Lead Exposure Reduces Academic Performance: Intensity, Duration, and Nutrition Matter
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ABSTRACT

We leverage a natural experiment, where a large national automotive racing organization switched from leaded to unleaded fuel, to study how ambient lead exposure and nutrition impact learning in elementary school. This provides quasi-experimental evidence linking measured quantities of lead emissions to decreased test scores, information essential for policies addressing ambient lead and emission sources. We find increased levels and duration of exposure to lead negatively affect academic performance, shift the entire academic performance distribution, and negatively impact both younger and older children. Exposure to 10 additional kilograms of lead emissions from lead-fuel races reduces standardized test scores by 0.06 standard deviations, where the average race emitted more than 10 kilograms of lead— a quantity similar to the annual emissions of an airport or a median lead-emitting industrial facility in the United States. This corresponds to an average income reduction of $2,600--$4,000 per treated student in present value terms, an effect size similar to improving teacher value added by one-sixth of a standard deviation, reducing class size by 3 students, or increasing school spending per pupil by$500. The marginal impacts of lead are larger in impoverished, non-white counties, and among students with greater duration of exposure, even after controlling for the total quantity of exposure. Factors correlated with better nutrition — most notably consumption of calcium-rich foods like milk — are associated with smaller negative effects of lead exposure. These results suggest that improved child nutrition can help combat the negative effects of lead, addressing several prominent social issues including racial test gaps, human capital formation across income groups, and disparities in regional environmental justice.

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Education drives future income, productivity, and upward mobility. The United States devotes a large and growing share of resources to the promotion of education through formal schooling, with public school spending in the United States exceeding $12,000 per student in 2017, and accounting for 30% of state and 8% of national expenditures (U.S. Census Bureau, 2017). A large body of work examines the education production function, showing how a wide range of inputs drive student achievement (Hanushek, 2020). Some inputs directly relate to formal schooling, such as teaching quality, pedagogy, and class size (Krueger, 1999; Chetty et al., 2011, 2014b); while others are primarily determined outside the bounds of school, such as socioeconomic status, sleep, the environment, and nutrition (Ladd, 2012; Frisvold, 2015; Ebenstein et al., 2016; Anderson et al., 2018; Jagnani, 2020; Park et al., 2020; Park, 2020).

Using a unique natural experiment in changing lead exposure, we examine the effect of two important and interacting education inputs: environmental quality and nutrition. We show that exposure to airborne lead—which causes neurological damage, increases impulsiveness, and hinders learning—has a negative and cumulative effect on student performance. We then use our causal framework to explore a correlational finding from the public health literature (e.g., Goyer, 1995) on nutrition and the impacts of lead exposure. We find that areas consuming more nutritious food have a weaker link between lead exposure and educational outcomes, and that the negative effects of lead are greatest in areas with larger shares of minority and impoverished students. Taken jointly, these results indicate that improved child nutrition, along with environmental quality improvements, can help address several prominent social issues, including racial test gaps, human capital formation across income groups, and environmental justice.

Separately identifying the role of lead—or any education input—is challenging, as many inputs are co-determined or endogenous. Education inputs also display complementarities where changes in one affect the marginal benefit of others. For example, improvements in teacher quality and reductions in class size have differential effects across income groups and race (Krueger, 1999; Chetty et al., 2014b), and socioeconomically disadvantaged students are generally more costly to educate (Duncombe and Yinger, 2005).[1] These interdependencies provide a rationale for policies that improve life outside of the classroom, enabling the argument that improving educational outcomes requires addressing core disparities (Ladd, 2012).

We estimate the causal effect of lead on test scores by taking advantage of a natural ex-

[1] There are substantial gaps in educational attainment by race and income (Fryer and Levitt, 2004; Reardon, 2018), which persist even when comparing students within the same school (Fryer and Levitt, 2006).

periment: in 2007 the National Association for Stock Car Auto Racing (NASCAR) switched from leaded to unleaded fuel, generating an exogenous decrease in lead exposure for areas near racetracks.[2] The sudden deleading generated a permanent drop in the annual flow of lead emissions in areas near racetracks, reducing nearby ambient lead concentrations, children's lead poisoning rates, and elderly mortality (Hollingsworth and Rudik, Forthcoming), but left lead exposure unaffected in farther locations. After 2007, each cohort attending schools exposed to NASCAR emissions experienced less lifetime lead exposure than the preceding cohort, allowing us to compare test scores both within and across schools as well as between cohorts with differential levels and duration of exposure to lead emissions. Our identification uses data on the location, timing, and quantity of emissions, which allows us to disentangle the effects of lead from both persistent socioeconomic confounders (e.g., household income) and time-varying confounders (e.g., co-emitted pollutants).

We document several new and important facts. First, we provide quasi-experimental evidence linking exposure to lead emissions, rather than blood lead levels, to decreased test scores.[3] Most research focuses on blood lead levels, and while blood lead is a direct measure of current health conditions, it is net of several other factors, including any mitigating behavior taken in response to blood lead information and selection into screening.[4] Our findings are less subject to such mitigating factors or selection, because proximity to NASCAR races was largely an unknown source of exposure.[5]

This paper also directly links quantities of lead emissions to outcomes, which can better inform policies addressing ambient lead and lead emission sources. Previous work using detailed microdata shows that elevated blood lead in *early* life is strongly associated with negative *future* school outcomes (Reyes, 2015; Aizer et al., 2018; Aizer and Currie, 2019; Gazze et al., 2020). By studying an abrupt change in lead emissions, we avoid confounding from unobservable socioeconomic factors correlated with early life blood lead that also affect student achievement.[6]

[2]Despite a Clean Air Act ban for on-road leaded fuel, both automotive racing and aviation have exemptions allowing its use. Prior to the unleaded fuel switch, NASCAR was one of the largest lead emitters in the US (Hollingsworth and Rudik, Forthcoming), providing ample power for statistical analyses.

[3]The economics literature has found that lead negatively impacts many outcomes including lifetime earnings (Grönqvist et al., Forthcoming), fertility (Grossman and Slusky, 2019; Clay et al., 2014), and adult IQ test performance (Ferrie et al., 2012). There is an extensive public health literature on lead impacts, but these studies tend to be associational (e.g Canfield et al., 2003; Lanphear et al., 2005, 2018).

[4]Blood lead testing and associated regulations are typically targeted at those at the highest risk for lead exposure. Thus, blood lead data, even when using the universe of blood lead tests, is often from a selected population. See Gazze (2020) for more information regarding selection and screening in blood lead tests for children.

[5]Our results still include any negative within-classroom spillover effects from exposure (Gazze et al., 2020), as well as mitigating behavior by parents or educators in response to observed poor academic performance, such as hiring tutors to help struggling students.

[6]Identifying the causal effects of lead exposure is timely, as the US EPA is currently reviewing the lead

Second, we study exposure to airborne lead in a modern setting where average lead exposure is low; other important work on dealeading, such as Clay et al. (2018), focuses on the large-scale removal of lead from commercial gasoline during a time when ambient lead levels were much higher. Our analysis is on children in Florida, which—unlike many of the other populous U.S. states—has comparatively low lead contamination. Florida has the lowest soil lead concentrations of any state in the contiguous U.S. (Smith et al., 2014), and one of the lowest lead poisoning rates (U.S. Centers for Disease Control, 2019). Given that lead exposure continues to decline, future lead policy must be informed by research on impacts when ambient levels are low.

Third, we document new evidence on the duration, quantity, and distributional impacts of lead exposure. The variation in our data is such that we can compare students exposed to the same lifetime total quantity of lead, but spread across different numbers of years. Our results indicate that exposure both in very early years and up to at least age 8 can have negative effects, and that the same quantity of exposure causes more harm when spread over a longer timeframe; "death by a thousand cuts" may be worse than a single large exposure dose.[7] We also find no evidence that the marginal effects of additional lead exposure change with total exposure, suggesting effects are largely linear in our observed range. Lead exposure has negative effects on students across the entire achievement distribution, but disproportionately affects those in school districts with larger shares of Black and low-income populations.

Finally, we provide new population-level evidence that nutrition plays a role in mitigating the effects of lead. While many programs designed to reduce blood lead specifically address nutrition, this is generally bundled with other components (e.g., Billings and Schnepel (2018)), which complicates evaluating the role of the nutritional link. We find the link between lead exposure and test scores is lower in areas with greater levels of per-capita spending on calcium-rich products. We further support this result with nationwide cross-sectional evidence of higher milk and calcium intake correlating with lower blood lead levels. This pathway is physiologically plausible because lead affects the brain by displacing calcium (Büsselberg, 1995; Peraza et al., 1998), an essential micronutrient.[8] Families were also likely unaware of the presence of NASCAR-caused lead exposure, so differences in nutrition are less likely to result from interventions; while families might respond to poor academic

National Ambient Air Quality Standards and is interested in causal effects on cognitive outcomes in children (U.S. Environmental Protection Agency, 2020).

[7]Importantly, our findings do not indicate that later life exposure is more harmful than early life exposure, but that additional lead exposure later in life, on top of early life exposure, causes additional harm.

[8]Bolstering milk consumption is a common recommendation for mitigating the effects of lead exposure (U.S. Centers for Disease Control, 1991) because evidence from experimental animal studies and associational human studies shows that higher calcium intake is associated with less lead absorption and lower blood lead levels for a given quantity of exposure (Six and Goyer, 1970; Ziegler et al., 1978; Mahaffey et al., 1986).

performance, without knowing it may be attributable to lead exposure they are unlikely to respond with increased calcium.

We find exposure to an additional 10kg of lifetime lead emissions by the third grade — equivalent to growing up near the average airport or a 42nd percentile lead-emitting Toxics Release Inventory (TRI) facility — decreases standardized test scores by 0.06 standard deviations.[9] Removing this exposure would generate returns similar in magnitude to decreasing class size by 3 students, having a more experienced teacher, or having a one standard deviation better teacher in terms of value added (Jepsen and Rivkin, 2009; Chetty et al., 2014a). The estimate is also of a similar magnitude to documented gender and racial gaps observed in test scores (Fryer and Levitt, 2006, 2010).

Combining our results with estimates of how test scores affect future income (Chetty et al., 2014b), we calculate the present value of lost future income for the average 3rd grader growing up exposed to emissions in our sample is approximately \$2,600–\$4,000 in 2020 dollars. For a 90th percentile exposure student in our data discounted lifetime income losses are closer to \$8,300. This suggests that the effects of living near a lead-intensive emissions source has drastic effects on lifetime earnings.

While many education inputs are often effectively fixed or costly to change, lead may be simpler to target.[10] Legacy lead can be mitigated by one-time expenditures such as home remediation, and other sources of lead emissions can be reduced by the removal of the exemptions from the Clean Air Act leaded fuel ban for off-road racing and aviation.[11] Our findings also point to improved nutrition and increased calcium intake as possible additional investments against some of the negative effects of both known and unknown lead exposure. Some portion of previously observed benefits of improved nutrition on test scores (e.g., Frisvold (2015); Anderson et al. (2018); Gassman-Pines and Bellows (2018); Figlio and Winicki (2005)) may be due in part to avoided lead absorption, which highlights the role that simple child nutrition can play in addressing issues of health, education, and environmental justice.

[9] 10kg of lead emissions is approximately one-third of the emissions caused by a 500 mile race, such as the Daytona 500. Prior research suggests this amount of lead emissions within a county in a single year increases county-level lead poisoning rates that year by approximately 1 percent (Hollingsworth and Rudik, Forthcoming).

[10] For example, parental income or education is nearly impossible to change, and meaningfully decreasing class size requires regular salary payments to newly hired teachers. Hiring more teachers may also decrease average teaching quality, offsetting some of the gains from smaller class size.

[11] Prior research has found that remediation of lead-contaminated homes improves test scores (Billings and Schnepel, 2018; Sorensen et al., 2019).

1 The Education Production Function, Identification, and Complementarities

To frame our contribution and model the relationship between lead and test scores, consider a stylized static education production function:

$$\text{test scores} = f(S, C, N, E, b(Pb)),$$

where test scores—averaged at the school-grade-year level, like our data—are a function of vectors of socioeconomic characteristics S, school/classroom characteristics C, nutrition variables N, environmental characteristics E, and blood lead concentrations $b(Pb)$, which are a function of lead exposure Pb. $Pb = x + l$ is the sum of exposure from NASCAR x, and from other lead sources l. We are interested in the marginal effect of Pb on test scores, holding other factors constant:

$$\frac{\partial f(S, C, N, E, b(Pb))}{\partial b(Pb)} \frac{\partial b(Pb)}{\partial Pb} = f_b b'.$$

In non-randomized settings, other inputs may also be a function of Pb. For example, due to residential sorting or pollutant co-emission, changes in Pb may correlate with changes in other inputs into f, yielding direct and indirect effects of lead on test scores. The total effect of lead on test scores is:

$$\frac{d\,\text{test scores}}{dPb} = f_b b' + f_C \frac{dS}{dPb} + f_S \frac{dC}{dPb} + f_N \frac{dN}{dPb} + f_E \frac{dE}{dPb}. \tag{1}$$

The first term on the right hand side, $f_b b'$, is the direct effect of lead on test scores, holding other inputs fixed. Our goal is to estimate this direct effect.

The last three terms capture common potential confounders for $f_b b'$ due to indirect effects of lead. For example, large, persistent changes in ambient lead—like those induced by deleading standard on-road gasoline in the 1970s or the opening or closing of a TRI plant (Currie et al., 2015)—may induce residential sorting, which will affect inputs in S, altering test scores by changing the student composition. Changes in S subsequently may affect the school tax base and alter classroom characteristics in C, such as classroom size. Changes in lead emissions from industrial sources may also cause changes in other pollutants in E if they are complements or substitutes in the industrial production process.[12]

[12] This is a particular concern for historical catalytic converter mandates. The devices reduce emissions of non-lead pollutants through chemical reactions and prohibit leaded fuel since lead renders them ineffective. This co-emission creates challenges in separately identifying the effects of lead from co-emitted pollutants.

Equation (1) illustrates two of our key contributions. First, research focuses largely on the relationship between outcomes and blood lead at a point in time, f_b, instead of the relationship between outcomes and exposure to emissions $f_b b'$. This is often due to a lack of data or a lack of quasi-experimental variation in measurable exposure. We can measure lead emissions using observed leaded race miles and the lead content of the fuel used. This helps identify the effect of lead exposure across distance, as well as the role of length of exposure conditional on total exposure.

Second, regressing learning outcomes on measures of total lead exposure will confound its impact through correlated inputs. To identify $f_b b'$, we need to isolate independent variation in Pb. The deleading of NASCAR satisfies this requirement. Hollingsworth and Rudik (Forthcoming) show deleading did not change ambient concentrations of other automotive pollutants captured by E, thus $\frac{dE}{dx} = 0$. There is no evidence that the deleading of NASCAR fuel associates with trends in socioeconomic variables S, nutrition choices N, or school characteristics C, indicating that $\frac{dS}{dx} = \frac{dN}{dx} = \frac{dC}{dx} = 0$. The robustness of our estimates to a wide range of fixed effects and socioeconomic controls supports this as well. This gives us:

$$\frac{d \, \text{test scores}}{dx} = f_b b',$$

and variation in lead exposure from NASCAR identifies the effect of gasoline lead on test scores.

The cross-partial derivatives of the production function give insight into heterogeneous effects. The nutrition and medical literature both emphasize the physiological mechanisms behind the role of calcium in mitigating the negative effects of lead exposure; lead displaces calcium in the body and additional calcium intake limits this displacement (Ahamed and Siddiqui, 2007). Taking the cross-partials of our production function with respect to lead and calcium $n \in N$ gives:

$$\frac{d^2 \, \text{test scores}}{dxdn} = f_{bN} b'.$$

Nutrition science suggests that this cross partial is positive and that the corresponding interaction term in a regression should be positive, reflecting that additional calcium dampens the negative effects of lead.

Finally, the cross partial derivatives show how lead matters for educational policy. Consider some policy that affects a variable $c \in C$. The policy's marginal effect depends on lead exposure Pb if the cross-derivative is non-zero:

$$\frac{d^2 \, \text{test scores}}{dxdc} = f_{bC} b'.$$

If lead-poisoned students obtain smaller marginal benefits from better teachers or smaller classrooms, lead mitigation is complementary and increases returns to educational investments. We leave this question for future research.

2 Data

2.1 Test scores

We obtain data on educational achievement from the Florida Department of Education. Each year, the Florida Department of Education records school-level outcomes from the Florida Comprehensive Assessment Test (FCAT), the standardized test used in Florida public schools in grades 3–10. The FCAT data we use span 2003–2014.[13]

FCAT data report test score outcomes at the school-grade-subject-year level, averaged across all students. We standardize school-grade-subject-year average scores within each grade, year, and subject to be mean zero and standard deviation one. The z-score gives us how many standard deviations a group is above the state-wide test average in that year. This means that our treatment effect estimates will be based on *school-level* rather than individual-level standard deviations. Following Ost et al. (2017) we adjust our school-level estimates to be comparable with estimates from individual-level data whenever such comparisons are made.[14]

The data also report the percentage of students in each of five achievement levels. Level 5 contains the highest-achieving students, while level 1 contains the lowest-achieving students. Achievement levels proxy for the distribution of scores within a school. We define students in level 3 and above to be *proficient*, as level 3 is the threshold for "passing" the test. For example, a level 3 score in grade 10 reading is required for graduation.

In this paper we focus on mathematics and reading tests for grades 3–5. Focusing on the earliest grades provides the most variation in lead exposure. These grades also correspond to elementary schools, which have smaller catchment areas than middle or high schools. Since

[13] After 2014 Florida changed its standardized test to the Florida Standards Assessment. Prior to 2003 FCATs were not taken in each grade.

[14] Ost et al. (2017) demonstrate that treatment effect estimates reported in standard deviation units will reflect the level of aggregation used in the analysis. Even when studying the same test, 1) a more aggregate group will tend to have a smaller standard deviation than the a less aggregated one and 2) this difference must be accounted for when comparing treatment effects across the studies. In Table A7, we use data from the Florida Department of Education on a subset of data used in our paper to demonstrate that—for the same test—a school-level standard deviation is around 37% the size of a student-level standard deviation. Following Ost et al. (2017), we use this FCAT-specific deflator whenever we compare school-level results to results from individual-level data. Thus includes our estimates of monetary damage since the studies linking test scores to future income are based on individual-level data.

we lack data on where students live, we assign lead exposure based on school location, and smaller catchment areas reduce measurement error. Our estimates will be biased toward zero from any remaining measurement error in exposure from this source or if students move to different districts. We weight observations by the number of students in each school-grade-year.

2.2 Lead, NASCAR, and the TRI

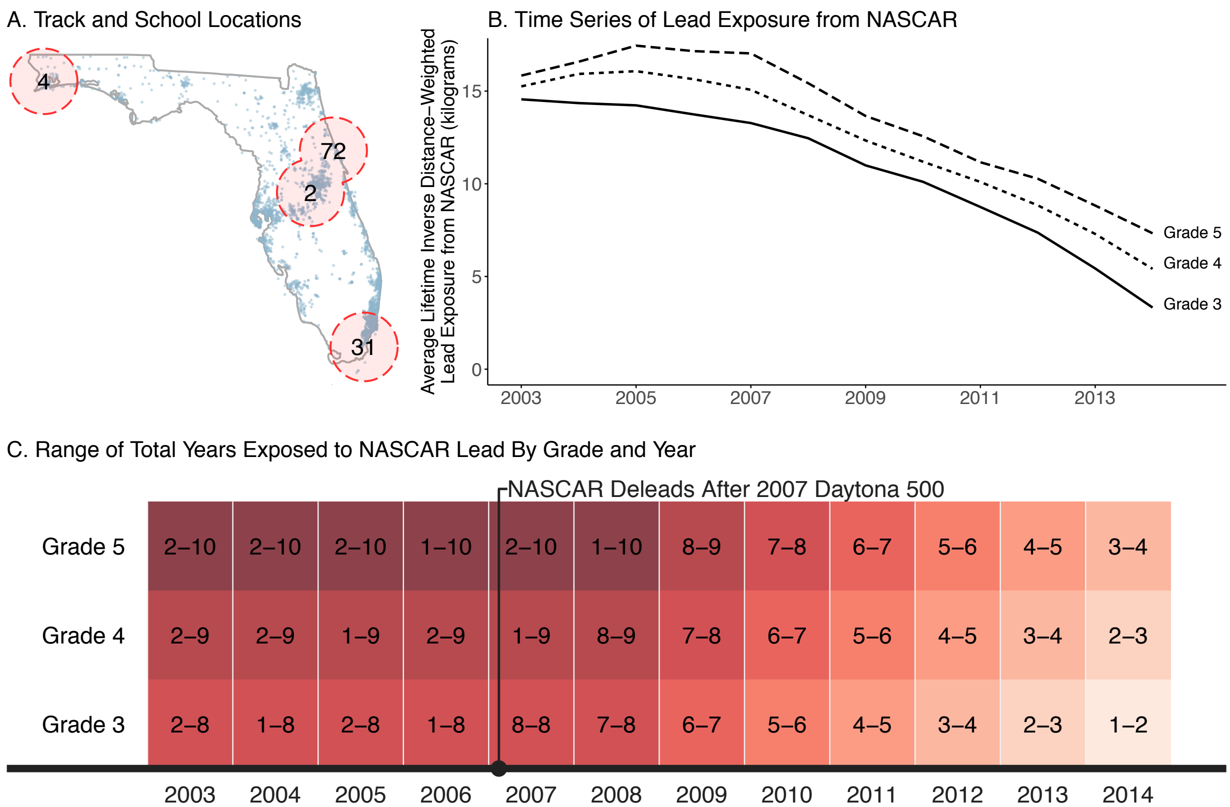
Race data come from Racing-Reference, an archive maintained by NASCAR.[15] The data detail the number of drivers, the number of laps completed by each driver, track length, and day and time for each race. Hollingsworth and Rudik (Forthcoming) describe the leaded fuel status of each NASCAR race and its evolution over time. Section 3 describes our main treatment variable, which we base on our NASCAR lead measure.

Data on industrial lead emissions come from the Toxics Release Inventory, which reports emissions from facilities that use, manufacture, or process more than 100 pounds of lead and have 10 or more employees.

2.3 Income, demographics, and nutrition

Data on county median income come from the U.S. Census Small Area Income Poverty Estimates, and data on county unemployment rates come from the Bureau of Labor Statistics Local Area Unemployment Statistics. Data on the percent of individuals in a county who are Black or Hispanic, and the percent of homes built before 1940, come from the American Community Survey. County median household income and poverty rates come from the U.S. Census Small Area Income Poverty Estimates. Fast food establishments per capita come from the USDA Food Atlas. We proxy for school district average home calcium consumption using data from Nielsen Homescan, calculating the average per-person spending in each school district on milk, non-milk dairy products like cheese, fresh produce, canned and dried vegetables, and vitamin supplements. As a demonstration of the link between calcium intake and blood lead, we use information on daily food dairies and blood lead measures from the 2005-2006 wave of the National Health and Nutrition Examination Survey (NHANES).

Figure 1: Locations of tracks, schools, and number of races at each track, time series of lifetime inverse distance-weighted lead exposure by year, and timeline of years of life exposed to leaded races.



Panel A: We plot schools in our dataset as blue points. The shaded red area shows all places within 50 miles of a racetrack. The number in the center of the red circle is the location and number of leaded races that occurred at that racetrack between the birth year of the oldest students in our sample and the final year of our sample.
Panel B: The inverse distance-weighted lead exposure in kilograms for each grade's cohort, averaged across all schools within 50 miles of a racetrack. Lead exposure is estimated assuming an average race fuel efficiency of 3.2 race miles per gallon and 5.2 grams of tetraethyl lead per gallon.
Panel C: For each year's cohort, the minimum and maximum years of life exposed to leaded NASCAR races, ignoring exposure during the year of the cohort's test, for those schools within 50 miles of a racetrack. The left number is the minimum number of years exposed by a school cohort, the right number is the maximum number of years. The 2007 Daytona 500 was leaded, so maximum exposure for 2008 does not drop despite the fact that NASCAR deleaded in 2007.

3 Summary Data and Methods

We begin with an overview of the cross-sectional and longitudinal variation in our data. Our data contain variation across space, time, age at exposure, duration of exposure, and intensity

[15] The data also include races from the Automobile Racing Club of America, a related organization that deleaded at the same time as NASCAR; we refer to both as NASCAR.

of exposure. This enables use to include a rich set of fixed effects to reduce concerns of omitted confounders. Figure 1 Panel A shows racetracks featuring leaded races, the location of schools, and the number of leaded races at each racetrack over the lifetime of all children in our sample. Shaded red areas depict the treatment radius around each track, with a cutoff of 50 miles, which we base on our own cubic spline estimates on detectable correlations between distance from racetracks and student outcomes, and on prior work showing effects on ambient concentrations out to 50 miles (Hollingsworth and Rudik, Forthcoming). We use schools outside these areas as controls and assign them zero lead exposure from NASCAR. We inverse distance-weight exposure by school-racetrack distance, which follows the shape of detectable distance effects, though weighting does not affect the net magnitude or significance of our estimates. Because some schools are very close to racetracks, use of inverse distance-weighting to calculate exposure means values for the 100th percentile of observations are an extreme outlier, more than 10 times the 99th percentile. In our primary results, we Winsorize the data to omit the top 1% of observations in terms of inverse distance-weighted lead emissions. We show results are robust to alternate distance weighting metrics and inclusion of the upper 1%. Prior to deleading, average lifetime lead exposure is approximately flat for all grades. After deleading, exposure steadily declines to 5–8 kilograms at the end of our sample in 2014.

Panel C shows the range of possible years exposed to leaded races for the treatment group of schools by grade and cohort.[16] For example, the 2003 grade 3 cohort was exposed to races between 2–8 years of life, depending on their proximity to each racetrack, as some tracks have annual races and others do not. Cohorts that took the test in 2008 or earlier, within 50 miles of a racetrack holding annual races, have the largest possible number of exposure years.[17] As races generally occur annually, the maximum exposure of each subsequent test cohort declines by 1 as they phase out of leaded exposure years, until the end of our sample. Note that later cohorts are receiving reduced exposure largely through fewer race-years later in life (e.g., an 8-year old with 6 years of exposure got them from ages 0-6, with the two most recent years free of exposure). Minimum exposure for each cohort is generally either one less or equal to the maximum exposure. However, some school cohorts have just 1 or 2 years of exposure due to two uniquely occurring races at Walt Disney World in Orlando. The most exposed third grade cohorts have 8 cumulative years of leaded-race exposure, and the least exposed (treated) third grade cohorts have 1 year of leaded-race exposure.

We estimate the effect of lead emissions on test scores using the following general speci-

[16]We ignore exposure during the year of the test to avoid capturing short-term effects (Ebenstein et al., 2016; Marcotte, 2017). Our results are robust to including this year.

[17]The 2007 Daytona 500 was leaded; thus the 2008 and 2007 cohorts were exposed each year of life before the test year.

fication:

$$Y_{sgty} = f(\text{cumulative lead exposure}_{sgy}; \beta_{\textbf{lead}}) + \mathbf{X}_{syt}\beta_{\mathbf{X}} + \alpha_{sgt} + \gamma_{tgy} + \varepsilon_{sgty}. \qquad (2)$$

Y_{sgty} is the school z-score, proficiency rate, or percent of students at a specific achievement level for school s, grade g, year y, and subject t. $f(\text{cumulative lead exposure}_{sgy}; \beta_{\textbf{lead}})$ is a function f of cumulative lead emitted from NASCAR races near the school during a student's lifetime. For example, for a 9-year old third grader, cumulative lead emissions are the sum of all lead emissions within some distance d of the school in the 8 years before year y — our main results omit exposure in year y to avoid potential confounding from the role of contemporaneous particulate pollution from races on test outcomes (e.g., Ebenstein et al. (2016)). We compute lead emitted using the observed miles driven during each race, the known lead content of the fuel, and the average of two estimates of gasoline used per mile driven in the race.[18]

In our simplest specifications, f sums inverse distance-weighted cumulative lead emissions within 50 miles of each school s. A simple cubic spline regression estimate, which Figure 3 shows, support that in our framework 50 miles is the distance where statistically detectable test score effects disappear, and economic effects approach zero. This means the exposure in a given year for school s from lead-emitting racetrack r with a distance of distance$_{sr}$, the emissions treatment assigned to a school is:

$$\text{cumulative lead exposure}_{sgy} = \sum_{r \in racetracks} 1\left(\text{distance}_{sr} \leq 50\right) \frac{\text{cumulative lead emitted}_{rgy}}{\text{distance}_{sr}}$$

where cumulative lead emitted$_{rgy}$ is the cumulative lead emitted at racetrack r during the lifetime of students in grade g in year y. We use this inverse distance-weighting procedure because we do not observe the actual level of ambient lead exposure at each school and the inverse distance-weighting recognizes that schools closer to racetracks have exponentially greater exposure than those farther away. We explore both linear distance weighting, which puts comparatively less weight on nearby lead emissions than inverse distance-weighting, and unweighted specification, which treats all distances under 50 miles equally, in our appendix. We also test specifications where f is a flexible binned function of inverse distance-weighted emissions, or where f is a cubic spline in distance, instead of assuming a distance-weighting scheme.

$\mathbf{X}_{syt}$ is our set of controls to address potential observable confounders. It includes county

[18]Using the estimated quantity of lead emitted rather than miles driven also helps clarify when we mean quantities of exposure versus distances.

median income, county unemployment rate, and cumulative TRI facility lead emissions within 50 miles of each school over the same set of years described above. Controlling for income and unemployment addresses potential differential trends in socioeconomic status that influence school average test scores and spuriously correlate with declining NASCAR lead exposure for schools near racetracks. Controlling for cumulative TRI lead emissions addresses potential differential trends in industrial lead exposure for schools near racetracks versus those farther away.[19]

α_{sgt} is a set of school-grade-subject fixed effects that control for time-invariant school characteristics, allowing for within-school differences across grades and subjects. γ_{tgy} is a set of subject-grade-year fixed effects addressing common annual shocks across all schools specific to each grade and subject, such as subject-specific test difficulty and state-level education policy. ε_{sgty} is the error term. We cluster standard errors at the school district level, which in Florida aligns with county borders.

Our estimates of the effect of lead emissions on test scores are well-identified if—conditional on our controls—there remain no omitted variables varying within a school, within a grade, for a specific subject, or over time that correlate with both test scores and cumulative lead emissions. The exogenous nature of the fuel switch circumvents many such concerns, since deleading did not affect other pollutants and is unrelated to changes in socioeconomic confounders for those who live nearby. In the appendix, we show our estimates are robust to a wide range of control, specification, and fixed effects choices. The stability regardless of our sets of controls and fixed effects further supports the exogeneity of our treatment measure.

4 Results

Table 1 presents estimates using our preferred specification across outcomes and subsets of the data. Panels A and B show the effect of lead emissions on school z-scores; Panels C and D show the effect on proficiency rates. Panels A and C inverse distance-weight lead emissions, while Panels B and D leave them unweighted. Panel A contains our preferred combination: z-scores and inverse distance-weighted emissions.

Our main estimates in column 1 correspond to equation (2) and indicate that 10 additional inverse distance-weighted kilograms of lifetime lead emissions, 2/3rds of the mean exposure in our data of 15 kilograms, decreases average test scores by 0.060 standard deviations and the proficiency rate by 0.952 percentage points. To get a better sense of how large

[19]TRI facilities represent another possible source of variation in lead exposure (Currie et al., 2015), but other economic and demographic factors that correlate with plant emissions complicate using such variation for identification.

10 inverse distance-weighted kilograms is, we compare it to emissions of TRI facilities: an additional 10 inverse distance-weighted kilograms is equivalent to locating a 42nd percentile lead-emitting facility 1 mile away from a school for the life of a 3rd-grader.

Panels B and D shows that 10 unweighted kilograms of lead decrease test scores by 0.003 standard deviations and the proficiency rate by 0.056 percentage points. The mean exposure in unweighted terms is 390 kilograms. Thus depending on weighting, the effect for the mean treated school cohort is a z-score decrease of between 0.09–0.12 standard deviations, and a proficiency rate decrease of between 1.4–2.2 percentage points.

Columns 2–6 show estimates when our sample consists of only a specific grade or subject. All estimates are economically significant in size, but are 0–30% larger for math than for reading, and tend to be larger for testing in grades 3 and 4 compared to grade 5.

Figures 2–4 display estimates of heterogeneous marginal effects in terms of quantity, proximity, and length of exposure. Figure 2 plots the estimated dose-response function in black which allows the treatment effect to vary by quantity of exposure. The figure comes from estimating equation (2), where the function f is eleven indicator variables corresponding to lifetime inverse distance-weighted lead exposure in 3 kilogram bins up to 30 kilograms, and an additional bin for greater than 30 kilograms. The estimated effects are relative to 0 kilograms of exposure. Increased lead emissions decrease z-scores, but detectable effects level off around 20 kilograms, suggesting that the negative marginal effects of lead may decrease once lifetime exposure reaches a sufficiently high level.

In red and blue, Figure 2 also plots the results from two permutation tests: one across all schools, and the other across treatment schools. The first should yield results close to zero, and the second should yield a significantly attenuated dose-response curve if our identification is valid. In red, we permute lifetime lead exposure across all schools and then re-estimate the dose-response function 50 times. The permuted dose-response functions are all flat and close to zero. In blue, we permute lead exposure only amongst schools within the 50 mile treatment distance in Figure 1. This is equivalent to permuting the location of treated schools, or randomly assigning treatment levels across treated schools, but still maintaining the true treatment versus control status of each school. By permuting treatment intensity only within the treatment group, this serves to test whether schools in our treatment group and close to racetracks had upward trending test scores relative to those schools further away. The permuted dose-response functions are slightly declining, but close to zero, indicating that our estimated effect is not spuriously driven by trends where schools very close to racetracks happened to be on a better test score trend.

Figure 3 shows how the estimated effect varies by how far away the lead source is from the school. The panel plots result from equation (2), where the function f is a cubic spline

Table 1: Effect of lead emissions from NASCAR on school z-score and proficiency rate.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Outcome: Z-Score, Treatment: Inverse-Distance Weighted						
Lifetime Lead Emissions (10 kg)	-0.060^{**}	-0.067^{**}	-0.053^{**}	-0.067^{**}	-0.063^{***}	-0.048^{**}
	(0.024)	(0.029)	(0.021)	(0.026)	(0.022)	(0.024)
Panel B: Outcome: Z-Score, Treatment: Unweighted						
Lifetime Lead Emissions (10 kg)	-0.003^{**}	-0.003^{*}	-0.003^{***}	-0.004^{**}	-0.003^{**}	-0.003^{*}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Panel C: Outcome: Proficiency Rate, Treatment: Inverse-Distance Weighted						
Lifetime Lead Emissions (10 kg)	-0.952^{**}	-1.110^{**}	-0.795^{**}	-1.077^{**}	-1.021^{**}	-0.722
	(0.432)	(0.546)	(0.364)	(0.443)	(0.434)	(0.445)
Panel D: Outcome: Proficiency Rate, Treatment: Unweighted						
Lifetime Lead Emissions (10 kg)	-0.056^{**}	-0.059	-0.053^{**}	-0.069^{**}	-0.055^{**}	-0.041
	(0.026)	(0.036)	(0.022)	(0.029)	(0.025)	(0.025)
Grades Included	All	All	All	3	4	5
Subjects Included	All	Math	Reading	All	All	All
Observations	136,384	68,170	68,214	45,710	45,364	45,310

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered at the school district level. School-subject-grade-year observations are weighted by number of students. Panels A and B contain estimates where the outcome is the z-score of the school's average test score. Z-scores are calculated by standardizing within a grade-year-subject across all schools. Panels C and D contain estimates where the outcome is the proficiency rate and the proficiency rate spans from 0 to 100. Panels A and C inverse distance-weight the lead emissions, while Panels B and D leave them unweighted. The control variables included in all regressions are cumulative TRI facility emissions within 50 miles, county unemployment rate, and county median income. All regressions include school-grade-subject and grade-subject-year fixed effects.

in distance from the racetrack to the school. The spline shows the marginal effect of 10 *unweighted* kilograms of lead up to 100 miles away from the school. This plot is to test how the treatment effect of emissions on test scores decays as emissions are further away, and to investigate where the treatment effect falls to zero allowing us to delineate treated versus control schools for our other specifications. The estimated effect is highest for schools closest to racetracks, as expected; it declines with distance and levels off close to zero at around 50 miles, which drives our choice of cutoff for treatment versus control. Given the average treated exposure of about 390 unweighted kilograms, schools very close to racetracks experienced test score reductions of over 0.4 standard deviations for the average cohort.

Our main estimates are a function of both duration of exposure (number of cumulative years) and level of exposure (exposure in any given year). To better isolate how duration of exposure matters, we use a specification where treatment is a set of indicator variables corresponding to how many years of life a cohort experienced leaded race emissions, while conditioning on the total quantity of emissions. For example, take two 3rd grade cohorts in two districts, A and B. In district A, the cohort was exposed to 5 years of races, with 2 kg of lead in each year. In district B, the cohort was only exposed to 2 years of races, but each year had 5 kg of lead. This model tests whether these should be considered equivalent dangers. Appendix Figure A3 shows the distribution of quantity of lifetime exposure by duration of exposure and provides evidence we can separately identify effects of duration from effects of total lifetime quantity, given the substantial overlap in total exposure across years of exposure.

Figure 4 plots estimates of the effect of each additional year of exposure during a student's lifetime relative to zero years of exposure, *conditional on a given lifetime quantity of exposure.*[20] This plot teases out the difference between being exposed to a large amount of lead over a short period versus spread out over more consecutive years of a child's life. Since races happen annually in Daytona and Homestead, the two largest sources of exposure in our data, the estimate for X years of exposure maps almost perfectly into the cumulative effect of being exposed every year until a particular age. The figure depicts an escalating negative effect of additional exposure length, holding quantity of total exposure fixed. The effects of one, five, and eight years of exposure by grade 3 are -0.03, -0.08, and -0.24 standard deviations, respectively.

There are several possible reasons that length of exposure might matter for a given intensity. Lead exposure may have differential long-term effects depending on the stage of an child's development, so lasting exposure could increase the probability of being affected at a given fundamental moment. For example, although early childhood is well-known to be important for aspects of cognitive development such as control of attention (Anderson, 2002), other key stages of development occur throughout childhood. Development of working memory — which is related to test performance and test anxiety (LeFevre et al., 2005; Ashcraft and Krause, 2007) — is largely linear up to around age 13 (Gathercole et al., 2004), while the abilities to process multiple sources of information and efficiently tackle defined tasks have a critical development stage closer to ages 7–9 (Anderson, 2002). It is

[20] These estimates are similar to equation (2), where treatment is a set of indicator variables for whether a particular student cohort was exposed to 1, 2, . . . , 8 years of leaded races, and now controlling for total exposure to separate the effects of duration and levels.

also important to recall that for the majority of exposed students in our sample, differences in duration of exposure are driven by later years of life. For example, comparing two students with 4 vs. 8 years of exposure means one was exposed from ages 0-4, and the other from ages 0-8.

We later show results that suggest nutrition plays a large role in reducing the impacts of lead, which may also interact with the role of duration. If children cycle through periods of poor nutrition, lasting exposure may increase the probability of hitting a low-nutrition cycle. Regardless of the reason, our results support that "death by a thousand cuts" may be more illustrative of how the lasting damages of lead accumulate.

Robustness checks: Appendix Figure A1 shows the stability of our main estimates to combinations of controls, fixed effects, and subsets of the data. Similarly, Appendix Tables A2 and A3 demonstrate the robustness of our estimates to alternative treatment variables, distance weights, observation weights, placebo tests, and sets of fixed effects to control for time-varying unobservables across school districts.

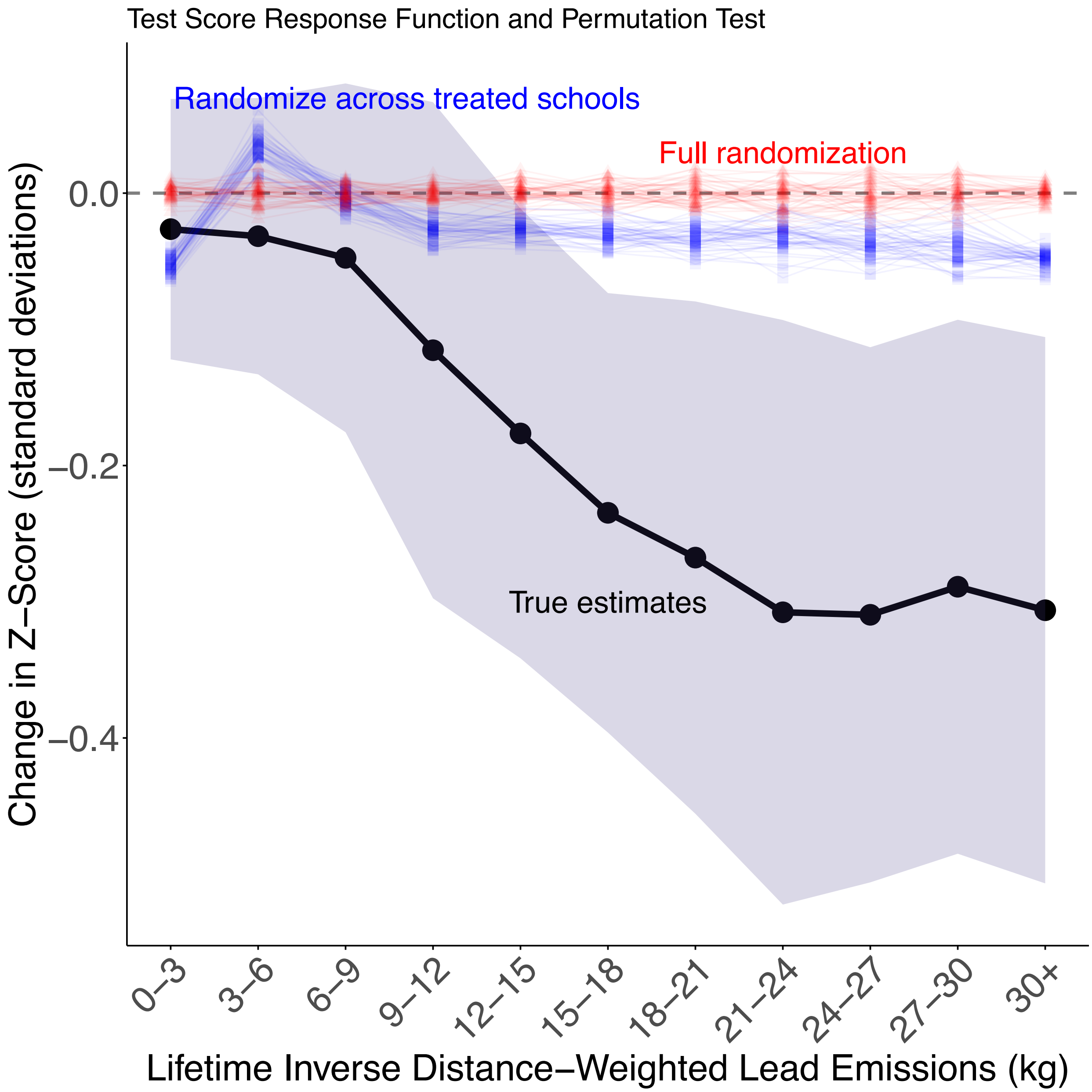
4.1 Distributional Effects and Heterogeneity

4.1.1 Heterogeneity in Achievement

Figure 5 depicts how lead exposure affects the share of students in different parts of the achievement distribution in order to understand which types of students are being affected. It plots the marginal effect of 10 inverse distance-weighted kilograms of lead on the fraction of students that fall in each achievement level. We find lead exposure shifts the entire distribution of achievement, harming both high- and low-performing students. 10 kilograms of exposure reduces the school-level share of students in achievement levels 4 and 5 by 0.5 percentage points each. The shares of the lowest two achievement levels increase by about 0.5 percentage points each. The effect on the share of students in the middle achievement level is approximately zero. This need not mean lead does not impact students in that portion of the distribution; rather, the share of students transitioning out into the lower achievement levels is approximately equal to the share of students transitioning in from higher achievement levels.

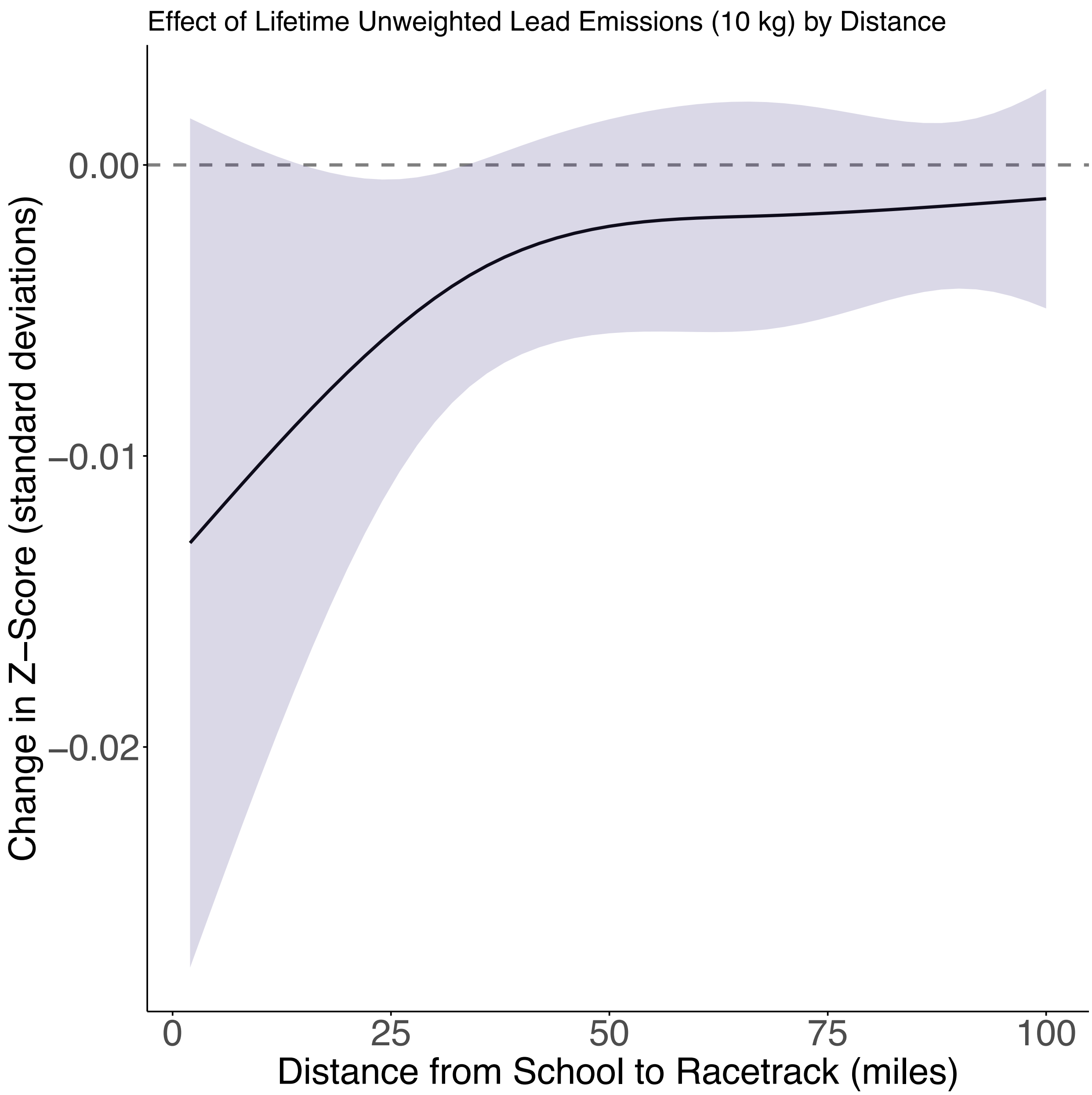
Figure A4 shows how changes in the share of students at each achievement level are affected by cumulative years of exposure. Similar to Figure 5, additional years of exposure decrease the share of students at the highest two achievement levels and increase the share in the lowest levels. The effect is approximately linear in years of exposure.

Figure 2: Flexible effect of lifetime lead emissions on test scores by quantity and randomization tests.



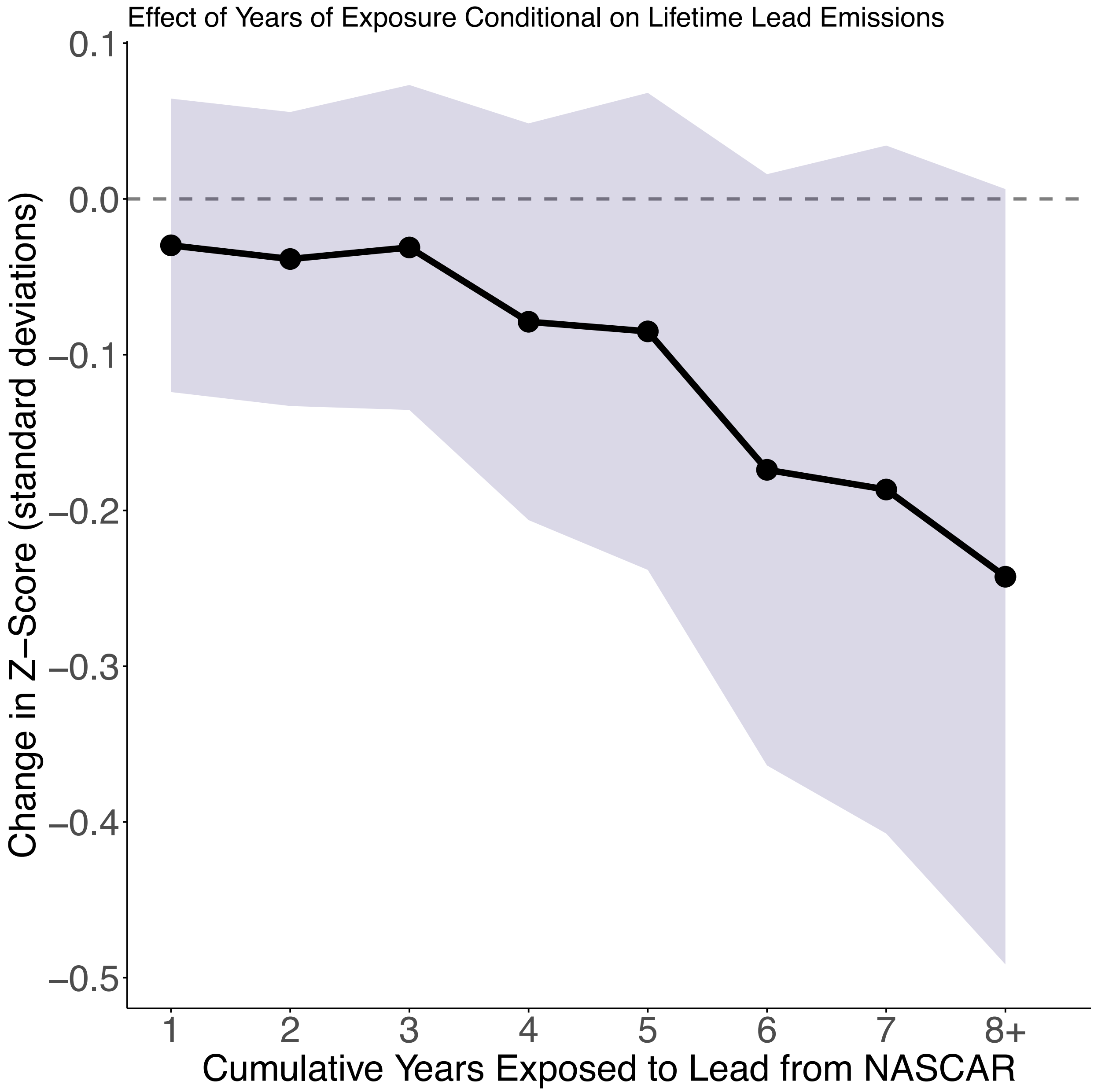
The treatment variables are a set of indicators equal to 1 if a school's inverse distance-weighted lead exposure was in a particular range. Bins are open on the left and closed on the right so the first bin does not contain zero kilograms. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. The red points are the point estimates for 50 alternative dose response functions when lead exposure is permuted across all schools. The blue points are the point estimates for 50 alternative dose response functions when lead exposure is randomized only across schools within the treatment group. The black points or lines are the point estimates and the blue shaded area is the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2).

Figure 3: Effect of lifetime lead emissions on test scores by distance of emissions from school.



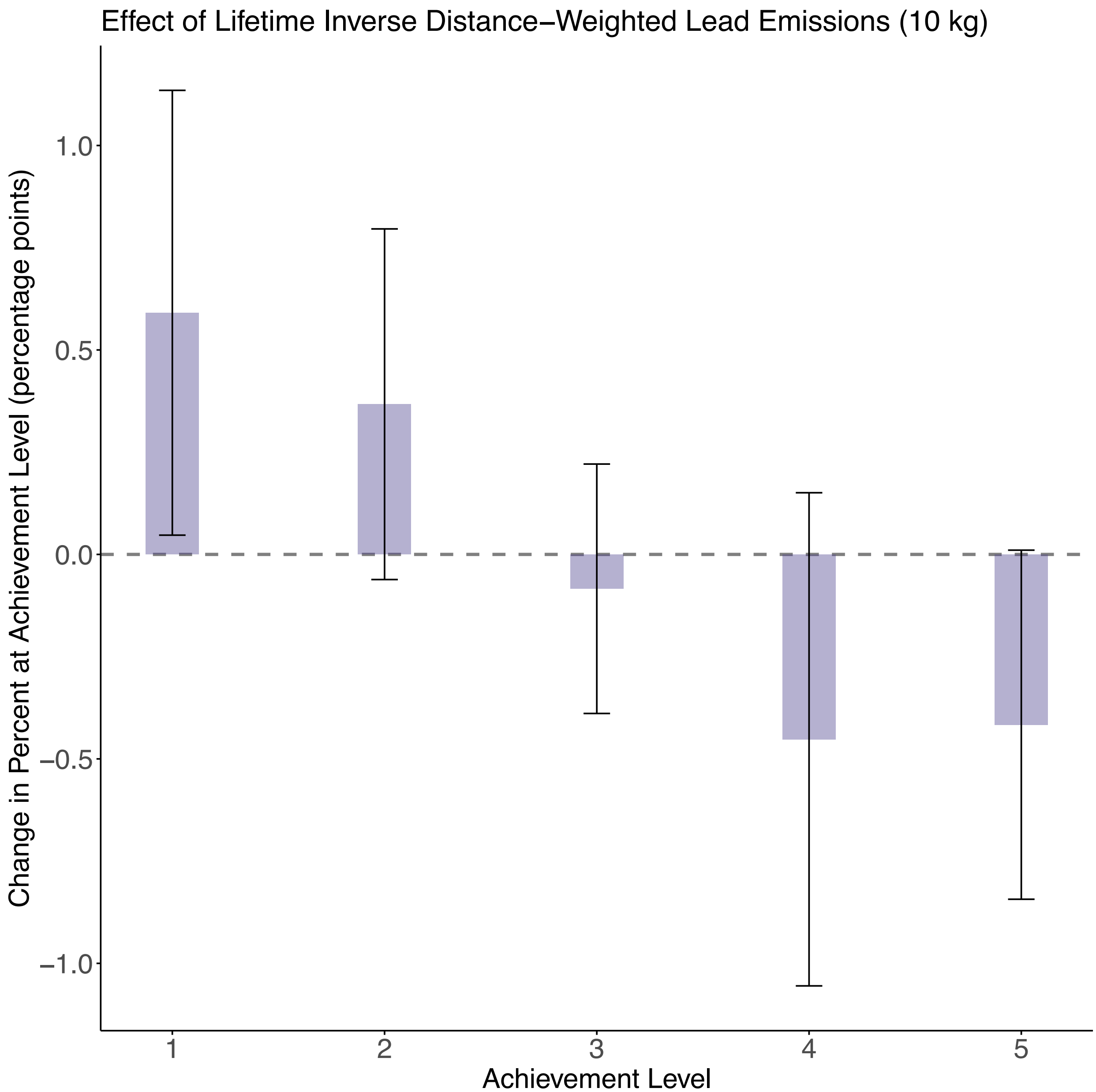
The cubic spline is constructed with knots at the 33rd and 67th percentiles of the data. The treatment variable is now unweighted lead emissions. For all panels, the black points or lines are the point estimates and the blue shaded area is the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2).

Figure 4: Effect of lifetime lead emissions duration of exposure on test scores conditional on total quantity of lifetime exposure.



The treatment variables are a set of indicators equal to 1 if the school cohort was exposed to positive amounts of lead from NASCAR for the past 1, 2, 3,...,8 years. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. The estimates are conditional on the lifetime quantity of lead exposure, the treatment variable in Panels A and C of Table 1. Appendix Figure A3 shows common support of lifetime exposure totals by years of cumulative exposure. For all panels, the black points or lines are the point estimates and the blue shaded area is the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2).

Figure 5: Effect of 10 kilograms of inverse distance-weighted lead on percent of students in each achievement level.



The blue bars indicate the estimated effect of 10 inverse distance-weighted kilograms of lead emissions on the fraction of students in each achievement level. The black bars indicate the 95% confidence interval of the estimates computed from robust standard errors clustered at the school district level.
Note: The outcome variable is in terms of percentage points and ranges from 0 to 100. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. School-subject-grade-year observations are weighted by the number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2).

4.1.2 The Protective Role of Nutrition

We next use our setting to help evaluate the open and important question of how nutrition, and specifically calcium, impact damages from exposure to lead. The medical literature establishes a physiological basis for the idea that improved nutrition—particularly consumption of high calcium foods like dairy products—can mitigate the health effects of lead exposure. Lead competes with and displaces calcium in the body and additional calcium intake limits this displacement (Ahamed and Siddiqui, 2007). Appendix Figure A5 and Table A4 show correlational support for this link. Using data from the 2005-2006 wave of the National Health and Nutrition Examination Survey (NHANES), we show that higher daily calcium intake and greater milk consumption are both associated with lower blood lead levels.

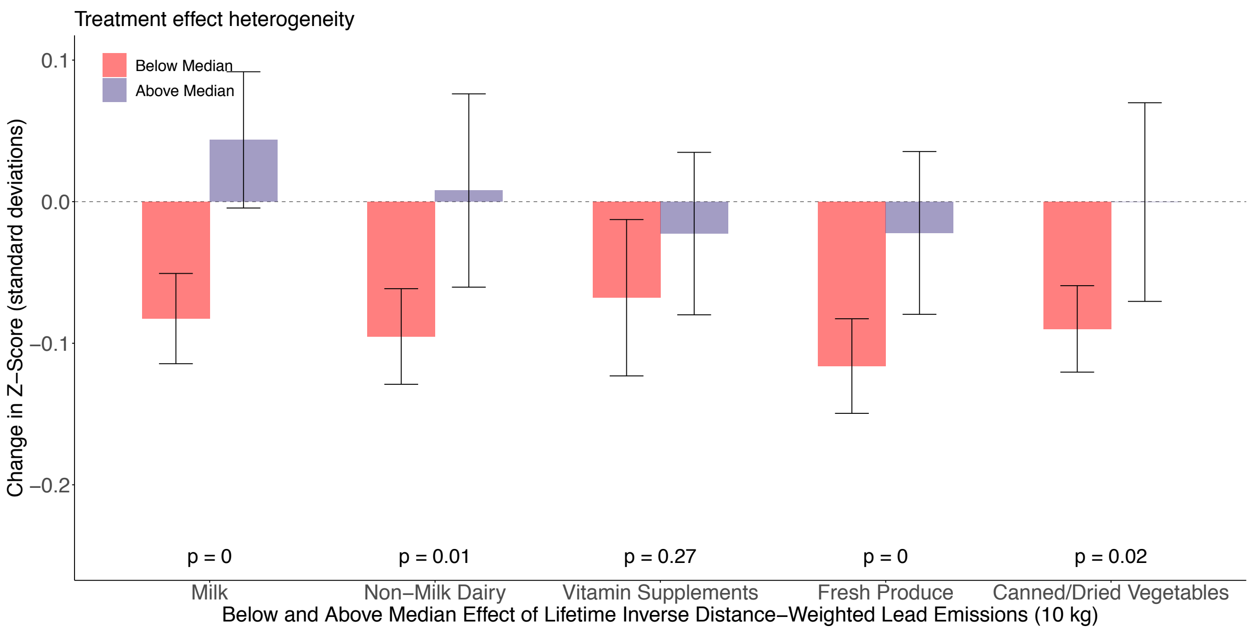
In Figure 6, we explore how the effect of lead exposure varies depending on nutrition. The figure plots estimates from our main specification, but we interact treatment with a dummy variable for whether the county is above or below the median per capita spending on calcium-rich products in the Nielsen dataset. Each bar shows the estimated effects of 10 inverse distance-weighted kilograms of lead for counties below and above the median value. In each case, we take the average value of the separating variable across all years, and assign rank using this stationary value. We do not include the interacted variable alone in our regression, as it is a linear combination of county fixed effects. Red (left) corresponds to counties below the median of the relevant variable, while blue (right) corresponds to above the median.

We focus on three sets of calcium-rich products: dairy, vitamins, and produce. We find strong negative effects of lead on test scores in school districts with below median spending on milk, and non-milk dairy products, while the school districts with above median spending levels show no statistically significant effects of lead. We find similar results for vitamin supplements, however the differences between the above and below median groups are not statistically significant. Last, results for fresh and canned or dried produce mirror that of dairy. In total, these results indicate that nutrition, specifically consumption of calcium-rich foods, may play a protective role. These effects are net of income differences, suggesting they are not just a result of comparing high- vs. low-income areas.

4.1.3 Other Heterogeneous and Distributional Impacts

Figure 7 plots estimates of heterogeneous effects by proxies for race, age of home (related to lead exposure from leaded paint), socioeconomic status, and penetration of fast food establishments, another possible measure of nutrition. The interpretation of the plot is the same as Figure 6. The first estimate shows negative effects of lead exposure for counties with

Figure 6: Heterogeneous effects of 10 inverse distance-weighted kilograms of lead by above or below median in consumption of calcium-rich products.



The treatment variables are 10 inverse distance-weighted kilograms of lead interacted with dummy variables for whether a school is in a county that is above or below the median for the variable on the x-axis. We estimate the regressions separately for each variable on the x-axis. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. The bars are the point estimates, and the error bars denote the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2). The p-values at the bottom of the figure are for testing the null hypothesis that the two coefficient estimates are equal.

higher penetration of fast food establishments, which may indicate a greater prevalence of low-nutrition foods.

The second set of estimates show effects by district racial makeup. We find noisy zero effects for counties that are below median in terms of percent Black or Hispanic residents, and negative effects of around 0.1 standard deviations for counties above median. The estimates are statistically distinguishable for percent Black, but not Hispanic.

The third set of estimates shows the effect by percent of homes built before 1940. Homes built before 1940 likely have lead-based paint, potentially raising the baseline level of exposure for children in these homes, and putting them on a different part of the lead dose-response curve. We find little difference in the estimated effects between counties with above or below median fractions of homes built before 1940.

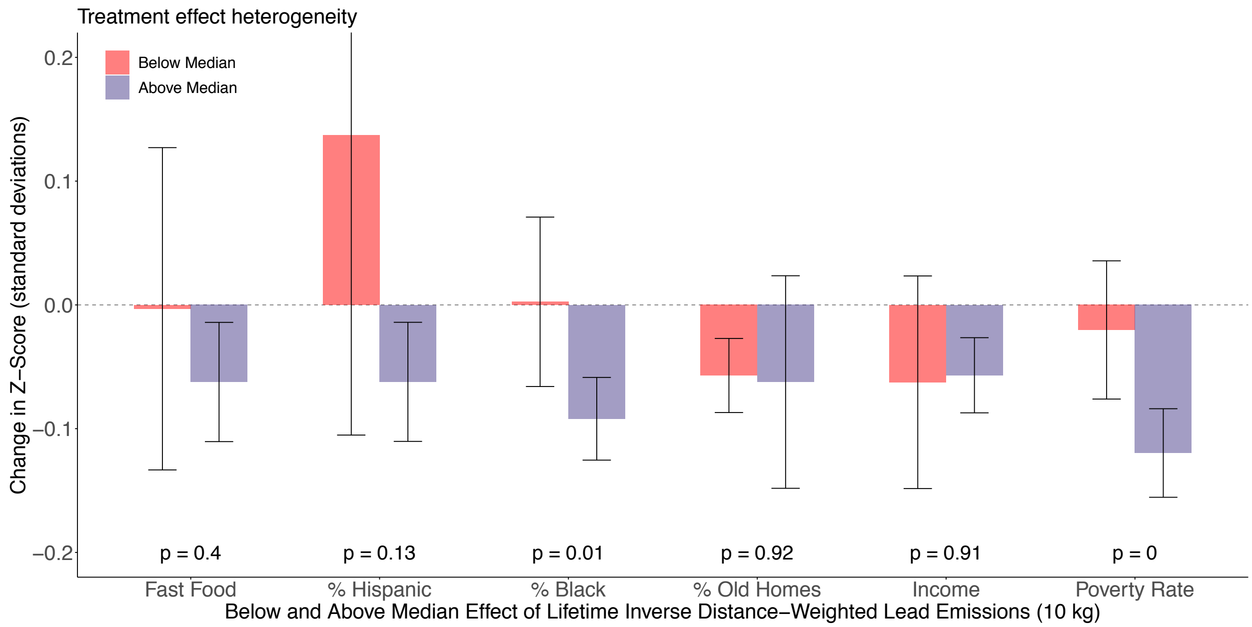
The last set of estimates show the effect by measures of socioeconomic status (SES). Lower SES families may have less ability to counteract the negative effects of lead exposure with remediation efforts or by adjusting other education inputs like tutoring. Here we find mixed results: there is little difference in terms of median income, but larger and statistically different effects in counties with higher poverty rates relative to those with lower poverty rates. The lower tail of the income distribution may matter the most in terms of ability to mitigate exposure.

An important consideration in interpreting these heterogeneous estimates causally is that levels of these variables are not randomly assigned. Fast food restaurants tend to locate in more populous areas, and we may expect those who consume more calcium-rich products to be different on other relevant dimensions as well. Appendix Figure A7 shows pairwise correlations of the heterogeneous effects variables, along with Nielsen spending, to determine whether one variable is likely to be picking up the effect of another observable variable. For example, percent Black is moderately correlated with poverty in Florida, and tends to be negatively correlated with consumption of calcium-rich foods. While income presents a potential confounder in identifying nutrition effects, calcium-rich food consumption is weakly correlated with either income or poverty.

The purchase of calcium-rich foods could be a proxy for nutrition programs, which carry other health benefits unrelated to lead. If program take-up correlates with proximity to race tracks, this creates a potential confounder. Appendix Table A5 directly considers the correlation between nutrition and public programs. We add a control for the log of dollar benefits per person paid out by the Supplemental Nutrition Assistant Program (SNAP) at the county level.[21] Ideally, we would have quasi-random variation in SNAP take-up to best

[21]Given the use of logs, our inclusion of year fixed effects adjusts for any inflationary factors across time, as they are common to all counties.

Figure 7: Heterogeneous effects of 10 inverse distance-weighted kilograms of lead by above or below median in socioeconomic or nutrition variables.



The treatment variables are 10 inverse distance-weighted kilograms of lead interacted with dummy variables for whether a school is in a county that is above or below the median for the variable on the x-axis. We estimate the regressions separately for each variable on the x-axis. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. The bars are the point estimates, and the error bars denote the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2). The p-values at the bottom of the figure are for testing the null hypothesis that the two coefficient estimates are equal.

identify the effects. However, since data are limited to participation levels across counties, we draw no causal conclusions from the coefficient estimates on SNAP payouts. Columns 1 and 4 show our baseline results with and without interactions including spending on calcium-rich foods. Columns 2 and 5 repeats 1 and 4, but restrict to county-years for which we have SNAP data. Columns 3 and 6 repeat 2 and 5, but now directly control for log of benefits per person. While including the SNAP data increases our standard errors and reduces our point estimate by changing our sample, it has little effect on the magnitude of our estimates holding the sample fixed when comparing column 2 to column 3 and column 5 to column 6. Appendix Table A6 shows the correlation between milk purchases and lead is robust to controlling for purchases of other products generally classified as unhealthy, healthy, or calcium-rich. While some have a statistically significant correlation with our outcome of interest, controlling for each does nothing to change our main estimates.

5 Valuation of Test Score Effects

Here we present two valuations of the effect of lead on academic achievement. First, we estimate the effect on future earnings by linking estimated reductions in test scores to estimated changes in future income. Second, we make non-monetary comparisons to test score improvements found from manipulating other in-school inputs to the education production function.

Test scores and future income: We use results from Chetty et al. (2014b) to translate changes in test scores into changes in lifetime earnings. Chetty et al. (2014b) report effects in terms of student-level standard deviations, while we report effects in terms of school-level standard deviations of the school mean score. To make a valid comparison we need to map our school-level standard deviations to student-level standard deviations following Ost et al. (2017).

For the average treated third grader in 2005, we find that lead exposure from racing results in a 0.47% reduction in earnings. Using a 3% real discount rate puts the present value of total lost future income per average student is \$2,600–\$4,000.[22] As a point of comparison, Isen et al. (2017) find that reduced fetal particulate exposure under the Clean Air Act raised lifetime earnings for relevant cohorts by approximately \$4,300 (discounted similarly).

Comparison to school-based inputs: To provide additional context for our test score effects, we compare them to the value of other school-based inputs. For exposed students, test scores are reduced by around 0.02 student-level standard deviations per 10 kilograms of lead exposure. Removing that exposure would generate returns similar to: one-sixth the magnitude of improving instructor value added by one standard deviation for one year—around a 0.15 standard deviation improvement in test scores (Chetty et al., 2014a; Hanushek and Rivkin, 2010; Bau and Das, 2020); reducing class size by 3 students—around a .03 standard deviation increase (Jepsen and Rivkin, 2009); increasing school spending per pupil by \$500—around a .02 standard deviation improvement (Jackson et al., Forthcoming); or a quarter of the effect of avoiding an instructor with no previous teaching experience—around a .085 standard deviation reduction (Jepsen and Rivkin, 2009). Using estimates on the average increases in test scores grade over grade, our estimated effect of 10 kilograms of lead is equivalent to 14% of the expected annual increase for the third grade, which is roughly 6 weeks of lost learning (Hill et al., 2008).

[22] On a per-kilogram basis, this equates to 10.53 dollars per student per kilogram of lead emitted within 50 miles. A more detailed exposition of this calculation can be found in Appendix section A.3.

6 Discussion and Conclusion

Using a natural experiment in removal of intense leaded fuel use, we estimate the causal effects of exposure to lead emissions on student achievement. We demonstrate that exposure to lead emissions has economically significant effects for elementary students living near emission sources, and show that exposure to airborne lead correlates with reduced standardized test performance across the student achievement distribution. Our results bolster prior work suggesting that environmental quality is a key input in the education production function. We also find that duration of exposure matters, even conditional on total lifetime exposure. While all treated students in our sample are exposed to leaded races for the first years of their lives, only some see exposure continue up until the year of the our observed exam. For a given quantity of nearby lead emissions, effects are larger if that quantity is spread across a greater span of years. Importantly, our findings are for students in Florida, a state with some of the lowest levels of lead contamination and measured blood lead in the United States. This suggests that there remain significant returns to further reductions in lead exposure even at lower modern levels. A basic model of interacting educational inputs suggests mitigating lead exposure may also increase the returns of other educational programs.

Our findings also point to another promising avenue for dealing with lead exposure at the population level: improved childhood nutrition and consumption of milk and other calcium-rich foods. We find that students living in areas with greater per-person spending on calcium-rich foods see lower effects on test scores from lead exposure, even after controlling for income and participation in public health programs. This aligns with the prior medical and public health literature on the importance of calcium in reducing lead exposure's harmful effects, and provides new evidence for a causal link. This result is promising but requires additional investigation. Although we do not find any evidence that our estimates are confounded by other factors, more sophisticated research designs exploiting quasi-experimental variation in calcium intake—for example, through differences in the nutritional content of school lunch vendors (Anderson et al., 2018)—would bolster claims of causality. We also find that lead exposure effects are most dramatic in school districts with higher shares of Black students and higher poverty rates. These two factors jointly indicate that childhood nutrition programs could play a pivotal role in addressing racial and socioeconomic test score gaps and issues of environmental justice.

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A Appendix

A.1 Summary Statistics

Table A1 displays the summary statistics for the 2,326 schools in our dataset. The data are almost evenly balanced across grades 3–5. The average cohort of about 100 students has a proficiency rate of 63%, with students mostly falling in achievement levels 3 and 4. Nearly 40% of students have limited success on the FCAT and fall into achievement levels 1 or 2. School average proficiency rates span the full range from 0 to 100 percent, and z-scores span from over 6 standard deviations below average to almost 5 standard deviations above average. On average across both control and treated schools, cohorts are exposed to 126 unweighted kilograms, or 5 inverse distance-weighted kilograms, of lead. The average lifetime exposure to TRI lead emissions is over 500 metric tons, but with a substantial amount of variation.

A.2 Robustness Tests

Specification chart Figure A1 presents a specification chart and shows the robustness of our main estimates of the effect of inverse distance-weighted lead emissions on test z-scores to different combinations of controls, fixed effects, and subsets of the data. The filled in circles in the bottom panel show which controls, fixed effects, grades, and tests were included. Our preferred specification in red produces a point estimate of -0.060, near the middle of the set of estimates, which range from -0.05 to -0.1. Larger effects are generally found for math and grades 3 and 4, while smaller effects are found for reading and grade 5.

Weighting, placebos, building up FEs Table A2 demonstrates the robustness of our regressions to alternative choices of treatment variable, distance weighting, and observation weighting. It also shows estimates from several placebo tests. Column 1 is our base specification corresponding to Table 1 Panel A Column 7. Column 2 is the same as column 1 but does not weight the observations by number of students. Column 3 corresponds to our unweighted results in Table 1 Panel B Column 7, while Column 4 is identical but does not weight the observations by number of students. Weighting by number of students has little effect on our estimates. Column 5 replaces lead emissions with just a count of the number of leaded races, indicating that each leaded race is associated with a 0.01 standard deviation reduction in test scores. Columns 6-8 perform three placebo tests where we assign all races after 1997, 1998, and 1999 to be unleaded. We estimate these specifications solely for the cohorts in our data that took tests during leaded years: 2003–2006. If our results were simply picking up on differential improvements in test scores for schools near racetracks that started even before deleading, then these placebos should show negative effects of lead exposure in the pre-period versus the placebo (unleaded) post-period. All three estimates have a positive sign and are statistically indistinguishable from zero, but the placebo tests reduce our sample size by about two thirds.

Table A3 shows how our estimates change as we build up to our main regression from just a simple correlation. The top two panels show that our z-score outcomes are robust to adding more granular fixed effects once we control for school and year fixed effects. The bottom two panels show a similar story for the proficiency rate, however they are also sensitive to the inclusion of subject and grade fixed effects.

Controlling for Supplemental Nutrition Assistance Program Table A5 shows our estimated effects when controlling for county-level log total benefits in the Supplemental Nutrition Assistance Program (SNAP) which likely matters for test score outcomes and may be correlated with NASCAR lead exposure or milk consumption. The first two columns correspond to our preferred specification in Table 1. The first column is the same as our preferred specification but where we use the same sample for which we have SNAP data — until 2011. This cuts our sample by over a quarter and drops the years for which the treated group had the least amount of exposure. This attenuates our estimates, but the inclusion of controls for the log SNAP benefits does not affect our estimates.

The last two columns replicate the specification for our milk result in Figure 7. Again, the estimates are attenuated but above median milk consumption school districts have significantly different effects than below median milk consumption school districts as in the main text, regardless of the smaller sample size and whether we control for log SNAP benefits per person.

Other foods and products Table A6 further tests the robustness of our finding that better nutrition and greater milk consumption mitigates the effect of lead exposure on test scores. Column 1 replicates our specification in Figure 7 in the main text. Column 2 is the same as column 1, but using the same sample as columns 3–5 where we include additional Nielsen variables. Column 3 includes controls for "unhealthy" products. Column 4 controls for healthy products, other dairy sources, and vitamins — things that are likely to have substantial quantities of calcium. Column 5 controls for both. We find that these additional controls have virtually no effect on our results.

Wind direction One potentially important margin for exposure is wind direction. Figure A2 plots wind roses for each of the four tracks. The wind roses show the distribution of direction and speed of wind at each track using the nearest wind monitor, which for each track, is in the same city. The plots indicate the direction that the wind is blowing from, so for example, Miami-Homestead tends to have winds that blow from east to west while Daytona has a relatively uniform distribution of wind direction. This presents challenges for common upwind vs downwind empirical specifications. In Daytona, there is no general upwind versus downwind direction because of the uniformity of the distribution. In Miami, areas to the west of the racetrack are downwind while those to the left are upwind. However, to the east of Miami-Homestead Speedway is the Southern Glades Conservation Park and then the ocean, without any schools.

A.3 Detailed welfare calculations

Here we use associated estimates linking test scores to future earnings to construct an estimate of how lead exposure may affect future earnings. For this exercise we estimate lost earnings for the average 2005 treated third grader in Florida as a result of their cumulative lifetime exposure. Conditional on being exposed to at least one leaded race within the 50 mile treatment radius, the average third grader in 2005 was exposed to 15.7 inverse distance-weighted kilograms of lead. Column 4 of Table 1 indicates that this amount of lead exposure decreases school-level test scores at for third graders by 0.0672 standard deviations.

We translate these effects on test scores into lost lifetime earnings using results from Chetty et al. (2014b), who report that a 1 standard deviation improvement in student-level standardized test scores is associated with 12% higher lifetime earnings.[23] Combining this with the 0.0672 standard deviation reduction estimate, and that the ratio of school to student-level standard deviations is .371, the average 2005 treated third grader in our sample experienced a 0.47% decrease in lifetime earnings. Chetty et al. (2014b) also report that the present value of expected future earnings at age 12 is $618,705 in 2020 dollars using a 3% real discount rate (5% discount minus 2% wage growth). At grade 3 (age 9), the present value is $566,203. A 0.47% lifetime earnings loss is $2,659.80 in 2020 dollars. When using the unweighted leaded miles estimate in the appendix we obtain an average income loss of $4,058.06 for an average treated exposure of 385 unweighted kilograms.

We use the unweighted leaded miles estimate to provide a back of the envelope approximation of the external cost of a gram of lead from gasoline. We put the external cost in per student per kilogram terms so that our estimate is not a function of Florida's population

[23]While this estimated relationship should not be interpreted to be causal, it represents the best estimate we can find between standardized test scores and future earnings. The estimate is conditional on teacher fixed effects as well as student and class-level controls. Chetty et al. (2014b) also report the unconditional relationship, which is 36%.

distribution around racetracks. The external cost of a kilogram of lead per exposed student within 50 miles is the income loss per student divided by the average lifetime exposure:

$$\frac{\$4,058.06}{\text{student}} \Bigg/ 385 \text{ kilograms} = \$10.53/\text{student}/\text{kilogram}.$$

Being exposed to 1 kilogram of lead emitted within 50 miles by the third grade results in a present value income loss of $10.54 dollars. Next we aggregate to the total loss to the entire Florida 2005 third grade cohort. There were 83,975 third graders in Florida in 2005, which amounts to a total income loss of over $340 million from NASCAR lead exposure. Note that this is only for students in a single cohort in a single state. One limitation to our approach is that our test score outcome is a school average, not an individual student's. The average treatment effect at the school-grade-test level—even when deflated to approximate student-level data—may not be the same as the average treatment for the treated student.

A.4 Lead emissions and miles traveled

Our quantity estimates are based on two unique data elements and an estimate of average race fuel economy. First, we observe the actual distance driven by each racecar in each race.[24] Second, we observe the lead content of the race fuel.[25] The fuel for every race is provided by NASCAR and Sunoco, ruling out any potential cheating by using leaded fuel in the unleaded period. We combine miles driven and fuel lead content with an estimate of the average fuel economy of the racecars, derived from reported fuel usage over a full racing season. Fryer (2008) reports that the top series in NASCAR used 175,000 gallons of fuel in 2008. Our race data show that 566,130 in-race miles were run in the 2008 season, indicating that roughly 3.24 in-race miles awere traveled per gallon of race fuel used. This provides our estimate of the total quantity of lead emitted per race.

Note that we find a similar estimate when considering additional information from a single race. In-race miles per gallon have been estimated to be between four and five miles per gallon (Belson, 2011). This does not account for out-of-race miles traveled in qualifying and practice rounds and we want to account for fuel used for these purposes. Following Hollingsworth and Rudik (Forthcoming), we obtain estimates of the share of miles that

[24] Actual distance driven may vary due to crashes or weather, so inferring distance from the maximum potential distance driven, for example 500 miles per racer for the Daytona 500, would overstate the amount of lead emitted and bias our estimates toward zero.

[25] NASCAR rules mandated the use of Sunoco Supreme, a 112 octane fuel with 5.2 grams of tetraethyl lead per gallon. The exact fuel can be found here: https://www.sunocoracefuels.com/fuel/supreme. It is still available to be purchased by the public as of 2020, and is continued to be used in a number of racing series such as TransAm Racing and the National Hot Rod Association.

come from these portions of the race using data from the 2019 Ticket Guardian 500. This race had 10,766 race miles and 3,053 practice miles.[26] Assuming that 330 miles were driven as a part of qualifying (see Hollingsworth and Rudik (Forthcoming) for more detail on this estimate), the 10,766 in-race miles are 76% of the total miles driven as a part of the whole event. Accounting for these additional non-race miles would mean adjusting in-race fuel economy estimates to be between 3 and 3.8. This is consistent with the 3.24 mpg estimate provided from the first approach.

A.5 Supplementary figures

Quantity of exposure by duration of exposure Figure A3 shows the distribution of quantity of lifetime exposure by duration of exposure. The densities shows total exposure for students with specific years of exposure. For a given level of cumulative exposure, years of exposure range widely, making for substantial overlap across densities. The dash-dotted line indicates 10 kg of lifetime exposure, approximately the mean level for treated children in our data. The dotted line, about 32 kilograms of lifetime exposure, corresponds to the 90th percentile of exposure for treated children. The significant amount of overlap across densities indicates that there is variation in duration for a given intensity, and variation in intensity for a given duration.

Achievement effects by duration Figure A4 shows the effect of duration of exposure on achievement levels, effectively a combination of Figure 4 and Figure 5. Greater duration of exposure decreases the share of students in the top achievement levels and increases the share of students in the lowest achievement levels.

Correlation between calcium intake and measured blood lead from the National Health and Nutrition Examination Survey (NHANES) Figure A5 shows ventiles of average daily calcium intake from food diaries reported in the NHANES data set 2005-2006 wave, along with a linear fit estimate of the relationship Higher calcium intake is strongly associated with lower blood lead levels.

Distribution of exposure by above and below median milk consumption Figure A6 shows the support of lifetime inverse distance-weighted lead exposure for all treated cohorts, split by above and below median milk consumption. There is significant overlap

[26] https://www.nascar.com/results/race_center/2019/monster-energy-nascar-cup-series/ticketguardian-500/stn/practice1/

across the distributions ruling out that high versus low levels of milk consumption is simply picking up on differential exposure to lead.

Pairwise correlations for heterogeneous effects Figure A7 shows the pairwise correlations between the heterogeneous effect variables in Figure 7 to better understand whether one variable is simply proxying for another. For our main nutrition variable of interest, milk consumption, we find that it is not strongly correlated with measures of income or poverty, however it does have a strong negative correlation with the percent of the population that is Black.

Table A1: Summary statistics.

Statistic	Mean	St. Dev.	Min	Max	N
Z-Score	0.001	1.00	−6.77	4.88	136,384
Proficiency Rate	63.20	18.01	0	100	136,384
Grade	4.00	0.82	3	5	136,384
% Achievement Level 1	17.36	12.28	0	100	136,384
% Achievement Level 2	19.47	9.24	0	80	136,384
% Achievement Level 3	31.11	8.39	0	94	136,384
% Achievement Level 4	23.82	11.03	0	94	136,384
% Achievement Level 5	8.27	7.60	0	87	136,384
Number of Students	102.46	46.53	10	448	136,384
Lifetime Unweighted Lead Emissions (10 kg)	12.67	24.31	0.00	102.72	136,384
Lifetime Inverse Distance-Weighted Lead Emissions (10 kg)	0.50	1.11	0.00	9.53	136,384
Lifetime Leaded Years	1.80	2.97	0	8	136,384
Median Income ($)	44,754.86	5,893.04	25,201	67,238	136,384
Unemployment Rate	6.36	2.78	2	14	136,384
Lifetime Industrial Lead Emissions (metric tons)	545.14	559.38	0.00	2,927.36	136,384

Note: An observation is a school-grade-subject-year.

Table A2: Robustness checks for the effect of lead emissions on school z-score.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lifetime Inverse Distance-Weighted Lead Emissions (10 kg)	-0.060^{**}	-0.067^{**}	-0.028^{*}	-0.032^{**}						
	(0.024)	(0.026)	(0.014)	(0.014)						
Lifetime Linear Distance-Weighted Lead Emissions (10 kg)					-0.010^{**}					
					(0.004)					
Lifetime Unweighted Lead Emissions (10 kg)						-0.003^{*}				
						(0.002)				
Lifetime Leaded Races							-0.007^{**}			
							(0.003)			
Lifetime Inverse Distance-Weighted Lead Emissions (10 kg): 1997 Placebo								0.014		
								(0.013)		
Lifetime Inverse Distance-Weighted Lead Emissions (10 kg): 1998 Placebo									0.013	
									(0.011)	
Lifetime Inverse Distance-Weighted Lead Emissions (10 kg): 1999 Placebo										0.013
										(0.011)
Base Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-Subject-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subject-Grade-Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	No	No	Yes	No	No	No	No	No	No	No
District-Subject-Grade-Year FE	No	No	No	Yes	No	No	No	No	No	No
Observation Weights	# Students	None	# Students	# Students	# Students	# Students	# Students	# Students	# Students	# Students
Observations	136,384	136,384	136,384	136,384	136,384	137,761	136,384	42,076	42,076	42,076

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered at the school district level. The control variables included in all regressions are cumulative TRI facility emissions within 50 miles, county unemployment rate, and county median income. All regressions include school-grade-subject and grade-subject-year fixed effects.

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Table A3: Effect of lead emissions from NASCAR on school z-score and proficiency rate with different fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Outcome: Z-Score, Treatment: Inverse-Distance Weighted							
Lifetime Lead Emissions (10 kg)	-0.023	-0.051^{**}	-0.050^{**}	-0.054^{**}	-0.060^{**}	-0.060^{**}	-0.060^{**}
	(0.043)	(0.023)	(0.021)	(0.022)	(0.024)	(0.024)	(0.024)
Panel B: Outcome: Z-Score, Treatment: Unweighted							
Lifetime Lead Emissions (10 kg)	0.000	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel C: Outcome: Proficiency Rate, Treatment: Inverse-Distance Weighted							
Lifetime Lead Emissions (10 kg)	-0.113	-1.752^{***}	-1.662^{***}	-0.749^{*}	-0.883^{**}	-0.952^{**}	-0.952^{**}
	(0.648)	(0.431)	(0.400)	(0.389)	(0.407)	(0.432)	(0.432)
Panel D: Outcome: Proficiency Rate, Treatment: Unweighted							
Lifetime Lead Emissions (10 kg)	0.020	-0.109^{***}	-0.096^{***}	-0.039^{*}	-0.049^{**}	-0.056^{**}	-0.056^{**}
	(0.035)	(0.030)	(0.028)	(0.021)	(0.024)	(0.026)	(0.026)
Controls	No	No	Yes	Yes	Yes	Yes	Yes
School FE	No	Yes	Yes	Yes	No	No	No
Year FE	No	Yes	Yes	Yes	Yes	No	No
School-Subject-Grade FE	No	No	No	No	Yes	Yes	Yes
Subject FE	No	No	No	Yes	No	No	No
Grade FE	No	No	No	Yes	No	No	No
Grade-Year FE	No	No	No	No	No	Yes	No
Subject-Grade-Year FE	No	No	No	No	No	No	Yes
Observations	136,384	136,384	136,384	136,384	136,384	136,384	136,384

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered at the school district level. School-subject-grade-year observations are weighted by the number of students. Outcome is the z-score of the school's average test score. Z-scores are calculated by standardizing within a grade-year-subject across all schools. Control variables include cumulative TRI facility emissions within 50 miles, the county unemployment rate, and county median income.

Table A4: Greater milk consumption is related to lower blood lead levels.

Milk consumption	Mean BLL	S.D.	N
Never	2.00	1.84	932
Rarely	1.71	1.51	987
Sometimes	1.68	1.90	2117
Often	1.61	1.56	5735

Note: Note: Data come from the 2005-2006 wave of the National Health and Nutrition Examination Survey (NHANES). Milk consumption refers to past 30 day milk consumption. The halflife of lead in the blood stream is also approximately 30 days. We omit two categories, Varied and Refused. Data come from 9,771 observations.

Table A5: Effect of lead emissions from NASCAR on school z-score controlling for SNAP benefits.

	(1)	(2)	(3)	(4)	(5)	(6)
Lifetime Lead Emissions (10kg)	-0.060^{**}	-0.033	-0.032	-0.128^{*}	-0.018	-0.016
	(0.024)	(0.028)	(0.028)	(0.068)	(0.059)	(0.061)
Lifetime Lead Emissions $\times$ Calcium-Rich Product Sales ($1,000)				0.328	0.316	0.332
				(0.258)	(0.296)	(0.282)
Calcium-Rich Product Sales ($1,000)				0.333	-0.120	-0.127
				(0.285)	(0.193)	(0.198)
Controls	Base	Base	Base + Snap Benefits	Base	Base	Base + Snap Benefits
School-Subject-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes
Subject-Grade-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,384	119,378	119,378	125,359	109,660	109,660

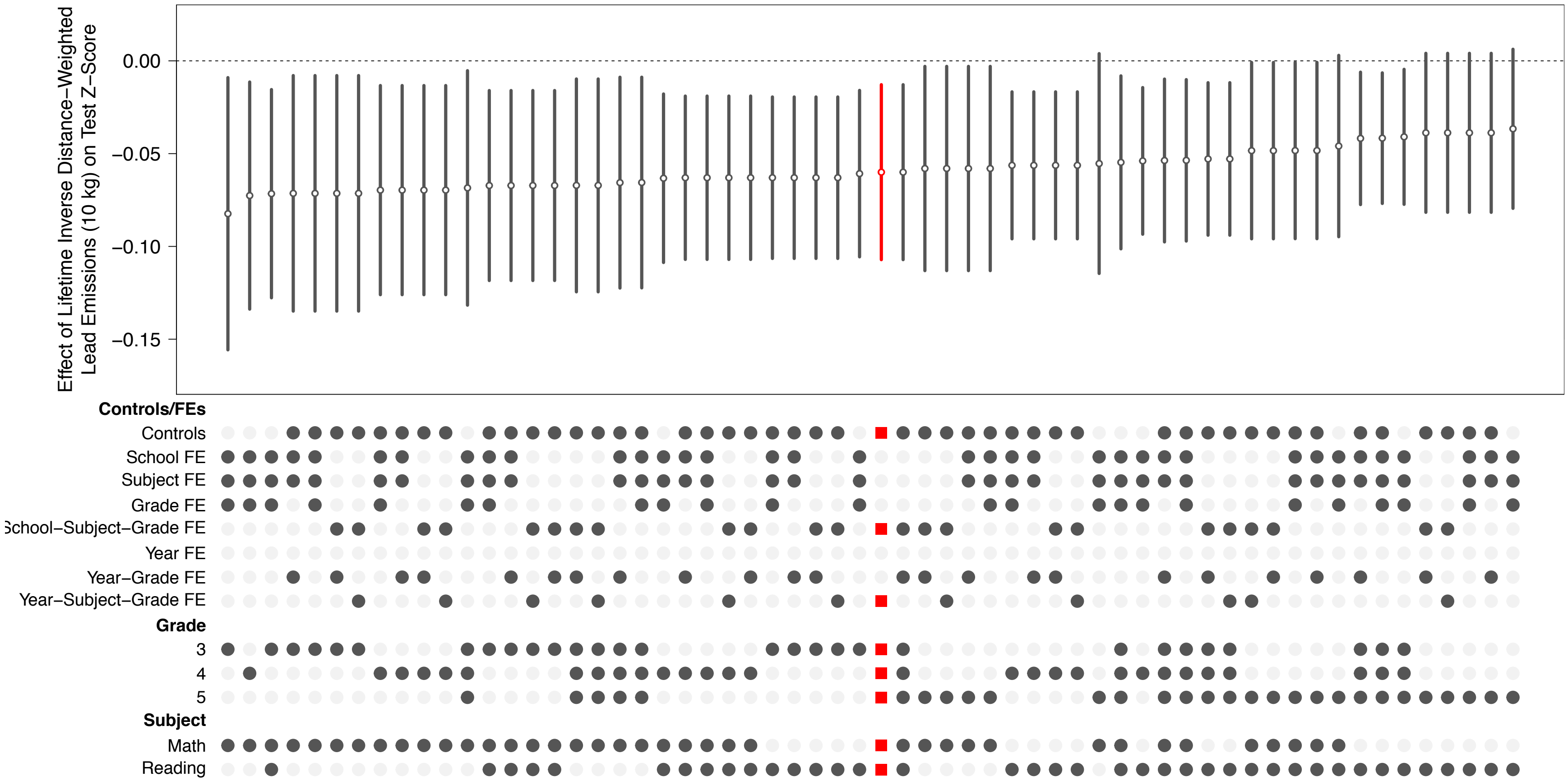
Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors are clustered at the school district level. School-subject-grade-year observations are weighted by the number of students. Control variables include cumulative TRI facility emissions within 50 miles, the county unemployment rate, county median income, and log SNAP benefits.

Table A6: Effects of lead emissions from NASCAR controlling for consumption of unhealthy products and calcium-containing products.

	(1)	(2)	(3)	(4)	(5)
Lifetime Lead Emissions (10kg)	-0.131^{*}	-0.131^{*}	-0.131^{*}	-0.131^{*}	-0.132^{**}
	(0.068)	(0.068)	(0.067)	(0.067)	(0.065)
Lifetime Lead Emissions $\times$ Calcium-Rich Product Sales (\$1000)	0.389	0.389	0.387	0.390	0.388
	(0.308)	(0.308)	(0.301)	(0.298)	(0.292)
Calcium-Rich Product Sales (\$1000)	0.190	0.190	0.213	0.188	0.187
	(0.272)	(0.272)	(0.263)	(0.264)	(0.259)
Alcohol Sales (\$1000)			-0.304		-0.308
			(0.192)		(0.193)
Tobacco Sales (\$1000)			-0.055		-0.058
			(0.153)		(0.152)
Non-Diet Soda Sales (\$1000)			1.425^{*}		1.376^{*}
			(0.730)		(0.732)
Fresh Produce Sales (\$1000)				-0.320	-0.205
				(0.776)	(0.739)
Canned and Dried Vegetable Sales (Including Grains) (\$1000)				0.962	0.916
				(1.068)	(1.049)
Grades Included	All	All	All	All	All
Subjects Included	All	All	All	All	All
Base Controls	Yes	Yes	Yes	Yes	Yes
School-Subject-Grade FE	Yes	Yes	Yes	Yes	Yes
Subject-Grade-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	125,359	125,359	125,359	125,359	125,359

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered at the school district level. School-subject-grade-year observations are weighted by the number of students. The first column uses all available data, while the second column restricts the sample to be the same data as is used in columns three through five. Z-scores are calculated by standardizing within a grade-year-subject across all schools. Base control variables include cumulative TRI facility emissions within 50 miles, the county unemployment rate, and county median income.

Figure A1: Sample and fixed effects subsets for the effect of 10 kg of lead emissions on school z-scores.



Note: We highlight our main specification in red and mark included coefficients with squares. All other models are in black and mark coefficients with circles. Top panel: The points are the point estimates from separate specifications. The bars are the 95% confidence interval computed from robust standard errors clustered at the school district level. School-subject-grade-year observations are weighted by number of students. Estimates are ordered by their magnitude.
Bottom panel: The filled-in circles indicate which combinations of controls and fixed effects are included in the regression used to estimate the coefficients in the top panel. The filled-in circles also indicate the subset of grades and subjects in the data used to produce the estimates in the top panel.

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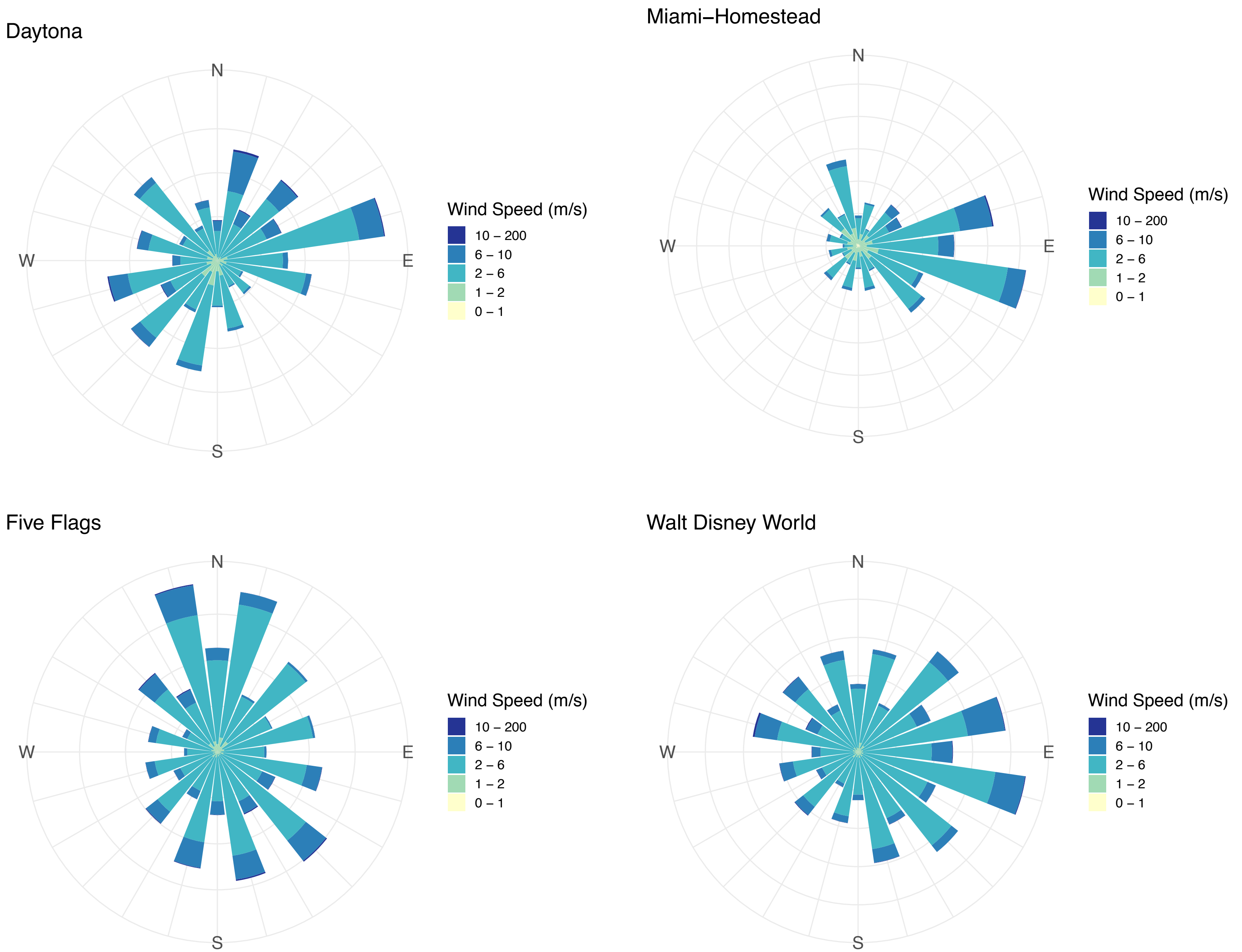
Figure A2: Distribution of wind direction and speed at each racetrack.



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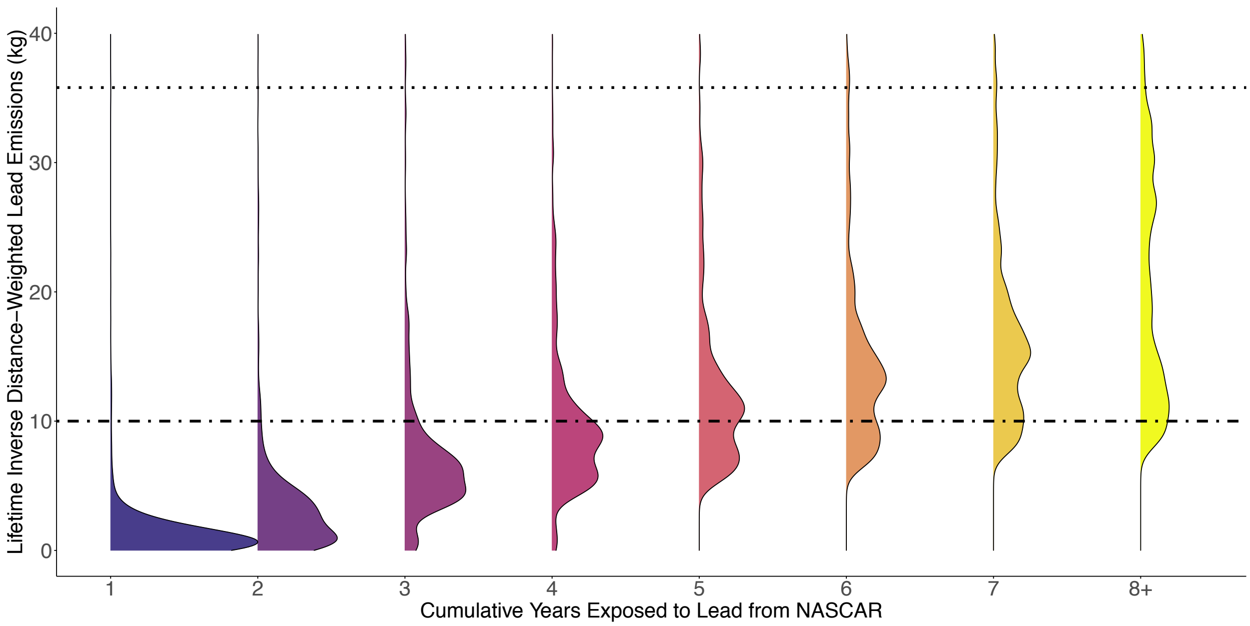
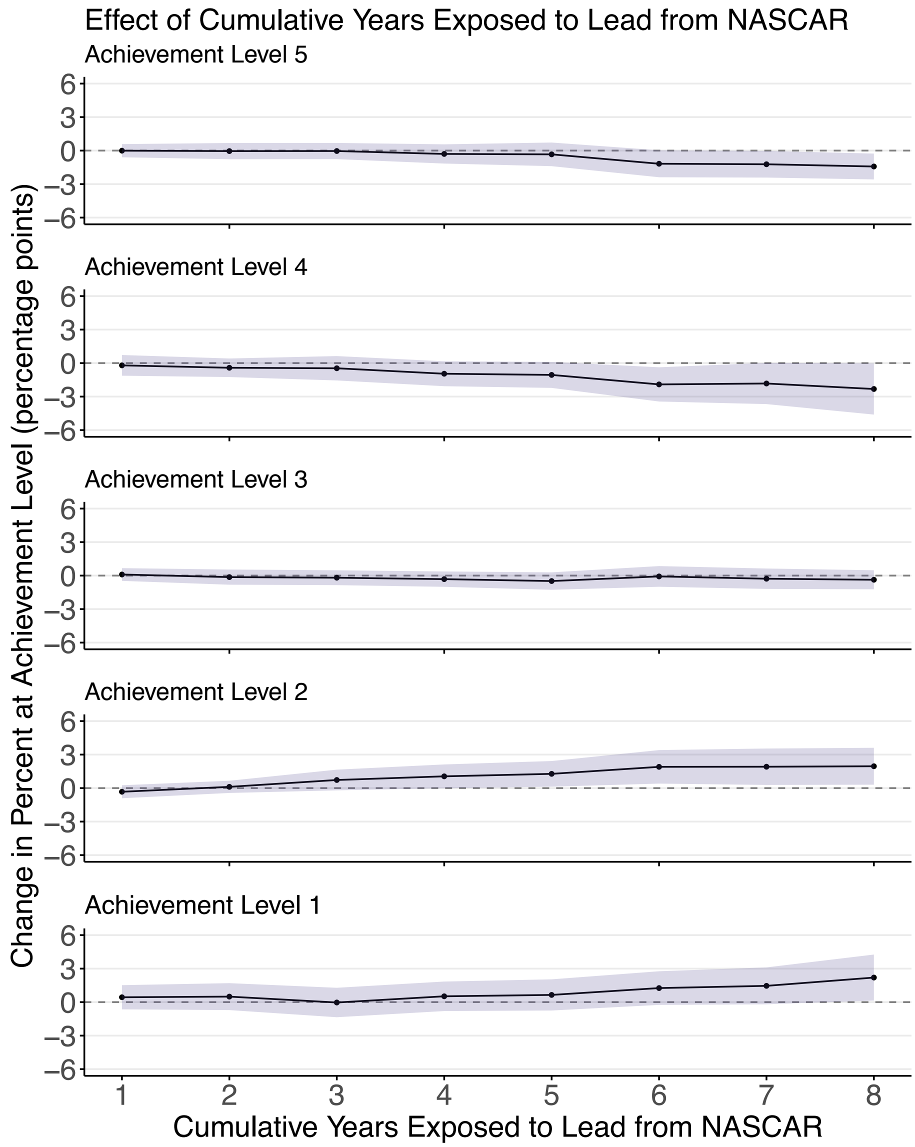
Note: The windroses show the distribution of daily average wind direction. The plots show where the wind is blowing from, not where the wind is blowing toward. Darker colors indicate higher speed winds.

Figure A3: Lifetime inverse distance-weighted exposure quantity by years of exposure.



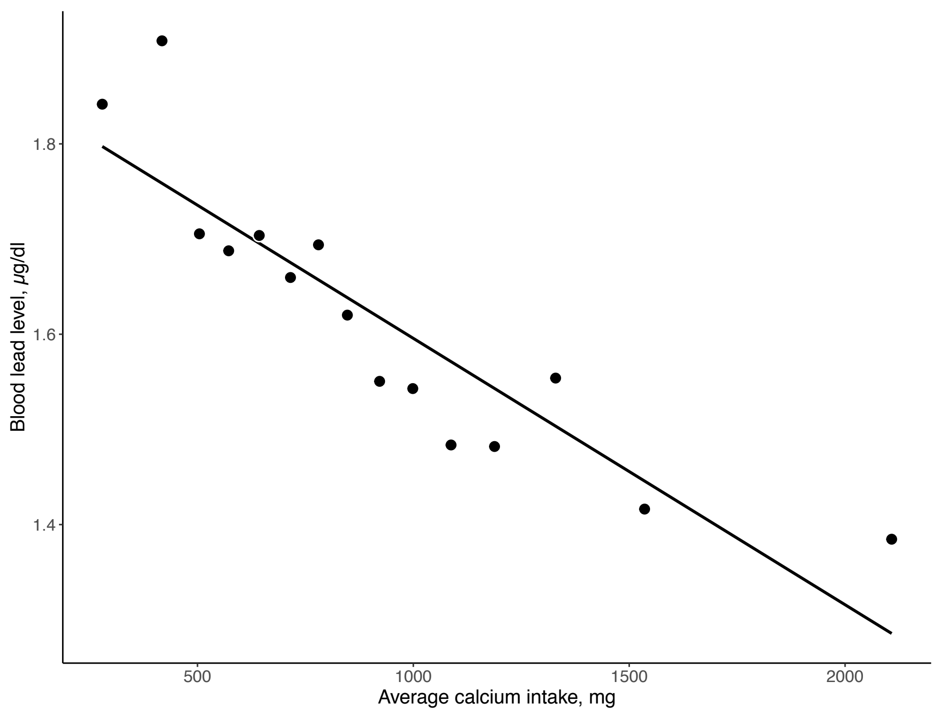
Note: Histograms are zoomed in to 0–40 inverse distance-weighted lifetime kilograms. Each density shows the distribution of inverse distance-weighted lifetime lead exposure (vertical axis) for a cohort with a given number of exposure years (horizontal axis). The dash-dotted line corresponds to 10kg of exposure, the amount reflected in our inverse distance-weighted estimates of marginal effects throughout the paper. The dotted line corresponds to the 90th percentile of exposure amongst treated schools. See Section 4 for discussion. Cumulative years of exposure align with estimates provided in Figure 4.

Figure A4: Effect of 10 kilograms of lead on percent of students in each achievement level.



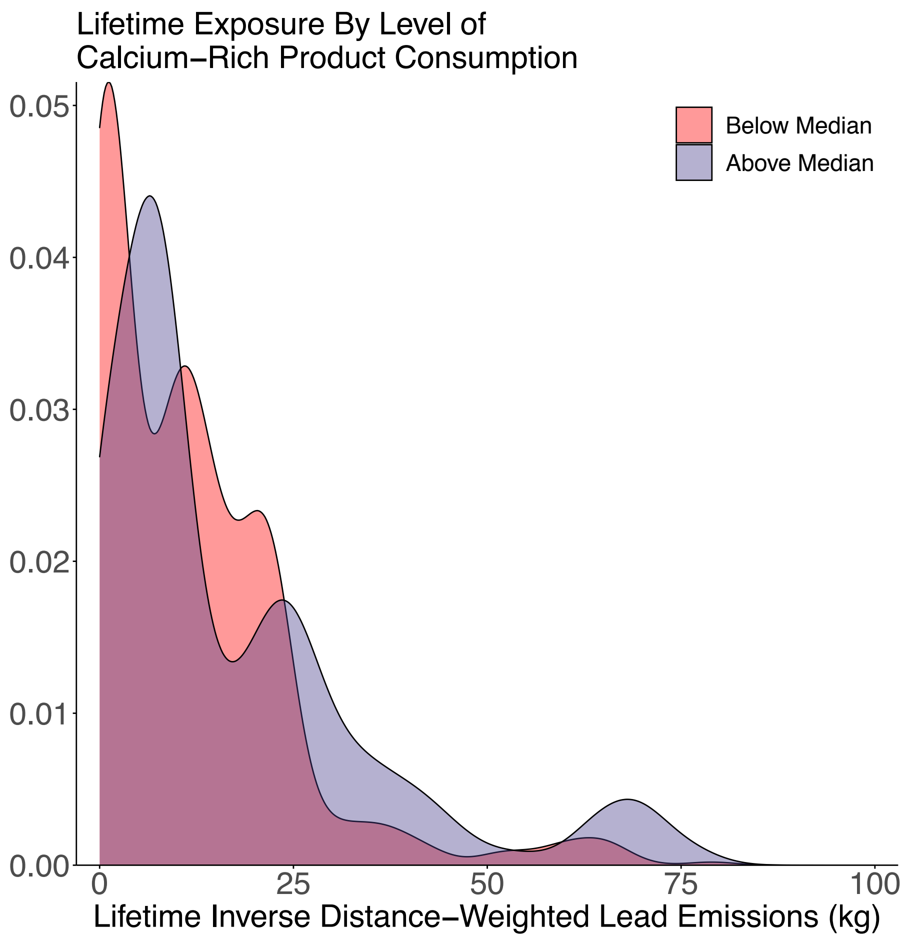
Note: The treatment variables are a set of indicators equal to 1 if the school was exposed to positive amounts of lead from NASCAR for 1, 2, 3,...,8 years. The black points are the point estimates, and the blue shaded area is the 95% confidence interval computed from robust standard errors clustered at the school district level. The outcome variable is in terms of percentage points and ranges from 0 to 100. We assign treatment only if the school was within 50 miles of the track where the leaded race occurred. School-subject-grade-year observations are weighted by the number of students. The estimates are conditioned on the set of controls and fixed effects in equation (2).

Figure A5: Correlation of calcium intake and blood lead



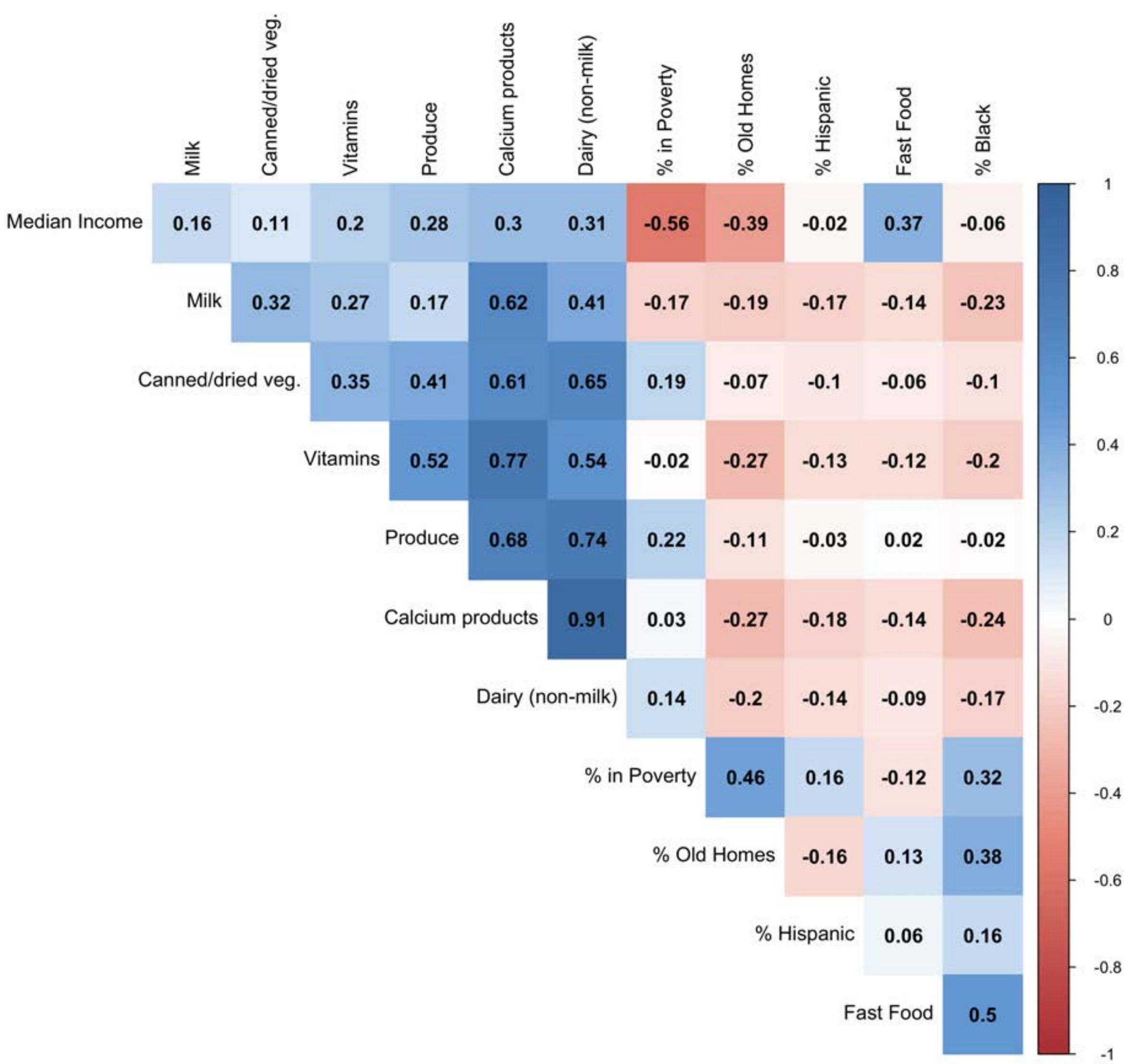
Note: This figure presents the non-parametric conditional expectation of blood level across twenty ventiles of average daily calculated calcium intake. Data come from the 2005-2006 wave of the National Health and Nutrition Examination Survey (NHANES). Mean average daily calcium intake from 7,255 observations is 920. Mean blood lead level from 7,255 observations is 1.68.

Figure A6: Lead exposure density by above and below median milk consumption.



Note: Distribution shows lead exposure by above and below median milk consumption. Densities only include data from treated schools. "Lead exposure" refers to estimated total lifetime exposure to inverse-distance weighted lead emissions. See Section 4.1 for discussion of effects by milk consumption.

Figure A7: Pairwise correlations between each pair of variables interacted with treatment in Figure 7.



Note: The numbers are the correlation coefficients. Data sources are outlined in Section 2.

Table A7: Comparison of grade 4 mean and standard deviation across student-level and school-level data for the same test.

Year	Student mean	School mean	Student S.D.	School S.D.	S.D. Ratio
Math					
2003	298	298	63.4	24.4	0.384
2004	312	312	58.7	21.7	0.370
2005	312	312	57.8	22.2	0.385
2006	318	318	60.8	24.1	0.396
2007	319	320	59.9	23.0	0.385
2008	324	325	60.8	23.0	0.378
Average	314	314	60.2	23.1	0.383
ELA					
2003	305	305	60.5	22.2	0.368
2004	318	318	51.4	18.1	0.352
2005	319	319	55.1	19.3	0.350
2006	314	314	53.5	19.2	0.359
2007	316	316	57.7	21.0	0.363
2008	319	319	56.2	20.0	0.357
Average	315	315	55.7	20.0	0.358

Notes: Student-level means and standard deviations come from Tables FL-5 and FL-6 from this document https://files.eric.ed.gov/fulltext/ED506142.pdf. School-level means and standard deviations are calculated using the data used in our analysis. Since we do not have access to the restricted student level data, we can only compare the means and standard deviations for the years, tests, and grades in this report.