Pollution at Schools and Children's Aerobic Capacity

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Abstract

Poor respiratory health is a major cause of mortality and morbidity worldwide. 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. Existing research has documented the effect of pollution on severe health outcomes, such as hospitalizations for asthma and infant death. However, there is little evidence on how air pollution affects less extreme measures of respiratory health, suggesting that previous literature could underestimate the costs of air pollution. Less extreme effects on respiratory health 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. I combine school-grade level data from the California Physical Fitness Test from 2009-2017 with local air pollution and weather data to estimate the impact of fluctuations in daily pollution levels on student aerobic capacity. Ozone affects child aerobic capacity at levels even below the EPA thresholds. I explore heterogeneous effects by race, ethnicity, income, and gender, and find the effects are especially large for disadvantaged groups.

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Poor respiratory health is a major cause of mortality and morbidity worldwide, with children being especially vulnerable. As required by the Clean Air Act, the US EPA sets National Ambient Air Quality Standards (NAAQS) with the goal of protecting public health from the harmful effects of air pollution. These standards are required to be reviewed and revised every five years. In 2015, the EPA strengthened the standard 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. 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 due to their higher respiratory rate, narrower airways, and developing lungs. While child hospitalizations for asthma or another respiratory illness are likely to be a more sensitive measure than adult hospitalizations, 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 2009-2017 with local air pollution and weather data to estimate the impact of fluctuations in test date pollution levels on the aerobic capacity for students in grades 5, 7, and 9.

Estimates measure the health impact of air pollution near 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 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. 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 differences in pollution exposure across school locations and to capture any differential characteristics driven by sorting of residents across schools. Identification comes from variation in pollution levels on testing dates at a given school location over time, 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). Additional work has shown that air pollution, from highways and industrial sources for example, can impact absences, student test scores, and behavioral incidents (Persico and Venator, 2019; Heissel et al., 2019; Currie et al., 2009a). These findings are important as they document an impact of air pollution on more sensitive outcomes among a broader set of individuals. However, they do not measure respiratory capacity directly.

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, as there is no parent opt-out for the physical fitness test. 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. 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.

As some school districts have required students to pass the physical fitness test, poor air quality on the test date can have important educational consequences and may potentially impact graduation rates and later life outcomes. For example, the Los Angeles Unified School District requires students to meet physical fitness standards for 5 out of the 6 test components. Students who do not meet these standards in grades 9 or 10 must continue to take physical education classes until they pass or graduate. Poor air quality on the test date can impact pass rates and may preclude some students from taking other courses needed for graduation. As non-white and economically disadvantaged students tend to have higher exposure to pollution at school and may be more sensitive to exposure, these educational impacts from poor air quality on the physical fitness test date may widen existing disparities and have long-run consequences on graduation rates and later life earnings.

I find that exposure to ozone increases the percent of students with unacceptable levels of aerobic capacity at levels of pollution even below the NAAQS threshold. If aerobic capacity is measured on a day with ozone levels above the NAAQS threshold, there is a 5.1 percentage point (12 percent) increase in the number of students with poor aerobic capacity. When ozone is between 75 and 100 percent of the threshold, the increase in poor aerobic capacity is a 4.6 percentage point

(11 percent). I find especially large estimates among Hispanic and economically disadvantaged students, suggesting large potential gains in respiratory health for these group from a reduction in ozone 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 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 2009 to 2017. Fitness measures are released for each grade in each school, and additional sub-categories report fitness measures by gender, race, ethnicity, and economic status. Although the fitness measures are not at the individual level, additional information provided by the California Department of Education contains individual dates of test administration for each student in each grade and school.[1] These test dates are important because they can be linked to pollution and weather information at the daily level to better measure exposure to poor air quality on the test date. For each school-grade, exposure is measured as the fraction of all student test dates that fall within a particular range of air pollution, relative to each pollutant's

[1] These data do not include information for charter schools, so these schools are not included.

NAAQS threshold.

Figure 2 shows, within a school and grade, most students take the physical fitness test on the same date. The left panel shows the distribution of percent of students within a school-grade who take the PFT on the most common date. On average, about 80 percent take the test on the same day. The right panel shows the distribution of the range of dates over which students in a school-grade take the test. On average, all students within the school-grade take the test within a 17 day range.

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 May, 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.

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.

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 8 km of the school location, using the inverse of distance squared to the school as the weight.[2] The results are robust to using the nearest monitor within 8 km, as described

[2] Neidell (2004); Currie and Neidell (2005) also test the validity of inverse distance weighted averages by comparing

in the robustness section.

The EPA thresholds for each of the criteria pollutants are shown in Table 1. I classify daily pollution levels on test days as within 0-25%, 25-50%, 50-75%, 75-100%, or above 100% of the EPA pollution threshold for each pollutant. As shown in Table 1, about 1.5 percent of testing days are over the threshold for ozone and about 14 percent are just below the threshold, within 75 to 100 percent of the threshold. For nitrogen dioxide, less than 1 percent of testing days are over 75 percent of the threshold level. For fine particulate matter, about 1.3 and 3 percent of testing days are over the threshold and 75 to 100 percent of the threshold, respectively.

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-squared weighted average of maximum temperature and precipitation values for each day using grid squares with centroids within 8km 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 during the testing month and link to schools by county. This will help control for local economic activity that could

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).

be related to pollution and child outcomes.

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. These controls help account for changes in respiratory capacity due to changing student body characteristics.

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 at different school locations 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.

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 testing days for a school-grade-year 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:

$$LowVO2max_{st} = \alpha_0+\alpha_1 P_{st}^{25-50}+\alpha_2 P_{st}^{50-75}+\alpha_3 P_{st}^{75-100}+\alpha_4 P_{st}^{100+}+\delta_t+\sigma_s+G_g+W_{st}+X_{st}+\epsilon \quad (1)$$

where s indexes school, t indexes school-year, and P represents one of three criteria pollutants: OZ, NO_2, and $PM_{2.5}$. $LowVO2max_{st}$ is the percentage of the grade that is outside of the "Healthy Fitness Zone" in school s and year t. The single-pollutant model is estimated separately for each of the three pollutants. P_{st}^{25-50} is equal to the fraction of testing days 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. 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 test days 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 individually, I also estimate a model that includes all three 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:

$$LowVO2max_{st} = \pi_0 + \sum_{P=1}^{3}[\pi_1 P_{st}^{25-50} + \pi_2 P_{st}^{50-75} + \pi_3 P_{st}^{75-100} + \pi_4 P_{st}^{100+}] + \delta_t + \sigma_s + G_g + X_{st} + \epsilon \quad (2)$$

where P represents one of three criteria pollutants and controls are defined analogously to equation 1.

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

4 Results

Table 3 shows the results from estimating equation 1 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. Columns 1-3 show the single pollutant models, in which only ozone appears to have a statistically significant impact on aerobic capacity. However, since these criteria pollutants are possibly correlated, especially nitrogen dioxide and ozone, it is important to estimate the multiple-pollutant model shown in equation 2.

Column 4 shows the multiple-pollutant model with school fixed effects, grade dummies, and weather controls. The next two columns add 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. Increases in the fraction of testing days with ozone between 25-50, 50-75, and 75-100 percent of the threshold level are associated with a higher fraction of children who are outside of the HFZ for aerobic capacity. Point estimates are slightly smaller in magnitude for lower levels of pollution, although not statistically significantly smaller. Focusing on the fully specified model in column 6, if ozone is above the EPA threshold for all students on the test day, the percent of students with poor aerobic capacity is 5 percentage points higher than if ozone had been 0 to 25 percent of the threshold. Relative to a mean of 41.2 percent, this represents a 12 percent increase in the percent of students with poor aerobic capacity. Importantly, ozone also has an effect at levels below the EPA threshold. For example, if ozone is 75 to 100 percent of the EPA threshold on the test date, the percent of students with poor aerobic capacity is 4.6 percentage points higher than on a low ozone day. For the other pollutants, there is little evidence of an impact on health.

Table 4 explores heterogeneous effects by gender, ethnicity, race, and income. The first column replicates the results from Table 3 column 5 for the multiple pollutant model, which includes school fixed effects and controls for grade, weather, unemployment, and free/reduced price lunch. Although fine particulate matter and nitrogen dioxide were not found to have a significant impact on respiratory capacity, they are still included as controls. 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. It is helpful to consider each gender separately as the healthy fitness zone standards differ specifically by gender. The estimates for ozone are statistically significant for both genders, with slightly larger point estimates for females.

Columns 4-6 show the effects by ethnicity and race. The results for ozone are large and statistically significant for Hispanic students. If all Hispanic students take the test on a day with ozone 75 to 100 percent of the EPA threshold, poor aerobic capacity increases by 5 percentage points, or 11 percent from the mean for Hispanic students. Although the estimates are statistically insignificant for black students due to a smaller sample size, the point estimate for ozone above the threshold is especially large. The point estimate suggests an 8 percentage point increase in poor aerobic capacity for black students when the test is administered on a day with ozone above the EPA threshold, which is a 19 percent increase from the mean for black students. Column 8 shows the point estimates for white students are much smaller and statistically insignificant.

Columns 7 and 8 show the results for economically disadvantaged and non-economically disadvantaged students, respectively. For ozone, the estimates are positive and statistically significant only for the economically disadvantaged students. For ozone above the EPA threshold on the test date, there is a 5.8 percentage point, or 19 percent, increase in poor aerobic capacity for economically disadvantaged students. For non-disadvantaged students, there is no evidence of negative impacts on aerobic capacity.

The overall effects appear to be driven by non-white and economically disadvantaged 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 non-minority and non-economically disadvantaged students may be more likely to administer the test indoors in general. Lowering ozone near schools could have a larger improvement on respiratory health among low income and minority groups, which could help diminish existing health disparities.

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 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, and the results are consistent with the main findings.

Columns 4 and 5 show the results without weighting by the number of students in each cell, and by limiting the sample to test dates within the official testing window (Feb-May), respectively. Across both specifications, the results are very similar and continue to suggest that aerobic capacity is lower for levels of ozone even below the EPA's threshold levels.

Finally, column 6 tests the sensitivity of the results to using inverse distance weighted pollu-

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

tion. Column 6 shows the estimates based on the pollution recorded at the nearest monitor within 8km. Again, the results are very similar to the baseline specification.

Next, one potential threat to identification would be if changes in pollution are correlated with changes demographic characteristics within schools. For example, if a particular area decided to reduce pollution due to new political leadership or a sudden influx of wealthy families, and the resulting change in pollution accompanied changes in the demographics of the student body. To test if this is driving the results, Table 6 repeats the main specification but with school-grade demographic characteristics as the outcome variables, including the percent receiving free or reduced price lunch and the percent in each race group. Almost all of the coefficients on ozone are statistically insignificant and small in magnitude, and there is no strong pattern of results. This indicates that the main findings are not driven by demographic changes in the underlying student population over time.

In addition, Table 7 shows the effect of air pollution on other physical fitness test measures. Some of these fitness tests can be thought of as placebos, such as body composition and flexibility, since they should not be impacted by air pollution. However, there may be some impact on other measures of fitness, such as abdominal strength, trunk strength, and upper body strength. Column 1 replicates the main results for aerobic capacity, showing significant impacts of ozone exposure. 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. Columns 1 and 2 show there is no significant impact of ozone on body composition or flexibility, as expected. This is reassuring since we would not expect higher ozone on the testing date to impact body composition or flexibility. Columns 4, 5, and 6, present the results for each of the three strength measures. There is no consistent evidence of an impact on any of these strength measures.

Finally, to show that the effect of ozone on aerobic capacity is driven by exposure during the physical fitness test, Table 8 shows the effect of pollution measured on each of three days before and after the test date. Pollution measured on surrounding dates can be though of as placebos as they should not have an impact on aerobic capacity performance on the test date. Columns 1-3 show the effect of pollution 3 days, 2 days, and 1 day before the test date. For each of these columns the coefficients for ozone are statistically insignificant. Similarly, columns 5-7 show that the effects of pollution 1 day, 2 days, and 3 days after the test date are also statistically insignificant. The only statistically significant results for ozone appear on the actual day of testing in column 4. This is reassuring and gives additional evidence that the effects of pollution during testing 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 increases the fraction of students with poor aerobic capacity above the EPA threshold and even 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 pollution measures. Importantly, the effects of ozone are driven through changes in aerobic capacity rather than other test areas that can be considered placebos, such as body composition or flexibility. Also, pollution measured on days surrounding the actual test date has no significant impact 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 disadvantaged groups, including Hispanic and economically disadvantaged students. This may be due to higher susceptibility to the negative health effects of air pollution among these groups. Alternatively, it may be that schools with few disadvantaged students administer the test indoors more often. Nevertheless, lowering ozone near schools could have a large improvement on overall respiratory health, but especially large improvements for disadvantaged groups, thus diminishing existing health disparities.

For districts that require students to pass the physical fitness test, such as the Los Angeles Unified School District, poor air quality on the test date may have important educational consequences. Students who do not pass must continue taking physical education courses until they pass or graduate, which may preclude them from taking other courses they may need to graduate on time. As disadvantaged students have higher exposure to poor air quality and may be more susceptible to the negative health effects of air pollution, poor air quality on the test date can widen existing educational gaps and may have important long-run consequences for graduation rates and later life outcomes.

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7 Figures

Figure 1: Aerobic Capacity Fitnessgram Performance Standards

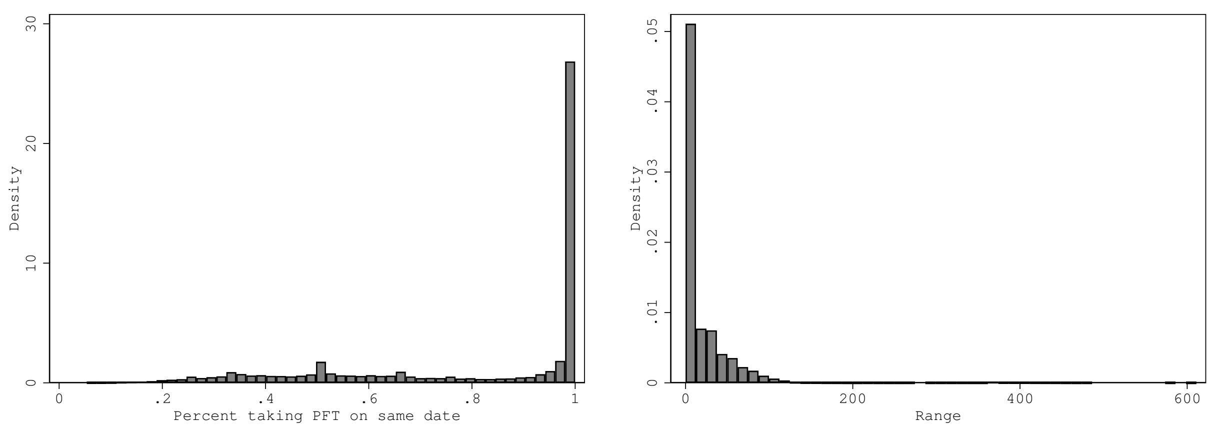
	One-Mile Run/20m PACER/Walk Test VO_2max (ml/kg/min)[2]		
Age	NI – Health Risk	NI	HFZ
5	VO_2max standards not available for students ages 5 through 9[4]. **For Walk Test only, standards also not available for students ages 10, 11, and 12.**		
6			
7			
8			
9			
10	≤ 37.3	37.4 – 40.1	≥ 40.2
11	≤ 37.3	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: Testing dates within each school-grade



8 Tables

Table 1: Pollution: Summary statistics

	OZ (1)	NO2 (2)	PM25 (3)
EPA's NAAQS	0.070 ppm	100 ppb	35 μ g/m^3
Averaging Time	8-hour	1-hour	24-hour
0-25%	0.0110	0.341	0.464
	(0.0960)	(0.433)	(0.450)
25-50%	0.194	0.549	0.389
	(0.358)	(0.443)	(0.429)
50-75%	0.639	0.109	0.105
	(0.424)	(0.279)	(0.265)
75-100%	0.142	0.00124	0.0291
	(0.306)	(0.0284)	(0.148)
over 100%	0.0147	0.0000127	0.0132
	(0.104)	(0.000938)	(0.0943)
Observations	9,581	9,075	6,870

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	Econ Dis.	Non-Dis.
Aerobic Capacity	0.412	0.453	0.362	0.433	0.445	0.320	0.309	0.446
	(0.188)	(0.211)	(0.177)	(0.182)	(0.198)	(0.177)	(0.177)	(0.167)
Body Comp.	0.419	0.403	0.432	0.458	0.405	0.306	0.326	0.472
	(0.143)	(0.166)	(0.149)	(0.133)	(0.151)	(0.139)	(0.155)	(0.127)
Flexibility	0.284	0.251	0.311	0.302	0.258	0.220	0.182	0.298
	(0.175)	(0.186)	(0.182)	(0.179)	(0.180)	(0.162)	(0.153)	(0.179)
Ab. Strength	0.258	0.270	0.239	0.276	0.230	0.175	0.183	0.289
	(0.197)	(0.209)	(0.187)	(0.202)	(0.187)	(0.155)	(0.167)	(0.203)
Trunk Ext. Strength	0.128	0.110	0.140	0.131	0.128	0.0976	0.0999	0.135
	(0.156)	(0.145)	(0.162)	(0.158)	(0.148)	(0.129)	(0.129)	(0.159)
Up. Body Strength	0.352	0.377	0.323	0.375	0.291	0.275	0.263	0.379
	(0.188)	(0.215)	(0.174)	(0.193)	(0.169)	(0.166)	(0.166)	(0.187)
Students	157.6	80.25	83.32	112.6	34.67	58.38	27.32	115.5
	(164.0)	(80.83)	(84.71)	(131.8)	(31.67)	(64.14)	(34.82)	(122.5)

mean coefficients; sd in parentheses

Table 3: Effect of pollution on aerobic capacity

	Fraction Not in HFZ					
	(1)	(2)	(3)	(4)	(5)	(6)
OZ 25-50%	0.0436**			0.0430***	0.0422**	0.0388**
	(0.0170)			(0.0166)	(0.0168)	(0.0176)
OZ 50-75%	0.0403**			0.0395**	0.0388**	0.0364**
	(0.0175)			(0.0171)	(0.0172)	(0.0183)
OZ 75-100%	0.0510***			0.0504***	0.0494***	0.0466**
	(0.0193)			(0.0189)	(0.0191)	(0.0200)
OZ over 100%	0.0529**			0.0530**	0.0506**	0.0505*
	(0.0249)			(0.0250)	(0.0253)	(0.0263)
NO2 25-50%		0.00285		0.00211	0.00290	0.000988
		(0.00571)		(0.00585)	(0.00577)	(0.00578)
NO2 50-75%		0.00692		0.00697	0.00783	0.00963
		(0.00809)		(0.00835)	(0.00833)	(0.00868)
NO2 75-100%		0.0113		0.0146	0.0118	0.0127
		(0.0559)		(0.0566)	(0.0583)	(0.0657)
PM25 25-50%			-0.00479	-0.00533	-0.00443	-0.00578
			(0.00495)	(0.00510)	(0.00511)	(0.00533)
PM25 50-75%			-0.00396	-0.00464	-0.00513	-0.00534
			(0.00702)	(0.00723)	(0.00718)	(0.00737)
PM25 75-100%			0.00162	0.000398	0.00149	-0.00478
			(0.0109)	(0.0108)	(0.0109)	(0.0113)
PM25 over 100%			0.00904	0.00821	0.00773	0.0105
			(0.0173)	(0.0172)	(0.0173)	(0.0188)
Observations	6,195	6,195	6,195	6,195	6,171	5,484
R-squared	0.619	0.618	0.619	0.619	0.619	0.635
Unemployment					yes	yes
Free/Reduced Lunch					yes	yes
Student Demographics						yes

Notes: All regressions include school fixed effects, 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 are in parentheses.

Table 4: Heterogeneous effects: Gender, race/ethnicity, and income

	All	Female	Male	Hispanic	Black	White	Econ Disadv.	Non-Econ Disadv.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OZ 25-50%	0.0422**	0.0496**	0.0346*	0.0411**	0.00631	0.0276	0.0494**	-0.0202
	(0.0168)	(0.0199)	(0.0179)	(0.0172)	(0.0491)	(0.0373)	(0.0214)	(0.0364)
OZ 50-75%	0.0388**	0.0466**	0.0310*	0.0400**	0.000281	0.0109	0.0432*	-0.0250
	(0.0172)	(0.0204)	(0.0181)	(0.0177)	(0.0519)	(0.0365)	(0.0221)	(0.0378)
OZ 75-100%	0.0494***	0.0569**	0.0426**	0.0497**	0.0395	0.0233	0.0451*	-0.0302
	(0.0191)	(0.0225)	(0.0198)	(0.0199)	(0.0570)	(0.0372)	(0.0238)	(0.0385)
OZ over 100%	0.0506**	0.0579*	0.0369	0.0459	0.0832	0.0208	0.0583*	-0.0148
	(0.0253)	(0.0304)	(0.0247)	(0.0295)	(0.0601)	(0.0479)	(0.0316)	(0.0469)
NO2 25-50%	0.00290	-6.12e-05	0.00526	0.000576	0.00750	0.00587	0.00289	0.0102
	(0.00577)	(0.00721)	(0.00564)	(0.00600)	(0.0150)	(0.0103)	(0.00558)	(0.00800)
NO2 50-75%	0.00783	0.00517	0.0101	0.00705	0.00884	-0.0176	0.00897	0.000830
	(0.00833)	(0.0107)	(0.00813)	(0.00877)	(0.0276)	(0.0217)	(0.00837)	(0.0168)
NO2 75-100%	0.0118	-0.0399	0.0646	-0.00343	0.175***	-0.414***	0.0691*	-0.537***
	(0.0583)	(0.0681)	(0.0668)	(0.0647)	(0.0389)	(0.125)	(0.0358)	(0.150)
PM25 25-50%	-0.00443	-0.00293	-0.00625	-0.00481	-0.0178	0.000301	-0.00559	-0.000449
	(0.00511)	(0.00638)	(0.00492)	(0.00541)	(0.0138)	(0.00911)	(0.00597)	(0.00699)
PM25 50-75%	-0.00513	-0.00558	-0.00556	-0.00830	-0.00903	0.00769	-0.00764	-0.0209**
	(0.00718)	(0.00940)	(0.00663)	(0.00726)	(0.0229)	(0.0134)	(0.00732)	(0.0105)
PM25 75-100%	0.00149	-0.000660	0.00369	0.00867	-0.0316	-0.0200	0.0175	-0.0399**
	(0.0109)	(0.0133)	(0.0114)	(0.0110)	(0.0373)	(0.0240)	(0.0143)	(0.0182)
PM25 over 100%	0.00773	0.0107	0.00608	0.0162	-0.0487	-0.0464	0.00618	-0.0305
	(0.0173)	(0.0210)	(0.0163)	(0.0160)	(0.0499)	(0.0365)	(0.0170)	(0.0333)
Observations	6,171	5,881	5,958	5,906	1,412	2,235	4,675	2,177
R-squared	0.619	0.605	0.597	0.564	0.563	0.611	0.623	0.691

Notes: All regressions include school fixed effects, 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 are in parentheses.

Table 5: Robustness of main results

	Baseline (1)	School-Grade FE (2)	Demo×Yr (3)	No weights (4)	Feb-May (5)	Nearest Monitor (6)
OZ 25-50%	0.0388**	0.0397**	0.0368**	0.0320	0.0431**	0.0350**
	(0.0176)	(0.0176)	(0.0164)	(0.0245)	(0.0189)	(0.0168)
OZ 50-75%	0.0364**	0.0366**	0.0333*	0.0375	0.0356*	0.0323*
	(0.0183)	(0.0182)	(0.0173)	(0.0250)	(0.0192)	(0.0175)
OZ 75-100%	0.0466**	0.0471**	0.0432**	0.0507*	0.0503**	0.0422**
	(0.0200)	(0.0200)	(0.0188)	(0.0264)	(0.0209)	(0.0192)
OZ over 100%	0.0505*	0.0524**	0.0543**	0.0578*	0.0443*	0.0417
	(0.0263)	(0.0262)	(0.0253)	(0.0348)	(0.0266)	(0.0262)
NO2 25-50%	0.000988	0.000961	-0.00107	0.00733	0.00554	-0.00130
	(0.00578)	(0.00580)	(0.00589)	(0.00674)	(0.00581)	(0.00652)
NO2 50-75%	0.00963	0.00961	0.00709	0.0101	0.0136	0.00758
	(0.00868)	(0.00867)	(0.00886)	(0.0105)	(0.00916)	(0.00896)
NO2 75-100%	0.0127	0.0258	0.0150	-0.0454	0.0204	0.0105
	(0.0657)	(0.0672)	(0.0634)	(0.0880)	(0.0672)	(0.0660)
PM25 25-50%	-0.00578	-0.00586	-0.00470	-0.00394	-0.00334	-0.00605
	(0.00533)	(0.00535)	(0.00526)	(0.00568)	(0.00567)	(0.00537)
PM25 50-75%	-0.00534	-0.00534	-0.00651	-0.00150	-0.00467	-0.00684
	(0.00737)	(0.00736)	(0.00734)	(0.00849)	(0.00742)	(0.00744)
PM25 75-100%	-0.00478	-0.00469	-0.000907	-0.00302	-0.00307	-0.00206
	(0.0113)	(0.0114)	(0.0110)	(0.0127)	(0.0109)	(0.0117)
PM25 over 100%	0.0105	0.00873	0.0143	0.0207	0.0142	0.00984
	(0.0188)	(0.0187)	(0.0185)	(0.0182)	(0.0197)	(0.0189)
Observations	5,484	5,461	5,484	5,484	5,030	5,484
R-squared	0.635	0.641	0.646	0.605	0.644	0.635

Notes: All regressions include school fixed effects, 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. Unless otherwise noted, regressions are weighted by number of students. Standard errors clustered at the school level are in parentheses unless otherwise noted.

Table 6: Demographic changes

	Free/Reduced Lunch (1)	White (2)	Black (3)	Hispanic (4)	Asian (5)	Other (6)
OZ 25-50%	0.00874	-0.00440	0.00400*	0.000145	0.00152	-0.00524
	(0.0110)	(0.00487)	(0.00205)	(0.00532)	(0.00310)	(0.00330)
OZ 50-75%	0.0112	-0.00618	0.00376*	0.00140	0.000615	-0.00545
	(0.0111)	(0.00476)	(0.00211)	(0.00550)	(0.00323)	(0.00353)
OZ 75-100%	0.0117	-0.00689	0.00391	0.00260	0.00158	-0.00548
	(0.0116)	(0.00536)	(0.00241)	(0.00616)	(0.00357)	(0.00400)
OZ over 100%	0.0170	-0.00842	0.00349	-0.00720	0.0108	-0.00240
	(0.0146)	(0.00674)	(0.00473)	(0.0121)	(0.00783)	(0.00416)
NO2 25-50%	-0.00266	3.28e-05	0.00177*	0.000584	0.00180	-0.00330**
	(0.00380)	(0.00172)	(0.00104)	(0.00209)	(0.00117)	(0.00146)
NO2 50-75%	-0.00571	0.00288	0.00165	-0.00133	0.000617	-0.00296*
	(0.00588)	(0.00205)	(0.00147)	(0.00302)	(0.00164)	(0.00155)
NO2 75-100%	0.0270	-0.0146	0.00673	-0.00824	0.00588	0.0128
	(0.0215)	(0.00950)	(0.0115)	(0.0219)	(0.00770)	(0.0144)
PM25 25-50%	-0.00816**	-0.00130	-0.00221**	-0.000136	0.000198	0.00263**
	(0.00369)	(0.00143)	(0.000902)	(0.00183)	(0.000912)	(0.00115)
PM25 50-75%	-0.0111**	0.00215	-0.00138	-0.000560	-0.000705	-0.000405
	(0.00541)	(0.00230)	(0.00121)	(0.00304)	(0.00148)	(0.00134)
PM25 75-100%	-0.0174**	0.00309	-0.00304	-0.00647	0.00207	0.00280*
	(0.00770)	(0.00259)	(0.00186)	(0.00467)	(0.00303)	(0.00163)
PM25 over 100%	0.00614	0.00711**	0.00330	-0.0231***	0.00544**	0.00620
	(0.0106)	(0.00318)	(0.00268)	(0.00660)	(0.00234)	(0.00573)
Observations	6,170	6,194	6,194	6,194	6,194	6,194
R-squared	0.942	0.974	0.930	0.977	0.968	0.604

Notes: Outcomes are measured as the percent of students by race and the percent of students receiving free or reduced price lunch. All regressions include school fixed effects, 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 are in parentheses.

Table 7: Other fitness tests

		Other Fitness Tests				
	Aerobic Capacity	Body Comp.	Flexibility	Abdom. Strength	Trunk Ext Strength	Up. Body Strength
	(1)	(2)	(3)	(4)	(5)	(6)
OZ 25-50%	0.0388**	0.0126	0.00904	0.0160	-0.000998	0.0116
	(0.0176)	(0.0102)	(0.0161)	(0.0141)	(0.0177)	(0.0160)
OZ 50-75%	0.0364**	0.00619	0.0118	0.0275*	0.00605	0.0116
	(0.0183)	(0.00985)	(0.0160)	(0.0141)	(0.0175)	(0.0159)
OZ 75-100%	0.0466**	0.00252	0.0124	0.0253	0.00680	0.0137
	(0.0200)	(0.0102)	(0.0169)	(0.0157)	(0.0193)	(0.0174)
OZ over 100%	0.0505*	-0.000703	0.00868	0.0171	-0.0137	0.0424
	(0.0263)	(0.0145)	(0.0249)	(0.0249)	(0.0273)	(0.0264)
NO2 25-50%	0.000988	-0.000413	0.00774*	-0.00378	0.00161	0.00223
	(0.00578)	(0.00359)	(0.00457)	(0.00567)	(0.00516)	(0.00591)
NO2 50-75%	0.00963	0.00287	0.00448	0.00379	0.00610	0.00344
	(0.00868)	(0.00541)	(0.00686)	(0.00818)	(0.00892)	(0.00962)
NO2 75-100%	0.0127	0.0164	-0.0220	-0.0501	-0.0305	0.0741
	(0.0657)	(0.0289)	(0.0482)	(0.0460)	(0.0290)	(0.0543)
PM25 25-50%	-0.00578	-0.00406	-0.00271	0.00397	-0.000275	-0.0109**
	(0.00533)	(0.00296)	(0.00423)	(0.00452)	(0.00428)	(0.00507)
PM25 50-75%	-0.00534	-0.00437	-0.000725	0.00490	-0.00293	-0.00623
	(0.00737)	(0.00406)	(0.00609)	(0.00754)	(0.00777)	(0.00692)
PM25 75-100%	-0.00478	0.00552	-0.0127	-0.0160	-0.0184**	-0.0228*
	(0.0113)	(0.00671)	(0.00859)	(0.0103)	(0.00818)	(0.0126)
PM25 over 100%	0.0105	0.00875	0.00390	-0.00919	-0.00638	-0.0000586
	(0.0188)	(0.00905)	(0.0155)	(0.0161)	(0.0192)	(0.0167)
Observations	5,484	5,484	5,484	5,484	5,484	5,484
R-squared	0.635	0.761	0.707	0.645	0.569	0.670

Notes: All regressions include school fixed effects, 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 are in parentheses.

Table 8: Pollution before and after the test

	Days Before PFT				Days After PFT		
	-3	-2	-1	Test Date	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OZ 25-50%	-0.0235	-0.00641	0.0195	0.0388**	0.000177	0.0596	-0.00300
	(0.0178)	(0.0227)	(0.0272)	(0.0176)	(0.0212)	(0.0386)	(0.0248)
OZ 50-75%	-0.0131	0.00895	0.0281	0.0364**	0.0118	0.0523	-0.00400
	(0.0192)	(0.0225)	(0.0271)	(0.0183)	(0.0205)	(0.0377)	(0.0247)
OZ 75-100%	-0.00443	0.0167	0.0456	0.0466**	0.0115	0.0598	0.00523
	(0.0199)	(0.0236)	(0.0284)	(0.0200)	(0.0223)	(0.0391)	(0.0255)
OZ over 100%	0.0166	0.0180	0.0506	0.0505*	0.00882	0.0527	-0.00456
	(0.0275)	(0.0316)	(0.0366)	(0.0263)	(0.0328)	(0.0421)	(0.0331)
NO2 25-50%	0.00623	-0.00101	-0.00367	0.000988	-0.00473	0.000323	0.00413
	(0.00601)	(0.00563)	(0.00583)	(0.00578)	(0.00652)	(0.00589)	(0.00667)
NO2 50-75%	-0.00458	-0.0120	-0.00982	0.00963	-0.00524	-0.0128	-0.0214**
	(0.0120)	(0.0126)	(0.0118)	(0.00868)	(0.00988)	(0.0111)	(0.0109)
NO2 75-100%	0.0224	0.530***	-0.0814	0.0127	0.0282	-0.0625*	0.0186
	(0.0346)	(0.194)	(0.0712)	(0.0657)	(0.129)	(0.0339)	(0.0235)
PM25 25-50%	-0.00422	0.00672	-0.00705	-0.00578	-0.00458	-0.0112**	-0.00793
	(0.00519)	(0.00493)	(0.00507)	(0.00533)	(0.00508)	(0.00490)	(0.00516)
PM25 50-75%	-0.0162**	0.00290	-0.00738	-0.00534	0.00806	-0.00775	-0.00614
	(0.00663)	(0.00759)	(0.00899)	(0.00737)	(0.00788)	(0.00774)	(0.00720)
PM25 75-100%	-0.0231*	-0.00942	-0.0120	-0.00478	-0.00648	0.0104	0.0129
	(0.0135)	(0.0125)	(0.0147)	(0.0113)	(0.0126)	(0.0193)	(0.0139)
PM25 over 100%	0.000959	0.0182	-0.00696	0.0105	-0.00295	-0.00636	0.0165
	(0.0212)	(0.0301)	(0.0194)	(0.0188)	(0.0146)	(0.0163)	(0.0157)
Observations	5,494	5,421	5,467	5,484	5,399	5,472	5,469
R-squared	0.639	0.641	0.634	0.635	0.640	0.638	0.641

Notes: All regressions include school fixed effects, 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 are in parentheses.