Aerobic Capacity and Pollution at Schools

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Abstract

As required by the Clean Air Act, the EPA sets National Ambient Air Quality Standards (NAAQS) to protect public health, including the health of sensitive populations such as children. Exiting research has documented the effect of pollution on severe health outcomes, such as hospitalizations for asthma and infant death. However, lacking information on less extreme measures of respiratory health, standards for criteria pollutants have been set without full knowledge of the health consequences of air pollution for children. Less extreme effects on respiratory health, even among non-asthmatic children, are possible at levels even below the EPA's thresholds, but these effects are difficult to measure. I use a more sensitive measure, aerobic capacity (VO_2max), to study the impact of air pollution on respiratory health at levels below current NAAQS thresholds. I combine school-grade level data from the California Physical Fitness Test from 2001-2017 with local air pollution and weather data to estimate the impact of fluctuations in daily pollution levels during the testing window on the aerobic capacity for students in grades 5, 7, and 9. Ozone and particulate matter affect child aerobic capacity at levels even below the EPA thresholds. I explore heterogeneous effects by race, ethnicity, and gender, and find effects are especially large for minority groups.

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As required by the Clean Air Act, the EPA sets National Ambient Air Quality Standards (NAAQS) with the goal of protecting public health. These standards are required to be reviewed and revised every five years. In 2015, the EPA strengthened the National Ambient Air Quality Standards (NAAQS) for ground-level ozone from 75 to 70 parts per billion (ppb), with the goal of improving public health protection, especially for at-risk groups including children, older adults, and individuals with respiratory illnesses such as asthma. Such regulations are costly to industries and often spark debate over whether additional pollution reductions are worthwhile, despite the costs. Therefore, it is important to accurately quantify the associated health benefits from a reduction in pollution, especially for levels of pollution at or below the current thresholds set by the EPA. However, existing research has been limited to studying the effects of air pollution on extreme health outcomes such as hospitalizations and death (Neidell, 2004; Currie and Neidell, 2005; Currie et al., 2009b), meaning that existing standards have been set without a full understanding of the respiratory health effects of pollution.

In general, children are more sensitive to pollution than adults, so child hospitalizations are a more sensitive measure than adult hospitalizations. However, it is possible that pollution may have an even more subtle effect on child health. Even if a child is not sick enough to go to the hospital, he or she may experience some respiratory distress or difficulty breathing. Moreover, pollution may impact the aerobic capacity of non-asthmatic children as well. If this is the case, then previous estimates of the impact of pollution on child health may have been understated.

In this paper, I use a more sensitive measure, aerobic capacity (VO_2max), to study the impact of air pollution on respiratory health at levels below current NAAQS thresholds for three important criteria pollutants: ozone, nitrogen dioxide, and fine-particulate matter. I combine school-grade level data from the California Physical Fitness Test from 2001-2017 with local air pollution and weather data to estimate the impact of fluctuations in daily pollution levels during the testing window on the aerobic capacity for students in grades 5, 7, and 9.

Estimates measure the health impact of air pollution within 5 km of schools, unlike most previous research that has focused on pollution near residential location. Pollution levels near schools may have a large impact on child respiratory capacity that has yet to be quantified, since children spend a considerable amount of time at their school. Epidemiological research suggests that asthma risk increases with traffic-related pollution exposure near both homes and near schools, and that a disproportionate number of economically disadvantaged and nonwhite children attend high-exposure schools in California (McConnell et al., 2010; Green et al., 2004). Although these

studies present some descriptive evidence of the importance of pollution near schools, they do not account for the fact that families with different preferences for clean air may sort across school districts.

Families may exhibit avoidance behavior in their choice of residential location and school district. For example, a family with a high valuation for clean air may chose to live in an area with strict regulations on polluting industries. On the other hand, a family with low valuation for clean air might chose to purchase a house in a heavily polluted industrial area, to take advantage of low property values. Therefore, in estimating the impact of pollution on health it is important to account for sorting behaviors that lead to endogenous pollution exposure. In this paper, regressions include school fixed effects to control for level differences in pollution across school locations and to capture any differential characteristics driven by sorting of residents across schools. Identification comes from variation in pollution levels at a given school location across years, rather than across locations.

Previous literature establishing the link between air pollution and health has exploited natural experiments to avoid the inherent endogeneity problems of cross-sectional comparisons. These studies find important effects of air pollution on extreme health outcomes, such as hospitalizations and emergency room visits (Jans et al., 2018; Schlenker and Walker, 2015; Moretti and Neidell, 2011; Lleras-Muney, 2010; Neidell, 2009, 2004) and infant mortality (Knittel et al., 2016; Arceo et al., 2016; Currie et al., 2009b; Currie and Neidell, 2005; Chay and Greenstone, 2003b,a). While these outcomes are important and costly, they cannot capture more subtle effects of pollution on respiratory capacity in the general population. In addition to these extreme measures, some work has shown effects of air pollution on worker productivity and labor supply (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012). These findings are important as they document an impact of air pollution on a more sensitive outcome among a broader set of individuals. However, they do not measure respiratory capacity directly nor do they observe effects on children, who tend to be more sensitive to pollution. On the other hand, Currie et al. (2009a) study the effect of air pollution on school absences, as a more sensitive proxy for child respiratory health. However, they cannot disentangle the effect of absences that occur because of poor respiratory health from those that occur because parents keep the child home to avoid pollution exposure. The measure used here, aerobic capacity, does not suffer from this problem.

The first major contribution of this work is to explore the impact of pollution on a new and more sensitive measure of respiratory health, aerobic capacity (VO_2max). Unlike extreme events,

such as hospitalizations or death, aerobic capacity provides a measure of respiratory health for all children in grades 5, 7, and 9 in California. Although non-asthmatic children would be unlikely to show up in hospitalization data, they may still be negatively affected by air pollution and aerobic capacity can provide a measure of their respiratory health as well. Moreover, aerobic capacity may be useful in detecting effects of pollutants at low levels that might not show up when using respiratory measures such as hospitalizations or death.

Unlike much of the previous work, I focus on pollution levels below the EPA's National Ambient Air Quality Standards to determine whether low levels of pollution can also impact child respiratory health. Since pollutants are often correlated with each other, it is important to also estimate these pollutants simultaneously. Whereas many studies focus only on single-pollutant models, I explore the effects of ozone, nitrogen dioxide, and particulate matter simultaneously, in multiple-pollutant models.

Not only does this work contribute to our understanding of the child respiratory impacts of air pollution at low levels, but it expands our knowledge of the importance of exposure to pollution at locations other than the home. Because children spend a large amount of time at school and exposure to pollution at school tends to be higher among non-white and economically disadvantaged students, these results are especially important in understanding respiratory health gradients.

I find that both ozone and fine-particulate matter increase the percent of students with unacceptable levels of aerobic capacity at levels of pollution even below the NAAQS threshold. A 10 percent increase in days between 75 and 100 percent of the threshold for ozone and particulate matter is expected to increase the percent of students with poor aerobic capacity by 2.6 and 1.6 percentage points, or about 6 and 4 percent from the mean, respectively. I find especially large estimates among Hispanic and black students, suggesting large potential gains in respiratory health for these group from a reduction in ozone and particulate matter regulatory standards.

1 Background

Outdoor air pollution almost always occurs as a mixture, which makes it difficult to disentangle the causal impact of individual pollutants (Barnes, 1995; Esposito et al., 2014). In general, we know relatively little about the exact mechanisms through which each pollutant impacts health in isolation. The EPA regulates six criteria air pollutants: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, particulate matter, and lead. This study does not consider the impacts of sulfur

dioxide or lead, as few monitors record these pollutants and levels of contamination are generally very low during the study period. Carbon monoxide levels were also very low during this period in California, with very few days near the EPA threshold. Given the limited variation in CO levels, this pollutant is not considered in the results below.

Ozone is not emitted directly into the air, but is a secondary pollutant formed by chemical reaction between nitrogen oxides (NO_x) and volatile organic compounds (VOCs) in the presence of warmth and sunlight. Although ozone is most likely to reach unhealthy levels during warm weather, it can still reach high levels in colder months. Ozone is thought to cause constriction of muscles in the airway, trapping air in the alveoli, which can cause wheezing and shortness of breath. Ozone is associated with many respiratory problems, such as difficulty breathing, inflammation and damage of the airways, increased susceptibility to infection, and chronic obstructive pulmonary disease (COPD). In addition, ozone is likely to aggravate respiratory diseases, such as asthma, emphysema, and chronic bronchitis.

Particulate matter includes all pollution particles under a certain diameter and can be made up of many different toxic materials. Small particles can be inhaled deep into the lungs and may even enter the bloodstream. While previous studies often focused on particulate matter under 10 $\mu g/m^3$ diameter due to data limitations, this study focuses on fine-particulate matter, which includes particles less than 2.5 $\mu g/m^3$ in diameter. Fine-particulate matter is considered by many experts to be a better measure of harmful pollutants because smaller particles may more easily enter the lungs and are more likely to contain toxic materials. Studies have linked particulate matter to many health problems, including heart attacks, premature death for those with poor lung function, aggravated asthma, and other respiratory problems.

Nitrogen dioxide is part of a group of highly reactive gasses known as nitrogen oxides (NO_x), which include nitrous acid and nitric acid. Measures of nitrogen dioxide are used as indicators for the presence of the larger group of nitrogen oxides. Nitrogen dioxide is primarily released from the burning of fossil fuels and forms from emissions of cars, trucks, buses, power plants, and other off-road equipment. Inhalation of nitrogen dioxide can irritate airways and cause respiratory distress, aggravate respiratory diseases, and increase hospital and emergency room admissions. Longer exposure may increase the chance of developing asthma or respiratory infections. When nitrogen oxides react with other chemicals in the air, they can form both particulate matter and ozone. These reactions make it particularly important to consider possible correlations across these pollutants and to estimate their effects simultaneously in a multiple-pollutant model, rather than

in isolation.

Children are especially vulnerable to air pollution. Not only can early exposure to pollution can alter lung development and function, but children also spend a considerable amount of time outdoors engaging in physical activity. Children tend to have a high breathing rate, which increases the intake of pollutants into the respiratory tract. Finally, children are predominantly oral breathers, meaning that air by-passes the nasal filter allowing more particles to enter lower airways (Esposito et al., 2014).

2 Data

Aerobic Capacity Data

The California Physical Fitness Test (PFT), administered in the spring, provides data on students in grades 5, 7, and 9, yearly from 2001 to 2017. Grade level data is provided for each school, which is linked to the exact geographic location of the school. For the main analysis I remove charter schools, but I show that the results are robust to their inclusion. PFT data includes the fraction of students in the "healthy fitness zone" (HFZ) with regard to aerobic capacity, body fat, flexibility, abdominal strength, trunk strength, and upper body strength. For this paper, I will focus on the measure of aerobic capacity reported as VO_2max, which is the maximum rate that oxygen can be taken into and used by the body during exercise. During the PFT testing window from February to March, students are administered one of three tests to determine their aerobic capacity: One-Mile Run, 20 meter Progressive Aerobic Cardiovascular Endurance Run (PACER), or Walk Test. For the One-Mile Run, students are instructed to run a mile as fast as possible, which is recorded in minutes and seconds. For the 20 meter PACER, students run a 20 meter distance repeatedly to a specified pace set to music which gets faster each minute. Aerobic capacity is estimated from the number of laps completed. For the Walk Test, students are told to walk one mile as fast as possible and aerobic capacity is measured from both heart rate and walk time. PFT documentation shows that VO_2max is calculated for each child based on the following equation, which takes into account a student's gender, age, and BMI:

$$VO_2max = 108.94 + 0.21age \times male - 0.84BMI - 8.41RunTime + 0.34RunTime^2 \quad (1)$$

$$VO_2max = 132.853 + 6.315male - 0.0769weight - 0.3877age - 3.2649WalkTime - 0.1565HeartRate \quad (2)$$

where *male* is equal to 1 for males and 0 for females, age is measured in years, weight is in pounds, BMI is the child's body mass index calculated from height and weight, heart rate is measured in beats per minute, and walk and run times are measured in minutes. The formula for scoring the PACER using laps, age, and gender is proprietary to Human Kinetics and The Cooper Institute.

According to program documentation, the test options of the One-Mile Run and the 20 meter PACER begin with age 10 and the Walk Test begins with age 13. These measures of aerobic capacity are not available for children under the age of ten. Grade five students who are nine years old are scored using the standards for ten year old students. Figure 1 shows the standards for aerobic capacity for both females and males by age. There have been some changes to these standards over the study period in 2006, 2011, and 2014, with the largest changes occurring in 2011.[1] Some of these changes have differential impacts by gender and age, which makes it important to test for the robustness of the results to year-by-gender and year-by-grade controls. These results are shown in the robustness section.

Air Pollution Data

Daily data on air pollution comes from the EPA's Air Quality System (AQS) Data Mart through AirData. I obtain daily air quality summary statistics for the criteria pollutants OZ, NO_2, and $PM_{2.5}$ by monitor for the state of California. I create a weighted average of daily pollution from all monitors within 5 km of the school location, using the inverse of distance to the school as the weight.[2] The results are robust to using the nearest monitor within 5 km, as described in the robustness section.

The EPA has chosen thresholds for each of the criteria pollutants as shown in Table 1. I classify daily pollution levels during the PFT testing window as within 0-25%, 25-50%, 50-75%, 75-100%, or above 100% of the EPA pollution threshold for each pollutant. The total number of days within these pollution level bins will generate the variation necessary to estimate the impact of pollution on aerobic capacity. Figure 2 shows the distribution of pollution across schools each year. For ozone, about 60 percent of days are between 50-75% of the EPA's threshold with little evidence of declining levels of ozone over the study period. For nitrogen dioxide, the percent of

[1] Documentation of changes in the Fitnessgram Healthy Fitness Zones can be found here: www.cde.ca.gov/ta/tg/pf/healthfitzones.asp

[2] Neidell (2004); Currie and Neidell (2005) also test the validity of inverse distance weighted averages by comparing the actual level of pollution at each monitor location in California with the level of pollution that would be assigned using their method if the monitor in question was not located there. These correlations between actual and predicted levels of pollution were very high (0.77-0.92).

days within 0-25% of the threshold has been increasing, while the percent of days with higher levels of pollution have been declining. Given that very few days are in the highest two bins for nitrogen dioxide, these estimates are likely to be imprecise. For particulate matter, there are large variations in the percent of days in each category each year with some evidence that the frequency of days in the highest two categories has declined over this period.

Weather Data

It is important to control for weather given its direct impact on pollution levels. Additionally, California Physical Fitness Test documentation suggests that the aerobic capacity measure could be affected by "extreme weather," and to avoid potential health and safety issues with students and with generating invalid estimates, tests are not to be administered in unusually high temperatures or humidity or when the wind is strong.

Daily weather data for each 2.5 by 2.5 mile square in California comes from Schlenker and Roberts (2009) and is based on the PRISM weather data set. For each school, I calculate the inverse distance weighted average of maximum temperature, and precipitation values for each day using grid squares with centroids within 10km of the school. Next, I calculate the percent of days during the testing window with daily a maximum temperature that fall within 7 temperature bins in degrees Celsius: below 0, 0-5, 5-10, 10-15, 15-20, 20-25, and over 25. In addition to these temperature bins, I include controls for the percent of days with any precipitation and the average precipitation during the testing window for all regressions.

Other Data

Additional control variables include employment rates, school-grade enrollment demographics, and school-grade free/reduced price lunch.

Employment rates at the county-month level come from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS) data. I use the mean employment rate within the testing window and link to schools by county.

School enrollment and free/reduced price lunch information comes from the California Department of Education's school data files. From the enrollment data, I calculate the percent of students by race and gender in each school-grade for each year. From the free and reduced price lunch data, I calculate the percent of students receiving free or reduced price lunch in each school for each year.

3 Methods

Previous epidemiological research suggests that a disproportionate number of economically disadvantaged and nonwhite children attend schools with high exposure to air pollution in California (Green et al., 2004; McConnell et al., 2010). However, residential location is endogenously determined, as families may sort into high exposure schools based on preferences. To overcome this challenge, the empirical strategy used here exploits variation in pollution over time within different schools in California. School fixed effects will capture time-invariant characteristics of schools, such as average income of families, school facilities, and location in relation to highways and other stationary sources of pollution.

Although I cannot identify the exact date of testing for each school, I know the window of time in which testing occurs in the spring. In order to allow for non-linear effects of pollution and to estimate the impact of pollution levels below the EPA threshold, I include a series of variables for the percentage of days in the administration window that are 25-50%, 50-75%, 75-100%, or above 100% of the EPA pollution threshold for each pollutant, where the omitted category is the percent of days 0-25% of the threshold.

First, I estimate the following single-pollutant model:

$$VO2max_{st} = \alpha_0 + \alpha_1 P_{st}^{25-50} + \alpha_2 P_{st}^{50-75} + \alpha_3 P_{st}^{75-100} + \alpha_4 P_{st}^{100+} + \delta_t + \sigma_s + G_g + W_{st} + X_{st} + \epsilon \quad (3)$$

where s indexes school, t indexes school-year, and P represents one of three criteria pollutants: OZ, NO_2, and $PM_{2.5}$. $VO2max_{st}$ is the percentage of the grade that is outside of the "Healthy Fitness Zone" in school district s in year t. The single-pollutant model is estimated separately for each of the three pollutants. P_{st}^{25-50} is equal to the number of days in the administration window that fall within 25 to 50 percent of the EPA threshold level of pollution for pollutant P. P_{st}^{50-75}, P_{st}^{75-100}, and P_{st}^{100+} are defined analogously. State-wide trends are captured non-parametrically with year dummies, δ_t. Individual school fixed effects are included as σ_s, and G_g is a set of grade dummies. W_{st} is a set of weather controls for the percent of days in the testing window within 7 temperature bins, the percent of days with any precipitation, and the average precipitation. X_{st} is a set of controls for the local county employment rate, the percent of the class receiving free or reduced price lunch, and the percent of the class by race, ethnicity, and gender. Standard errors are clustered at the school level.

In addition to these single-pollutant models, which study the effect of each pollutant indi-

vidually, I also estimate a model include all 3 pollutants simultaneously. As criteria pollutants often co-vary with each other, this specification is especially important. For example, since ozone is formed primarily through a photochemical reaction between volatile organic compounds and nitrogen oxides, it may be that ozone and nitrogen dioxides are negatively correlated. Therefore, the preferred specification is the following multi-pollutant model:

$$VO2max_{st} = \pi_0 + \sum_{P=1}^{3}[\pi_1 P_{st}^{25-50} + \pi_2 P_{st}^{50-75} + \pi_3 P_{st}^{75-100} + \pi_4 P_{st}^{100+}] + \delta_t + \sigma_s + G_g + X_{st} + \epsilon \quad (4)$$

where P represents one of three criteria pollutants and controls are defined analogously to equation 3.

To explore possible heterogeneous effects of pollution exposure by age, gender, race and ethnicity, I exploit additional data on aerobic capacity by demographic groups to estimate the same models by race, ethnicity, grade, and gender.

4 Results

Table 3 shows the results from estimating equation 3 for ozone, nitrogen dioxide, and particulate matter, separately. The outcome variable is the fraction of the grade that is not in the healthy fitness zone (HFZ) for aerobic capacity. This is the fraction of the grade that has an unacceptable level of aerobic capacity, as defined in Figure 1. All regressions include school fixed effects, grade dummies, and weather controls. In column 1, increases in the fraction of ozone days within the testing window that are between 25-50%, 50-75%, and 75-100% of the threshold level are associated with a higher fraction of children who are outside of the HFZ for aerobic capacity. If the percent of days in the testing window between 75-100% of the threshold increased by 10 percentage points, this would increase the percent not in the HFZ by 2.5 percentage points, or 5.8 percent from the mean of 42.8% for all students. Point estimates are slightly smaller in magnitude for lower levels of pollution, although not statistically significantly smaller. Interestingly, there is no significant impact of pollution over 100% of the EPA threshold on aerobic capacity. This result is consistent with test administrators avoiding testing days with very high levels of ozone. During this time period, information about air quality was becoming more readily available. Since ozone is typically formed in the presence of heat and sunlight, and because test administrators were instructed to avoid testing on days with extreme heat, it could be that they indirectly avoid high ozone days as

well.

In column 2, there does not seem to be a statistically significant impact of nitrogen dioxide on aerobic capacity at any level. In column 3, there appears to be some statistically significant increase in poor aerobic capacity at the 25-50% and over 100% range for particulate matter. If the percent of days in the testing window between 25-50% of the threshold increased by 10 percentage points, the percent not in the HFZ is expected to increase by 0.75 percentage points, which is relatively small in magnitude. For a similar increase in days over the threshold, the percent not in the HFZ is expected to increase by about 1.5 percentage points, or 3.5 percent of the mean.

Given that these criteria pollutants are possibly correlated, especially nitrogen dioxide and ozone, it is important to estimate the multiple pollutant model shown in 4. Column 4-6 show these estimates with additional controls for unemployment rates and the percent with free/reduced price lunch included in column 5 and additional controls for the percent of students by race and gender included in column 6. Across all specifications, the results are very consistent. Focusing on column 6, both ozone and particulate matter harm aerobic capacity at levels even below the EPA thresholds. The effect for ozone is statistically significant at both the 50-75% and 75-100% range. For particulate matter, both the 25-50% and 75-100% ranges significantly impact aerobic capacity, with the 75-100% range having a larger point estimate.

Table 4 explores heterogeneous effects by gender, ethnicity, race, and grade. The first column replicates the main results from Table 3 for the multiple pollutant model, which includes school fixed effects and controls for grade, weather, unemployment, and free/reduced price lunch. Although nitrogen dioxide was not found to have an impact on respiratory capacity, it is still included as a control. Test results are reported separately for each of the demographic categories shown in Table 4 and the regressions are weighted by the number of students in each category.

Columns 2 and 3 show the results for females and males, respectively. The estimates of the impact of ozone and particulate matter are statistically significant for both genders, with slightly larger point estimates for females. It is helpful to consider each gender separately as the healthy fitness zone standards differ specifically by gender.

Columns 4-6 show the effects by ethnicity and race. The results for both ozone and particulate matter are large and statistically significant for Hispanic students. For a 10 percentage point increase in ozone days between 75-100% of the threshold, the percent of Hispanics not in the HFZ is expected to increase by 3.5 percentage points, or 8 percent from the mean for Hispanic students. A similar increase in particulate matter between 75-100% of the threshold would increase

the percent of Hispanic students not in the HFZ by 1.8 percentage points, or about 4 percent. For black students, the sample size is reduced substantially. Although generally insignificant, the point estimates are very large for black students in column 7. For example, a 10 percentage point increase in ozone days between 75-100% of the threshold would increase poor aerobic capacity by 4.8 percentage points, or about 10 percent from the mean among black students. This is almost twice as large as the overall effect, although not statistically significant. The coefficients on particulate matter over the threshold are also statistically significant for both Hispanics and black students, suggesting that there may be less avoidance of high particulate matter days among these students or among schools with a large fractions of Hispanic and black students.

Interestingly, there appears to be no effect on white students in column 8. In fact, many of the point estimates for both ozone and particulate matter are negative in sign. The overall effects appear to be driven by non-white children. These children may be more susceptible to the negative health effects of air pollution. In fact, black children had higher rates of asthma prevalence and visited the ED at a rate 5 times higher than white children in 2010 (Akinbami et al., 2014). Alternatively, it may be that schools with few minority students may be more likely to administer the test indoors in general, or especially on days with poor air quality. Lowering ozone and particulate matter near schools could have a larger improvement on respiratory health among minority groups, which could help diminish existing health disparities.

Columns 7-9 show the results separately by grade. The sample size is limited for grades 7 and 9, but point estimates are relatively similar across grades for ozone. For particulate matter, the estimates appear to be driven by older students in grades 7 and 9. It is difficult to draw strong conclusions from these comparisons as both the fitness standards and the methods of test administration differ across grades. For example, the Walk Test is not administered to children under 13. In addition, there are no aerobic capacity measures for children under ten, so grade five students who are nine years old are scored using the standards for ten year old students.

5 Robustness

Table 5 tests the robustness of the main results to alternate specifications with the main results replicated in column 1 for comparison. Given that fitness standards and test administration both differ across grade, school fixed effects may not be sufficient. Column 2 includes school-grade specific fixed effects and the results are almost identical to the first column.

Second, it is important to note that the fitness standards were updated in 2006, 2011, and 2014, with the largest changes occurring in 2011.[3] As these changes differentially impact students by gender and age, year fixed effects may not sufficiently capture the shifts in aerobic capacity over time driven by changing standards. To account for the differential impacts by gender and age, column 3 includes year-by-gender, year-by-grade, and year-by-race controls. The results are consistent with the main findings and adding these controls suggests that levels of particulate matter over the threshold may also have significant impacts on health.

Columns 4, 5, and 6 show the results without weights by number of students in each cell, by limiting the sample to administration windows with at least 20 observation days for each pollutant, and including charter schools, respectively. Across all these specifications, the results are very similar and continue to suggest that aerobic capacity is lower for levels of ozone and particulate matter even below the EPA's threshold levels.

Table 6 tests the sensitivity of the results to alternate measures of pollution. The main results, replicated in column 2, use inverse distance weighted measures based on monitors within 5 km of the school. Columns 1 and 3 show results based on inverse distance weighted measures from monitors within 3 km and 8 km, respectively. The point estimates are very similar for the 3 km results shown in column 1 and remain significant for particulate matter. The precision of the ozone results is reduced as the sample size is limited for this narrow distance. When all pollution monitors within 8 km are included, in column 3, the estimates are smaller and imprecise, although still positive. Columns 4-6 show results based on pollution measures from the nearest monitor within 3 km, 5 km, and 8 km. The estimates are very similar to the inverse distance weighted results with slightly larger coefficients for the nearest monitors and smaller coefficients for the furthest distance.

Finally, Table 7 shows a variety of placebo tests. Columns 2-6 show the effect of air pollution on other physical fitness measures from the Fitnessgram test: body composition, flexibility, abdominal strength, trunk extensor strength, and upper body strength. Each regression shows the effect of pollution at various levels on the fraction of students not in the healthy fitness zone for each test. While it is possible that air pollution could impact performance on some of these tests, the predominant impact should be on aerobic capacity, shown in column 1. The effects of ozone only have significant impacts on aerobic capacity, while the coefficients are smaller and statistically

[3]Documentation of changes in the Fitnessgram Healthy Fitness Zones can be found here: www.cde.ca.gov/ta/tg/pf/healthfitzones.asp

insignificant for other fitness measures. The effects of particulate matter between 75-100% of the threshold are only positive and significant for aerobic capacity. However, particulate matter 25-50% of the threshold appears to increase not only poor aerobic capacity but also all three strength measures, although these effects are relatively small in comparison to the effect of pollutants at higher levels.

Column 7 of Table 7 shows another placebo test by using measures of pollutants from future months, rather than during the test administration window. There should be no impact of future pollution on test results. From column 7 we can see that all estimates are statistically insignificant for all pollutants. This is reassuring and gives additional evidence that the effects of pollution during the testing window drive the results.

6 Discussion & Conclusion

Results shown above indicate that important air pollutants are harmful to child health at levels even below the EPA's thresholds. Using a more sensitive measure of respiratory health, aerobic capacity (VO_2max), this paper shows that ozone and fine-particulate matter increase the fraction of students with poor aerobic capacity between 75-100 percent of the threshold levels, with possible additional impacts at even lower levels.

These results are shown to be robust to many alternate specifications, such as school-grade fixed effects, demographic characteristic-by-year controls, and alternate distances for measuring pollution near schools. While other portions of the physical fitness test could potentially be impacted by poor air quality, the effects are driven through changes in aerobic capacity rather than other test areas that can be considered placebos, such as body composition or flexibility. There is also no impact of pollution measured in future months on aerobic capacity. These findings are reassuring and suggest that the main results operate through the effect of air pollution on respiratory capacity, rather than through another channel.

Heterogeneous results across race and ethnicity groups show that the results are driven by minority groups, including Hispanic and black students. This may be due to higher susceptibility to the negative health effects of air pollution among these groups. For example, black children had higher rates of asthma prevalence and visited the ED at a rate 5 times higher than white children in 2010 (Akinbami et al., 2014). Alternatively, it may be that schools with few minority students administer the test indoors more often, or especially on days with poor air quality. Nevertheless,

lowering ozone and fine-particulate matter near schools could have a large improvement on overall respiratory health, but especially large improvements for minority groups, thus diminishing existing health disparities.

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7 Figures

Figure 1: Aerobic Capacity Fitnessgram Performance Standards

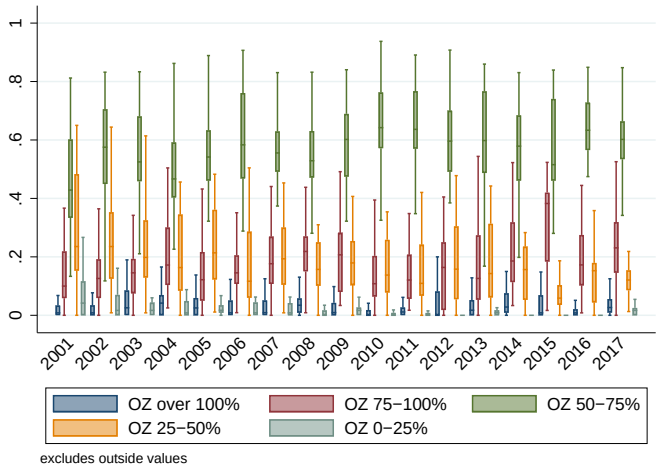
Age	One-Mile Run/20m PACER/Walk Test VO_2max (ml/kg/min)[2]		
	NI – Health Risk	**NI**	**HFZ**
5	VO_2max standards not available for students ages 5 through 9[4]. **For Walk Test only, standards also not available for students ages 10, 11, and 12.**		
6			
7			
8			
9			
10	≤ 37.3	37.4 – 40.1	≥ 40.2
11	≤ 37.3	37.4 – 40.1	≥ 40.2
12	≤ 37.0	37.1 – 40.0	≥ 40.1
13	≤ 36.6	36.7 – 39.6	≥ 39.7
14	≤ 36.3	36.4 – 39.3	≥ 39.4
15	≤ 36.0	36.1 – 39.0	≥ 39.1
16	≤ 35.8	35.9 – 38.8	≥ 38.9
17	≤ 35.7	35.8 – 38.7	≥ 38.8
17+	≤ 35.3	35.4 – 38.5	≥ 38.6

(a) Females

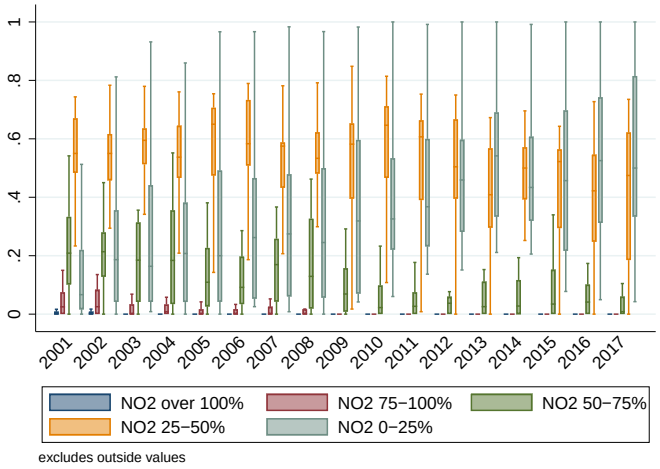
One-Mile Run/20m PACER/Walk Test VO_2max (ml/kg/min)[2]		
NI – Health Risk	**NI**	**HFZ**
VO_2max standards not available for students ages 5 through 9[4]. **For Walk Test only, standards also not available for students ages 10, 11, and 12.**		
≤ 37.3	37.4 – 40.1	≥ 40.2
≤ 37.3	37.4 – 40.1	≥ 40.2
≤ 37.6	37.7 – 40.2	≥ 40.3
≤ 38.6	38.7 – 41.0	≥ 41.1
≤ 39.6	39.7 – 42.4	≥ 42.5
≤ 40.6	40.7 – 43.5	≥ 43.6
≤ 41.0	41.1 – 44.0	≥ 44.1
≤ 41.2	41.3 – 44.1	≥ 44.2
≤ 41.2	41.3 – 44.2	≥ 44.3

(b) Males

Figure 2: Pollution Distribution by Year



(a) OZ



(b) NO2



(c) PM25

8 Tables

Table 1: Pollution: Summary Statistics

	OZ	NO2	PM25
	(1)	(2)	(3)
EPA's NAAQS	0.070 ppm	100 ppb	35 $\mu g/m^3$
Averaging Time	8-hour	1-hour	24-hour
0-25%	0.0179	0.392	0.429
	(0.0366)	(0.286)	(0.233)
25-50%	0.186	0.490	0.397
	(0.147)	(0.200)	(0.153)
50-75%	0.579	0.107	0.111
	(0.154)	(0.117)	(0.0915)
75-100%	0.181	0.00962	0.0368
	(0.123)	(0.0228)	(0.0483)
over 100%	0.0357	0.000848	0.0-258
	(0.0499)	(0.00446)	(0.0504)
Observations	11,344	10,690	9,259

Notes: Mean coefficients and std. dev. in parentheses.

Table 2: Physical Fitness Test: Summary Statistics

	Fraction Not in HFZ					
	All	Female	Male	Hispanic	Black	White
Aerobic Capacity	0.428	0.444	0.404	0.444	0.471	0.367
	(0.205)	(0.227)	(0.197)	(0.200)	(0.211)	(0.205)
Body Comp.	0.399	0.344	0.451	0.441	0.382	0.298
	(0.139)	(0.158)	(0.140)	(0.131)	(0.143)	(0.135)
Flexibility	0.297	0.258	0.332	0.315	0.276	0.251
	(0.177)	(0.177)	(0.190)	(0.181)	(0.177)	(0.175)
Ab. Strength	0.230	0.235	0.218	0.245	0.209	0.164
	(0.187)	(0.191)	(0.180)	(0.190)	(0.172)	(0.152)
Trunk Ext. Strength	0.133	0.119	0.142	0.134	0.139	0.108
	(0.163)	(0.154)	(0.164)	(0.161)	(0.159)	(0.144)
Up. Body Strength	0.354	0.382	0.324	0.378	0.299	0.293
	(0.190)	(0.216)	(0.176)	(0.195)	(0.175)	(0.178)
Students	163.5	87.83	90.94	112.1	37.88	63.83
	(164.6)	(90.42)	(95.16)	(126.3)	(40.56)	(73.13)

mean coefficients; sd in parentheses

Table 3: Multi-pollutant Model: Full sample

	Fraction Not in HFZ					
	(1)	(2)	(3)	(4)	(5)	(6)
OZ 25-50%	0.188**			0.248**	0.263**	0.202
	(0.0942)			(0.125)	(0.120)	(0.127)
OZ 50-75%	0.185**			0.273**	0.288**	0.248**
	(0.0865)			(0.116)	(0.111)	(0.119)
OZ 75-100%	0.250***			0.267**	0.291**	0.262**
	(0.0934)			(0.121)	(0.116)	(0.122)
OZ over 100%	-0.0406			0.0890	0.0682	0.0400
	(0.0956)			(0.135)	(0.130)	(0.135)
NO2 25-50%		-0.00743		-0.00971	0.00255	-0.00150
		(0.0328)		(0.0403)	(0.0394)	(0.0398)
NO2 50-75%		0.0146		-0.0505	-0.0353	-0.0297
		(0.0463)		(0.0595)	(0.0588)	(0.0591)
NO2 75-100%		-0.195		0.0886	0.119	0.241
		(0.142)		(0.164)	(0.161)	(0.172)
NO2 over 100%		0.621		-0.663	-0.546	-0.825
		(0.536)		(0.795)	(0.770)	(0.883)
PM25 25-50%			0.0747***	0.0978***	0.0925***	0.0994***
			(0.0214)	(0.0251)	(0.0258)	(0.0264)
PM25 50-75%			0.0112	0.00486	0.0148	0.000706
			(0.0422)	(0.0417)	(0.0432)	(0.0461)
PM25 75-100%			0.0694	0.143**	0.146**	0.156**
			(0.0614)	(0.0631)	(0.0635)	(0.0658)
PM25 over 100%			0.150*	0.174	0.175	0.167
			(0.0827)	(0.123)	(0.117)	(0.119)
Constant	2.327***	2.695***	3.043***	2.071**	1.925**	1.732*
	(0.768)	(0.804)	(0.895)	(0.883)	(0.872)	(0.915)
Observations	11,306	10,652	9,244	7,997	7,973	7,029
R-squared	0.558	0.545	0.515	0.518	0.518	0.535
Unemployment					yes	yes
Free/Reduced Lunch					yes	yes
Student Demographics						yes

Notes: All regressions include grade dummies and weather controls. Weather controls include percent of days that fall into 7 temperature bins, percent of days with any precipitation, and average precipitation for the testing window. For each pollutant, the omitted category is 0-25% of the EPA threshold. Regressions are weighted by number of students. Standard errors clustered at the school level in parentheses.

Table 4: Heterogeneous Effects: Gender, Race/Ethnicity, and Grade

	All	Female	Male	Hispanic	Black	White	Grade 5	Grade 7	Grade 9
	(1)	(2)	(3)	(6)	(7)	(8)	(9)	(10)	(11)
OZ 25-50%	0.263**	0.340**	0.262**	0.314**	0.515	-0.124	0.324**	0.184	0.271
	(0.120)	(0.141)	(0.106)	(0.128)	(0.373)	(0.193)	(0.149)	(0.215)	(0.191)
OZ 50-75%	0.288**	0.381***	0.286***	0.344***	0.448	-0.134	0.331**	0.196	0.333*
	(0.111)	(0.129)	(0.0991)	(0.117)	(0.355)	(0.179)	(0.136)	(0.204)	(0.181)
OZ 75-100%	0.291**	0.380***	0.304***	0.346***	0.484	-0.0245	0.354**	0.184	0.305
	(0.116)	(0.137)	(0.104)	(0.124)	(0.352)	(0.191)	(0.146)	(0.209)	(0.194)
OZ over 100%	0.0682	0.00754	0.0162	0.0341	0.540	-0.316*	0.144	-0.185	0.313
	(0.130)	(0.154)	(0.111)	(0.138)	(0.344)	(0.178)	(0.159)	(0.247)	(0.240)
NO2 25-50%	0.00255	0.0335	0.0171	-0.0368	0.0567	0.0213	0.0222	-0.00636	-0.00819
	(0.0394)	(0.0496)	(0.0335)	(0.0455)	(0.112)	(0.0459)	(0.0392)	(0.0627)	(0.0736)
NO2 50-75%	-0.0353	-0.0586	-0.0357	-0.0628	-0.0188	0.161	0.0172	-0.104	0.0417
	(0.0588)	(0.0783)	(0.0550)	(0.0642)	(0.182)	(0.104)	(0.0703)	(0.103)	(0.0988)
NO2 75-100%	0.119	0.285	0.0933	0.187	-0.331	0.00314	-0.264	0.611*	-0.104
	(0.161)	(0.197)	(0.132)	(0.147)	(0.967)	(0.363)	(0.209)	(0.324)	(0.245)
NO2 over 100%	-0.546	-0.713	0.396	-0.851	-0.386	-0.588	-0.292	-0.482	0.267
	(0.770)	(0.901)	(0.745)	(0.728)	(3.672)	(1.893)	(0.889)	(1.890)	(1.280)
PM25 25-50%	0.0925***	0.0816**	0.0642***	0.105***	0.0779	0.0134	0.0164	0.158***	0.107**
	(0.0258)	(0.0358)	(0.0239)	(0.0300)	(0.0661)	(0.0343)	(0.0308)	(0.0411)	(0.0478)
PM25 50-75%	0.0148	0.0123	0.0137	0.0188	0.0722	-0.0457	0.00925	0.0734	-0.0348
	(0.0432)	(0.0570)	(0.0388)	(0.0438)	(0.107)	(0.0982)	(0.0467)	(0.0644)	(0.0797)
PM25 75-100%	0.146**	0.134*	0.0956	0.180***	0.112	-0.0892	0.0205	0.254**	0.233**
	(0.0635)	(0.0738)	(0.0600)	(0.0646)	(0.183)	(0.125)	(0.0959)	(0.117)	(0.0923)
PM25 over 100%	0.175	0.176	0.136	0.228*	0.668**	0.149	0.106	0.229	0.386*
	(0.117)	(0.135)	(0.0985)	(0.123)	(0.301)	(0.176)	(0.134)	(0.210)	(0.206)
Observations	7,973	7,874	7,924	7,648	1,627	2,886	5,273	1,379	1,302
R-squared	0.518	0.517	0.536	0.488	0.506	0.611	0.408	0.605	0.708

Notes: All regressions include grade dummies, unemployment, percent free or reduced price lunch, and weather controls. Weather controls include percent of days that fall into 7 temperature bins, percent of days with any precipitation, and average precipitation for the testing window. For each pollutant, the omitted category is 0-25% of the EPA threshold. Regressions are weighted by number of students. Standard errors clustered at the school level in parentheses.

Table 5: Robustness of main results

	Baseline	School-Grade FE	Demo×Yr	No weights	>20 obs/poll	Include Charter
	(1)	(2)	(3)	(4)	(5)	(6)
OZ 25-50%	0.202	0.190	0.215*	0.203	0.195	0.203
	(0.127)	(0.126)	(0.118)	(0.125)	(0.127)	(0.126)
OZ 50-75%	0.248**	0.236**	0.262**	0.219*	0.245**	0.243**
	(0.119)	(0.119)	(0.110)	(0.117)	(0.119)	(0.119)
OZ 75-100%	0.262**	0.250**	0.279**	0.258**	0.258**	0.257**
	(0.122)	(0.122)	(0.116)	(0.124)	(0.125)	(0.122)
OZ over 100%	0.0400	0.0318	0.0451	0.0838	0.0381	0.0390
	(0.135)	(0.135)	(0.132)	(0.131)	(0.137)	(0.135)
NO2 25-50%	-0.00150	-0.00222	-0.00562	0.0140	0.0329	-0.00435
	(0.0398)	(0.0398)	(0.0373)	(0.0318)	(0.0382)	(0.0392)
NO2 50-75%	-0.0297	-0.0325	0.00688	-0.0263	-0.0331	-0.0456
	(0.0591)	(0.0591)	(0.0572)	(0.0576)	(0.0605)	(0.0592)
NO2 75-100%	0.241	0.247	0.206	0.0236	0.390*	0.238
	(0.172)	(0.172)	(0.178)	(0.190)	(0.202)	(0.171)
NO2 over 100%	-0.825	-0.705	-1.244	-0.797	-0.909	-0.933
	(0.883)	(0.877)	(0.841)	(0.953)	(0.930)	(0.886)
PM25 25-50%	0.0994***	0.101***	0.0975***	0.0616**	0.0629**	0.102***
	(0.0264)	(0.0264)	(0.0261)	(0.0243)	(0.0274)	(0.0259)
PM25 50-75%	0.000706	0.00142	0.0319	0.0213	-0.00575	0.00799
	(0.0461)	(0.0460)	(0.0431)	(0.0405)	(0.0470)	(0.0455)
PM25 75-100%	0.156**	0.157**	0.123*	0.0932	0.167**	0.151**
	(0.0658)	(0.0657)	(0.0633)	(0.0723)	(0.0656)	(0.0654)
PM25 over 100%	0.167	0.162	0.296***	0.0473	0.201	0.177
	(0.119)	(0.119)	(0.106)	(0.110)	(0.124)	(0.119)
Observations	7,029	7,014	7,029	7,029	6,579	7,419
R-squared	0.535	0.540	0.566	0.475	0.554	0.531

Table 6: Robustness to alternate pollution measures

	IDW			Nearest		
	3km	5km	8km	3km	5km	8km
	(1)	(2)	(3)	(4)	(5)	(6)
OZ 25-50%	0.135	0.202	0.0171	0.144	0.207	0.0385
	(0.170)	(0.127)	(0.0951)	(0.170)	(0.127)	(0.0919)
OZ 50-75%	0.196	0.248**	0.0383	0.206	0.253**	0.0576
	(0.160)	(0.119)	(0.0918)	(0.161)	(0.120)	(0.0886)
OZ 75-100%	0.294	0.262**	0.106	0.302*	0.265**	0.121
	(0.182)	(0.122)	(0.0945)	(0.182)	(0.123)	(0.0912)
OZ over 100%	-0.0686	0.0400	-0.125	-0.0702	0.0473	-0.121
	(0.155)	(0.135)	(0.0989)	(0.154)	(0.135)	(0.0955)
NO2 25-50%	-0.0405	-0.00150	0.00808	-0.0363	-0.000130	-0.00661
	(0.0608)	(0.0398)	(0.0248)	(0.0588)	(0.0380)	(0.0239)
NO2 50-75%	0.0440	-0.0297	-0.0199	0.0411	-0.0344	-0.0356
	(0.117)	(0.0591)	(0.0376)	(0.115)	(0.0581)	(0.0337)
NO2 75-100%	0.192	0.241	0.0991	0.229	0.261	0.151
	(0.329)	(0.172)	(0.120)	(0.328)	(0.175)	(0.119)
NO2 over 100%	0.537	-0.825	-0.301	0.281	-0.894	-0.620
	(1.463)	(0.883)	(0.601)	(1.427)	(0.807)	(0.625)
PM25 25-50%	0.115***	0.0994***	0.0667***	0.115***	0.102***	0.0739***
	(0.0380)	(0.0264)	(0.0183)	(0.0379)	(0.0264)	(0.0182)
PM25 50-75%	-0.0616	0.000706	-0.0172	-0.0614	0.00158	-0.00901
	(0.0721)	(0.0461)	(0.0316)	(0.0722)	(0.0460)	(0.0309)
PM25 75-100%	0.270***	0.156**	0.0381	0.275***	0.154**	0.0278
	(0.103)	(0.0658)	(0.0465)	(0.103)	(0.0652)	(0.0460)
PM25 over 100%	0.00711	0.167	0.0456	0.0126	0.173	0.0501
	(0.199)	(0.119)	(0.0620)	(0.198)	(0.118)	(0.0620)
Observations	3,280	7,029	15,610	3,280	7,029	15,610
R-squared	0.516	0.535	0.542	0.516	0.535	0.542

Table 7: Placebos

		Other Fitness Tests					
	Aerobic Capacity	Body Comp.	Flexibility	Abdom. Strength	Trunk Ext Strength	Up. Body Strength	Future Pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OZ 25-50%	0.202	0.0425	0.0705	0.0981	-0.228*	0.0907	0.271
	(0.127)	(0.0786)	(0.106)	(0.108)	(0.125)	(0.136)	(0.330)
OZ 50-75%	0.248**	0.0414	0.113	0.126	-0.171	0.125	0.367
	(0.119)	(0.0731)	(0.100)	(0.0997)	(0.119)	(0.125)	(0.320)
OZ 75-100%	0.262**	0.0792	0.131	0.147	-0.187	0.169	0.350
	(0.122)	(0.0793)	(0.108)	(0.110)	(0.123)	(0.132)	(0.319)
OZ over 100%	0.0400	0.0933	0.0788	0.141	-0.0894	0.0210	0.310
	(0.135)	(0.0819)	(0.130)	(0.129)	(0.133)	(0.145)	(0.320)
NO2 25-50%	-0.00150	0.0349*	-0.101***	-0.0323	-0.0437	-0.0677*	-0.0285
	(0.0398)	(0.0207)	(0.0357)	(0.0308)	(0.0304)	(0.0381)	(0.0351)
NO2 50-75%	-0.0297	0.0262	0.0164	0.00524	-0.0214	-0.00822	-0.0583
	(0.0591)	(0.0408)	(0.0618)	(0.0573)	(0.0557)	(0.0729)	(0.0482)
NO2 75-100%	0.241	0.115	-0.160	-0.215	-0.367**	-0.0715	0.138
	(0.172)	(0.104)	(0.170)	(0.171)	(0.178)	(0.202)	(0.151)
NO2 over 100%	-0.825	-0.00129	0.489	2.040*	2.466**	0.803	-0.379
	(0.883)	(0.611)	(0.947)	(1.192)	(1.133)	(1.085)	(0.337)
PM25 25-50%	0.0994***	0.00994	-0.00863	0.0513**	0.0550**	0.0698***	-0.0210
	(0.0264)	(0.0131)	(0.0293)	(0.0229)	(0.0238)	(0.0260)	(0.0247)
PM25 50-75%	0.000706	0.0111	0.0672	0.0555	0.0403	0.0171	-0.00796
	(0.0461)	(0.0239)	(0.0497)	(0.0525)	(0.0498)	(0.0519)	(0.0307)
PM25 75-100%	0.156**	-0.115**	-0.0932	-0.0821	0.0521	-0.0864	0.0891
	(0.0658)	(0.0462)	(0.0854)	(0.0629)	(0.0666)	(0.0723)	(0.0740)
PM25 over 100%	0.167	0.0227	0.183*	0.0628	0.189	0.136	-0.0733
	(0.119)	(0.0592)	(0.106)	(0.119)	(0.122)	(0.135)	(0.112)
Observations	7029	7029	7029	7029	7029	7029	6993
R-squared	0.535	0.640	0.550	0.537	0.450	0.497	0.531

Notes: All regressions include grade dummies, unemployment, percent free or reduced price lunch, demographic characteristics, and weather controls. Weather controls include percent of days that fall into 7 temperature bins, percent of days with any precipitation, and average precipitation for the testing window. For each pollutant, the omitted category is 0-25% of the EPA threshold. Regressions are weighted by number of students. Standard errors clustered at the school level in parentheses.