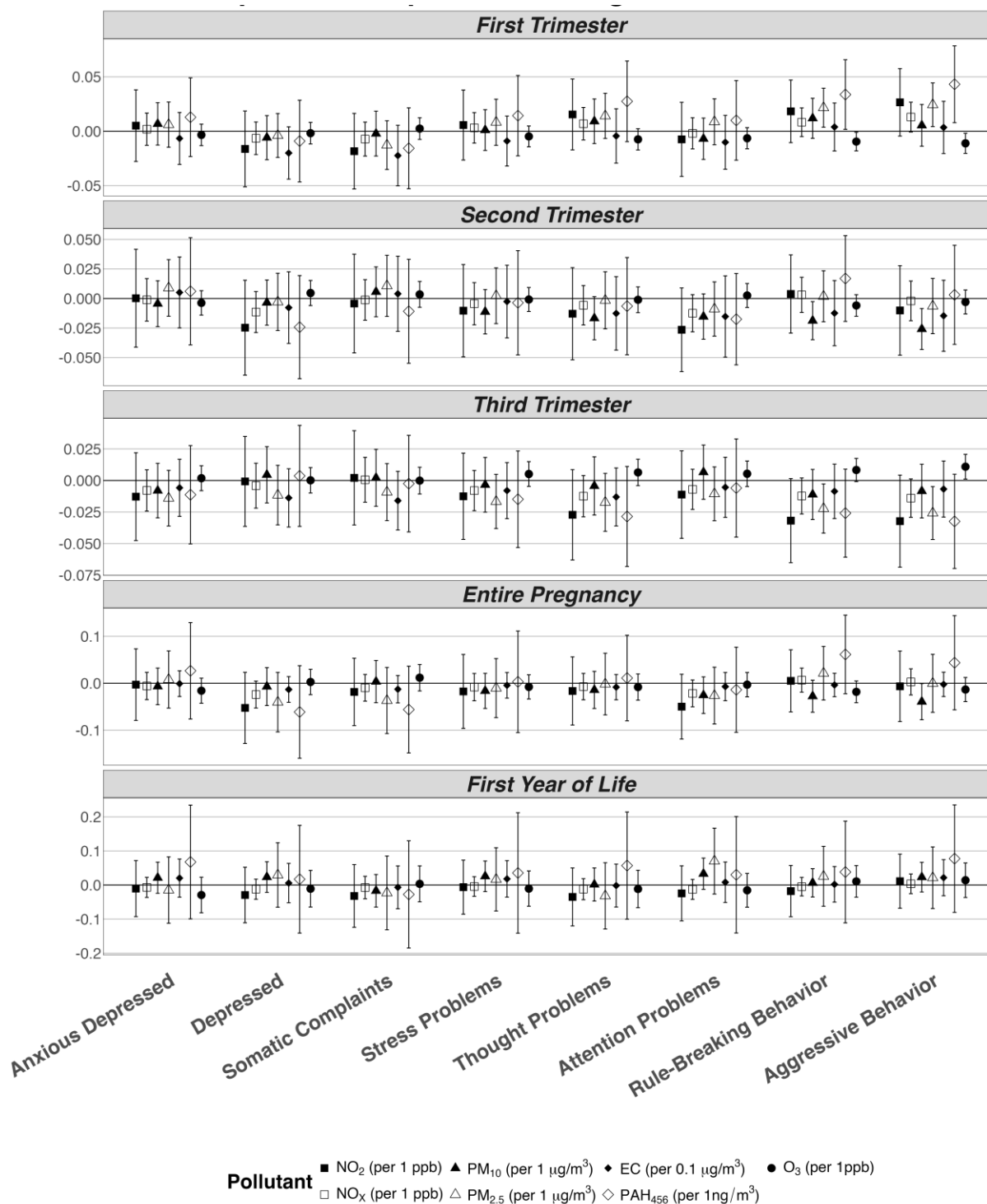


Figure D6. Estimated Change in Brief Problem Monitor Scores associated with Pollutant Exposures during Different Time Frames using Linear Models

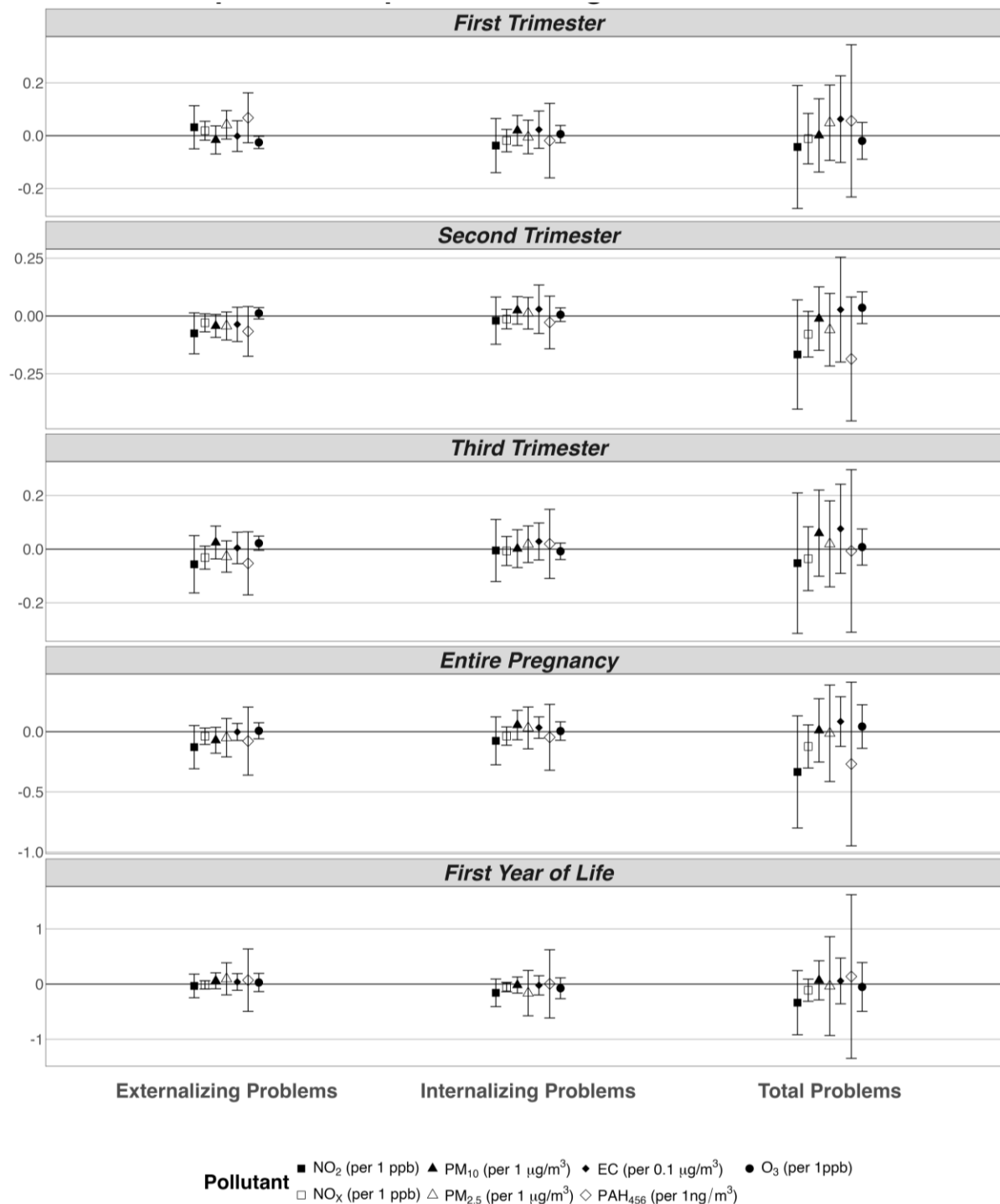


Figure D7. Estimated Change in Brain-Derived Neurotrophic Factor Serum Concentrations associated with Pollutant Exposures during Different Time Frames using Linear Models

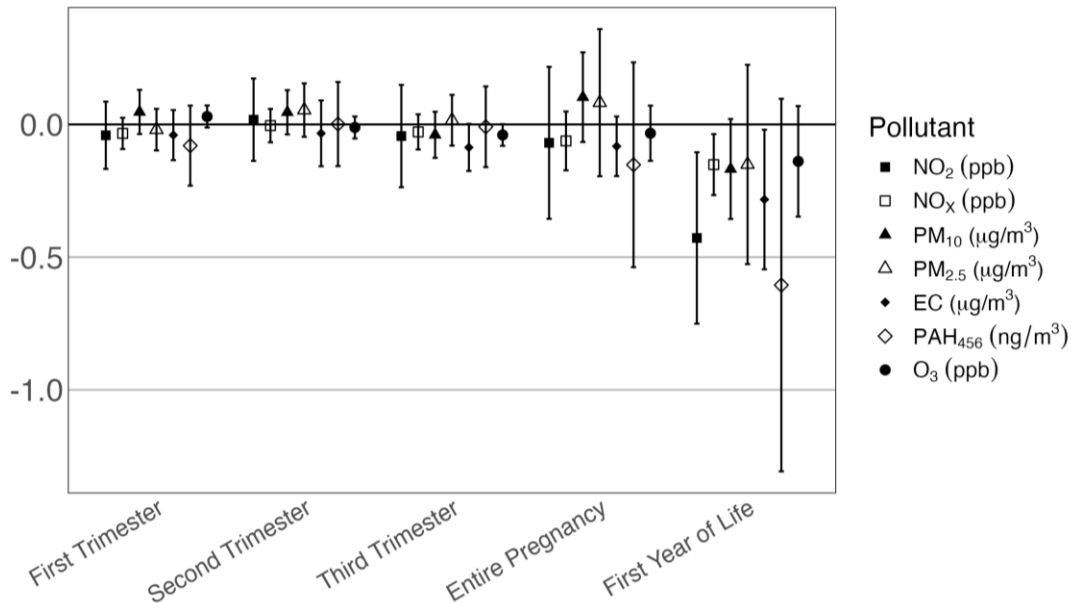


Figure D8. Estimated Change in 8-hydroxy-2'-deoxyguanosine Urinary Concentrations associated with Pollutant Exposures during Different Time Frames using Linear Models

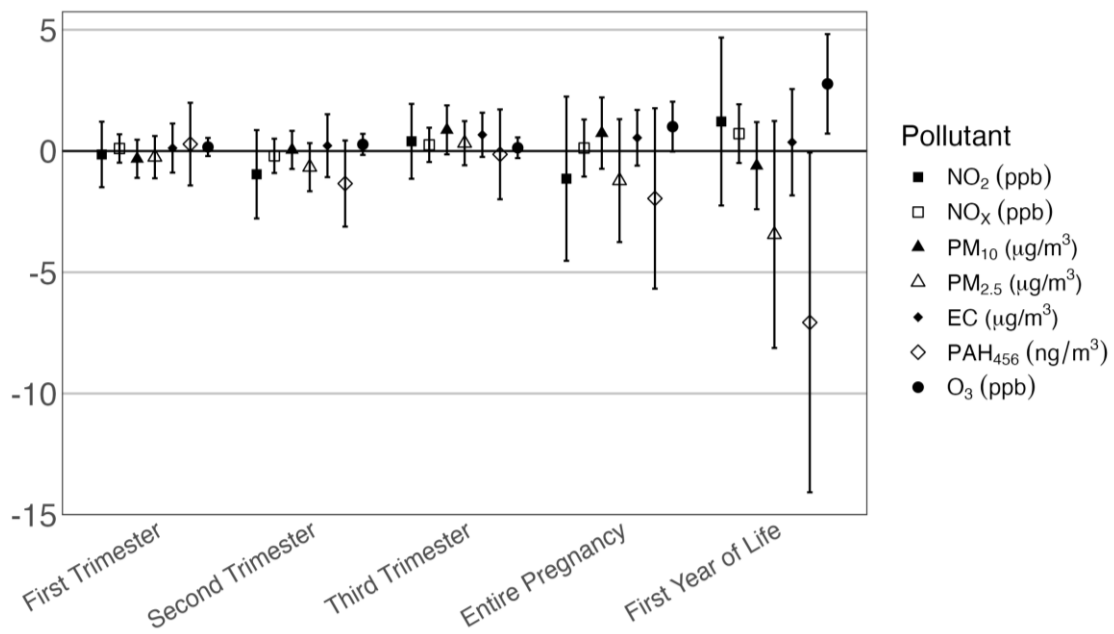
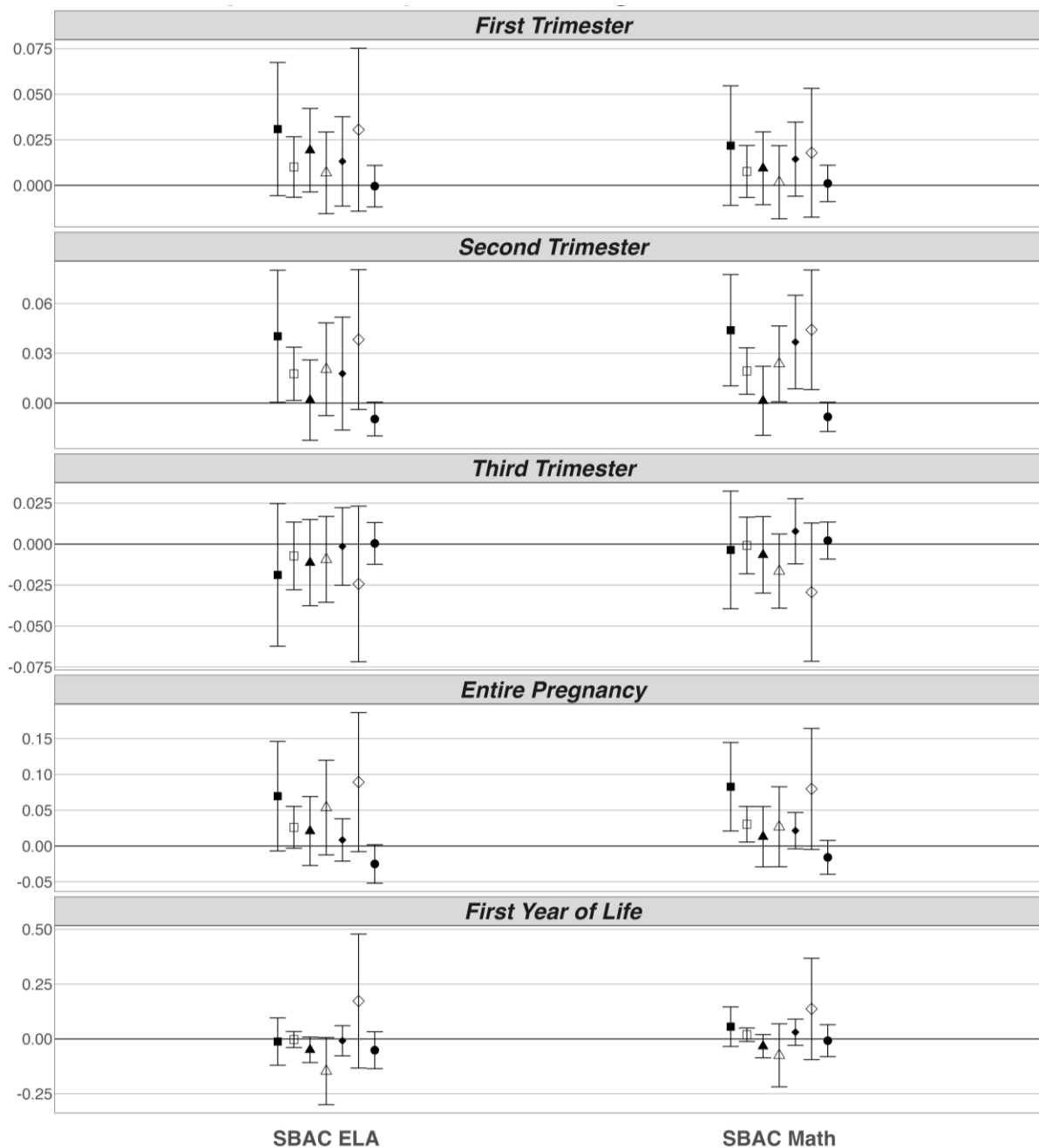


Figure D9. Estimated Standardized Test (SBAC) Scores at 3rd Grade associated with Pollutant Exposures during Different Time Frames using Linear Models



Pollutant ■ NO₂ (per 1 ppb) ▲ PM₁₀ (per 1 µg/m³) ◆ EC (per 0.1 µg/m³) ● O₃ (per 1ppb)
 □ NO_x (per 1 ppb) △ PM_{2.5} (per 1 µg/m³) ◇ PAH₄₅₆ (per 1ng/m³)

Figure D10. Sensitivity Analysis for change in SBAC score associated with 2nd trimester exposure, Stratified by Age at School Entry

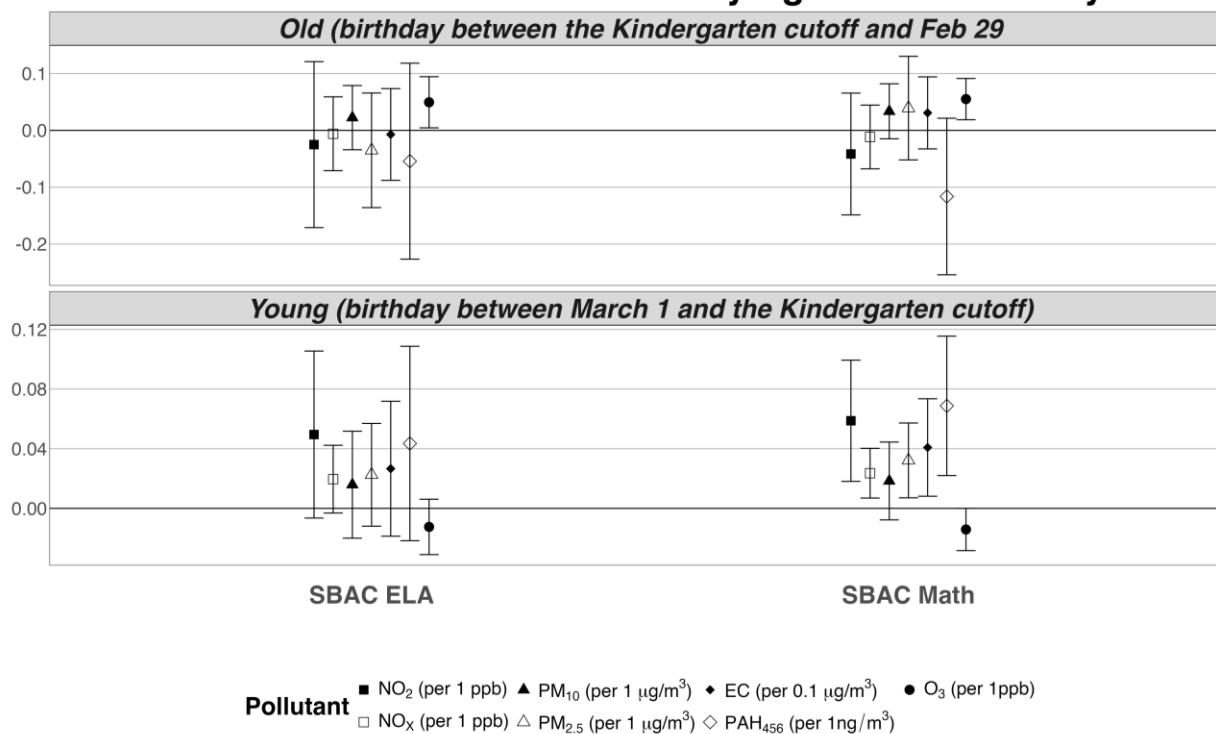
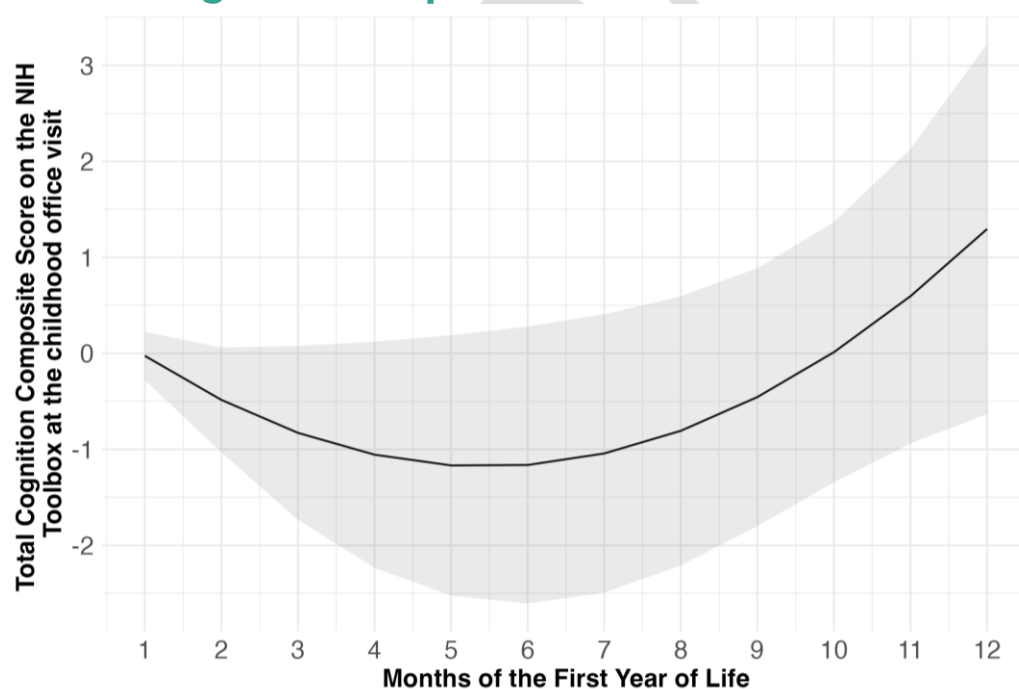


Figure D11. Critical Windows of Exposure during the First Year of Life and Associations between:

a. Brain-Derived Neurotrophic Factor Concentrations and NO₂



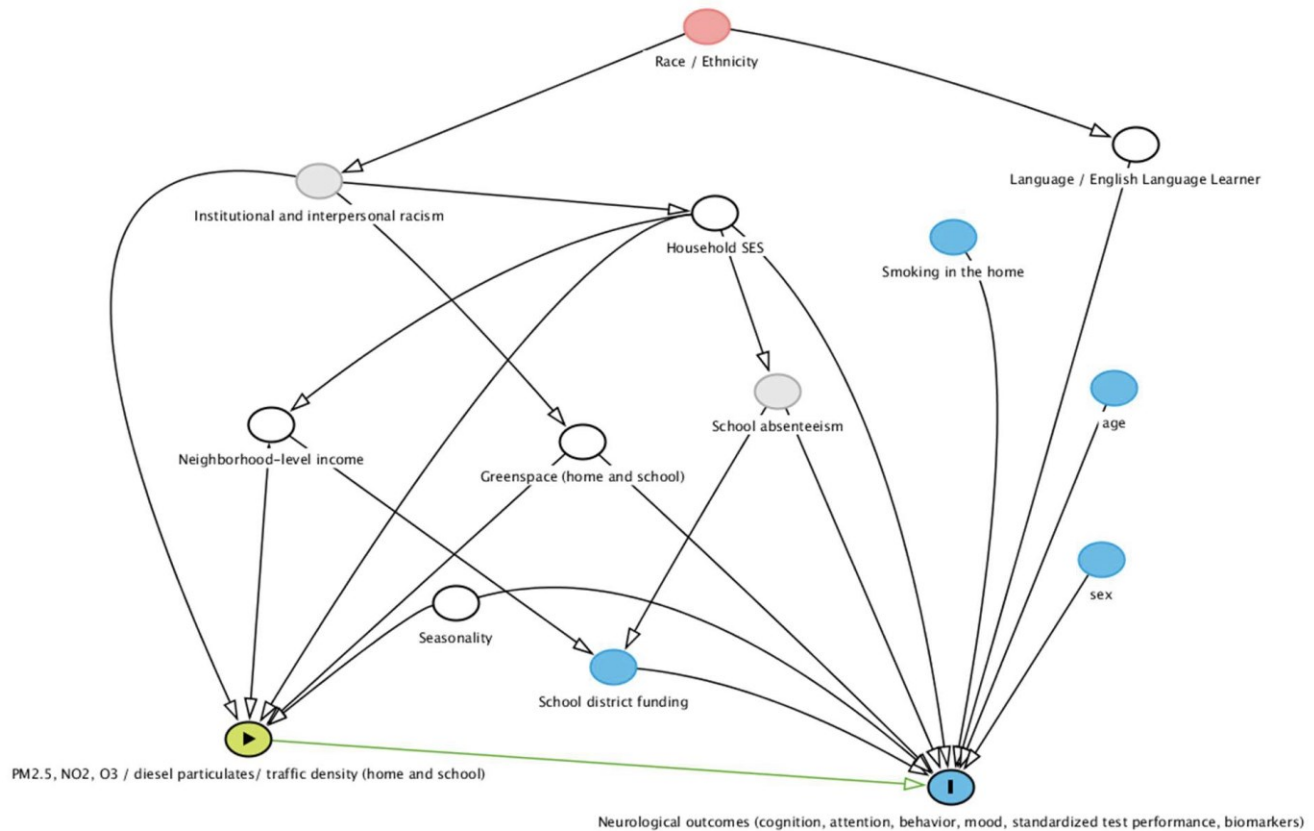
b. Total Cognition Composite Score and NO₂



Supplementary Material

Supplementary material for this study includes spreadsheets of coefficients for each of the linear models and at each time point within the DLM models. They are attached in a zip file.

Supplemental Figure S.D1. *A priori* specified Directed Acyclic Graph



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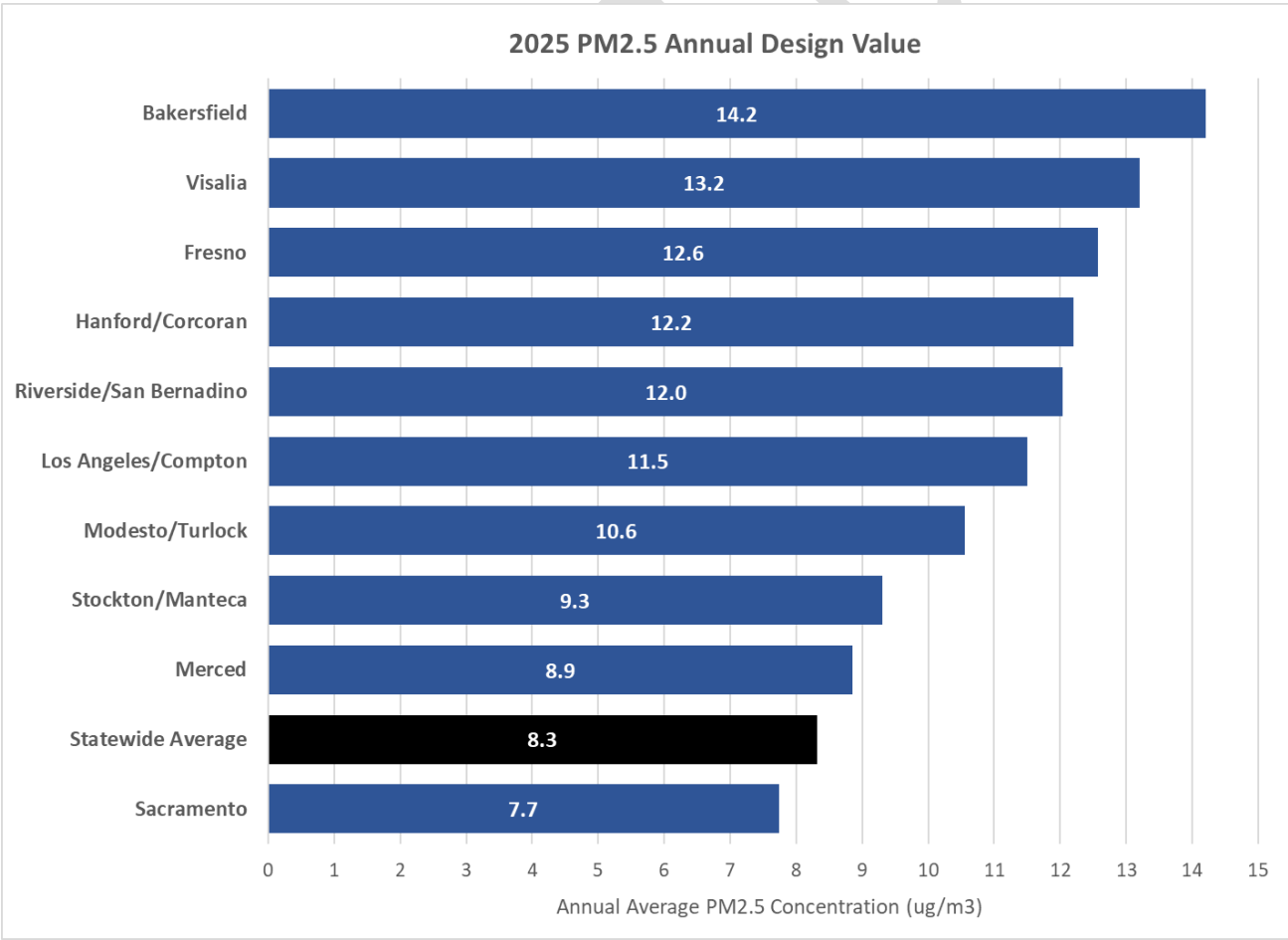
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Appendix E: Outreach and reporting materials

CHAPS: STACK: Public Outreach Document in English

Existing research indicates that air pollution has a negative impact on children’s health. For almost 10 years, the Children’s Health and Air Pollution Study (CHAPS) examined how air pollution affects a child’s health by testing children’s blood and urine samples for markers of inflammation and measuring their lung function and body mass for indicators of asthma and pre-diabetes, respectively, both examples of inflammatory diseases. CHAPS recently received funding from the California Air Resource Board to study potential links between air pollution and a child’s brain development.

The new study, called the Children’s Health and Pollution Study: Standardized Assessments, Attention and Cognition in California Kids (CHAPS: STACK), compared air pollution levels and standardized test scores of children in public schools across California between 2014 and 2019. After adjusting for factors that may also impact test scores, like SES, percent of English language learners, school district funding, and chronic absenteeism, schools located in areas with higher levels of air pollution—especially fine particulate matter (PM_{2.5}) and diesel-related pollution—had fewer students meeting state standards in Math and English.



The impacts of air pollution were most pronounced among younger students. A small increase in annual PM_{2.5} exposure (1 microgram) was associated with 2% fewer 3rd grade students meeting Math or English test standards. As shown in the graph, annual PM_{2.5} levels in Bakersfield, CA were 5.9 micrograms higher than the state average, equating to approximately 12% fewer kids meeting test standards.

In addition to the statewide assessment, CHAPS STACK also studied hundreds of individual children living in and attending schools in Fresno, CA. The study team found that higher individual exposure to air pollution, at school and home, was similarly associated with lower performance on standardized Math tests. In addition to test scores, CHAPS STACK also collected data related to other aspects of a child's neurodevelopment, including mood, attention span, behavior, and learning ability. Analysis of these additional neuro-indicators and their potential relationships to air pollution exposure are currently ongoing.

CHAPS has previously demonstrated that exposure to air pollution during critical growth stages can have long-term consequences for a child's health and development. The CHAPS STACK research suggests that air pollution may also play a meaningful role in shaping children's academic outcomes—particularly for younger students and those exposed over longer periods of time. While more research is needed, the existing evidence highlights the importance of clean air not only for children's health, but also for their ability to learn and succeed in school.

Public Outreach Document - web/flier version with enhanced graphics



CLOUDED SKIES CLOUDED MINDS

Air Pollution's Impact on Learning

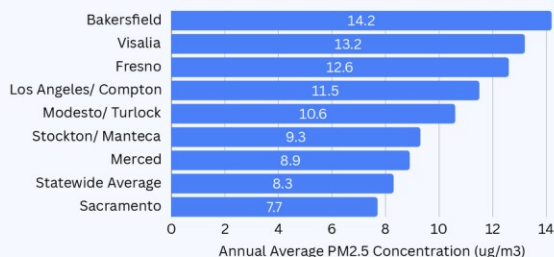
A recent University of California, Berkeley study suggests that air pollution affects more than children's lungs—it may also impact how well they perform in school. Across California, higher exposure to fine particles like PM2.5 is linked to fewer students meeting grade-level standards in math and English, after considering factors like income, percent of English language learners, school district funding, and number of school days missed. With over 90% of Californians exposed to unhealthy air at times each year, the risks are widespread—especially for younger children, whose brains are still developing. While scientists are still learning more, the evidence suggests that cleaner air can help children stay healthy and support their learning.

AIR POLLUTION
CONTRIBUTES UP TO

12%

FEWER STUDENTS MEETING
STATE STANDARDS IN
VALLEY SCHOOLS

2025 PM2.5 Annual Design Value



Most students in CA take the Smarter Balanced Assessment Consortium (SBAC) standardized tests. These help measure what students know and can do every year.



WHY IT MATTERS



Children's developing brains are more sensitive to air pollution.



Exposure to air pollution in early childhood can lead to developmental delays, disabilities and health consequences.



Meeting grade-level standards is one of the strongest predictors of future academic success.

LEARN MORE ABOUT THE STUDY

Visit our website for tips and resources on how to protect yourself and your family from air pollution.
centralcalasthma.org/health-research

Environmental Protection Agency. (n.d.). Air Quality Design Values. EPA. <https://www.epa.gov/air-trends/air-quality-design-values#previous>

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Slide Deck for Community Meetings

CHAP STACK

Children's Health and Air Pollution Study:
Standardized Assessments, Attention and Cognition in California Kids

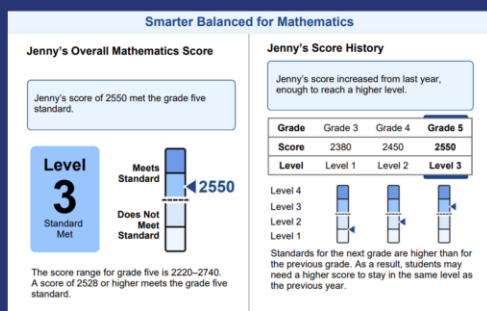
Air Pollution's Impact on Children's Learning

A recent University of California, Berkeley study suggests that air pollution affects more than children's lungs—it may also impact how well they perform in school.

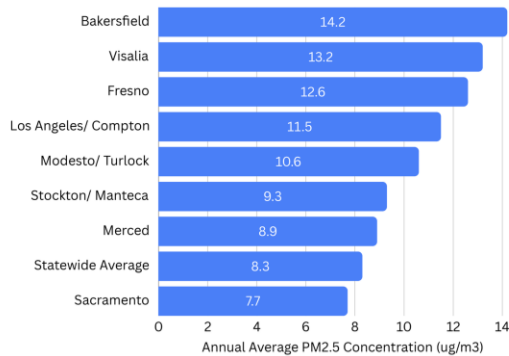


THE STUDY

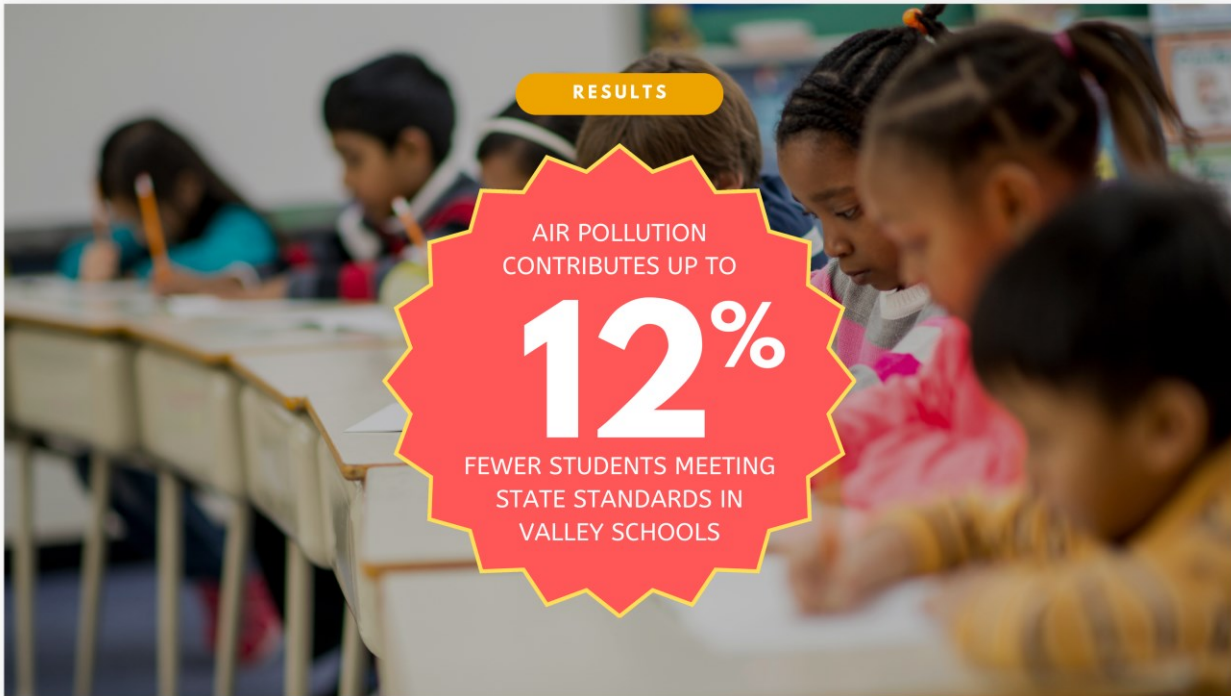
Most students in CA take the Smarter Balanced Summative Assessments. These help measure what students know and can do every year using the Common Core State Standards for English language arts/literacy (ELA) and mathematics.



2025 PM2.5 Annual Design Value



Across California, higher exposure to fine particles like PM2.5 is linked to fewer students meeting grade-level standards in math and English. With over 90% of Californians exposed to unhealthy air at times each year, the risks are widespread—especially for younger children, whose brains are still developing.



WHY IT MATTERS

While scientists are still learning more, the evidence suggests that cleaner air can help children stay healthy and support their learning.



Children's developing brains are more sensitive to air pollution.



Exposure to air pollution in early childhood can lead to developmental delays, disabilities and health consequences.



Meeting grade-level standards is one of the strongest predictors of future academic success.

AIR POLLUTION

WHERE IT COMES FROM

Most outdoor air pollution comes from seven everyday sources. Together they release fine particles (PM2.5), nitrogen dioxide and other pollutants that affect children's lungs — and their learning.



22%

FARMING OPERATIONS

Livestock, fertilizers, and field operations release ammonia and fine dust particles.



15%

ROAD DUST

Unpaved roads and vehicle traffic stir up settled PM2.5 particles.



12%

WIND-BLOWN DUST

Wind erosion from bare agricultural fields and disturbed land surfaces.



7%

COOKING

Commercial and residential cooking, especially open-flame charbroiling.



6%

FIREPLACES & WOOD STOVES

Residential wood burning for heating and recreational use.



5%

AGRICULTURE WASTE BURNING

Post-harvest crop residue burning and forest management burns.



15%

MOBILE SOURCES

Off-road equipment, trains, and other mobile combustion sources. Includes freight trucks and diesel vehicles.



18%

OTHER SOURCES

Miscellaneous local emissions not categorized in major source groups (e.g. power plants, refineries, gas stations, dry cleaners).

Source: San Joaquin Valley Air pollution Control District. Data represents directly entitled annual PM2.5