Pollution, Test Scores and the Distribution of Academic Achievement: Evidence from California Schools 2002-2008[1]

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Abstract

One of the main arguments in favor of stricter regulations on air pollution is that it has harmful effects on child and adult health. Air pollution is associated with asthma, lower lung function, hay fever, infant mortality, and emergency room visits. Moreover, economists and epidemiologists also have found that increased air pollution increases school absenteeism, and that asthma may reduce school performance. If air. Given the strong (heavily documented) relationship between academic performance and future labor earnings, a potential negative relationship between pollution educational attainment suggests a heretofore unappreciated additional cost of air pollution in terms of reduced future earnings. Further, since low-income children tend to live in high pollution areas, reducing pollution may decrease income inequality and increase social mobility.

We first use regression analysis to examine the effect of changes in air pollution on the performance of 2nd through 6th grade students in California on standardized tests. Specifically, our four outcomes of interest are the mean scaled score and the percent of students at least proficient in both Mathematics and in English/Language Arts at the grade-school level. Our measures of pollution are carbon monoxide, nitrogen dioxide, ozone, coarse particulate matter, and fine particulate matter. We use grade-school FEs and a large number of time changing control variables in our analysis. Secondly, we examine the effect of an additional unit of pollution on different quantiles of the educational achievement distribution of these four performance measures using FE quantile regression analysis.

We find that a one standard deviation reduction in ozone, fine particulate matter, and especially coarse particulate matter generally increases these four performance measures at the mean and at the different quantiles by a small, but statistically significant, amount. A one standard deviation in nitrogen dioxide has a small but significant effect only on Mathematics scores, while in the vast majority of cases, the carbon monoxide coefficients are insignificant. These results are robust to a number of changes in how pollution is measured. In terms of comparing the quantile and regression estimates, the median estimates are similar to the FE regression results. In many cases, if the quantile estimates are significant for some quantiles, they are statistically significant for all quantiles. In a slight majority of cases where the pollutant has a significant coefficient in the quantile estimates, the effect increases across quantiles, while in the other cases the coefficient for a given pollutant is constant across quantiles.

1. Introduction

The effects of air pollution on child and adult health have been widely studied. In fact, one of the main arguments in favor of stricter regulations on air pollution is that it has harmful effects on child and adult health. Air pollution is associated with asthma, lower lung function, hay fever, infant mortality, and emergency room visits (Chay and Greenstone, 2003ab; Currie and Neidell, 2005, Gauderman et al., 2000; McConnell et al., 2002; McConnell et al., 2003; Neidell, 2004; and Rabinovitch, Strand, and Gelfand, 2006). Moreover, economists and epidemiologists have found that increased air pollution also increases school absenteeism (Currie, Hanushek, Kahn, Neidell, and Rivkin, 2009; Gilliland et al., 2001; Ransom and Pope, 1992), and that asthma may reduce school performance (Currie, Stabile, Manivong, and Roos, 2010).

If air pollution negatively affects children's health and increases school absenteeism, it is plausible that these children's educational attainment would also be negatively affected. Given the strong relationship between academic performance and future labor income, this suggests a heretofore unappreciated additional cost of air pollution in terms of reduced future earnings. Further, pollution may also have different effects across the income distribution; for example, if another unit of pollution negatively affects disproportionately the lower quantiles of the academic distribution, it will disproportionately affect the achievement of low-income children, given the strong relationship between children's academic achievement and family background. Further, even if these effects are constant across the achievement distribution, low-income children will be disproportionately affected because low-income households live in more highly polluted areas. Thus, an additional unit of overall pollution may increase income inequality and social mobility.

The central difficulty in identifying the effects of air pollution on academic performance is that air pollution is likely to be correlated with socioeconomic status; as noted above, higher income families are likely to sort into lower-pollution neighborhoods. Because children from lower income families tend to have lower test scores than those from higher income families, a finding of a negative effect of pollution on test scores may simply reflect selection. Of course, this problem is not unique to our paper: all papers in the economics literature attempt to eliminate the confounding factor of socioeconomic status when estimating the effect of pollution on an outcome variable. Many of these articles use appropriate conditioning variables and fixed effects (hereafter FEs). Some studies aim to reduce this selection problem by using variation across time intervals that presumably are too short to reflect location behavior, albeit at the cost of making the assumption that variables outside this short time interval do not affect the outcome of interest.

In this paper we follow the first strategy described above and use appropriate FEs to control for selection when investigating the effect of pollution on academic achievement. First, we examine the effect of changes in air pollution on the mean academic performance of school children in California, using standard FE regression analysis. Second, we examine the effect of an additional unit of pollution on different quantiles of the educational achievement distribution, using FE quantile regression analysis. Quantile regression analysis has been sparingly used to study the effect of pollution; one obvious explanation for its infrequent use is that, up until recently, it has not been possible to incorporate FEs into this framework. Canay (2011) presents a feasible means of using FEs in this framework, and we exploit his work in this paper.

We use the results of the California Standards Tests in Mathematics (hereafter math) and English/Language Arts (hereafter ELA) as measures of academic performance (California Department of Education, 2002-2008c). Specifically, our four outcomes of interest are the mean scaled score and percent of students at least proficient in math and in ELA at the grade-school level. Our pollution variables are the percent of days above the standard for carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), coarse particulate matter (PM_{10}), and fine particulate matter ($PM_{2.5}$). We calculate the pollution measures for each school in California from all monitors (weighted by distance from the school) within a twenty mile radius of the school. Our sample is limited to the years 2002 to 2008 because that is the period during which the content of the tests remained constant. We use an average of the daily pollution levels for September through May. We also consider the sensitivity of our results to different ways of measuring pollution and find that our original results are generally robust to such changes.

To avoid the problem of confounding factors or selection biasing our results, we include grade-school FEs, year effects, as well as a host of time-varying school quality, demographic, and community characteristics in the regressions. Thus, this paper makes two important contributions to the pollution literature. We are the first to estimate what economists view as the causal effect of pollution on the mean of measures of academic performance at the grade-school level. Moreover, we are the first to exploit Canay's (2011) results and look at the effect of pollution on different quantiles of the outcome of interest after controlling for appropriate FEs.

The paper proceeds as follows. We review the relevant literature in section 2. We first discuss the economics literature to date on the related topics of the effect of pollution on health, the effect of pollution on school absenteeism, and the effect of asthma, which is exacerbated by and possibly caused by pollution, on academic performance. Next, we review work from the public health literature concerning the above issues as well as examining correlations between pollution and test scores. We conclude that because the epidemiological literature is based on cross-section data, papers in this literature are unlikely to have sufficient controls for economists to consider the estimated effects as causal. In section 3 we outline our econometric approach and discuss our identification strategy. We describe the data in section 4.

We present our results in section 5, where we measure (separately) the effects of five pollutants on four measures of academic performance: i) mean math scores; ii) the percent of students at least proficient in math; iii) mean ELA scores; and iv) the percent of students at least proficient in ELA. In terms of statistical significance, the effects are strongest for O_3, $PM_{2.5}$, and especially PM_{10}. NO_3 significantly affects only the math outcome variables, while in the vast majority of cases, the CO coefficients are insignificant. However, all of the pollution effects we measure are relatively small. The above results are robust to a number of changes in how pollution is measured.

In terms of comparing the quantile and regression estimates, the median estimates are similar to, but generally a bit more significant than, the regression results. In many cases, if the quantile estimates are significant for some quantiles, they are statistically significant for all quantiles. In a slight majority of cases where the pollutant has a significant coefficient in the quantile estimates, the effect increases across quantiles, while in the other cases the coefficient for a given pollutant is constant across quantiles. Again, the estimated effects of the different forms of pollution are small. We carry out comparative static results concerning the effect of changing pollution levels on the difference between high and low-income students, and high achievement and low achievement students. Section 6 concludes the paper.

2. Literature Review

Pollution can affect academic performance by way of three mechanisms: (i) school absenteeism due to illness caused by pollution; (ii) attention problems in school due to illness caused by pollution; (iii) fatigue when doing homework due to illness caused by pollution, and (iv) a direct negative effect of pollution on brain development. All of the research on (iv) is drawn from epidemiological and neuropathology research; thus, we discuss it in section 2.2, where we review such research.

2.1 Mechanisms by Which Pollution Can Affect Academic Performance–Evidence from the Economics Literature

Mechanisms (i)-(iii) above rely on pollution having a negative effect on health, and then health impacting students' academic performance. In this subsection, we highlight some of the economics articles investigating these mechanisms.[2] Chay and Greenstone (2003ab) examine the effect of air pollution on infant mortality rates in United States counties between 1980 and 1982. Their initial identification strategy is based on assuming that county FEs, state trends, year effects, and socioeconomic controls are sufficient to eliminate most spurious correlations between pollution and infant mortality. Their socioeconomic controls include mother-specific characteristics aggregated to the county-level, including education, ethnicity, income, prenatal care, and age. They chose the period from 1980 to 1982 with the belief that/on the assumption that much of the remaining variation in pollution after controlling for these variables comes from the differential impacts of the 1980 recession on pollution levels. Therefore, they argue, changes in pollution are transitory and less likely to affect location choice. One caveat to this identification strategy is that one must ignore the fact that the recession will also directly affect location decisions as adults move from hard-hit labor markets to more prosperous labor markets, i.e. there may still be selection at work.

Chay and Greenstone weaken their identifying assumptions in several ways. First, they treat current pollution as endogenous, instrumenting for the change in pollution with lagged pollution levels; the latter will be a valid instrumental variable (IV) if there is no autocorrelation in pollution. Second, they group the treatment and control counties based on the size of income changes between 1980 and 1982 and use their first differences estimation strategy. Finally, they restrict the sample to

[2] Several articles outside the economics literature establish this link as well (see McConnell et al., 2002, Gauderman et al., 2000, and McConnell et al., 2003); however, for brevity, we focus on the economics papers.

counties with low manufacturing employment. They compare changes in infant mortality rates across low manufacturing counties that bordered a county with high manufacturing employment in 1980 to those counties that bordered other low manufacturing counties. In the former case, a substantial decrease in a neighboring county's manufacturing employment is likely to cause a reduction in Total Suspended Particles (TSPs) in the county of interest because of wind and other weather components. Thus, their new identifying assumption is that demand shocks in a neighboring county will not have spillover effects that induce migration from the county under consideration.

Neidell (2004) evaluates how seasonal changes in pollution affect asthma-related hospital admission rates for different age groups by month, conditional on zip code-year FEs and year-month FEs. For each zip code, he constructs a monthly measure of pollution by taking the average of pollution levels recorded at monitors within 20 miles of the centroid of the zip code weighted by the inverse distance to the monitor. The outcome variable is the number of asthma-related emergency room visits in each zip code-month observation, where a visit is classified as asthma-related based on the principle diagnosis from the California Hospital Discharge Data. The control variables include the sex, race, and age of the patient, expected source of payment to the hospital, weather, and housing prices. Neidell finds that, of the pollutants considered, carbon monoxide has a significant effect on hospitalizations for asthma among children ages 1–18, while none of the pollutants considered has a clear impact on hospitalizations for infants. Using estimated coefficients and the expected number of asthma admissions from 1992 and 1998 pollution levels, Neidell calculates that the decline in pollution during this time period caused asthma admission rates to decrease from 13.5% to 4.6%. Neidell also tests, by including the number of smog alerts as a control variable, whether families display avoidance behavior. He concludes that they do exhibit avoidance behavior; the smog alert coefficient is negative and significant, while the magnitude of the negative coefficient on O_3 is smaller when smog alerts are included in the regressions. Because he uses a large number of FEs, the only caveat to Neidell's results is that he must assume that pollution in previous months does not affect admissions in subsequent months; this assumption would be violated if previous pollution caused individuals to develop asthma, which made them more sensitive to current pollution. While of course this criticism could also be leveled at studies using annual data it is likely that this type of separability over time periods is less credible as the size of the period decreases (as in the consumer demand literature),.

Currie and Neidell (2005) evaluate the effect of increased air pollution on infant mortality during the period from 1989 to 2000. The authors construct a weekly pollution measure similar to that in Neidell (2004) by taking the average of pollution levels recorded at monitors within 20 miles from of centroid of the zip code weighted by the inverse distance to the monitor. The authors include zip code month FEs and zip code year FEs. The authors include various mother-specific factors, including mother's age, race, ethnicity, education, marital status, zip code of maternal residence, use of prenatal care, and private/public insurance. Other covariates include weekly county-level averages for weather, date of birth, birth weight and gestation period. They use a flexible discreet hazard model where the outcome variable is equal to one if the child died within the week. They find that, in periods of higher pollution, although infant mortality rates are higher, prenatal exposure to pollution does not affect infant mortality. They often find that ozone has the incorrect sign, but attribute this finding to a negative correlation between ozone and other pollutants. We offer two criticisms of their work. First, they must assume that there is no unobserved heterogeneity at the individual or zip code level, since either form of heterogeneity will cause their parameter estimates to be biased. Second, they must assume that, conditional on duration (age), pollution levels in previous periods do not affect mortality.

Currie et al. (2009) investigate the effect of pollution on school absences, using data from the Texas Schools Project, a longitudinal administrative data set on student absenteeism in Texas. They aggregate pollution data from the Texas Commission on Environmental Quality into six-week time blocks, and merge these data with the administrative absenteeism data. Their identification comes from the variation in pollution across six-week attendance periods within a year or within an attendance period across years. In the former case, they include school by attendance period FEs; in the latter case, they include school by year FEs. They measure pollution by determining whether each day is 0-25%, 25-50%, 50-75%, 75-100% or greater than 100% of the relevant Environmental Protection Agency (EPA) threshold for a particular pollutant. They then calculate the shares of days in each category for the six-week attendance period. Their main finding is that CO between 75-100% of the air quality standards threshold and above the threshold has a positive and significant effect on school absences. Ozone is not statistically significant in most specifications, but they did find a statistically significant increase in absences associated with PM_{10} levels between 50-75% of the EPA threshold. This latter result is somewhat surprising since in this case one would also expect pollution levels between 75% to 100% of the threshold, and above the threshold, to matter; of course, it may be that the effects of the higher levels of pollution simply have large confidence intervals. Indeed, as the authors acknowledge, the result of a significant effect for PM_{10} levels between 50-75% of the threshold must be viewed with caution, since one significant result among many coefficients can occur by chance. Again, the identifying assumption in their work is that past pollution levels do not affect current absences; as noted above, this assumption would be violated if previous pollution levels increased the incidence of asthma, which in turn accentuated the effects of pollution in the current period.

Of course, air pollution affects academic performance through health only if health problems affect performance. Currie et al. (2010) evaluate the effect of various childhood diseases, including asthma, on (i) how students performed on a literacy exam, (ii) whether the students enrolled in a college preparatory math class, (iii) whether they were in the twelfth grade by age 17, and (iv) whether they used social assistance. They match school administrative data, social assistance records, and health records for young adults in Manitoba, Canada born between 1979 and 1987. With a mother FE (which controls for time constant family characteristics), they investigate whether having been treated for asthma at various ages (0-3, 4-8, 9-13, 14-18) affects these young adult outcomes by using the variation across siblings in the incidence of asthma. They find (at the 10% level) that (a) asthma at ages 9 to 13 had a significant negative effect on taking a college preparatory math class and (b) asthma at ages 14 to 18 sometimes had a negative effect on the literacy score in the 12th grade. They find no effect of earlier asthma, conditional on current asthma. As the authors acknowledge, their results must be viewed with caution since, again, two significant coefficients could happen by chance in this framework. Their identifying assumption is that there are no time varying family characteristics, i.e., socioeconomic status, that would be correlated with both asthma and these outcome variables, and that the asthma effect does not pick up the effect of current pollution.

2.2 Mechanisms by Which Pollution Can Affect Academic Performance–Evidence from the Epidemiological Literature

All of the studies from the epidemiological literature are based on cross-section data and use a relatively small number of controls. As a result, these researchers are much more limited in their ability to deal with selection and endogeneity issues; this latter problem is accentuated by the fact that none consider instrumental variable estimation.

Gilliland et al. (2001) use the Children's Health Study data to evaluate the effect of pollution on absenteeism. They study a cohort of 2,081 4th grade students who reside in 12 southern California communities. They track the students' absences for the first 6 months of 1996, following up with the students' parents to determine whether the absence is illness-related or not, and if so, whether it is an upper-respiratory, lower-respiratory, or gastro-intestinal illness. The type of illness is determined by the symptoms described during phone interviews with the parents. Using daily pollution levels from monitors located near the schools and a community FE model, the authors use within-community variation in pollution across the six-month period to determine its effect on average daily absences due to respiratory illness. They find that ozone has a statistically significant relationship (partial correlation) with reported absences from upper-respiratory and lower-respiratory illness rates. To obtain a causal effect, they need to assume that, within a community, families do not sort themselves based on permanent differences in pollution across the community.

We now consider a number of other studies that use cross-section data and no FEs, rendering them less credible in terms of estimating causal effects. Fowler, Davenport, and Garg (1992) analyze the effect of asthma on different outcomes for the United States. They use data for 10,362 children in the 1st through 12th grade from the 1988 United States National Health Interview Survey. They find that children with asthma are more likely to have a learning disability than children who do not have asthma. In addition, among households with incomes below $20,000, asthmatic children are twice as likely to fail a grade as those without asthma. However, among higher income families, asthmatic children have only a slightly higher failure rate than non-asthmatic children. With a sample of 1,058 kindergarten-age children from Rochester, New York in 1998, Halterman et al. (2001) compare the parent-reported development skills of asthmatic children to those of non-asthmatic children. After controlling for type of health insurance, education of the care-giver, gender, and pre-kindergarten education, the authors find that asthmatic kindergarten-aged children scored lower in school readiness skills (one category of reported development skills) than their non-asthmatic peers. Butz et al. (1995) obtain demographic asthma symptoms and psychosocial information for 392 children in kindergarten through the 8th grade in 42 schools in Baltimore, Maryland. Asthma symptoms are divided into low, medium, and high levels. A child is considered to exhibit behavioral problems if her score on a questionnaire containing standardized psychosocial questions is higher than a given threshold. Using logistic regressions, the authors conclude that parents who report that their children have higher levels of asthma symptoms are twice as likely to report a behavioral problem compared to parents who report lower levels of asthma symptoms.

Bussing, Halfon, Benjamin, and Wells (1995) first use responses to the 1988 National Health Interview Survey on Child Health to categorize children into those who suffer from asthma alone, those who suffer from asthma combined with other chronic conditions, those who suffer from other chronic conditions alone, or those who have no chronic (including asthmatic) conditions. They then combine this information with a Behavior Problem Index constructed from psychosocial questions in the NHI survey. Using logistic regressions, the authors find that children with severe asthma alone are nearly three times as likely to have severe behavioral problems as children without a chronic condition. Halterman et al. (2006) investigate the relationship between behavioral problems and asthma symptoms for a cohort of 1,619 inner-city students in Rochester, New York. The parents of these kindergarten-age children were surveyed about their children's health and behavior. The authors find that children with persistent asthma score worse on peer interactions and task orientation, and are more likely to exhibit shy and anxious behaviors compared to non-asthmatic children.[3]

Epidemiologic, neuropathological, and brain imaging studies also provide evidence of a negative relationship between ambient air pollution and brain development conditional on observable demographic factors. Among 202 children who were approximately 10 years old in Boston, Massachusetts, higher levels of black carbon (a marker for traffic particles) were associated with decreased cognitive function across assessments of verbal and nonverbal intelligence and memory constructs (Suglia et al. 2008). The authors estimate exposure to black carbon for each participant's current residence and control for age, gender, mother's education, and language spoken at home. In a prospective study of a birth cohort of 249 children whose mothers lived in New York's Harlem and South Bronx areas during pregnancy, Perera et al. (2009) investigate the effect of

[3] According to the National Heart, Blood and Lung Institute of the National Institutes of Health (2007, p. 72), asthma is considered persistent if the patient experiences symptoms more than two days per week, limitation in activities, some nighttime awakenings or use of short acting beta$_2$ agonists combined with either more than two exacerbations requiring oral steroids or more than four wheezing episodes longer lasting than a day per year.

polycyclic aromatic hydrocarbons (PAHs) on a child's intelligence quotient (IQ).[4] (Motor vehicles are a major source of PAH in Harlem and the South Bronx.) PAH levels are measured through personal monitoring of the mothers in their third trimester of pregnancy, while IQ was evaluated using the Wechsler Preschool and Primary Scale of Intelligence-revised. The researchers find that children with prenatal exposure to high levels of PAHs have full scale and verbal IQ scores at age 5 that are 4.31 and 4.67 points lower, respectively, than those of less exposed children. In a cross-sectional study in Quanzhou, China, Wang et al. (2009) find that 8- to 10-year-old children attending a school located in a high traffic exhausts pollution area perform worse on multiple neurobehavioral function tests compared to those studying at another school, located in a clean air area. The authors chose the schools based on traffic density and air pollution monitoring data, and they control for, among other things, father's education, age, sex, birth weight, and second-hand smoke.

Calderón-Garcidueñas et al. (2008a, 2008b) led a series of clinical, neuropathological, and neuroimaging studies on clinically healthy and neurocognitively intact children and adolescents growing up either in Mexico City (a place with high ambient air pollution) or in clean air areas. In Calderón-Garcidueñas et al. (2008a), the authors find that among the forty-seven subjects who died suddenly, accumulations of amyloid β42 (a marker of neurodegenerative disease) in the prefrontal brain region and disruption of the blood-brain-barrier were observed in the lifetime residents of Mexico City (n=35) but not in the comparison group (n=12).[5] In another study, Calderón-Garcidueñas et al. 2008b find that children from Mexico City exhibit significant deficits in a combination of fluid and crystallized cognition tasks, as compared to other children from Polotitlán, a selected clean-air city. Fluid cognition is supported by working memory, while crystallized cognition is supported by long-term memory. The 55 subjects from Mexico City and the 18 subjects from Polotitlán cities were from middle-class families. Their mothers had similar average years of formal schooling groups, and their households had a bedroom separate from the kitchen. Brain MRI-measured hyperintense white matter lesions substantially increased in children from Mexico City (56.5% vs. 7.6% in the control city). White matter lesions may affect cognitive dysfunction and particulate matter may contribute to neuroinflammation.

Pastor, Sadd, and Morello-Frosch (2004) evaluate the relationship between academic performance and environmental hazards in the Los Angeles Unified School District in 1999. They

[4] Polycyclic aromatic hydrocarbons are formed by incomplete combustion of fossil fuels, among other organic material. Prenatal exposure to PAH has been linked with adverse immune, metabolic, and neurological functions and reduced birth weight.

[5] The comparison group consisted of residents of Tlaxcala and Veracruz.

combine data on schools' Academic Progress Index (API) with information on their proximity to Toxic Release Inventory (TRI) emissions and census tract-level estimated respiratory risks associated with concentrations of 148 ambient air toxins. This latter measure of exposure at the tract level is the sum of hazard ratios for each pollutant, where the hazard ratio is calculated by dividing the EPA's tract-level exposure estimate for a particular pollutant by the amount of toxicant below which there should be no adverse health effects. According to the California Department of Education (2010, p. 6), the API "is calculated by converting a student's performance on statewide assessments across multiple content areas into points on the API scale. These points are then averaged across all students and all tests." Each school receives one API score. In an OLS regression, the authors regress the API score on the respiratory risk index, a dummy equal to one if a facility releasing substances covered by the TRI and in the 33/50 program is within one mile of the school.[6] The authors find that having a 33/50 facility within a one-mile radius has a negative and significant effect on academic performance, even after controlling for socioeconomic status variables such as parents' education, percent minority, and percent who are English learners.

Finally Pastor, Morello-Frosch, and Sadd (2006) expand their previous analysis to all schools in California. They again use the API score as their measure of academic performance and construct similar respiratory risk indices. To examine whether the mechanism by which exposure to air pollution affects academic performance is through asthma, the authors first run a Tobit regression of the three-year averaged, age-adjusted, asthma hospitalization rates by Zip Code Tabulation Area on their measure of exposure controlling for socioeconomic status. They find that areas with higher respiratory risk have higher hospitalization rates. They then turn to academic performance, and find, again, that schools located in higher pollution areas have lower API scores. They estimate that moving from the seventy-fifth quantile to the median level of the respiratory hazard ratio would improve test scores by about 1.2%. However, the assumptions necessary to interpret their estimates of the effect of pollution on school performance as causal are identical to the epidemiological studies discussed above and hence likely to be much too strong. In the section below, we aim to use an econometric approach very similar to those used in the economics papers discussed above so that our estimates of the effect of pollution on school performance can be credibly viewed as causal.

[6] The 33/50 program was a voluntary program by the EPA established to reduce the release of 17 targeted priority chemicals. Enacted in 1991, its goals were to reduce the release and transfer of chemicals by 50% by 1995, as measured against a 1988 baseline (EPA, 1999).

3. Empirical Strategy

3.1 Estimating Pollution Effects Using a Fixed Effect Regression Model

Our data, described in detail below, consist of approximately 24,000 grade-school units observed for up to seven years. Given that we have panel data, our first empirical specification for our outcome of interest (S_{gst}) which is a performance measure for a given standardized test for grade *g* in school *s* (located in county *c*) in year *t*, is given by

$$S_{gst} = \beta_1 P_{st} + \beta_2 X_{gst} + \beta_3 W_{st} + \beta_4 Z_{ct} + f_{gs} + D_t + \varepsilon_{gst}, \qquad (1)$$

where P_{st} represents pollution at school *s* at time *t*, X_{gst} represents the racial composition in grade *g* at school *s* at time *t*, W_{st} represents school specific characteristics for school *s* at time *t*, Z_{ct} represent time-changing county level factors, f_{gs} represents a school-grade FE, D_t represents a year dummies, and ε_{gst} is an idiosyncratic error term.

As noted above, being able to account for confounding factors is crucial to the credibility of our analysis (or any such analysis). To account for these factors, in addition to grade-school FEs and year effects, we first use students' ethnicity from the California Basic Educational System Data (California Department of Education, 2002-2008b) as a control variable. Our other educational controls are from the Academic Performance Index (API) data files (California Department of Education, 2002-2008a). We first condition on average class size, which is measured separately for grades 4 through 6 and kindergarten through grade 3. We also control for the following variables at the school-year level: the percent of students receiving free or reduced-price lunches; the educational make-up of parents; the percent of students who are native English speakers; the percent of teachers who are fully certified; and total enrollment. In addition, we control for annual expenditure per student at the district level using data from the National Center for Education Statistics' Common Core of Data (2002-2008).[7] Finally, we control for a number of business cycle variables at the county level: the unemployment rate and taxable transactions (the lowest level of geographical aggregation available). We adjust taxable transactions and expenditures per student for inflation.

Thus, our identification comes from assuming that all the variation in pollution over time at a specific school, after controlling for X_{gst}, W_{st}, Z_{ct} and year dummies D_t, is uncorrelated with any remaining unobservables driving school performance. We argue that our rich set of FEs and control

[7] All monetary quantities are measured in real dollars.

variables renders our identifying assumptions on a par with those made in the economic studies discussed above. Finally, we make the standard GLS (heteroskedasticity) adjustment of weighting observations by the respective square root of the number of students in the grade-school-year observation. However, to allow for autocorrelation over time and any other sources of heteroskedasticity, the standard errors are still clustered at the school level.

3.2 Estimating Pollution Effects Using a Fixed Effect Quantile Regression Model

In the previous section we presented our strategy for identifying the effect of pollution on mean test scores. In this section we consider pollution's effect on test scores at other points in the distribution. We first consider the following equation for the τth quantile of the distribution for an outcome of interest:

$$Quant_{\tau}(S_{gst}) = \gamma_1(\tau) P_{gst} + \gamma_2(\tau) X_{gst} + \gamma_3(\tau) W_{st} + \gamma_4(\tau) Z_{ct} + f_{gs}(\tau) + \sum_t \gamma_{5t}(\tau) D_t, \qquad (2)$$

where $f_{gs}(\tau)$ is a quantile specific FE for grade *g* in school *s*, and the other variables are defined below equation (1)[8]. (Our parameters of interest are the coefficients $\gamma_1(\tau)$.)[9] In other words, if grade *g* in school *s* is in quantile τ, its achievement consists of its quantile-specific fixed effect and the quantile-specific (other) coefficient times its time-changing characteristics (including pollution). Note that this is an extremely rich specification because it involves estimating a fixed effect for grade *g* in school *s* for every quantile, including quantiles where it is never observed; not surprisingly, we cannot consistently estimate (2) as specified. This is an important problem given our claim above that including FEs is crucial for obtaining estimates of the causal effect of pollution on academic performance. However, Canay (2011) provides a solution to this problem, which allows for consistent estimation of a FE quantile model: assume that the FEs are constant across quantiles for grade *g* in school *s*:[10]

$$Quant_{\tau}(S_{gst}) = \gamma_1(\tau) P_{gst} + \gamma_2(\tau) X_{gst} + \gamma_3(\tau) W_{st} + \gamma_4(\tau) Z_{ct} + f_{gs}^* + \sum_t \gamma_{5t}(\tau) D_t. \qquad (3)$$

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[8] A very accessible treatment of quantile regression is presented in Imbens and Wooldridge (2008). They also provide the assumptions necessary for quantile regression to result that are of use in policy ananlysis.

[9] Consider the median for a symmetric distribution, since in that case the mean and median are equal, and $\gamma_1(\tau)$ for the median will equal (in an expected value sense) the regression coefficient on pollution β_1 from equation (1).

[10] That is, $f_{gs}(\tau) = f_{gs}^*$ for all τ.

This specification has a natural intuitive interpretation – the achievement of grade *g* in school *s* if it in quantile τ in year *t* is the sum of its fixed effect plus the quantile specific coefficients times its time-changing characteristics. Using this assumption, Canay shows that the first step is to run the standard FEs regression model (1), and solve for the least squares estimates of the FEs. Next, one subtracts the estimated FEs from the respective outcome variables to obtain new outcome variables. Finally, one uses standard quantile regression using these new outcome variables. There still remains the problem of calculating standard errors for the parameter estimates when we assume that observations across grades in the same school are correlated in a given year and across years. We use the bootstrap to calculate these standard errors.

While necessary for estimation, the common fixed effect assumption across quantiles may be considered too strong. To shed some light on this issue, we note that if the outcome variables have a symmetric distribution, the mean and median will be equal for such a distribution. Since linear regression allows the mean to have its own FE, while the quantile analysis for the median assumes a constant FE across the different quantiles, if the coefficients from the linear regression and median regression are similar, this would suggest that the quantile estimates are not unduly affected by the common FE assumption.[11]

4. Data, Variable Definitions, and Summary Statistics

The summary statistics for the variables used in this study are shown in Table 1. Panel A contains summary statistics for our OLS outcome variables at the grade-school-year level; here, for both math and ELA we use the i) mean scaled score *and* ii) the percentage at least proficient. The average scaled scores for math and ELA are 358 and 341 respectively, while the average percentage at least proficient for and ELA are 50.8% and 43.5% respectively. (The goal in California is for all students to score at least proficient; a student with a scaled score above 350 out of 600 is considered at least proficient.) We include only data on years 2002 through 2008 because the test format changes outside this time interval. Our analysis includes grades 2 through 6 because the same tests are administered to all students within each grade. We do not use data from grade 7 on because at that

[11] Of course, the contrary is not true – the mean and median coefficients may be different because the distribution is not symmetric or the common FE assumption is inappropriate.

point students may take different mathematics courses based on ability – for example, algebra, geometry, or basic math – which would raise difficult selection issues for our analysis.

As noted above, we focus on the coefficients for five pollution variables: coarse particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), nitrogen dioxide (NO_2), carbon monoxide (CO), and Ozone (O_3). We use these specific pollutants in our analysis because they have been studied in the previous literature (Currie et al., 2009, Gilliland et al., 2001) and are correlated with various diseases (Gauderman et al., 2005; Grahame and Schlesinger, 2007; Kurt, Mogielnicki, Chandler, 1978; Linn, Szlachcic, Gong, Kinney, and Berhane, 2000; McConnell et al., 2002, Pope and Dockery, 2006; Russell and Brunekreef, 2009; and Yu, Sheppard, Lumley, Koenig, and Shapiro, 2000). Vehicle exhaust is a major source of PM_{10}, $PM_{2.5}$, NO_2, and CO. Other sources of particulate matter include dust from the earth's surface, pollen, forest fires, power plants, and factories. The greatest exposure to CO comes from smoking cigarettes, but it is also formed through the improper burning of various fuels. NO_2 is emitted from coal-burning power plants and the burning of fossil fuels. O_3 is formed through a chemical reaction between nitrogen oxides, sunlight, and various gaseous pollutants, which are often emitted from vehicles.[12]

Pollution data are from the Air Resources Board of California, (Daily Data, 2010). The only feasible way of measuring pollution is at the school-year level, as we do not have access to students' addresses. (Thus, there is no variation in pollution across grades for a given school in a specific year.) The pollution measure used in this study is the percent of days that exceed the California Standard for that pollutant. The California one-hour standards are 20 parts per million (ppm) for CO, 0.18 ppm for NO_2, and 0.09 ppm for O_3. The standards for PM_{10} and $PM_{2.5}$ are based on a 24-hour measure rather than a one-hour measure. The 24-hour standard is 50 $\mu g/m^3$ (micrograms per cubic meter) for PM_{10} and 35 $\mu g/m^3$ for $PM_{2.5}$ (California Environmental Protection Agency, 2009). The California standards are stricter than the federal standards for all pollutants except for $PM_{2.5}$, which is the same as the federal standard.

To obtain our pollution measures, we first use the longitude and latitude of each school and of each pollution monitor in California to find all monitors within a 20-mile radius of each school. For a given pollutant and monitor, we calculate the total number of days that exceed the standards for that pollutant and then divide by the total number of days that are tested. Since students usually take the California Standards Tests in April or May, we use pollution data from September through May as an approximation of the pollution experienced during the school year. Then, for a given

[12] For additional information on these pollutants, see Environmental Protection Agency (2011).

pollutant at a given school in a given year, we take the weighted average of the percent of days exceeding the standard at each monitor, where the weighting is based on the inverse distance to the school. Thus, we give monitors that are closer to the school more weight relative to ones that are further away. However, we also consider results based a number of alternative means of measuring pollution at the school levels. We present the results of this exercise below, and find that our results are robust to these changes.

The summary statistics for our pollution variables are shown in Panel B of Table 1. In Table 2 we show the correlation matrix for the pollution variables. Table 1 indicates that an average of 0.0039%, 0.0033%, 1.94%, 11.78%, and 6.45% days of the school year are above the California standards for CO, NO_2, O_3, PM_{10}, and $PM_{2.5}$. The correlation matrix in Table 2 indicates that some of the pollution measures are highly correlated.[13] This latter result suggests that simultaneously using the different pollution measures is likely to cause a serious multicollinearity problem among at least some of the pollution measures; thus, we follow the literature and enter them one at a time.

We also include the control variables outlined in the previous section. The summary statistics for these are presented in Panel C of Table 1. In terms of ethnic composition of the students, on average 35.0% of the students are White, 11.0% are Asian, 42.6% are Hispanic, 7.6% are African American, and 3.8% are other ethnicities. The average class size is 26.5 students, and 94.7% of all teachers are fully certified. Further, on average, 51.4% of students receive a free or reduced-price lunch, and the percent of students who are non-native English speakers is 26.2%. The average enrollment and real expenditure per student are 406.9 and $8,828, respectively.[14] The average county unemployment rate is 6.3%, and the average real value of county taxable transactions is approximately $384 million. Unlike some other studies, we did not include weather as a conditioning variable since it is difficult to obtain a meaningful measure of weather at an annual level. Further, Morretti and Neidell (2009) show that including weather does not affect estimates of the impact of ozone on health.

5. Empirical Results

5.1 Main Fixed Effect Linear Regression Results

[13] PM_{10} and $PM_{2.5}$ are particularly highly correlated, while O_3 is essentially uncorrelated with the other measures.

[14] Again all $ values are in real terms.

In Table 3A we show the estimated effects of pollution on mean scaled math scores from the standard FE linear regression model. In column (1), our pollution measure is the percent of days above the standard for carbon monoxide (CO). In columns (2)-(5), we include (separately) the percent of days above the standard for nitrogen dioxide (NO_2), ozone (O_3), coarse particulate matter (PM_{10}), and fine particulate matter ($PM_{2.5}$), respectively. To reiterate, we include the control variables listed in Table 3A and year effects (coefficients not shown). The regressions are weighted by the square root of the number of students in each grade-school-year cell. The errors are clustered at the school level and are robust to heteroskedasticity.

In Table 3A, two of the pollution variables, CO and O_3, have positive but insignificant coefficients, while NO_2, PM_{10} and $PM_{2.5}$ have negative coefficients. However, only the PM_{10} coefficient is statistically significant at the 10% level (and almost significant at the 5% level); the NO_2 coefficient has a t-statistic of 1.6 and thus is almost significant at the 10% level. The PM_{10} coefficient implies that a one standard deviation in the percent of days that this pollutant exceeds the California standard lowers mean scaled math scores by 0.287 (of a point). The 95% confidence interval on this effect is [-0.5816, 0.0065]; which implies a small effect for even the largest element (in absolute value) in the confidence interval. (In the discussion below, we refer to the percent of days that pollution variable X is above the California daily standard simply as "pollution level X" for ease of exposition.)

While our focus is not on the control variables, it is worth noting that many of these variables have the expected sign and are statistically significant at standard confidence levels. An increase in the average class size, decrease in the percent of the staff that are full-time equivalent, increase in the percent of the school that receives free or reduced price lunches, or an increase in the percent of the student body that are non-native English speakers, decreases test scores. Expenditures per student, the unemployment rate, and the total number of students in the school have no significant effect on test scores. The amount of taxable transactions in the county, a measure of economic activity, has a negative effect on test scores; this result may reflect the fact that schools in more prosperous areas (after conditioning on the FEs) will have more in-migration, everything else held equal.

Table 3B shows the effect of the pollution variables on the percentage of the students in the grade-school-year who are at least proficient in math; here, we use the same explanatory variables as in Table 3A. Interestingly, now all the pollution coefficients are negative, with the NO_2 coefficient significant at the 10% level and the O_3 and PM_{10} coefficients significant at the 5% level. A one standard deviation increase in NO_2 is estimated to lower the percentage of students at least proficient in math by 0.0698 (i.e. less than 0.1 of a percentage point), with the 95% confidence interval for this effect equaling [-0.1435, 0.0039]. A one standard deviation increase in O_3 is estimated to lower the percentage of students proficient in math by 0.2225, with the 95% confidence interval for this effect equaling [-0.379, -0.066]. Finally, a one standard deviation increase in PM_{10} is estimated to lower the percentage of students a least proficient in math by 0.2995, with the 95% confidence interval for this effect equaling [-0.4732, -0.1258]. Thus, the results in Table 3B suggest that the effect of pollution on the percentage at least proficient in math is quite small.

One natural question arising at this point is whether the effect of a pollutant (for example, PM_{10}) on mean math scores is consistent with its effect on the percentage of students proficient in math. We do not have access to the distribution of math scores by school, so we cannot provide a rigorous answer to the question. However, we can make a back-of-the-envelope calculation for PM_{10} by using the summary statistics in Table 1 and assuming that test scores are, on average, distributed[15] as $N(357.57, 38.97)$. In this case the probability of a school being at least proficient in math, i.e. having a math score above 350 points, is 0.5769. Using the estimate from Table 3A, a one standard deviation increase in PM_{10} will lower the mean by 0.287 of a point, and the percentage at least proficient by 0.280 of a percentage point. Comparing this calculation with the estimate of 0.2995 of a percentage point from Table 3B, we see that the results for PM_{10} are compatible across Tables 3A and 3B. One may also ask whether it makes sense for NO_2 to significantly affect the percentage at least proficient in math when it has no significant effect on mean scaled math scores. However, the estimated NO_2 coefficient in Table 3A has a large confidence interval, and elements of the confidence interval are consistent with it taking on a relatively sizeable negative value.

Table 4A presents the results when the dependent variable is the mean scaled ELA score. Now all pollution coefficients are negative, and the coefficients for O_3, PM_{10} and PM2.5 are statistically significant at the 5% level. The coefficients for PM_{10} and $PM_{2.5}$ are of magnitudes similar to those in Table 3A for mean math scores, but the O_3 coefficient is much larger in absolute value than its coefficient in Table 3A. A one standard deviation in O_3 is estimated to lower mean scaled ELA scores by 0.5125, with the 95% confidence interval for this effect equaling [-0.654, -0.3704]. A

[15] This assumption may overstate the effect on the percentage at least proficient because we are using the variance of the mean across schools in the mean Math scores, which is smaller than the variance for an individual school. On the other hand, the normality assumption may overstate the variability of mean Math scores since it ignores the fact that test scores are bounded above at 600 points and below at 200 points. Although we cannot be certain about the appropriateness of this assumption, we think the approximation is suitable for this informal analysis.

one standard deviation in PM_{10} is estimated to lower mean scaled ELA scores by 0.2371, with the 95% confidence interval for this effect equaling [-0.4009, -0.-0.0732]. Finally, a one standard deviation in $PM_{2.5}$ is estimated to lower mean scores scaled ELA by 0.1747, with the 95% confidence interval for this effect equaling [-0.3141, -0.-0.0352]. Thus, the effect of pollution on mean scaled ELA scores is also small.

Table 4B presents the results when the dependent variable is the percentage at least proficient in ELA. As was the case in Table 4A, the coefficients for O_3, PM_{10} and $PM_{2.5}$ are statistically significant, but now this significance is at the 1% level. A one standard deviation increase in O_3 is estimated to lower the percentage of students at least proficient in English by 0.4150, with the 95% confidence interval for this effect equaling [-0.5228, -0.3072]. A one standard deviation increase in PM_{10} is estimated to lower the percentage of students at least proficient in English by 0.2371, with the 95% confidence interval for this effect equaling [-0.3619, -0.1123]. Finally, a one standard deviation increase in $PM_{2.5}$ is estimated to lower the percentage of students at least proficient in English by 0.2135, with the 95% confidence interval for this effect equaling [-0.3187, -0.1083].

We summarize our regression results as follows. CO never significantly affects mean scaled scores or percentage at least proficient for math or ELA. NO_2 significantly affects only the math mean scaled score (treating its t-statistic of 1.6 in Table 3A as significant). O_3 significantly affects all outcome measures except that for mean scaled math scores, while $PM_{2.5}$ significantly affects all outcome measures except for the percentage at least proficient in math. Finally PM_{10} significantly affects all outcome variables. However, in each case where a coefficient is significant, it predicts a relatively small impact of a one standard deviation increase in the respective pollution measure.

5.2 Sensitivity Analysis for the Fixed Effect Regression Results

We perform a sensitivity analysis by considering alternative pollution measures and sample selection in Tables 5-7. In each table we present the estimated coefficients on the pollution variables for the four outcome variables while suppressing the coefficient estimates for the control variables. In Table 5 we use only pollution monitors that were functioning over the entire sample period. Columns (1), (2), (3) and (4) show the results for mean scaled math scores, percentage at least proficient in math, mean scaled ELA scores, and percentage at least proficient in ELA, respectively. Column (1) shows that the results for mean scaled math scores are slightly stronger than those in Table 3A since now

PM_{10} is significant at the 5% level instead of at the 10% level, and NO_2 is significant at the 10% level instead of having a t-statistic of 1.6. Columns (2), (3), and (4) for the other outcome variables present results that are very similar to those in Tables 3B, 3C and 3D, respectively.

Table 6 presents the analogous results when we use only monitors within a ten-mile radius of the schools. Column (1) indicates that most of the estimated coefficients for mean scaled math scores are somewhat smaller than in Table 3A; this is especially true for PM_{10}, which now is insignificant. However, one should not put too much weight on these differences, since the confidence intervals for the coefficients in column 1 and Table 3A have considerable overlap.[16] Column (2) indicates a similar pattern for the coefficients for the percentage at least proficient in math as compared to those in Table 3B. The coefficients for O_3 and PM_{10} are somewhat smaller but still statistically significant, while the NO_2 coefficient falls by two-thirds and is no longer significant. When we compare the results in column (3) for mean scaled ELA scores to those in Table 4A, the new coefficients for O_3, PM_{10}, and $PM_{2.5}$ are somewhat smaller but still statistically significant. The CO coefficient is larger and now significant at the 10% level. The coefficients in column 4 are similar to those in Table 4B. A similar pattern emerges for the percentage at least proficient in ELA in Column (4) compared to Table 4B. All in all, we consider Table 6 to replicate qualitatively our main results, but possibly with somewhat smaller effects.[17]

In Table 7 we repeat the analysis using a grade-school-year observation only if all five pollution measures are available for it. Comparing the Column (1) results for mean scaled math scores with those in Table 3A shows that the two sets of estimates are generally similar, although now the PM_{10} coefficient is smaller in absolute value and insignificant. The results for the other outcome variables are very similar to those in Tables 3B-4B. In summary, we conclude that results in Table 7 also are quite similar to those for our main pollution measures.

5.3 Fixed Effect Quantile Regression Estimates

Table 8 presents the FE quantile regression results for our base sample. (The actual quantiles for the four outcome variables are presented in Table 9.) Again, in Table 8 we report only the

[16] This is of course an informal comparison; a formal comparison would entail terms involving both the variances of the estimates and the covariance between the estimates. Unfortunately, available software does not allow one to estimate a seemingly unrelated estimation procedure with weights, FEs, and clustered standard errors, making obtaining the covariance much more difficult.

[17] To the extent that the coefficients are smaller, the effects of a one standard deviation increase in the respective pollutant is smaller since the standard deviations of the pollutants for this sample are essentially equal to those for our base sample.

coefficients for the pollution variables, and cluster the standard errors at the school level.[18] Consider the results in section A for mean scaled math scores. To maximize intuition, we first focus on the results for the 50th quantile or the median in column (4), that indicate how the *median* of mean scaled math scores change as the pollution variables change; recall that the results in Table 3A indicate how the *mean* (from the FE regression) of mean scaled math scores changes as the pollution variables change. As in Table 3A, the coefficients for CO and O_3 are insignificant in column (4) of part A of table 8. The coefficients for NO_2, PM_{10} and $PM_{2.5}$ are similar in size to those in Table 3A, but now the coefficients for NO_2 and $PM_{2.5}$, in addition to the coefficient for PM_{10}, are statistically significant.

Considering the estimated coefficients for all of the quantiles, the coefficients in column (1) indicate the effect of changing the pollution variables for those at the tenth quantile of the distribution, i.e. lowest achieving students. The results in columns (2)-(7) show the analogous results for students at the twentieth quantile through the ninetieth quantile, respectively. The CO estimated coefficients are insignificant for all quantiles. The NO_2 coefficients are of similar magnitude across the different quantiles, but are significant only from the fortieth quantile through the ninetieth quantile. (Note that the similar coefficient sizes imply that a one standard deviation increase in NO_2 will have a larger percentage effect at the lower quantiles.) O_3 significantly affects performance for only the ninetieth quantile, and then only at the 10% level. PM_{10} has a similar effect in terms of magnitude, and is statistically significant, across all quantiles. Finally, $PM_{2.5}$ is significant for the fortieth quantile, and has a larger effect as one moves up the distribution of mean scaled math scores.

Section B of Table 8 presents our quantile regression results when the outcome is the percentage of students at least proficient in math. Comparing the *median* estimates in Column 4 to the mean estimates in Table 3B, the coefficients for O_3, NO_2, PM_{10} and $PM_{2.5}$ are similar in magnitude across the two sets of results. However, the median coefficient for $PM_{2.5}$ is now statistically significant in Section B, while the coefficients for NO_2, PM_{10} and $PM_{2.5}$, are statistically significant in both the regression and median estimates. (CO had no significant effect on the median or the mean for this outcome variable.) Considering all of the quantiles in Section B of Table 9, the magnitude of the NO2 coefficients are similar across quantiles, but significant only for the fortieth through ninetieth quantiles. The PM_{10} and $O_{3\ \text{coefficients}}$ are significant for all quantiles, and both

[18] However, we find that clustering made little difference in terms of the standard errors but is significantly more computationally demanding.

increase in size as one moves up the distribution. Finally, the coefficients for $PM_{2.5}$ increase across the quantiles and are significant from the median through the ninetieth quantile.

Section C presents the quantile regression results when the outcome is mean scaled ELA scores. The median results in column (4) are very similar in size and significance to the regression coefficients in Table 4A. All of the CO coefficients across quantiles (except for the median) are statistically significant and are largest for the lowest quantiles; the CO coefficient was insignificant in the regression results in Table 4A. The coefficients for O_3 and $PM_{2.5}$ are also all significant and similar in size across the quantiles, while the coefficients for PM_{10} are all significant but increase in size as one moves up the distribution. Recall that the O_3, $PM_{2.5}$ and PM_{10} coefficients are also significant in the regression results in Table 4A.

Section D presents the quantile regression results when the outcome is the percentage of students at least proficient in ELA. The median results in column (4) again are very similar in size and significance to those for the mean in Table 4B. Further, across quantiles, the coefficients for O_3 and $PM_{2.5}$ are all significant and larger at higher quantiles, while all of the PM_{10} coefficients are significant but of similar magnitude across quantiles. Note that the O_3, $PM_{2.5}$ and PM_{10} coefficients are also significant in the regression results in Table 4A.

We summarize our quantile regression results as follows. The CO coefficients are significant only when the outcome variable is mean ELA scores; recall that none of the CO coefficients was significant in any of the FE regression results in section 5.1. NO_2 significantly affects only mean math scores and the percentage at least proficient in math from the fortieth quantile and up; in the FE regression results it was almost significant for mean scaled math scores and significant for the percentage at least proficient in math at the 10% level. O_3 significantly affects all quantiles for all outcome measures except that for mean math scores, which is consistent with the FE regression results. $PM_{2.5}$ significantly affects mean math scores at all quantiles except the tenth, and significantly affects the percentage at least proficient in math from the median up, while it significantly affects both of the ELA outcome measures at all quantiles. In the FE regression results, $PM_{2.5}$ significantly affects all outcomes except for the percentage at least proficient in math.) Finally, PM_{10} significantly affects all outcome variables at all quantiles; it also significantly affects all outcome variables in the FE regression results. The median estimates and the FE mean regression estimates are quite similar,; this is reassuring since we assume that the FEs are constant across quantiles for a given outcome, while for a symmetric distribution the regression results are equivalent to allowing the median to have its own FE. Thus, we argue that the quantile regression results produce a richer picture of the effect of pollution on test scores than simply considering the FE regression results. Finally, again, in each case where a coefficient is significant, the quantile regression results predict a relatively small impact of a one standard deviation in the respective pollution measure.

We carry out the same sensitivity analysis for the quantile estimates as we did for the FE regression results.[19] The results are very similar to those in Table 8, even when we used the monitors only within a ten-mile radius of the school.

5.4 Comparative Statics Exercises

To put these results in perspective, we do some back-of-the-envelope calculations of the benefits of a decrease in pollution for disadvantaged neighborhoods; for ease of exposition, we focus on reductions in PM_{10}. Using the median of free or reduced-price lunches as the threshold to determine high- and low-income schools, the percentage at least proficient in math is 22.5 percentage points higher in high-income schools (61.8%) compared to low-income schools (39.3%). The percentage of days above the standard for PM_{10} is 14.3 for low-income schools and 9.3 for high-income schools − a gap of 5.0 percentage points. If these low-income schools had the pollution levels of the high-income schools, then the percentage at least proficient in math would increase by 0.12; in other words, the gap between high-income and low-income schools would fall to 22.38 percentage points, or by about 0.5%. In a similar vein, the difference between high-income and low-income schools in the percentage at least proficient in ELA is 28.04 percentage points. Equalizing PM_{10} exposure in terms of days above the standard between high-income and low-income schools would increase the percentage at least proficient in ELA in low-income schools by 0.095 and would decrease the gap between high- and low-income schools to 27.945 by 0.34 %.

For a starker comparison, the percentage at least proficient in math at the ninetieth quantile is 80 percentage points and at the tenth quantile it is 22 percentage points (see Table 9)—a gap of 58 percentage points. To obtain the corresponding average number of days that PM_{10} is above the daily standard for the ninetieth (tenth) quantile, we take the average of schools over the eighty-fifth to ninety-fifth (fifth and fifteenth) quantiles. This produces the 'average' percent of PM_{10} days above the standard of 8.82 and 14.28 for the ninetieth and tenth quantile, respectively, for a difference of

[19] These results are available at xxx. In these results we have not clustered the standard errors, given how computationally demanding it was to do so in Table 9 and how little it changed the estimates of the standard errors. **John add to website.**

5.47 percent of days. If we decrease air pollution for the tenth quantile to that of the ninetieth quantile, we see that the percentage at least proficient in math at the tenth quantile would rise by 0.092 percentage points. When we do this calculation for the percentage at least proficient in ELA, we find that the tenth quantile increases by 0.13 percentage points.

Finally, we consider the decrease in the average percent of days above the limit for PM_{10} between 1990 and 2008. To calculate the average percent of days above the standard for California in these two years, we determine whether, for each monitoring site and date, the maximum 1-hour value for PM_{10} is above the standard. If the value for PM_{10} for one of the monitors within an air basin was above the standard for a particular day, we designate that day as being above the standard for that air basin. Then, for each air basin, we calculate the percent of days within the year when PM_{10} was above the standard. Finally, we take the average of the air basin values for each year and designate that average as the percent of days above the standard for California for PM_{10} in each year. In this calculation, we use all sites that were functioning in 1990 and all sites that were functioning in 2008, and we use the entire calendar year, not just the school year. Using this approach, we estimate that there is an 8.28 percentage point reduction in the percent of days above the standard between 1990 and 2008 for PM_{10}. The regression results suggest that this reduction would increase the percentage at least proficient in math and in ELA by 0.198 and 0.157 percentage points, respectively. To put this number in perspective, recall that the percentage at least proficient in math is 22.5 percentage points higher in high-income schools than in low-income schools. Using either outcome variable, the contribution of the decrease in pollution to the improvement in the mean of the percentage at least proficient is small. In terms of the quantile estimates, decreasing PM_{10} for the tenth quantile by 8.28 while keeping the PM_{10} level for ninetieth quantile constant would decrease the gap in the percentage at least proficient between the quantiles by 0.14 percentage points for math and by 0.16 percentage points for ELA.

6. Conclusion

In this paper we present FE linear regression and quantile regression estimates that suggest that a reduction in air pollution generally increases academic performance on standardized tests in both Mathematics and English/Language Arts by a small but significant amount, even when we also use a large number of time changing control variables. The effects are strongest for O_3, $PM_{2.5}$, and especially PM_{10}. NO_2 significantly affects only the Mathematics outcome variables, while in the vast majority of cases, the CO coefficients are insignificant. The above results are robust to a number of changes in how pollution is measured.

In terms of comparing FE quantile and FE regression estimates, the median estimates are similar to the FE regression results. In many cases, if the quantile estimates are significant for some quantiles, they are statistically significant for all quantiles. In a slight majority of cases where the pollutant has a significant coefficient in the quantile estimates, the effect increases across quantiles, while in the remaining cases the coefficient for a given pollutant is constant across quantiles. Overall, the quantile estimates produce a richer picture of the effect of pollution on test scores. Given that the methodology now exists for estimating FE quantile regressions, we believe that it will be fruitful to explore its use in other contexts.

In terms of policy implications, this paper shows that efforts to reduce air pollution will not only improve children's health, as noted in previous articles, but also slightly increase children's academic performance.

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Table 1: Descriptive Statistics Across California Schools, 2002-2008

	Mean	Standard Deviation	Minimum	Maximum
Panel A: Test Score Variables				
Mathematics				
Mean scaled score	357.57	38.97	181.60	537.10
Percent at least proficient	50.74	21.36	0.00	100.00
English/language arts				
Mean scaled score	341.21	28.75	182.10	474.80
Percent at least proficient	43.35	21.25	0.00	100.00
Panel B: Pollution Variables				
Percent of Days that Exceed the Pollution Standard				
Carbon monoxide (CO)	0.0039	0.11	0.00	7.40
Nitrogen dioxide (NO_2)	0.0033	0.021	0.00	0.63
Ozone (O_3)	1.94	2.50	0.00	24.91
Coarse Particulate matter (PM_{10})	11.78	12.48	0.00	79.80
Fine Particulate matter ($PM_{2.5}$)	6.45	6.47	0.00	32.00
Panel C: Control Variables				
Time-varying Grade-School Characteristics				
White (%)	35.00	28.36	0.00	100.00
Asian (%)	11.04	15.05	0.00	100.00
Hispanic (%)	42.56	29.75	0.00	100.00
African American (%)	7.58	12.51	0.00	100.00
Other (%)	3.81	5.98	0.00	98.31
Time-varying School Characteristics				
Average class size	26.54	4.97	5.00	50.00
Reduced or free meals (%)	51.39	30.65	0.00	100.00
Parent is a high school graduate (%)	19.38	18.50	0.00	100.00
Parent has some college education (%)	24.98	13.20	0.00	100.00
Parent is a college graduate (%)	19.53	13.28	0.00	100.00
Parent attended graduate school (%)	11.82	13.91	0.00	100.00
Fully certified teachers (%)	94.72	9.31	0.00	100.00
Non-native english speakers (%)	26.24	21.91	0.00	100.00
School enrollment	406.89	214.76	13.00	3,110.00
Time-varying District Characteristics				
Expenditure per student (*10^-3)	8.83	2.56	1.87	70.76
Time-varying County Characteristics				
County unemployment rate	6.38	2.10	3.40	22.40
County taxable transactions (*10^-5)	384.52	417.05	0.17	1,215.06

Note: Average class size is measured separately for kindergarten through third grade and fourth through sixth grade. The means for CO, NO_2, O_3, PM_{10}, and $PM_{2.5}$ are based on 143,041 observations, 131,446 observations, 138,259 observations, 136,476 observations, and 131,467 observations, respectively. See Appendix A for data sources.

Table 2: Correlation Coefficients Across California Schools, 2002-2008

	Percent of days that exceed the standard for:				
	CO	NO_2	O_3	PM_{10}	$PM_{2.5}$
Percent of days that exceed the standard for:					
Carbon monoxide (CO)	1				
Nitrogen dioxide (NO_2)	0.23	1			
Ozone (O_3)	0.020	0.029	1		
Coarse Particulate matter (PM_{10})	0.15	0.53	0.54	1	
Fine Particulate matter ($PM_{2.5}$)	-0.020	0.064	0.50	0.66	1

Table 3A: The Effect of Air Pollution (percent of days that exceed the standard) on Mean Scaled Scores in Mathematics – Grade-School and Year Effects

	(1)	(2)	(3)	(4)	(5)
Percent of days that exceed the standard for:					
Carbon monoxide (CO)	0.523				
	[0.419]				
Nitrogen dioxide (NO_2)		-5.139			
		[3.226]			
Ozone (O_3)			0.009		
			[0.052]		
Particulate matter$_{10}$ (PM_{10})				-0.023+	
				[0.012]	
Particulate matter$_{2.5}$ ($PM_{2.5}$)					-0.024
					[0.019]
Asian (%)	0.142**	0.134**	0.143**	0.138**	0.136**
	[0.023]	[0.024]	[0.023]	[0.023]	[0.024]
Hispanic (%)	-0.359**	-0.375**	-0.363**	-0.371**	-0.372**
	[0.014]	[0.015]	[0.015]	[0.015]	[0.015]
African American (%)	-0.498**	-0.512**	-0.502**	-0.511**	-0.518**
	[0.022]	[0.023]	[0.023]	[0.023]	[0.023]
Other (%)	-0.154**	-0.149**	-0.144**	-0.155**	-0.149**
	[0.019]	[0.021]	[0.019]	[0.020]	[0.0196]
Average class size	-0.197**	-0.212**	-0.202**	-0.206**	-0.201**
	[0.028]	[0.0298]	[0.029]	[0.029]	[0.0297]
Reduced or free meals (%)	-0.109**	-0.113**	-0.113**	-0.115**	-0.117**
	[0.013]	[0.013]	[0.013]	[0.013]	[0.014]
Parent is a:					
High school graduate (%)	0.035*	0.032+	0.036*	0.034+	0.035+
	[0.017]	[0.018]	[0.017]	[0.018]	[0.018]
Some college (%)	0.018	0.026	0.022	0.021	0.019
	[0.017]	[0.019]	[0.018]	[0.018]	[0.019]
College graduate (%)	0.062**	0.054**	0.060**	0.058**	0.056**
	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]
Graduate school (%)	0.111**	0.110**	0.110**	0.108**	0.107**
	[0.020]	[0.021]	[0.020]	[0.021]	[0.021]
Fully certified teachers (%)	0.051**	0.041**	0.048**	0.044**	0.040*
	[0.015]	[0.016]	[0.015]	[0.016]	[0.016]
Expenditure per student	0.0297	0.025	0.044	0.0103	0.0196
	[0.050]	[0.059]	[0.051]	[0.051]	[0.054]
Non-native English speakers (%)	-0.151**	-0.152**	-0.149**	-0.148**	-0.145**
	[0.017]	[0.018]	[0.018]	[0.018]	[0.018]
School enrollment	-0.0015	-0.0015	-0.0016	-0.0015	-0.0016
	[0.0015]	[0.0015]	[0.0015]	[0.0015]	[0.0016]
County unemployment rate	-0.219	-0.206	-0.200	-0.143	-0.136
	[0.168]	[0.176]	[0.167]	[0.169]	[0.173]
County taxable transactions	-0.014**	-0.016**	-0.014**	-0.014**	-0.016**
	[0.0032]	[0.0033]	[0.0033]	[0.0033]	[0.0032]
Observations	142320	130832	137600	135693	130891
R-squared	0.877	0.881	0.879	0.879	0.881

Note: Standard errors in parentheses are clustered by school. Significance levels: **1% ,*5%,+10%.

Table 3B: The Effect of Air Pollution (percent of days that exceed the standard) on Percent of Students at Least Proficient in Mathematics – Grade-School and Year Effects

	(1)	(2)	(3)	(4)	(5)
Percent of days that exceed the standard for:					
Carbon monoxide (CO)	-0.123				
	[0.277]				
Nitrogen dioxide (NO_2)		-3.323+			
		[1.791]			
Ozone (O_3)			-0.089**		
			[0.032]		
Particulate matter$_{10}$ (PM_{10})				-0.024**	
				[0.0071]	
Particulate matter$_{2.5}$ ($PM_{2.5}$)					-0.012
					[0.011]
Asian (%)	0.013	0.008	0.013	0.011	0.008
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Hispanic (%)	-0.190**	-0.197**	-0.194**	-0.196**	-0.197**
	[0.0081]	[0.0086]	[0.0083]	[0.008]	[0.0085]
African American (%)	-0.292**	-0.299**	-0.296**	-0.298**	-0.306**
	[0.013]	[0.014]	[0.013]	[0.013]	[0.014]
Other (%)	-0.133**	-0.141**	-0.131**	-0.138**	-0.138**
	[0.011]	[0.012]	[0.011]	[0.012]	[0.012]
Average class size	-0.123**	-0.132**	-0.126**	-0.128**	-0.127**
	[0.017]	[0.018]	[0.017]	[0.017]	[0.018]
Reduced or free meals (%)	-0.038**	-0.039**	-0.039**	-0.039**	-0.041**
	[0.0073]	[0.0077]	[0.0074]	[0.008]	[0.0078]
Parent is a:					
High school graduate (%)	0.029**	0.0298**	0.031**	0.030**	0.031**
	[0.010]	[0.011]	[0.010]	[0.011]	[0.011]
Some college (%)	0.032**	0.036**	0.033**	0.035**	0.033**
	[0.010]	[0.011]	[0.011]	[0.011]	[0.011]
College graduate (%)	0.042**	0.038**	0.042**	0.041**	0.039**
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Graduate school (%)	0.026*	0.026*	0.026*	0.025*	0.024*
	[0.011]	[0.012]	[0.011]	[0.012]	[0.012]
Fully certified teachers (%)	0.065**	0.064**	0.066**	0.063**	0.062**
	[0.0085]	[0.0087]	[0.0086]	[0.009]	[0.0088]
Expenditure per student	0.019	0.0055	0.025	-0.0016	0.0056
	[0.029]	[0.034]	[0.030]	[0.030]	[0.032]
Non-native English speakers (%)	-0.063**	-0.063**	-0.061**	-0.061**	-0.059**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
School enrollment	-0.0032**	-0.0033**	-0.0033**	-0.003**	-0.0033**
	[0.00085]	[0.00087]	[0.00086]	[0.00086]	[0.00088]
County unemployment rate	0.235*	0.258*	0.302**	0.344**	0.341**
	[0.103]	[0.107]	[0.102]	[0.103]	[0.106]
County taxable transactions	-0.0063**	-0.0071**	-0.0057**	-0.006**	-0.0068**
	[0.0018]	[0.0019]	[0.0018]	[0.0018]	[0.0018]
Observations	142320	130832	137600	135693	130891
R-squared	0.86	0.865	0.862	0.862	0.864

See notes to Table 3A.

Table 4A: The Effect of Air Pollution (percent of days that exceed the standard) on Mean Scaled Scores in English/Language Arts – Grade-School and Year Effects

	(1)	(2)	(3)	(4)	(5)
Percent of days that exceed the standard for:					
Carbon monoxide (CO)	-0.418				
	[0.302]				
Nitrogen dioxide (NO_2)		-0.994			
		[1.915]			
Ozone (O_3)			-0.205**		
			[0.029]		
Particulate matter$_{10}$ (PM_{10})				-0.019**	
				[0.0067]	
Particulate matter$_{2.5}$ ($PM_{2.5}$)					-0.027*
					[0.011]
Asian (%)	0.045**	0.041**	0.045**	0.046**	0.045**
	[0.013]	[0.014]	[0.014]	[0.014]	[0.014]
Hispanic (%)	-0.270**	-0.277**	-0.275**	-0.273**	-0.274**
	[0.0088]	[0.0094]	[0.00905]	[0.00904]	[0.0093]
African American (%)	-0.304**	-0.313**	-0.309**	-0.312**	-0.315**
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
Other (%)	-0.127**	-0.127**	-0.125**	-0.128**	-0.125**
	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]
Average class size	-0.031*	-0.030+	-0.024	-0.026+	-0.022
	[0.015]	[0.016]	[0.016]	[0.016]	[0.016]
Reduced or free meals (%)	-0.069**	-0.068**	-0.071**	-0.070**	-0.073**
	[0.0074]	[0.0079]	[0.0076]	[0.0077]	[0.0080]
Parent is a:					
High school graduate (%)	0.033**	0.035**	0.036**	0.035**	0.035**
	[0.010]	[0.011]	[0.010]	[0.011]	[0.011]
Some college (%)	0.020+	0.029*	0.023*	0.025*	0.026*
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
College graduate (%)	0.062**	0.060**	0.062**	0.062**	0.061**
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Graduate school (%)	0.083**	0.086**	0.084**	0.082**	0.083**
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Fully certified teachers (%)	0.054**	0.049**	0.055**	0.0502**	0.047**
	[0.0088]	[0.0091]	[0.0089]	[0.00902]	[0.0091]
Expenditure per student	-0.0089	0.00304	-0.0039	-0.0196	-0.015
	[0.029]	[0.032]	[0.029]	[0.030]	[0.031]
Non-native English speakers (%)	-0.164**	-0.169**	-0.165**	-0.167**	-0.165**
	[0.0101]	[0.0106]	[0.0104]	[0.0104]	[0.0106]
School enrollment	-0.0021**	-0.0020*	-0.0022**	-0.0021**	-0.0019*
	[0.00078]	[0.00080]	[0.00078]	[0.00079]	[0.00081]
County unemployment rate	0.088	0.212*	0.205*	0.219*	0.200*
	[0.092]	[0.097]	[0.091]	[0.092]	[0.095]
County taxable transactions	-0.0046*	-0.0049**	-0.0037*	-0.0045*	-0.0064**
	[0.0018]	[0.0019]	[0.0018]	[0.0018]	[0.0019]
Observations	142320	130832	137600	135693	130891
R-squared	0.919	0.922	0.921	0.92	0.922

See notes to Table 3A.

Table 4B: The Effect of Air Pollution (percent of days that exceed the standard) on Percent of Students at Least Proficient in English/Language Arts – Grade-School and Year Effects

	(1)	(2)	(3)	(4)	(5)
Percent of days that exceed the standard for:					
Carbon monoxide (CO)	0.177				
	[0.176]				
Nitrogen dioxide (NO_2)		-0.876			
		[1.380]			
Ozone (O_3)			-0.166**		
			[0.022]		
Particulate matter$_{10}$ (PM_{10})				-0.019**	
				[0.0051]	
Particulate matter$_{2.5}$ ($PM_{2.5}$)					-0.033**
					[0.0083]
Asian (%)	0.0065	0.00404	0.00615	0.0064	0.0057
	[0.010]	[0.0102]	[0.010]	[0.0101]	[0.0102]
Hispanic (%)	-0.197**	-0.202**	-0.201**	-0.200**	-0.200**
	[0.0069]	[0.0073]	[0.00704]	[0.0071]	[0.0072]
African American (%)	-0.230**	-0.234**	-0.233**	-0.234**	-0.238**
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Other (%)	-0.106**	-0.107**	-0.104**	-0.109**	-0.106**
	[0.0091]	[0.0097]	[0.0093]	[0.0095]	[0.0097]
Average class size	-0.0054	-0.0057	-0.0014	-0.00398	-0.0027
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Reduced or free meals (%)	-0.044**	-0.042**	-0.045**	-0.044**	-0.044**
	[0.0055]	[0.0058]	[0.0056]	[0.0057]	[0.0059]
Parent is a:					
High school graduate (%)	0.026**	0.028**	0.028**	0.028**	0.029**
	[0.0074]	[0.0079]	[0.0075]	[0.0078]	[0.00796]
Some college (%)	0.025**	0.031**	0.026**	0.028**	0.027**
	[0.0077]	[0.0082]	[0.0078]	[0.00805]	[0.0082]
College graduate (%)	0.052**	0.052**	0.053**	0.054**	0.053**
	[0.00795]	[0.0085]	[0.0082]	[0.0084]	[0.0085]
Graduate school (%)	0.038**	0.0397**	0.039**	0.039**	0.039**
	[0.0082]	[0.0087]	[0.0083]	[0.0085]	[0.0086]
Fully certified teachers (%)	0.048**	0.046**	0.049**	0.046**	0.044**
	[0.0063]	[0.0066]	[0.0064]	[0.0065]	[0.0066]
Expenditure per student	0.012	0.032	0.0155	0.0026	0.0085
	[0.027]	[0.025]	[0.028]	[0.028]	[0.0298]
Non-native English speakers (%)	-0.110**	-0.113**	-0.111**	-0.112**	-0.110**
	[0.0074]	[0.0076]	[0.0075]	[0.0076]	[0.0077]
School enrollment	-0.0018**	-0.0018**	-0.0019**	-0.0018**	-0.0017**
	[0.00058]	[0.00060]	[0.00058]	[0.00059]	[0.00060]
County unemployment rate	0.358**	0.414**	0.425**	0.441**	0.407**
	[0.071]	[0.075]	[0.070]	[0.072]	[0.073]
County taxable transactions	0.00055	0.00068	0.00155	0.00058	-0.00096
	[0.0013]	[0.0013]	[0.0013]	[0.0013]	[0.0013]
Observations	142320	130832	137600	135693	130891
R-squared	0.904	0.908	0.905	0.905	0.907

See notes to Table 3A.

Table 5: The Effect of Air Pollution (percent of days that exceed the standard) on Academic Performance using Monitors Functioning Throughout the Period– Grade-School and Year Effects

	Mathematics		English/Language Arts	
	Mean scaled score (1)	Percent at least proficient (2)	Mean scaled score (3)	Percent at least proficient (4)
Percent of days that exceed the standard for:				
Carbon monoxide (CO)	0.745	-0.192	-0.533	0.249
	[0.600]	[0.402]	[0.423]	[0.261]
Nitrogen dioxide (NO_2)	-4.845+	-2.821+	0.068	-0.202
	[2.946]	[1.638]	[1.709]	[1.246]
Ozone (OZ)	0.007	-0.091**	-0.209**	-0.175**
	[0.052]	[0.032]	[0.029]	[0.022]
Particulate matter$_{10}$ (PM_{10})	-0.027*	-0.026**	-0.023**	-0.024**
	[0.011]	[0.007]	[0.006]	[0.005]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	-0.015	-0.006	-0.025*	-0.031**
	[0.019]	[0.011]	[0.011]	[0.008]

See notes to Table 3A.

Table 6: The Effect of Air Pollution (percent of days that exceed the standard) on Academic Performance using Monitors within a 10 mile Radius – Grade-School and Year Effects

	Mathematics		English/Language Arts	
	Mean scaled score (1)	Percent at least proficient (2)	Mean scaled score (3)	Percent at least proficient (4)
Percent of days that exceed the standard for:				
Carbon monoxide (CO)	0.354	-0.114	-0.570+	0.231
	[0.429]	[0.287]	[0.319]	[0.173]
Nitrogen dioxide (NO_2)	-4.192+	-1.349	-0.695	-0.149
	[2.352]	[1.354]	[1.378]	[0.992]
Ozone (O_3)	0.011	-0.068*	-0.149**	-0.120**
	[0.049]	[0.031]	[0.028]	[0.021]
Particulate matter$_{10}$ (PM_{10})	-0.002	-0.013+	-0.015*	-0.015**
	[0.012]	[0.007]	[0.007]	[0.005]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	-0.004	-0.009	-0.024*	-0.030**
	[0.020]	[0.012]	[0.012]	[0.009]

See notes to Table 3A.

Table 7: The Effect of Air Pollution (percent of days that exceed the standard) on Academic Performance using Observations where all Pollutants and Test Scores are Available – Grade-School and Year Effects

	Mean scaled score (1)	Percent at least proficient (2)	Mean scaled score (3)	Percent at least proficient (4)
Percent of days that exceed the standard for:				
Carbon monoxide (CO)	0.735+	-0.034	-0.264	0.259
	[0.429]	[0.277]	[0.305]	[0.174]
Nitrogen dioxide (NO_2)	-5.584	-2.730	0.142	-0.423
	[3.692]	[2.018]	[2.064]	[1.534]
Ozone (O_3)	0.017	-0.096**	-0.213**	-0.167**
	[0.057]	[0.035]	[0.032]	[0.024]
Particulate matter$_{10}$ (PM_{10})	-0.016	-0.023**	-0.018**	-0.020**
	[0.012]	[0.007]	[0.007]	[0.005]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	-0.015	-0.010	-0.022*	-0.030**
	[0.019]	[0.011]	[0.011]	[0.008]

See notes to Table 3A.

Table 8: Quantile Regressions Results for Mathematics and English/Language Arts

Quantile	10%	20%	40%	50%	60%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Mathematics Mean Scaled Score							
Carbon monoxide (CO)	0.496	0.087	0.022	0.52	0.266	0.412	0.536
	[0.478]	[0.498]	[0.555]	[0.411]	[0.401]	[0.766]	[0.438]
Nitrogen dioxide (NO_2)	-5.615	-3.786	-7.393**	-5.151*	-4.437*	-3.245	-5.056*
	[4.288]	[3.228]	[2.778]	[2.327]	[2.101]	[2.374]	[2.579]
Ozone (O_3)	0.005	0.012	0.019	0.016	0.005	-0.034	-0.051+
	[0.030]	[0.024]	[0.021]	[0.018]	[0.020]	[0.024]	[0.028]
Particulate matter$_{10}$ (PM_{10})	-0.024**	-0.027**	-0.022**	-0.017**	-0.022**	-0.025**	-0.020**
	[0.0056]	[0.0044]	[0.0043]	[0.0038]	[0.0039]	[0.0050]	[0.0060]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	0.0007	-0.021*	-0.025**	-0.030**	-0.029**	-0.046**	-0.048**
	[0.012]	[0.0010]	[0.0090]	[0.010]	[0.012]	[0.0086]	[0.012]
Panel B: Percent at Least Proficient in Mathematics							
Carbon monoxide (CO)	-0.641	-0.340	-0.256	-0.338+	-0.364+	-0.274	-0.332
	[0.409]	[0.414]	[0.388]	[0.200]	[0.199]	[0.378]	[0.457]
Nitrogen dioxide (NO_2)	-3.042	-1.878	-3.340**	-4.066**	-4.685**	-4.462**	-4.347+
	[2.228]	[1.759]	[1.229]	[1.395]	[1.257]	[1.729]	[2.308]
Ozone (O_3)	-0.040*	-0.066**	-0.095**	-0.105**	-0.116**	-0.143**	-0.151**
	[0.016]	[0.014]	[0.013]	[0.014]	[0.013]	[0.016]	[0.021]
Particulate matter$_{10}$ (PM_{10})	-0.017**	-0.020**	-0.025**	-0.026**	-0.030**	-0.030**	-0.032**
	[0.0040]	[0.0029]	[0.0030]	[0.0031]	[0.0033]	[0.0038]	[0.0047]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	0.012	0.0054	-0.0063	-0.011*	-0.022**	-0.028**	-0.032**
	[0.0077]	[0.0060]	[0.0051]	[0.0050]	[0.0055]	[0.0063]	[0.0066]
Panel C: English/Language Arts Mean Scaled Score							
Carbon monoxide (CO)	-0.998*	-0.744*	-0.502+	-0.339	-0.540**	-0.574+	-0.609*
	[0.469]	[0.332]	[0.264]	[0.235]	[0.185]	[0.348]	[0.290]
Nitrogen dioxide (NO_2)	0.422	-1.072	-1.777	-0.967	-0.501	-0.639	0.258
	[2.658]	[1.494]	[1.440]	[1.676]	[1.137]	[1.703]	[2.914]
Ozone (O_3)	-0.191**	-0.205**	-0.196**	-0.211**	-0.222**	-0.224**	-0.262**
	[0.015]	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]	[0.020]
Particulate matter$_{10}$ (PM_{10})	-0.014**	-0.015**	-0.019**	-0.021**	-0.021**	-0.022**	-0.025**
	[0.0047]	[0.0038]	[0.0026]	[0.0026]	[0.0023]	[0.0030]	[0.0039]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	-0.022**	-0.026**	-0.028**	-0.029**	-0.029**	-0.024**	-0.027**
	[0.0063]	[0.0051]	[0.0047]	[0.0044]	[0.0047]	[0.0064]	[0.0069]
Panel D: Percent at Least Proficient in English/Language Arts							
Carbon monoxide (CO)	0.320+	0.168	0.153	0.074	-0.032	-0.021	-0.186
	[0.194]	[0.140]	[0.230]	[0.171]	[0.107]	[0.214]	[0.247]
Nitrogen dioxide (NO_2)	-2.148	-1.826	-2.069+	-1.164	-0.576	-0.258	0.687
	[1.448]	[1.368]	[1.164]	[1.220]	[1.482]	[1.523]	[1.266]
Ozone (O_3)	-0.142**	-0.149**	-0.163**	-0.178**	-0.182**	-0.204**	-0.252**
	[0.013]	[0.010]	[0.008]	[0.010]	[0.011]	[0.013]	[0.016]
Particulate matter$_{10}$ (PM_{10})	-0.019**	-0.017**	-0.019**	-0.020**	-0.020**	-0.022**	-0.023**
	[0.0027]	[0.0022]	[0.0022]	[0.0025]	[0.0023]	[0.0027]	[0.0035]
Particulate matter$_{2.5}$ ($PM_{2.5}$)	-0.024**	-0.023**	-0.029**	-0.036**	-0.036**	-0.033**	-0.036**
	[0.0050]	[0.0046]	[0.0033]	[0.0032]	[0.0032]	[0.0047]	[0.0060]

See notes to Table 3a.

Table 9: Distribution of Outcome Variables

Quantile	10%	20%	40%	50%	60%	80%	90%
Mathematics							
Mean scaled score	310.2	324	344.5	354	364.3	389.9	410.2
Percent at least proficient	22	31	44	50	57	71	80
English/language arts							
Mean scaled score	306	316.3	331.7	339.1	346.7	365.9	380.3
Percent at least proficient	17	24	35	41	48	63	74