Air Pollution and Academic Performance:
Evidence from California Schools

Jacqueline S. Zweig*
Department of Economics
University of Southern California

John C. Ham*
Department of Economics
University of Maryland,
IZA and IRP (UW-Madison)

Edward L. Avol
Department of Preventive Medicine
University of Southern California

December 2009

*Ham and Zweig are co-first authors. We are extremely grateful to the Southern California Environmental Health Sciences Center for providing us with data from the Children's Health Study, to Tatiana Melguizo and Douglas Worsnop for their insights into the education and pollution literature respectively, as well as to Talat Islam and JC Chen for extensive comments on an earlier draft. Ham's work was supported by the National Science Foundation (NSF), Grant 0627934, and Avol's by the National Institute of Environmental Health Sciences (NIEHS), Grant P30 ES07048. Any opinions, findings, and conclusions or recommendations in this material are those of the authors and do not necessarily reflect the views of the NSF or the NIEHS. We are responsible for any errors. Ham is corresponding author: ham@econ.umd.edu.

ABSTRACT

Air pollution has been associated with a number of detrimental health effects for children. Another potentially substantive, but previously unappreciated, effect of air pollution on children is diminished academic performance, presumably resulting in reduced human capital accumulation and reduced future earnings. In this paper we investigate the relationship between outdoor air pollution levels and standardized state test scores of California public school children. To do this we combine individual family data and community pollution data from the Children's Health Study (CHS), a longitudinal respiratory health study of Southern California school children, with publicly available information on California standardized test scores by grade, school, and year. We find that a 10% decrease in outdoor PM_{10}, $PM_{2.5}$, or NO_2 would raise math test scores by 0.15%, 0.34%, or 0.18%, while a 10% decrease in outdoor $PM_{2.5}$ increases reading scores by 0.21%. To put these effects in perspective, if it were possible to reduce $PM_{2.5}$ by 10% for low-income students but not for high-income students, the gap in math test scores between high- and low-income 8th grade students would fall by nearly one thirtieth.

1. Introduction

Air pollution has been associated with a number of detrimental health effects for children. One of the main findings of the recent medical, epidemiological and economics literature is that pollution has a positive and significant effect on asthma exacerbation. Pollution has also been associated with new onset asthma (McConnell et al. 2002), as well as other respiratory diseases, lower lung function, hay fever (Gauderman et al. 2001, McConnell et al. 2003) and infant mortality (Chay and Greenstone 2003a, 2003b, Currie and Neidell 2005). Another potentially substantive, but previously unappreciated, effect of air pollution on children is diminished academic performance, presumably resulting in reduced human capital accumulation and reduced future earnings.

There are four mechanisms by which pollution could affect academic performance: (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. Earlier research (Gilliland et al. 2001, Ransom and Pope 1992, and Currie et al. 2007) established a statistically significant relationship between pollution and school absenteeism and thus relate to mechanism (i) above. Furthermore, there is evidence that children with asthma tend to have more behavioral problems in school than children who do not have asthma (Butz et al. 1995, Bussing et al. 1995, Halterman 2006), which provides support for mechanism ii) above. We do not know of any available evidence on mechanism iii) above. Recent neuropathological, epidemiological, and brain imaging literature suggests that air pollution may be harmful to the development of the brain and may affect cognitive ability (Calderón-Garcidueñas et al. 2008ab; Suglia et al. 2008; Wang et al. 2009), which supports mechanism (iv) above.

Since neurological effects, absenteeism, behavioral problems, and fatigue are directly caused by pollution (or associated with diseases that are exacerbated or caused by pollution) and since they have also been linked to poor academic performance, a natural question that arises is "what is the direct effect of pollution on academic performance?" This measured effect will incorporate mechanisms i) - iv) above. To our knowledge, there has been no published work on this subject, although there is a small related literature on the effect of asthma on school readiness, learning disabilities and academic performance. For example, Halterman et al. (2001) found that kindergarten-age children with asthma with limitation had lower scores than non-asthmatic kindergarten-age children in reported school readiness skills in Rochester, New York during 1998.[1] Further, Fowler, Davenport and Garg (1992) found that, after controlling for demographic factors, asthmatic children in grades 1-12 were more likely to have a learning disability than non-asthmatics. Finally, as we describe in more detail below, Currie et al. (2009) matched several data sources for young adults in Manitoba, Canada and found some limited evidence that current asthma affected current achievement, but that past asthma (conditional on current asthma status) had no effect on current performance.

In this paper, we fill this gap by investigating the relationship between outdoor air pollution levels and standardized state test scores of California public school children. To do this we combine individual family data and community pollution data from the Children's Health Study (CHS), a longitudinal respiratory health study of Southern California school children (Peters et al. 1999), with publicly available information on California standardized test scores and school characteristics by grade, school, and year. An additional benefit to our study is that our data set contains information on $PM_{2.5}$ (a marker for fine particulate matter) while many of the studies discussed in the literature review do not have data on $PM_{2.5}$.[2] Indeed below we find that $PM_{2.5}$ exposure has much stronger

[1] A child was considered to have asthma with limitation compared to without limitation if the parent described any ongoing health conditions that limited the child's activity.
[2] $PM_{2.5}$ represents the portion of the particle size distribution whose mean diameter is 2.5 micrometers or less.

effects on test scores than the other pollution measures that we investigate.[3] In our analysis we use school, and (in some cases) year, fixed-effects to account for unobserved factors that may be correlated with test scores and air pollution. Our study differs from Currie et al. (2009) by using U.S. data, considering the effect of air pollution (as opposed to asthma) on school performance, using different pollution measures, and using a different measure of school performance. Thus we provide an important compliment to the Currie et al. (2009) Canadian evidence, since the effect of air pollution in our case (or asthma in their case) on school performance may differ substantially across the two countries, given the presence of universal health care in Canada, which would be expected to provide more equal access to controller medications for respiratory illness.

The paper proceeds as follows. Section 2 discusses the related economic and epidemiological literature. We describe the data in Section 3 and discuss our empirical strategy in Section 4. We evaluate the effect of outdoor air pollution on academic performance by using a school fixed effects model. We find that a richer specification that includes year dummies is appropriate since omitting these dummies appears to lead to omitted variable bias. We present our results in Section 5. We find that higher levels of $PM_{2.5}$ (a marker for fine particulate matter), PM_{10} (a marker for coarse particulate matter), and NO_2 consistently lower math scores, while higher levels of $PM_{2.5}$ consistently reduce reading test scores. However, the magnitude of this effect is reduced by including year dummies, and a comparison of the results with and without year dummy variables suggests that year dummies are indeed necessary for obtaining consistent estimates. Specifically, when we include year dummies, we find that a 10% decrease in PM_{10}, $PM_{2.5}$, or NO_2 would raise math test scores by 0.11%, 0.14%, or 0.12%, while a 10% decrease in $PM_{2.5}$ increases reading scores by 0.21%. To put these effects in perspective and to gain some intuition on the potential importance of these effects, note that if it were possible to decrease $PM_{2.5}$ by 10% for low-income, but not high-income, students, the 10% gap

[3] On the other hand, note that we do not have data on community carbon monoxide levels, which related studies have found to be important.

in math test scores between high- and low-income 8th grade students would be reduced by a little less than one-thirtieth.[4] To reduce the gap in reading scores by the same amount, one would need to reduce $PM_{2.5}$ by 14%.

Exposure to particulate matter has been shown to have several negative health outcomes (Peng et al. 2005; Perera et al. 2009; Pope and Dockery 2006;; Russell and Brunekreef 2009; Stieb, Judek, and Burnett 2002; and, Suglia et al. 2008) which present important costs to society of pollution. Given the strong relationship between academic performance and future labor income, and a strong relationship between measures of ability and earnings conditional on schooling (see e.g., Neal and Johnson 1996), our results suggest a heretofore unappreciated additional cost of air pollution in terms of reduced future earnings. Moreover, given that more highly polluted areas tend to have lower-cost rentals and thus attract more low-income households, we might expect that decreasing $PM_{2.5}$ would disproportionately benefit low-income households. Thus to the extent one puts a positive weight on a more equitable distribution of income, a reduction in pollution also implies additional social benefits by decreasing inequality. We conclude the paper in Section 6 and discuss possible limitations of our study.

2. Literature Review

As noted above, we know of no papers on the effect of pollution on academic performance, although there is epidemiological and neuropathological research suggesting that pollution affects brain development and intelligence quotient (IQ), and there is a strong relationship between measures of ability and academic performance. The literature most relevant to our paper focuses on the related issues of: (i) does pollution affect brain development and cognition?; (ii) does air

[4] In 2007, the average eighth grade NAEP math score (at the national level) is 291 for high-income students and 263 for low-income students (Barton and Coley 2009). Therefore, the ratio of high to low-income students is 1.106, resulting in a 10.6% difference between high and low-income students. The reading scores are 271 and 248 for high and low-income students respectively, resulting in a 9.3% difference.

pollution increase school absenteeism?; (iii) does an asthmatic child have more behavioral problems than a non-asthmatic child?; (iv) do absenteeism and behavioral problems affect academic performance?; and (v) does an asthmatic child have lower academic performance than a non-asthmatic child? Research area (i) is very relevant given the well established relationship between measures of ability and school performance (Cameron and Heckman 2001; Lochner and Belley 2007; Murnane, Willett, and Levy 1995). Research areas (ii) and (iv) provide evidence of how pollution may affect academic performance through absenteeism while (iii) and (iv) relate to how pollution may affect it through behavioral problems. Research area (v) complements our findings since asthma may be caused by, and is certainly exacerbated by, pollution. Note that we will not be able to trace out the different paths by which pollution can affect test scores; on the other hand the presence of many paths does raise the issue of whether, estimated asthma effects on performance may be including other paths by which pollution affects performance.

2.1 Air Pollution and Brain Development

Epidemiologic, neuropathological, and brain imaging studies provide evidence of a negative relationship between ambient air pollution and with lower brain development conditional on observable demographic factors, and since we have not seen this issue discussed in the economics literature, we now spend some time describing existing research in this area. For example, among 202 children who were approximately 10 years old in Boston, Massachusetts, higher levels of black carbon (a marker for traffic particles) was associated with decreased cognitive function across assessments of verbal and nonverbal intelligence and memory constructs (Suglia et al. 2008). The authors estimated exposure to black carbon for each participant's current residence and controlled 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 Harlem and the South Bronx during pregnancy, Perera et al. (2009) investigated the effect of polycyclic aromatic hydrocarbons (PAHs) on a child's IQ.[5] Motor vehicles are a major source of PAH in Harlem and south Bronx. PAH levels were measured through personal monitoring of the mothers in their third trimester of pregnancy and IQ was evaluated using the Wechsler Preschool and Primary Scale of Intelligence-revised. Researchers found that children with prenatal exposure to high levels of PAHs had full scale and verbal IQ scores at age 5 years that were 4.31 and 4.67 points lower, respectively than those of less exposed children. In a cross-sectional study in Quanzhou, China, the performance in multiple neurobehavioral function tests was lower in children of 8-10 years old who came from a school located in a high traffic exhausts pollution area, as compared to those studying in the other school located in a clear air area (Wang et al. 2009). The schools were chosen based on traffic density and air pollution monitoring data and the authors controlled 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 who were growing up either in Mexico City (a place with high ambient air pollution) or in other areas with substantially cleaner air. In Calderón-Garcidueñas et al. (2008a), the authors found 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 both were found in those who were lifetime residents in Mexico City (n=35), but not in the comparison group (n=12).[6] In another study, Calderón-Garcidueñas et al. 2008b found that children from Mexico City exhibited significant deficits in a combination of fluid and crystallized

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

cognition tasks, as compared to other children from Polotitlán, a city with much lower pollution levels. Fluid cognition is supported by working memory, while crystallized cognition is supported by long-term memory. The fifty-five subjects from Mexico City and the eighteen subjects from Polotitlán were from middle-class families where their mothers had similar average years of formal schooling groups. Brain MRI-measured hyperintense white matter lesions were substantially increased (56.5%) in children from Mexico City (vs. 7.6% in the control city). The white matter lesions may affect cognitive dysfunction and the particulate matter may contribute to the neuroinflammation.

2.2 Pollution and Absenteeism

There are several studies in the economics and epidemiological literature on how pollution affects absenteeism, so we only present the findings of a few here. The first paper in the economics literature is Ransom and Pope (1992), who investigated how PM_{10} affected absenteeism in the Utah Valley between 1985 and 1990. This location and time period provided a "natural experiment" because a steel mill, which was the major polluter in the valley, shut down. They controlled for temperature, snowfall, day of week, month of school year, and days preceding and following holidays and extended weekends. Regression results suggested that "an increase in 28-day moving average PM_{10} equal to 100 micrograms/m3 was associated with an increase in the absence rate equal to approximately two percentage points (p. 210)." [7] This is approximately equal to a 40% increase over the average.

The second paper in the economics literature is Currie et al. (2007), which used the Texas Schools Project, a longitudinal administrative data set on student absenteeism in Texas. They aggregated pollution data from the Texas Commission on Environmental Quality into 6 week time

[7] They do not control for individual covariates in their analysis.

blocks to merge with the administrative absenteeism data. They used school-by-year, school-by-time block, and time block-by-year fixed effects to control for many unobserved characteristics of schools, years and time blocks that would be correlated with test scores and pollution. They identified the effect of pollution by the variation across years within the same six week block for each school. The pollution variables were a set of dummy variables that indicated for each pollutant, whether the maximum was between: (i) 25-50% of the threshold; (ii) 50-75% of the threshold; (iii) 75-100% of the threshold; or (iv) greater than 100% of the threshold. (The omitted category was 0-25% of the threshold.) Their main finding was that maximum CO in the six week period has a positive and significant effect on school absences when it was between 75-100% of the air quality standards threshold and when it exceeded the standard. Ozone was 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. They were not able to investigate $PM_{2.5}$ since it was not available for their study period.

In the epidemiological literature, Gilliland et al. (2001) also used the CHS data (but a different approach) as our present study, to evaluate the effect of pollution on absenteeism. They studied a cohort of 2,081 4th grade students who resided in 12 southern California communities. They tracked the students' absences for the first 6 months of 1996 and followed up with the students' parents to determine if the absence was illness-related or not, and if so, whether it was an upper-respiratory, lower-respiratory, or gastro-intestinal illness. The type of illness was determined by the symptoms described during the phone interview. Using daily pollution from monitors located near the schools, the authors used within-school variation in pollution over the six month period to determine its effect on average daily absences due to respiratory illness. They found that ozone had a statistically significant effect on both upper respiratory and lower respiratory illness rates.

2.3 Asthma and Attention Problems

While there is no work to our knowledge on how air pollution affects behavioral problems, there is related work on the association between asthma and attention or behavioral problems. Since asthma is thought either to be exacerbated or caused by pollution, this literature is relevant for our purposes. First, Butz et al. (1995) obtained demographic, asthma symptom and psychosocial information on children in kindergarten through eighth grade in 42 schools in Baltimore, Maryland. Asthma symptoms were divided into low, medium and high levels, while a child was considered to have behavior problems if she scored higher than a given threshold score in a survey comprised of standardized psychosocial questions. Using logistic regressions and controlling for demographic characteristics, the authors concluded that the parents who reported that their children had higher levels of asthma symptoms were twice as likely to report a behavioral problem as compared to parents who reported lower levels of asthma symptoms.

Bussing et al. (1995) first used responses to the 1988 National Health Interview Survey on Child Health to categorize children into those that suffered from asthma alone, those who suffered from asthma combined with other chronic conditions, those who suffered from other chronic conditions alone or those who had no chronic (including asthmatic) conditions. They then combined this information with the Behavior Problem Index constructed from psychosocial questions in the survey. Using logistic regressions, the authors found that children with severe asthma alone were nearly three times as likely to have severe behavioral problems as children without a chronic condition.

Halterman et al. (2006) investigated 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 found that children with persistent asthma scored worse on peer interactions and task orientation, and were more likely to exhibit shy and anxious behaviors compared to non-asthmatic children.[8]

2.4 Absenteeism and Behavioral Problems on Academic performance

Behavioral problems, including truancy and absenteeism, have been associated with dropping out (Bachman, Green, & Wirtanen, 1971; Segal 2008). Specifically, Segal (2008) used the National Educational Longitudinal Study of 1998 to evaluate how behavioral problems affect academic performance by employing a multinomial logit model to control for race, socioeconomic status, family background, and test scores. She found that maladaptive behavior in the eighth grade was associated with a decrease in the probability that the student graduated from college and an increase in the probability that the student dropped out of high school.

Much of the absenteeism research has focused on performance in postsecondary education. Marburger (2001) showed that students who were absent from class were 9 to 14% more likely to write an incorrect answer to a question related to material covered on the day of their absence than were students who were present.[9] In a more recent article, Marburger (2006) compared the performance of students who attended a college class with a mandatory attendance policy and one without the attendance policy. He found that the attendance policy increased performance by up to 2% on exams.

---

[8] According to the National Heart, Blood and Lung Institute of the National Institutes of Health, 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. For additional information, see pg. 72 of the "Expert Panel Report 3 (EPR3): Guidelines for the Diagnosis and Management of Asthma" available at http://www.nhlbi.nih.gov/guidelines/asthma/04_sec3_comp.pdf.

[9] See also Durden and Ellis (1995) and Romer (1993), cited by Marburger (2001).

2.5 Asthma and Academic performance

As noted above, there is a small literature on the relationship between asthma and academic performance. Fowler, Davenport and Garg (1992) analyzed data for 10,362 children in first through twelfth grade from the 1988 United States National Health Interview Survey. They determined that children with asthma were more likely to have a learning disability than children who did not have asthma. In addition, among households with incomes below $20,000, asthmatic children were twice as likely to fail a grade as those without asthma, but among higher income families, asthmatic children had only a slightly higher failure rate than non-asthmatic children.[10] Second, Halterman et al. (2001) compared the parent-reported development skills of asthmatic children to non-asthmatic children in Rochester, New York in 1998. After controlling for insurance, education of the care-giver, gender, and pre-kindergarten education, the authors found that asthmatic kindergarten-aged children scored lower in school readiness skills (one category of reported development skills), than their non-asthmatic peers.

Finally, Currie et al. (2009), matched school administrative data, social assistance records, and health records for young adults in Manitoba, Canada born between 1979 and 1987. They investigated whether having been treated for asthma, among other childhood diseases, at various ages (0-3, 4-8, 9-13, 14-18) affected (i) performance 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. The authors employed a mother fixed-effect to control for fixed family characteristics, and found (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 found no effect of earlier asthma, conditional on current asthma, on their outcomes of interest.

---

10 This suggests the possibility of heterogeneous asthma effects by socioeconomic status, but we felt we did not have sufficient data to explore this possibility in our analysis.

3. Our Data

We combine several data sources to evaluate the effect of pollution on academic performance. Long-term outdoor air pollution data and family background information come from the Children's Health Study (CHS) described above. Fourth, seventh, and tenth-grade students were originally recruited into the CHS in 1993 from twelve Southern California communities with differing air pollution profiles, and a number of health measurements were collected each school year until high school graduation. Upon graduation of the respective sub-groups from the twelfth grade, additional students (2,081 fourth graders in the 1995/96 school year, and 5,603 kindergarten and first grade students in the 2002/2003 school year) were enrolled into the study. Further, the CHS data set also contains information about community-level air pollution over the study period. Participating schools were selected for inclusion in the data set on the basis of: (i) location in a community of interest with differing pollution profiles; (ii) a sufficient population of study-aged children; (iii) a preponderance of children attending school from the immediate neighborhood; (iv) demographic similarity with other potential and participating community school sites; (v) the absence of localized air pollution sources such as close proximity to factories or freeways; (vi) proximal location to a fixed-site air monitoring station and (vii) the approval of the respective school district to proceed.

We are only able to use part of the CHS data since California test scores were not available until 1998, and then only for grades 2-11. As a result, from the CHS we investigated Cohort C and D students (fourth-graders in 1993 and 1996, respectively) for the years 1998-2002, as well as Cohort E students (kindergarteners and first-graders in 2002) for the years 2004 and 2005.[11] Participants completed annual questionnaires on demographic characteristics, family smoking behavior, and medical history. Annual medical history questionnaires contained questions on

[11] Since Cohort D ends in 2004 when the students graduate from high school, and the standardized test changed in 2003, we did not use the 2003 data.

respiratory symptoms and illnesses while most of the demographic data was only collected at each subject's enrollment into the study.

Continuously operating outdoor air pollution monitoring stations were placed in each of the CHS participating communities. Commercially available and USEPA-approved instrumentation was used to measure ozone (O_3), particulate matter with a diameter of less than 10 microns (PM_{10}), nitrogen dioxide (NO_2), and carbon monoxide (CO) at these locations. A two-week integrated sampler was developed for the CHS study and used to continuously measure particulate matter with a diameter of less than 2.5 microns ($PM_{2.5}$), acid vapors, and PM chemical constituents. For the current study, we focus on annual community averages of NO_2, O_3, PM_{10}, and $PM_{2.5}$, because they have been shown in previous studies to have negative effects on health and school absences and were measured consistently throughout the study period. Unlike the papers on absenteeism, our use of the CHS allows us to investigate $PM_{2.5}$. Currie et al. (2007) found that CO was associated with school absenteeism, but unfortunately, CO is unavailable for several periods in several CHS towns.

PM_{10} (often considered a marker of coarse particles) and $PM_{2.5,}$ (often considered a marker for fine particles) can be emitted directly from primary sources (such as combustion or vehicle exhaust or from entrained road or construction dust) or can be formed through a series of secondary photochemical reactions of airborne gaseous compounds and particulate matter. Particle diameter has been shown to be related to physical deposition in the lungs, with smaller particles generally thought to be of greater health concern.[12] PM_{10} and $PM_{2.5}$ have been associated with: mortality (Peng et al. 2005; Stieb, Judek, and Burnett 2002): pulmonary disease (Pope and Dockery 2006); allergic immune responses (Russell and Brunekreef 2009); asthma (Yu et al. 2000); lung development (Gauderman et al. 2004) and an increased incidence of cardiovascular disease (Grahame and Schlesinger 2007). NO_2 is a by-product of combustion exhaust (from vehicles,

[12] See "Particulate Matter" at http://www.epa.gov/particles/basic.html/.

boilers, or any combustion source). Gauderman et al. (2005) found that the incidence of asthma and wheezing in *all* children is associated with higher outdoor NO_2, while Shima and Adachi (2000) only obtained this result for female schoolchildren. Finally, Gauderman et al. (2004) found a negative association between NO_2 and lung development.

Ozone is formed in outdoor air when sunlight provides sufficient photochemical energy to drive reactions of oxygen with a number of gaseous pollutants.[13] McConnell et al. (2002) demonstrated that children who lived in high ozone areas and play sports outdoors were more likely to be diagnosed with asthma during the study period than those who did not play sports, while in the low ozone areas there was no difference in asthma rates between children who played sports and those who did not. Their result supports the hypothesis that the extra exposure to ozone in the high ozone areas causes either the onset of asthma or the earlier onset of asthma.

From the CHS data we construct average demographic information at the grade-school-year level for the CHS students, and then use these averages as proxies for averages of the demographic variables for *all* students in the grade at that school. Next we merge this data from CHS with publically available test score data, as well as other publically available information on the characteristics of the school at the school-year level (e.g., the percent of students receiving a free lunch, and the pupil-teacher ratio) and at the grade-school-year level (e.g., racial breakdown of the class).[14] We use the demographic data from CHS, as well as the publically available school data, to minimize bias in our pollution effects arising from time-changing omitted variables at the grade-school level, which may be correlated with pollution and not captured by the school and year dummies.

[13] Environmental Protection Agency, 1999."Smog—Who Does It Hurt? What You Need to Know About Ozone and Your Health."EPA-452/K-99-001 Available at http://www.epa.gov/airnow//health/smog.pdf .
[14] These additional data are from the California Department of Education.

Finally, we include data on the unemployment rate in each city in each year from the California Employment Development Departments' local area unemployment data.[15] We include the unemployment rate to control for several factors. Increased unemployment may create added stress for students through an increased probability that a parent will become unemployed, which could lower test scores. In addition, unemployment reduces family income, which again could lower test scores.

Our outcome measures are the math and reading comprehension scores at the grade-school-year level. After 1998, California school districts were required to test all students in the second through eleventh grades. The scores from 1998-2002 are from the Stanford Achievement Test, ninth edition (Stanford 9) administered each spring in California. The Stanford 9 is a multiple-choice test where scores are based on comparisons to a national sample of students. The test scores are adjusted so that mean scaled scores across years for a cohort (e.g., fifth grade in 1999 to sixth grade in 2000) are comparable. Starting in 2003, the State Board of Education replaced the Stanford 9 exam with the California Achievement Tests, Sixth Edition Survey (CAT/6). Like the Stanford 9, the CAT/6 is a national norm-referenced achievement test, but it is shorter in length than the Stanford 9.[16] Thus for 2004 and 2005 we use test scores from the CAT/6 and include a dummy variable for when this test was used. We focus on the reading comprehension and mathematics portions of the exam. Reading comprehension is part of the Language Arts section of the CAT/6, but was its own section of the Stanford 9. Reading comprehension scores, however, were reported separately from the rest of Language Arts in CAT/6, and thus we have these scores for our entire sample period.

---

[15] Since the unemployment rate for Lake Gregory was not available, the unemployment rate for Crestline was used there instead. In the CHS, study students were enrolled and studied from both these adjacent communities and combined as one community.
[16] We use the CAT/6 instead of the (also publicly available) California Standardized Test (CST) because the norm-referencing of the CAT/6 is most similar to the Stanford 9.

4. Empirical Specification

Our basic model is

$$(1)\quad T_{gstl} = \beta_1 P_{st} + \beta_2 X_{gst} + \beta_3 Z_{gst} + \beta_4 U_{st} + f_s + \gamma Y_{cat} + \varepsilon_{gstl},$$

where T_{gstl} represents the respective California Standards test scores in grade *g* at school s in year t for test l. Further, in (1) P_{st} represents various measures of pollution for school s in year t,[17] X_{gst} denotes time-changing family background characteristics of the students by grade from CHS (i.e. not available from public data), Z_{gst} denotes time-changing school characteristics from publicly available data, U_{st} denotes the city unemployment rate in year t, f_s denotes a school fixed effect, Y_{cat} is a dummy variable for the new test used in 2004 and 2005 and ε_{gstl} is an error term assumed to be correlated across schools in the same community for all time periods.[18] In our second specification we use a full set of year dummies denoted by Y_t in year *t:*

$$(2)\quad T_{gstl} = \beta_1 P_{st} + \beta_2 X_{gst} + \beta_3 Z_{gst} + \beta_4 U_{st} + f_s + \delta_t Y_t + \varepsilon_{gstl}.$$

The school fixed effect is used to address, at least partially, the concern that a spurious correlation between pollution and achievement might exist due to a tendency for low-income Americans to locate in highly polluted areas because of lower rents; on average, student test score achievement increases with parental income (Duncan et al. 1994, Hanushek 1992; and Korenman 1995). However, the school fixed effect only takes care of sorting based on time-constant factors, and will not control for time-varying factors that affect residential location decisions. Thus, in (2) we

[17] The data collection process required that we assume that pollution was the same for all schools in a given community in a given year.
[18] As noted above some of the school characteristics included in Z_{gst} are only reported at the school level. To keep the subscripts manageable, we do not distinguish these in the equations.

use dummies for each year to capture unobserved sample-wide effects in each year.[19] Of course, neither school nor time dummies capture unobserved time-changing factors at the grade-school-year level, which motivates our use of grade-school-year data.

As noted above, we focus on the impact of annual average community pollution measures NO_2, O_3, $PM_{10,}$ and $PM_{2.5}$ based on previous research findings and data availability. Thus we are we are identifying the effect of pollution on school test scores by the variation in community pollution over time. Previous work has shown that NO_2, PM_{10} and $PM_{2.5}$ are highly inter-correlated, while ozone is much less correlated with these pollution measures – the correlation rates for the pollution measures are presented in Table 1 and these results confirm the previous findings. Given these high correlations, one might suspect that it would be difficult to separately identify the effect of a given pollution variable, holding the others constant, and, indeed, that is what we found. Thus, we present results for pollution by entering the variables one at a time, but for completeness we also include the results using all pollutants simultaneously as explanatory variables. We do not focus on the latter results since we would expect that the correlation structure in the pollution variables would create a multicollinearity problem that will make it difficult to identify specific coefficients.

In terms of the individual level data, we calculate the means for students in the CHS data in year t at school s for grade g, for the following variables: the responding parent's education; the fraction of children whose parents smoked;[20] the fraction of children who had public health insurance; and the fraction of children who had no health insurance.[21] We divide parental education into dummy variables for those who graduated from high school, attended some college, graduated from college, and attended graduate school (with the control group being those who had less than a

[19] The year dummies eliminate the need to use the test change dummy since it is perfectly collinear with the year dummies.
[20] For Cohorts C and D, parental smoking is equal to one if the person who completed the questionnaire smoked. For Cohort E, parental smoking is equal to one if the mother or the father smoked.
[21] In making this calculation, we need to ignore the possibility of a student failing a grade.

high school degree).[22] As noted above, we use these variables to minimize omitted-variable-bias in the pollution coefficient estimates.[23]

We use the following variables available through the California Department of Education (CDE) at the school-year level: pupil-teacher ratio, the percent of staff that have masters or doctoral degrees and the percent of students who received free lunches for each school s in year t as well as the ethnic breakdown of students in each grade g at school s in year t. Finally, we include a dummy variable for years after the change in the test (when we do not use year dummies) and the community unemployment rate as conditioning variables. Further, in *some specifications* we use year dummy variables. By controlling for school demographics and quality from the CDE and CHS data, published community unemployment rates, as well as school dummies and year dummies (in our most general specifications), we believe that we control for many of the potentially confounding factors in our analysis.

Our data set consists of 229 grade-school-year observations covering 88 schools. Summary statistics for the grade-school-year observations are presented in Table 2. Considering variables from the CHS data set, about 65% of the students in each grade had private insurance, 21% had Medicaid, and the remaining 14% did not have insurance. Moreover, about 13% of the parents reported that they smoked, and 16% of the subjects came from a single-parent household. Further, 16% of parents had less than a high school degree, 20% had a high school degree, 42% had some college, 11% had a college degree, and 11% had more than a college degree. In terms of the publicly available information on schools, about 29% of students received a free lunch, about 45% of teachers had an MA or PhD, and the average pupil-teacher ratio was around 20:1. Moreover, 8% of the students self-reported being Black, 56% reported being White non-Hispanic, and 36% reported

[22] These variables are only measured at the base year, but will change over time in a given grade and school as students progress through the school.

[23] Given that they will being noisy estimates of the true values for the grade-school-year observation, the coefficients on these variables will be inconsistent because of measurement error.

being Hispanic.[24] We note that the minimum and maximum statistics indicate a wide range in all of these variables across grade-school-year observations. Since we would expect most or all of these variables to affect school test scores, and it is plausible that some or all of them might affect location decisions and thus exposure to pollution, we believe it is crucial to control for such factors.

4. Empirical Results

We first consider the case where we omit a full set of year dummies. For this case we have placed the results for the math test scores in Table 3A and the results for reading scores in Table 3B. In each set of results we cluster the standard errors by city to allow for arbitrary forms of heteroskedacticity and dependence across observations on schools in a given community at a point in time as well as over time.

Considering the results for the math scores in Table 3A, in column (1) we include all four pollution measures simultaneously. A Wald test indicates that the estimated pollution coefficients are jointly significant[25], and all except the coefficient for O_3 have the expected negative signs. However, $PM_{2.5}$ is the only pollution measure in column (1) that is individually statistically significant at standard confidence levels, indicating that the multicollinearity issue, as suggested by the high correlations in Table 1, is indeed a problem. Next, we enter the pollution measures individually in columns (2) - (5) of Table 3A. We find that when used as the only pollution measure, PM_{10}, $PM_{2.5}$, and NO_2 are statistically significant; the coefficient on O_3 continues to have an unexpected positive sign, but is far from attaining statistical significance.

To assess the magnitude of the effects implied by the coefficients, note first that a one-standard-deviation increase in PM_{10}, $PM_{2.5}$, or NO_2 would decrease test scores by 8.99, 26.72, or

[24] We group students who self-reported as Asian, Pacific Islander, Native American or other in the White non-Hispanic category.
[25] We use a Wald test since the error terms are assumed to not be independent or homoskedastic; an F-Test for the joint significance would be inappropriate since the errors are not assumed independent or homoskedastic.

18.45 points, respectively, out of 999 possible points.[26] The standard deviation in $PM_{2.5}$ is 5.88 μg/m3. and the annual average concentration of $PM_{2.5}$ in the South Coast Air Basin dropped by approximately 11 μg/m3 between 1999 and 2006. The standard deviations for PM_{10} and NO_2 are 12.27 and 9.14, respectively. For this same time period and location, the (statewide) annual average for concentrations of PM_{10} and NO_2 dropped by about 22 μg/mg and 19 ppb respectively.[27] For those less familiar with the units used for pollution measures, we also calculate the relevant elasticities and find that a 1% increase in PM_{10}, $PM_{2.5}$, or NO_2 would decrease math test scores by 0.036%, 0.088%, or 0.059%, respectively.

Our results for the reading scores (when we do not use a full set of year dummies) appear in columns (1) - (5) of Table 3B. In column (1), we again include all four pollution measures. As in the case of the math scores, $PM_{2.5}$ is the only pollution measure that is individually statistically significant. A Wald test indicates that the four pollution measures are jointly significant at the 10 percent level, and the coefficient on O_3 has an unexpected positive sign, but is very insignificant. In columns (2) - (5), we show the results of entering the pollution measures individually, and again as in the case of the math scores, all the pollution variables, except O_3, have the expected sign. However, in contrast to our results for the math scores, only $PM_{2.5}$ is statistically significant. In terms of the size of the $PM_{2.5}$ coefficient, a one-standard-deviation increase in $PM_{2.5}$ would decrease reading test scores by 4.26 points and a 1% increase in $PM_{2.5}$ would decrease reading test scores by 0.014%. Note that the effect of an increase in $PM_{2.5}$ on math scores is over six times as large as the effect of the same increase on reading scores.

We next consider the case when we include time dummies. We have placed the results for math and reading scores in Tables 4A and 4B, respectively. In column (1) of Table 4A, we again

---

[26] The CAT/6 is on a scale of 0 to 999 while the Stanford 9 was on a scale of 200 to 900. Therefore we subtracted 200 from the Stanford 9 scores and multiplied the remaining number by 1.427.

[27] For additional statistics on the trends, see chapters 3 and 4 of The California Almanac of Emissions and Air Quality– 2009 edition.

enter the pollution variables simultaneously. As in the case in column (1) of Table 3A, the Wald test indicates that the pollution coefficients are still jointly significant, only O_3 has an unexpected positive sign, and only $PM_{2.5}$ is individually statistically significant. When we enter the pollutants separately in columns (2) - (5), again as in Table 3A, $PM_{2.5}$, PM_{10} and NO_2 are individually significant with the expected signs, while O_3 has an unexpected positive sign but remains insignificant. Thus the results in Tables 3A and 4A are qualitatively very similar; however, they are not quantitatively similar, as now a one-standard-deviation increase in $PM_{2.5}$, PM_{10} or NO_2 would decrease test scores by 3.89, 10.23, or 5.53 points, respectively. In terms of elasticities, a 1% increase in PM_{10}, $PM_{2.5}$, or NO_2 would decrease math test scores by 0.015%, 0.034%, or 0.018%, respectively. Note that these estimated impacts are substantially smaller than those implied by Table 3A, but the largest effect is still associated with $PM_{2.5}$, illustrating the importance of having data on $PM_{2.5}$ for studying this problem. These effects are still substantial, especially for $PM_{2.5}$. For example a reasonable estimate of the difference in math test scores between high-income and low-income eighth graders is only about 10% (Barton and Coley 2009). To gain some intuition on the importance of these effects, our results imply that if it were possible to decrease $PM_{2.5}$ by 10% for low-income, but not high-income children, nearly one-thirtieth of this difference in eight grade math scores between the groups would be eliminated.

In Table 4B we show the effects of including year dummies in our specification for reading scores. Again column (1) shows the results of entering all four pollution measures simultaneously; similarly to column (1) of Table 3B, $PM_{2.5}$ is statistically significant with the appropriate sign. Among the remaining pollution variables, PM_{10} has the expected sign but NO_2 and O_3 do not. In this case the pollution variables are not jointly significant at standard test levels. As in table 3B, when we enter the pollution variables separately, $PM_{2.5}$ is the only individual pollutant that has a statistically significant coefficient with the expected sign. $PM_{10,}$ $NO_{2,}$ and O_3 are statistically insignificant, and the PM_{10} coefficient continues to have the expected negative sign while O_3 does not. However, now NO_2 also has an unexpected positive sign. Thus the only qualitative difference between Tables 3B and 4B is the positive (but still insignificant) coefficient on NO_2. Now a one-standard-deviation increase in $PM_{2.5}$ is predicted to decrease test scores by 6.51 points; in terms of elasticity, a 1% increase in $PM_{2.5}$ would change reading test scores by -0.021%. Given that a reasonable estimated difference in reading scores between high and low income eighth grade students is 9.3%, to reduce this gap by one-thirtieth one would need to reduce $PM_{2.5}$ by about 14% for low income, but not high income, students. Given these results, we conclude that results for reading test scores change quantitatively, but not qualitatively, when we use a full set of year dummies.

Of course one must choose whether to focus on the quantitative results generated from the specification that excludes a full set of year dummies or the specification that includes them. The benefit of including a full set of year dummies is that it allows one to control for the possibility of general unobserved time effects in test scores that are potentially correlated with pollution measures and not captured by our control variables. The potential cost of using year dummies is that if they are not needed, one is losing efficiency in terms of obtaining bigger standard errors. In other words, if we do not need a full set of year dummies, we would expect the coefficients to not change much between Tables 3A and 4A, and between Tables 3B and 4B, but that the standard errors should be larger in Tables 4A and 4B. However, this is not what happens. While the estimates without time dummies are qualitatively similar to those with time dummies, we see a considerable change between the coefficients in Table 3A and 3B and the respective entries in Tables 4A and 4B; moreover the standard errors with time dummies are often smaller than the respective standard errors without time dummies.[28] From these results it seems clear that the time dummy variables are indeed picking up unobserved factors correlated with the pollution measures and test scores, in spite of the fact that we have a large number of time changing control variables.

5. Conclusion

In this study, we examine the effects of four common and nationally-regulated outdoor air pollutants (PM_{10}, $PM_{2.5}$, NO_2 and O_3) on math and reading test scores. After controlling for a large number of possibly confounding factors using demographic variables, school dummies, and year dummies, we find that higher levels of $PM_{2.5}$ (a marker for fine particulate matter), PM_{10} (a marker for coarse particulate matter), and NO_2 consistently lower math scores, with $PM_{2.5}$ having the largest effect. Further, we find that higher levels of $PM_{2.5}$ consistently reduce reading test scores.

The results suggest a sizable effect of pollution on academic performance, which provides evidence of another avenue by which pollution is harmful. Not only is it bad for children's health, but it also impacts negatively on students' performance in school and their ability in general, which we would expect to reduce future labor earnings. Since lower socioeconomic households tend to reside in more highly polluted areas, our results suggest that a decrease in pollution will result in a decrease in inequality, everything else held equal. This effect will be accentuated by Fowler, Davenport and Garg (1992)'s finding that asthma has worse consequences for low income children than for high income children. Our results also identify some important methodological points. If quantitative effects, rather than qualitative effects, are of interest, it is important to include a full set of year dummies. Second, having monitoring data for $PM_{2.5}$ is crucial to our analysis; without it, we would have underestimated the effect of pollution on test scores.

[28] One could formally test whether, e.g., the coefficients in Table 3A and the respective coefficients in Table 4A are statistically different. One cannot use the formula in Hausman (1978) since neither set of estimates is efficient, but one could use the bootstrap to calculate appropriate standard errors for the difference in the coefficients. We do not follow this path since, *a priori,* there seems to be no reason to use the coefficients obtained without a full set of time dummies.

Of course, there are several limitations to our study that we should mention. First, while we control for a large number of possibly confounding factors, there is always the possibility that our results are biased by remaining unobserved factors correlated with pollution and test scores. Second, we assumed that pollution levels were the same at each school within a given community, since we used data from the regional air monitoring station located within that respective community. However, in most communities, there can be substantial variability in local pollution levels due to proximity to busy roadways, local sources, local topology, and meteorological factors. Thus it would clearly be desirable to obtain pollution levels by school. Third, it would be preferable to link individual test scores to individual factors, but given current confidentiality restrictions, it does not seem feasible to obtain such disaggregated data. A final limitation of our study is the lack of data on CO. Since other studies have found CO to have adverse health effects and be linked to absenteeism, it is an important pollutant to study the effect of CO when controlling for $PM_{2.5}$ and vice-versa.

References

Barton, P. and R.J. Coley 2009. "Parsing the Achievement Gap." Educational Testing Service Policy and Research Reports, p. 5. Available at http://www.ets.org/.

Lochner, L., and Belley, B 2007. "The Changing Role of Family Income and Ability in Determining Educational Achievement," *Journal of Human Capital* 1: 37-89.

Bussing, R., Halfon N., Benjamin, B., and K.B. Wells 1995. "Prevalence of Behavior Problems in US Children with Asthma." *Archives of Pediatric Adolescent Medicine* 149: 565–572

Bachman, J.G., Green, S., and I.D. Wirtanen 1971. *Dropping out: Problem or symptom?* Ann Arbor: Institute for Social Research, University of Michigan.

Butz, A.M., Malveaux F.J., Eggleston, P., Thompson, L., Huss, K., Kolodner, K., and C.S. Rand 1995. "Social Factors Associated with Behavioral Problems in Children with Asthma." *Clinical Pediatrics* 34: 581-590.

California Achievement Test, 6th Edition, Research Files. Standardized Testing and Reporting (STAR) Program. 2004-2005. California Department of Education. Available at http://star.cde.ca.gov/.

"The California Almanac of Emissions and Air Quality - 2009 Edition." Available at http://www.arb.ca.gov/aqd/almanac/almanac09/almanac09.htm.

Calderón-Garcidueñas, L., Solt, A.C., Henríquez-Roldán, C., Torres-Jardón, R., Nuse, B., Herritt, L., Villarreal-Calderón, R., Osnaya, N., Stone, I., García, R., Brooks, D.M., González-Maciel, A., Reynoso-Robles, R., Delgado-Chávez, R., and W. Reed 2008a. "Long-term Air Pollution Exposure is Associated with Neuroinflammation, an Altered Innate Immune Response, Disruption of the Blood-brain Barrier, Ultrafine Particulate Deposition, and Accumulation of Amyloid beta-42 and Alpha-synuclein in Children and Young Adults." *Toxicologic Pathology* 36: 289-310.

Calderón-Garcidueñas, L., Mora-Tiscareño, A., Ontiveros, E., Gómez-Garza, G., Barragán-Mejía, G., Broadway, J., Chapman, S., Valencia-Salazar, G., Jewells, V., Maronpot, R.R., Henríquez-Roldán, C., Pérez-Guillé, B., Torres-Jardón, R., Herrit, L., Brooks, D., Osnaya-Brizuela, N., Monroy, M.E., González-Maciel, A., Reynoso-Robles, R., Villarreal-Calderon, R., Solt, A.C., and R.W. Engle 2008b. "Air Pollution, Cognitive Deficits and Brain Abnormalities: A Pilot Study with Children and Dogs." *Brain Cognition* 68: 117-127.

California Basic Educational Data System (CBEDS) School Enrollment and Staffing Data Files. 1998-2005. California Department of Education. Available at http://www.cde.ca.gov/ds/sd/cb/studentdatafiles.asp.

Cameron, S., and J.J. Heckman 2001. "The Dynamics of Educational Attainment for Black, Hispanic and White Males." *The Journal of Political Economy* 109: 455-499.

Chay, K. and M. Greenstone 2003a. "Air Quality, Infant Mortality, and the Clean Air Act of 1970." NBER Working Paper #10053.

Chay, K. and M. Greenstone 2003b. "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession." *Quarterly Journal of Economics* 118: 1121-1167.

Currie, J. and Neidell, M. 2005. "Air Pollution and Infant Health: What if We Can Learn From California's Recent Experience?" *Quarterly Journal of Economics* 120: 1003-1030.

Currie, J., Stabile, M., Manivong, P., and L. Roos 2009. "Child Health and Young Adult Outcomes." Forthcoming in *Journal of Human Resources.*

Currie, J., Hanushek, E., Kahn, M., Neidell, M., and S. Rivkin 2007. "Does Pollution Increase School Absences?" Forthcoming in *Review of Economics and Statistics.* Previously National Bureau of Economic Research Working Paper 13252. Available at http://www.nber.org/papers/w13252.

Duncan, G., Brooks-Gunn, J. and P. Klebanov 1994. "Economic Deprivation and Early Childhood Development." *Child Development* 65: 296–318.

Durden, G., and L. Ellis 1995. "The effects of Attendance on Student Learning in Principles of Economics." *American Economic Review Papers and Proceedings* 85: 343-46.

Environmental Protection Agency 1999. "Smog—Who Does It Hurt? What You Need to Know About Ozone and Your Health." EPA-452/K-99-001. Available at http://www.epa.gov/airnow//health/smog.pdf.

Fowler M.G., Davenport, M.G., and R. Garg 1992. "School Functioning of US Children with Asthma." *Pediatrics* 90: 939–44.

Free and Reduced Price Meals/CalWORKS - School Level Files. 1998-2005. California Department of Education. Available at http://www.cde.ca.gov/ds/sh/cw/filesafdc.asp.

Gauderman, J., McConnell, R., Gilliland, F., London, S., Thomas, D., Avol, E., Vora, H., Berhane, K., Rappport, E., Lurmann, F., Margolis, H., and J. Peters 2000. "Association Between Air Pollution and Lung Function Growth in Southern California." *American Journal of Respiratory Critical Care Medicine* 62: 1383-1390.

Gauderman, J. Avol, E., Gilliland, F., Vora, H., Thomas, D., Berhane, K., McConnell, R., Kuenzli, N., Lurmann, F., Rappaport, E., Margolis, H., Bates, D., and J. Peters 2004. "The Effect of Air Pollution on Lung Development from 10 to 18 years of Age." *New England Journal of Medicine* 351: 1057-1067.

Gauderman, J., Avol, E., Lurmann, F., Kuenzli, N., Gilliland, F., Peters, J. and R. McConnell 2005. "Childhood Asthma and Exposure to Traffic and Nitrogen Dioxide." *Epidemiology* 16: 737-743.

Gilliland, F., Berhane, K., Rappaport, E., Thomas, D., Avol, E., Gauderman, J. London, S., Margolis, H., Islam, K. and J. Peters 2001. "The Effects of Ambient Air Pollution on School Absenteeism Due to Respiratory Illness." *Epidemiology* 12: 43-54.

Grahame, T.J., and R.B. Schlesinger 2007. "Health Effects of Airborne Particulate Matter: Do we Know Enough to Consider Regulating Specific Particle Types or Sources?" *Inhalation Toxicology* 19: 457-481.

Halterman, J., Conn, K., Forbes-Jones, E., Fagnano, M., Hightower, A., and P. Szilagyi 2006. "Behavior Problems Among Inner-City Children With Asthma: Findings From a Community-Based Sample." *Pediatrics* 117: e192-e199.

Halterman, J., Montes, G., Aligne, A., Kaczorowski, J., Hightower, A., P. Szilagyi 2001. "School Readiness among Urban Children with Asthma." *Ambulatory Pediatrics* 1: 201–05.

Hanushek, E.A. 1992. "The Tradeoff between Child Quantity and Quality." *Journal of Political Economy* 100: 84–117.

Hausman, J. 1978. "Specification Tests in Econometrics." *Econometrica* 46: 1251-71.

Korenman, S., Miller, J., and J.E. Sjaastad, 1995. "Long-Term Poverty and Child Development in the United States: Results from the NLSY." *Child and Youth Service Review* 17: 127-155.

Marburger, D. R. 2001. "Absenteeism and Undergraduate Exam Performance." *Journal of Economic Education* 32: 99-109.

Marburger, D. R. 2006. "Does Mandatory Attendance Improve Student Performance?" *Journal of Economic Education* 37: 148-155.

McConnell, R., Berhane, K., Gilliland, F., Islam T., Gauderman, W.J., Avol, E., Margolis, H., and J. Peters 2002. "Asthma in Exercising Children Exposed to Ozone: a Cohort Study." *Lancet* 359: 386-91.

McConnell, R., Berhane, K., Gilliland, F., Molitor, J., Thomas, D., Lurmann, F., Avol, E., Gauderman. W., and J. Peters 2003. "Prospective Study of Air Pollution and Bronchitic Symptoms in Children with Asthma." *American Journal of Respiratory and Critical Care Medicine* 168: 790-797.

Murnane, R., Willett, J. and F. Levy 1995. "The Growing Importance of Cognitive Skills in Wage Determination," *Review of Economics and Statistics* 77: 251–266.

Johnson, W. and D. Neal 1995. "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy* 104: 869-95.

National Heart Lung and Blood Institute, National Institutes of Health 2007. "Expert Panel Report 3 (EPR3): Guidelines for the Diagnosis and Management of Asthma" NIH 08-4051, National Institutes of Health. available at http://www.nhlbi.nih.gov/guidelines/asthma/04_sec3_comp.pdf.

"Particulate Matter." Environmental Protection Agency. 2009. Available at http://www.epa.gov/particles/index.html.

Peng, R.D., Dominici, F., Pastor-Barriuso, R., Zeger , S.L, and J.M. Samet 2005. "Seasonal Analyses of Air Pollution and Mortality in 100 U.S. Cities." *American Journal of Epidemiology* 161: 585-594.

Perera, F.P., Li, Z., Whyatt, R., Hoepner, L., Wang, S., Camann, D. and V. Rauh 2009. "Prenatal Airborne Polycyclic Aromatic Hydrocarbon Exposure and Child IQ at Age 5 years." *Pediatrics* 124: e195-202.

Peters, J., Avol, E., Navidi, W., London, S., Gauderman, W., Lurmann, F., Linn, W., Margolis, H., Rappaport, E., Gong, H. Jr., and D. Thomas 1999. "A Study of Twelve Southern California Communities with Differing levels and types of Air Pollution." *American Journal of Respiratory Critical Care Medicine* 159: 760-767.

Peters, J. 2004. "Epidemiological Investigation to Identify Chronic Effects of Ambient Air Pollutants in Southern California." Prepared for the California Air Resources Board and the California Environmental Protection Agency Contract No. 94-331.

Pope, C.A. and D.W. Dockery 2006. "Health effects of fine particulate air pollution: Lines that connect." *Journal of the Air and Waste Management Association* 54: 709-742.

Rabinovitch, N., Strand, M. and E. Gelfand 2006. "Particulate Levels are Associated with Early Asthma Worsening in Children with Persistent Disease." *American Journal of Respiratory Critical Care Medicine* 173: 1098–1105.

Ransom, M. and C. Pope 1992. "Elementary School Absences and PM_{10} Pollution in Utah Valley." *Environmental Research* 58: 204-219.

Romer, D. 1993. "Do Students Go to Class? Should They?" *Journal of Economic Perspectives* 7: 167-174.

Russell, A.G. and B. Brunekreef 2009. "A Focus on Particulate Matter and Health." *Environmental Science and Technology* 43: 4620-4625.

Segal, C. 2008. "Classroom Behavior." *Journal of Human Resources* 43: 783-814.

Shima, M. and M. Adachi 2000. "Effect of Outdoor and Indoor Nitrogen Dioxide on Respiratory Symptoms in Schoolchildren." *International Journal of Epidemiology* 29: 862–870.

Srám, R.J., Benes, I., Binková, B., Dejmek, J., Horstman, D., Kotěsovec, F., Otto, D., Perreault, S.D., Rubes, J., Selevan, S.G., Skalík, I., Stevens, R.K., and J. Lewtas 1996. "Teplice program--the impact of Air Pollution on Human Health." *Environmental Health Perspectives* 104 Suppl 4: 699-671.

Stanford Achievement Test, Ninth Edition, Research Files. Standardized Testing and Reporting (STAR) Program. 1998-2002. California Department of Education. Available at http://star.cde.ca.gov/.

Stieb, D.M., Judek, S., and R.T. Burnett 2002. "Meta-analysis of Time-series Studies of Air Pollution and Mortality: Effects of Gases and Particles and the Influence of Cause of Death, Age, and Season." *Journal of the Air and Waste Management Association* 52:470-484.

Sub-County Areas Labor Force and Unemployment Data. California Employment Development Department. Available at http://www.labormarketinfo.edd.ca.gov/cgi/dataanalysis.

Suglia, S.F., Gryparis, A., Wright, R.O., Schwartz, J., and R.J. Wright 2008. "Association of Black Carbon with Cognition among Children in a Prospective Birth Cohort Study." *American Journal of Epidemiology*167: 280-286.

Wang, S.Q., Zhang, J.L., Zeng, X.D., Zeng, Y.M., Wang, S.C., and S.Y. Chen 2009. "Association of Traffic-Related Air Pollution with Children's Neurobehavioral Functions in Quanzhou, China." *Environmental Health Perspectives* 117:1612–1618.

Yu, O., Sheppard, L., Lumley, T., Koenig, J., and G. Shapiro 2000. "Effects of Ambient Air Pollution on Symptoms of Asthma in Seattle-Area Children Enrolled in the CAMP Study." *Environmental Health Perspectives* 108: 1209-1214.

Table 1: Correlation across Pollution Variables

	PM_{10}	$PM_{2.5}$	O_3	NO_2
PM_{10}	1			
$PM_{2.5}$	0.88	1		
O_3	0.28	0.25	1	
NO_2	0.65	0.83	0.09	1

Table 2: Descriptive Statistics by Grade-School-Year

Variable	Mean	Std. Dev.	Min	Max
A. Student and School Dummy Variables:				
Parent's Education (%):				
< high school graduate	16.47	14.44	0.00	66.13
high school graduate	19.77	8.68	0.00	60.00
some college	41.63	12.21	11.43	70.00
college graduate	11.21	7.29	0.00	32.53
graduate school	10.92	8.06	0.00	30.36
Parent smokes (%)	13.28	6.60	0.00	36.36
Insurance (%):				
no insurance	13.76	10.05	0.00	58.33
medicaid	21.02	15.96	0.00	72.73
private insurance	65.22	16.66	18.18	96.00
Grade Characteristics (%):				
hispanic	36.30	22.30	6.00	95.92
black	7.51	8.16	0.00	38.76
white	56.18	23.16	30.52	90.32
School Characteristics:				
students who receive a free lunch (%)	28.67	18.98	0.00	93.12
staff with a MA or PHD (%)	45.39	14.43	0.00	79.00
pupil-teacher ratio	20.55	5.41	7.45	43.44
B. Community Characteristic:				
Unemployment rate	5.81	1.84	2.60	9.70
C. Pollution:				
PM_{10}	31.98	12.27	12.01	78.25
$PM_{2.5}$	12.70	5.88	4.72	28.85
NO_2	19.20	9.14	2.69	39.46
O_3	53.38	11.28	32.41	78.26
D. Test Scores:				
Mathematics mean scaled score	659.20	53.08	536.00	739.97
Reading mean scaled score	665.01	43.61	570.30	739.12

Note: Descriptive statistics are for the 229 grade-school-year observations.

Table 3A: The Effect of Pollution on Mathematics Test Scores
School Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Pollution:					
PM_{10}	-0.329	-0.733[d]			
	(0.28)	(0.34)			
$PM_{2.5}$	-4.050[c]		-4.546[c]		
	(0.87)		(0.98)		
NO_2	-0.841			-2.018[c]	
	(0.77)			(0.67)	
O_3	0.363				0.269
	(0.45)				(0.38)
Wald Statistic for Joint Significance[a]	40.07				
Personal Characteristics:					
Age	14.33[c]	17.19[c]	14.13[c]	17.62[c]	18.01[c]
	(1.17)	(0.98)	(1.31)	(1.45)	(1.40)
Parent's Education (%):					
high school graduate	0.438	0.303	0.355	0.163	0.215
	(0.31)	(0.34)	(0.30)	(0.32)	(0.38)
some college	0.772[c]	0.558[d]	0.761[c]	0.427	0.407
	(0.23)	(0.25)	(0.25)	(0.28)	(0.27)
college graduate	0.590[d]	0.292	0.594[e]	0.227	0.237
	(0.26)	(0.25)	(0.31)	(0.27)	(0.26)
graduate school	-0.102	-0.446	-0.101	-0.401	-0.587
	(0.42)	(0.43)	(0.45)	(0.42)	(0.45)
Parent smokes (%)	-0.299	-0.202	-0.283	-0.170	-0.282
	(0.39)	(0.38)	(0.41)	(0.35)	(0.38)
Insurance (%):					
medicaid	-0.092	-0.113	-0.078	-0.112	-0.122
	(0.11)	(0.13)	(0.12)	(0.11)	(0.14)
no insurance	-0.178	-0.279	-0.183	-0.047	-0.176
	(0.17)	(0.16)	(0.18)	(0.21)	(0.17)
School Characteristics:					
free lunch (%)	-0.358	-0.370	-0.306	-0.105	-0.163
	(0.42)	(0.47)	(0.39)	(0.41)	(0.44)
pupil-teacher ratio	0.366	0.537[e]	0.386	0.433	0.481
	(0.32)	(0.29)	(0.32)	(0.35)	(0.31)
staff w/MA or PhD (%)	0.001	0.000	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Grade Characteristics (%):					
hispanic	0.348	0.393	0.376	0.370	0.375
	(0.25)	(0.29)	(0.26)	(0.25)	(0.28)
black	0.203	0.251	0.224	0.210	0.222
	(0.25)	(0.30)	(0.29)	(0.33)	(0.33)
Unemployment Rate	-7.491[c]	-6.915[c]	-6.879[c]	-5.853[c]	-6.058[c]
	(1.72)	(1.63)	(1.94)	(1.60)	(1.54)
Test Change	-39.79[c]	-16.45[d]	-40.70[c]	-28.04[c]	-17.59[d]
	(8.63)	(7.71)	(7.22)	(7.17)	(6.51)
Constant	547.358[c]	482.753[c]	545.510[c]	485.359[c]	433.687[c]
	(56.31)	(40.37)	(44.07)	(44.94)	(60.73)
School Dummies	Y	Y	Y	Y	Y
Year Dummies	N	N	N	N	N
Observations	216	222	220	226	229
Number of Schools	88	88	88	88	88

Notes:

a. The critical values of the Wald test statistic at the .05 and .10 levels are 9.488 and 7.779, respectively.

b. Robust standard errors in parentheses.

c. $p<0.01$. d. $p<0.05$. e. $p<0.10$.

Table 3B: The Effect of Pollution on Reading Test Scores
School Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Pollution:					
PM_{10}	-0.188	-0.232			
	(0.16)	(0.14)			
$PM_{2.5}$	-0.473		-0.725[d]		
	(0.44)		(0.33)		
NO_2	-0.162			-0.414	
	(0.35)			(0.32)	
O_3	0.142				0.191
	(0.21)				(0.17)
Wald Statistic for Joint Significance[a]	9.09				
Personal Characteristics:					
Age	13.16[c]	13.32[c]	12.83[c]	13.35[c]	13.52[c]
	(0.77)	(0.58)	(0.77)	(0.61)	(0.59)
Parent's Education (%):					
high school graduate	0.277[d]	0.219[e]	0.239[d]	0.201[d]	0.199[e]
	(0.10)	(0.12)	(0.11)	(0.09)	(0.11)
some college	0.355[c]	0.290[d]	0.345[d]	0.277[d]	0.231[c]
	(0.11)	(0.13)	(0.12)	(0.12)	(0.12)
college graduate	0.270	0.228	0.292	0.190	0.200
	(0.23)	(0.23)	(0.22)	(0.22)	(0.20)
graduate school	-0.050	-0.117	-0.038	-0.071	-0.160
	(0.29)	(0.24)	(0.29)	(0.26)	(0.24)
Parent smokes (%)	-0.215	-0.187	-0.221	-0.186	-0.220
	(0.13)	(0.14)	(0.16)	(0.14)	(0.13)
Insurance (%):					
medicaid	-0.154[d]	-0.162[d]	-0.148[d]	-0.156[d]	-0.168[d]
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
no insurance	-0.252[e]	-0.255[e]	-0.232	-0.205	-0.212
	(0.14)	(0.14)	(0.14)	(0.12)	(0.12)
School Characteristics:					
free lunch (%)	-0.745[c]	-0.796[c]	-0.711[c]	-0.680[c]	-0.703[c]
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
pupil-teacher ratio	0.392	0.404	0.372	0.373	0.381
	(0.25)	(0.24)	(0.23)	(0.25)	(0.24)
staff w/MA or PhD (%)	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Grade Characteristics (%):					
hispanic	-0.054	-0.051	-0.060	-0.074	-0.073
	(0.10)	(0.10)	(0.09)	(0.10)	(0.11)
black	0.179	0.157	0.174	0.157	0.146
	(0.23)	(0.23)	(0.23)	(0.21)	(0.20)
Unemployment Rate	-1.771[d]	-1.556[d]	-1.522[d]	-1.287[e]	-1.405[d]
	(0.72)	(0.69)	(0.70)	(0.73)	(0.65)
Test Change	-8.462[e]	-5.754	-10.388[c]	-8.219[d]	-5.631
	(4.49)	(3.77)	(3.40)	(3.55)	(3.55)
Constant	527.523[c]	530.574[C]	533.761[c]	528.385[c]	511.351[c]
	(22.33)	(15.92)	(18.89)	(19.16)	(20.76)
School Dummies	Y	Y	Y	Y	Y
Year Dummies	N	N	N	N	N
Observations	216	222	220	226	229
Number of Schools	88	88	88	88	88

Notes:
a. The critical values of the Wald test statistic at the .05 and .10 levels are 9.488 and 7.779, respectively.
b. Robust standard errors in parentheses.
c. $p<0.01$. d. $p<0.05$. e. $p<0.10$.

Table 4A: The Effect of Pollution on Mathematics Test Scores
School and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Pollution:					
PM_{10}	-0.147	-0.317[d]			
	(0.13)	(0.11)			
$PM_{2.5}$	-1.648[d]		-1.741[d]		
	(0.57)		(0.69)		
NO_2	-0.430			-0.605[e]	
	(0.34)			(0.34)	
O_3	0.171				0.215
	(0.17)				(0.18)
Wald Statistic for Joint Significance[a]	13.100				
Personal Characteristics:					
Age	-8.905[e]	-2.057	-11.31[e]	-8.297[e]	-3.004
	(4.95)	(5.41)	(6.22)	(4.65)	(5.90)
Parent's Education (%):					
high school graduate	0.168	0.128	0.105	0.089	0.120
	(0.10)	(0.08)	(0.09)	(0.08)	(0.09)
some college	0.180	0.149	0.121	0.071	0.096
	(0.12)	(0.14)	(0.13)	(0.15)	(0.16)
college graduate	0.081	-0.016	0.059	-0.015	-0.019
	(0.16)	(0.17)	(0.17)	(0.18)	(0.18)
graduate school	0.119	0.085	0.132	0.036	0.041
	(0.25)	(0.27)	(0.26)	(0.24)	(0.25)
Parent smokes (%)	-0.140	-0.078	-0.125	-0.085	-0.105
	(0.10)	(0.08)	(0.09)	(0.07)	(0.08)
Insurance (%):					
medicaid	-0.070	-0.076	-0.060	-0.070	-0.072
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
no insurance	-0.004	-0.023	0.049	0.041	0.048
	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)
School Characteristics:					
free lunch (%)	-0.639[d]	-0.636[d]	-0.623[d]	-0.635[d]	-0.560[d]
	(0.26)	(0.22)	(0.25)	(0.22)	(0.20)
pupil-teacher ratio	0.135	0.120	0.135	0.116	0.118
	(0.19)	(0.19)	(0.19)	(0.20)	(0.21)
staff w/MA or PhD (%)	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Grade Characteristics (%):					
hispanic	-0.009	-0.061	-0.042	-0.073	-0.090
	(0.15)	(0.16)	(0.13)	(0.15)	(0.16)
black	-0.026	-0.113	-0.065	-0.133	-0.157
	(0.12)	(0.16)	(0.12)	(0.13)	(0.14)
Unemployment Rate	-0.566	-1.663	-0.618	-1.581	-2.116[e]
	(1.30)	(1.12)	(1.34)	(1.22)	(1.09)
Constant	828.147[c]	735.885[c]	862.827[c]	824.568[c]	730.871[c]
	(71.83)	(73.77)	(81.73)	(59.21)	(83.43)
School Dummies	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
Observations	216	222	220	226	229
Number of Schools	88	88	88	88	88

Notes:
a. The critical values of the Wald test statistic at the .05 and .10 levels are 9.488 and 7.779, respectively.
b. Robust standard errors in parentheses.
c. $p<0.01$. d. $p<0.05$. e. $p<0.10$.

Table 4B: The Effect of Pollution on Reading Test Scores
School and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Pollution:					
PM_{10}	-0.116	-0.125			
	(0.13)	(0.14)			
$PM_{2.5}$	-1.012[e]		-1.107[d]		
	(0.54)		(0.51)		
NO_2	0.307			0.207	
	(0.23)			(0.28)	
O_3	0.124				0.149
	(0.17)				(0.13)
Wald Statistic for Joint Significance[a]	7.026				
Personal Characteristics:					
Age	-3.979	-1.179	-3.714	-2.739	-0.508
	(6.79)	(4.76)	(6.03)	(6.83)	(4.57)
Parent's Education (%):					
high school graduate	0.194[e]	0.142	0.168	0.132	0.139
	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)
some college	0.236	0.170	0.225	0.159	0.136
	(0.16)	(0.17)	(0.16)	(0.16)	(0.17)
college graduate	0.161	0.111	0.168	0.073	0.089
	(0.29)	(0.30)	(0.28)	(0.28)	(0.27)
graduate school	0.149	0.073	0.148	0.097	0.043
	(0.27)	(0.25)	(0.27)	(0.26)	(0.24)
Parent smokes (%)	-0.162	-0.141	-0.159	-0.137	-0.160
	(0.12)	(0.11)	(0.13)	(0.11)	(0.10)
Insurance (%):					
medicaid	-0.127[d]	-0.140[d]	-0.127[d]	-0.133[d]	-0.145[d]
	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
no insurance	-0.113	-0.106	-0.091	-0.085	-0.076
	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
School Characteristics:					
free lunch (%)	-0.700[c]	-0.739[c]	-0.690[c]	-0.696[c]	-0.690[c]
	(0.22)	(0.21)	(0.22)	(0.22)	(0.20)
pupil-teacher ratio	0.471	0.443	0.459	0.441	0.438
	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)
staff w/MA or PhD (%)	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Grade Characteristics (%):					
hispanic	-0.102	-0.127	-0.106	-0.156	-0.152
	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)
black	0.153	0.095	0.157	0.074	0.080
	(0.21)	(0.23)	(0.22)	(0.22)	(0.22)
Unemployment Rate	-0.051	-0.154	0.195	-0.344	-0.229
	(1.42)	(1.38)	(1.46)	(1.17)	(1.23)
Constant	739.962[c]	711.704[c]	746.793[C]	727.118[C]	692.839[C]
	(84.37)	(62.33)	(78.78)	(85.48)	(61.80)
School Dummies	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
Observations	216	222	220	226	229
Number of Schools	88	88	88	88	88

Notes:
a. The critical values of the Wald test statistic at the .05 and .10 levels are 9.488 and 7.779, respectively.
b. Robust standard errors in parentheses.
c. $p<0.01$. d. $p<0.05$. e. $p<0.10$.