Something in the Air? Pollution, Allergens and Children's Cognitive Functioning

Dave E. Marcotte
School of Public Affairs
American University
4400 Massachusetts Avenue NW
Washington, DC 20016-8070

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Abstract:

In this paper I attempt to add to our understanding of the effects of air quality on human health and development, by incorporating data on an important natural threat with data on human-made pollutants. Using data on academic skills as they develop between the ages of 5 to 8 years old, I find the strongest evidence that math achievement is inhibited by poor air quality. In particular high levels of ambient pollen limit performance and growth on math assessments administered during the first three years of elementary school. I find weaker evidence that fine airborne particulate matter and ozone limit math or reading achievement. I find some evidence that long-term exposure affects math skills in early elementary school. I discuss the implications and limitations of the current findings.

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Economists have done a substantial amount of research linking poor air quality to health and education outcomes for children. This research has been limited to pollution emitted as a consequence of human activity and has focused either on long-run effects due to pre- and neo-natal exposure, or on the contemporaneous impact of ambient pollution on acute health episodes or cognitive performance. In this paper, I extend this literature in two ways. First, I incorporate a natural threat to air quality in the form of plant pollen. Pollen is potentially important because it contributes to the level of fine particulate matter in the air, and unlike other forms of particulate matter pollen has known effects on non-pulmonary aspects of human health including cognitive functioning via allergies. Second, using data on air quality over long periods, I distinguish between long and short-term effects of exposure to air pollution and pollen. To do so, I augment the Currie et al (2014) model, and make use of child level panel data to confront the substantial and well established empirical problems inherent in estimating air quality impacts: Tiebout sorting which threatens validity for establishing long-term effects and avoidance behavior in the short run is likely related to other factors that are beneficial for child development (Neidell, 2009)).

To estimate effects of poor air quality on children's cognitive ability I combine data on daily ambient pollution and pollen levels in 25 counties throughout the United States collected by the U.S. Environmental Protection Agency and the National Allergens Bureau. I merge these data on air quality with rich longitudinal data on young children from the restricted-use Early Childhood Longitudinal Survey – Kindergarten (ECLS-K) panel data. In addition to collecting rich data on child, family, and school characteristics, the ECLS-K administers batteries of cognitive tests to children. These batteries provide measures of early childhood problem solving and norm and criterion referenced measures of math and reading skills. Further, the date on which ECLS-K students are tested is recorded, so that we can know the ambient levels of pollution and pollen when students were tested as well as the period leading up to the test.

In the remainder of this paper I describe recent findings on the impact of air quality on child health, and describe the empirical challenges inherent in identifying these effects. I then discuss the impact of plant pollen on health and how these may be related to findings on human-made contributors to poor air quality. I then describe a modified version of the Currie et al. (2014) model and some testable hypotheses that derive from it. I describe the data employed here, and the results of the empirical analyses. I conclude with the tentative findings and their implications along with future directions.

Background:

Research on the human health consequences of poor air quality has paid special attention to effects on children. This attention is warranted because children are at elevated risk for harm, and because costs imposed are borne over a long time horizon for children relative to adults. One reason children more susceptible to harm from air pollution arises is that *in utero* and in early infancy physiologic development is rapid (U.S. EPA, 2013; Gluckman et al., 2008; and Currie et al., 2014). Further, children are more likely to be exposed to ambient pollutants since they spend more time out of doors than adults and are more active (U.S. EPA, 2013; Schwartz, 2004).

The impact of poor air quality has been found to effect health early in childhood, and then later in childhood, too. Exploiting variation in air pollution due to the implementation of the Clean Air Acts and the recession of the early 1980s, Chay and Greenstone (2003a and 2003b, respectively) report substantial and significant decreases in child mortality due to reduction in airborne particulate matter. Beyond effects on mortality, there is good evidence that ambient pollution affect child health via affecting birth weight. Currie et al. (2009) and Currie and Neidell (2011) illustrate that variation in carbon monoxide levels to which pregnant women are exposed affects the birth weight of their children. Birth weight is a well-known indicator of myriad long-term developmental outcomes. Indeed, using administrative data on birth and school records in Florida and identifying off of birth weight differences between twins, Figlio et al. (2014) find that birth weight effects on cognitive performance in school is "essentially constant through the school career…" of children. Two studies linking exposure to air pollution to lower performance on high school tests (Sanders, 2012) and earnings in adulthood (Isen et al., 2013) provide reduced form evidence consistent with this long-run, developmental effect of exposure to air pollution early in life.

Research on a contemporaneous link between levels of air pollution and children's health has made clear that poor air quality is a trigger for acute episodes of respiratory problems, including asthma. For example, Ransom and Pope (1995) provide early evidence of poor air quality due to industrial activity on hospitalization among children for pulmonary conditions, making use of a natural experiment due to the closing and re-opening of a steel mill in Utah. Similar findings come from studies of oil refinery closures in France (Lavaine and Neidell, 2013) and airport traffic in California (Schlenker and Walker, 2011).

The extent to which there is a concurrent relationship between ambient air quality and cognitive performance is less clear. The impact of air pollution on cognitive ability is mainly thought to operate through development in early childhood (e.g. Currie (2005)). Lavy et al (2014) extend this case by pointing out that in theory pollution can affect cognition because small particulate matter can penetrate the lungs and inhibit the flow of oxygen into the bloodstream and hence the brain. While the importance of this link has yet to be established, it is clear that acute respiratory response to high levels of pollutants can cause breathing problems and asthma attacks and thereby inhibit performance. For example, Graff Ziven and Neidell (2012) and Chang et al. (2014) illustrate that poor air quality lowers productivity of piece rate daily farm workers and produce packers, respectively. While they are unable to identify mechanisms, Lavy et el. (2014) illustrate that high levels of fine particulate pollution have a negative effect on performance of Israeli high school students on exams that determine admission to selective post-secondary schools.

There is a clearer link to cognitive functioning from levels of ambient pollen, as opposed to air quality more generally. Pollen induces seasonal allergies in approximately 15 to 20 percent of the population (Metzler et al., 2009).[1] The allergic reaction is due to the combination of antibodies that target allergens with receptor cells, releasing chemicals to combat the perceived threat. These chemicals include histamine and cytokines that cause inflammation of tissue and increased secretion of mucus membrane (Janeway et al. 2001). These are the common symptoms of SAR including nasal congestion, watery eyes, and irritated throat. These chemicals and their attendant symptoms can also affect levels of fatigue, cognitive function, and mood. The most obvious mechanism through which an allergic response to allergens affects cognitive function is through effects on sleep. A very common problem suffered by allergy sufferers is interrupted sleep and daytime somnolence (Santos et al. (2006)). Cytokines as well as histamines are involved in brain function, affecting cognition, and memory (McAfoose and Baune (2009) and Tashiro et al. (2002)). Additionally, cytokines appear to affect mood, and have been linked to mood disorders, such as major depression (Kronfol and Remick (2000); Dowlati, et al. (2009)).

There is a sizeable literature in medicine on the effects of SAR on functioning. Much of this work is based on clinical lab research, comparing subjects with a history of SAR in various settings. For example, Wilken et al. (2002) randomly divided subjects with SAR into a group exposed to pollen and a control group, and

[1] Estimating the prevalence seasonal allergies is difficult because many sufferers do not seek treatment, and a confirmed diagnosis requires a skin test (NIAID, 2012). The estimate from the National Health Interview Survey is that 7.3 percent of Americans have been diagnosed by a physician with hay fever in the 12 months prior to interview while the Agency for Health Care and Quality estimates that prevalence ranges between 10 and 30 percent. By all accounts, prevalence is higher among children than adults, with some estimates as high as 40 percent. There is also evidence that prevalence is rising (Linneberg et al., 2000).

found that exposed subjects scored lower on measures of computation and reasoning ability, and had longer response times and more difficulty with attention. Marshall et al (2000) find similar patterns for subjects with SAR when comparing tests administered during allergy season to those administered when pollen levels were essentially zero. Regardless of the design for establishing the treatment-control comparison, clinical studies overwhelmingly find lower measured cognitive processing abilities and speed among symptomatic SAR subjects (e.g., Bender, 2005; Druce, 2000; Marshall and Colon, 1993; and Fineman, 2002). It also appears that typical medical treatments do not offer much protection from fatigue and decrements in cognitive functioning (Bender, 2005, and Kay 2000).

To date, I am aware of only two papers that exploit natural experiments to identify the effects of pollen on cognitive performance in a quasi-experimental framework. Walker et al. (2007) compare students in one region of the UK who had a history of SAR with students with no such history as they sat for the General Certificate of Secondary Education (GCSE) exams, which are used to determine post-secondary placement. Importantly, practice CGSE exams are administered in winter when pollen counts are negligible, and then the actual exams in June, a period of high grass pollen in the region. The authors used a type of difference in difference analysis by comparing practice scores to final exam scores, and find that students with SAR are 40 percent more likely than comparison students to score one grade lower in one of three core subjects of the final than the practice CGSE, and 70 percent more likely to score lower if they reported taking antihistamine treatment at the time of the final exam (Walker et al (2007)). Marcotte (2015) studied the effect of ambient pollen levels in school districts around the United States. He found that the percent of students scoring proficient on state math and reading assessments were between 3 to 6 percent lower if tests were administered on days with high levels of pollen. The relationship between pollen levels and proficiency was more pronounced in math, and for students in elementary school grades.

Conceptual Model:

In this paper, I consider the threats of pollen and human-made pollutants to air quality together, and examine their respective effects on child cognitive functioning and development. As is clear from the literature review, poor air quality can affect cognitive performance of children in two ways: Prolonged exposure, especially early in life, can harm development, and; Exposure to high levels of pollution may have immediate effects on health and thereby limit performance on cognitively demanding tasks. The research on human made threats to air quality has focused most heavily on the first mechanism, while research on the impact of pollen has mainly focused on the second. Clearly, though, both air pollution and pollen could affect health and functioning via long-term development, or contemporaneously.

To start to think about this, consider a simple two-period model of human capital accumulation in the spirit of Grossman (1972).

Period 1: Early childhood	Period 2: School age
$H_p = f_0(E_p,F)$	$H_s = g_0(H_p, E_s, F)$
$C_p = f_1(H_p,F)$	$C_s = g_1(C_p, H_s, F)$

Where:

- H_p is health in period p and H_s is health in period s.
- E_p is exposure to air of poor quality in period p, E_s in period s.
- F is a vector of time invariant family characteristics, including genetic and family environment factors.
- C_p is cognitive ability in period p, and C_s in period s.

Poor air quality can contemporaneously affect health and cognitive ability in both periods. By the time a child is of school age, poor air quality can also have effects that are the consequence of exposure in the early childhood period.[2] In this paper, I focus on the effects of poor air quality on cognitive performance among children once they enter school. So, total differentiation of the outcome of interest, C_s yields:

$$(1) \qquad dC_s = \frac{\partial C_s}{\partial C_p} \cdot \frac{\partial C_p}{\partial H_p} \cdot \frac{\partial H_p}{\partial E_p} \cdot dE_p + \frac{\partial C_s}{\partial H_s} \cdot \frac{\partial H_s}{\partial H_p} \cdot \frac{\partial H_p}{\partial E_p} \cdot dE_p + \frac{\partial C_s}{\partial H_s} \cdot \frac{\partial H_s}{\partial E_p} \cdot dE_s$$

Equation 1 makes clear that exposure to air pollution and pollen during early childhood can affect cognitive performance of school-aged children through two pathways. First, exposure to low-quality air can harm health in early childhood, thereby limiting early cognitive development, which is a determinant of cognitive ability at later ages. Second, poor air quality in early childhood affects early childhood health, and through that channel health later on, which is an input into cognitive skill in school age. Exposure during the second period is a second pathway through which poor air quality can limit cognitive performance in school aged children, by limiting health contemporaneously.

[2] Clearly, even in early childhood, poor air quality could have near- and long-term effects. This two-period model abstracts from this,

While the conceptual model helps clarify the pathways through which poor air quality affects cognitive performance, it also highlights the substantial data requirements faced by researchers studying this relationship. Ideally, one would have access to data on a random sample of children with measures of ambient air quality throughout childhood along with cognitive ability in early childhood and during school ages, as well as data on respiratory health and other measures of developmental health impacted by poor pulmonary development or health. Clearly, such data are hard to come by, so researchers often focus on one period and/or reduced form approaches.

In this paper, I employ panel data that offers some hope for providing insight into the inter-temporal patterns at play here. But, the data I employ provides very limited data on child health. Consequently, I cannot sort out the effects of poor air quality during early childhood on health versus cognitive development. Nonetheless, if data on air quality and cognitive performance is available over time, it is possible to test whether poor air quality during early childhood has effects that persist later into childhood. Similarly, it is possible to test whether poor air quality in the second period has contemporaneous effects over and above the long-term effects of earlier exposure. Below, I describe the data and empirical models employed here to assess these near- and long-term effects of exposure to air pollution and pollen.

Data and Methods:

To study the relationship between air quality and cognitive performance of children, I combine data from a variety of sources. First, data on child outcomes come from the restricted use data from the Early Childhood Longitudinal Surveys (ECLS), maintained by the National Center for Education Statistics. Specifically, I use data from the ECLS survey of children starting kindergarten in 2010-11, called the ECLS-K:2011 cohort. This survey collects detailed information on children and their families as they begin kindergarten, and will follow them through primary school and into middle school. In addition to administering regular tests of math and reading skills, the ECLS data also provides information on family and school characteristics relevant for modeling cognitive outcomes.

The ECLS data include information on the location of children's schools, and the dates on which students' math and reading skills were assessed. Using the schools' locations I merge in data on air pollution levels from the U.S. Environmental Protection Agency's Air Quality System, which regularly collects data on air pollution in sites around the country. I also merge in data on the level of ambient pollen in the atmosphere from the National Allergens Bureau. The resultant data set will allows us to observe ambient air quality in the county where students were tested in the days leading up to, on and then after the ECLS-K:2011 administered math and reading tests to students. Further, because the ECLS-K data provides information on location early in childhood, I include measures of ambient air quality during early childhood, in addition to contemporaneous measures of air quality during cognitive assessments later in childhood.

The ECLS-K:2011 cohort began kindergarten in the Fall of 2010. They were assessed during that term, in Spring 2011. They were then assessed again during the 1st and 2nd grades.[3] Importantly, during the 1st and 2nd grade follow-ups, only a subset of the full sample was also surveyed/assessed in Fall, while the full sample was surveyed/assessed in Spring. Consequently, the panel employed here is unbalanced both because of survey design as well as attrition. Figure 1 illustrates the distribution of the number of times each unique ECLS-K:2011 student in my analytic sample was interviewed and assessed over the three school years from 2010-11 through 2012-13. The vast majority was interviewed either four or six times.

An important limitation of the ECLS-K:2011 is that the exact date on which students were given math, reading and other assessments. Rather, the information available on assessment timing includes the year and month of assessment along with the day of the month reported in four categories, which approximate weeks[4]. Since these periods are either seven or eight days in length, I refer to them as weeks, below. I use the air quality to generate measures of mean levels of ambient pollen counts and particulate matter, ozone and sulfur dioxide air quality during these weeks.

An important advantage of the ECLS-K:2011 is that data on ambient pollution and pollen is available since birth. However, since no data are available on a child's residence in years leading up to kindergarten, I assume that children were born in the same county where they reside at the start of kindergarten. This is surely a

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[3] The ECLS-K:2011 sample will be interviewed and assessed (not always annually) until the typical student is in 8th grade. The restricted-use 2nd grade follow up dataset was released in July 2015.

[4] The days of the month are categorized into groups as: 1) 1-7, 2) 8-15, 3) 16-22, 4) 23-31.

source of error, despite fact that the 2005-2010 period saw the lowest rate of moving (35.4%) in the past 60 years, and nearly two-thirds of moves were within the same county (Ihrke and Faber, 2012). Nonetheless, the measurement error that results is a source of attenuation bias.

For the ECLS-K:2011 data I restrict my analyses to children residing in a county wherein air quality monitors for pollutants and atmospheric pollen are available. In each of these counties, I am able to measure levels of various pollutants found to affect health and development in children. These are carbon dioxide (CO_2), sulfur dioxide (SO_2), ozone and airborne particulate matter (APM2.5).[5] I also use measures of ambient pollen, as grains recorded per cubic meter of air in a 24-hour period. The dependent variables will be grade-specific standardized measure s of performance on math and reading assessments when students are in kindergarten, 1st and 2nd grades. The NCES oversaw the development and validation of the Item Response Theory procedures used to develop the measures of knowledge and skills reported in the ECLS-K (Najarian et al. forthcoming; Tourangeau, K. et al., 2009). The control variables available in the ECLS-K include student demographics, family income, education and structure, as well as measures of school climate and quality.

Empirical models:

To estimate the relationship between ambient air pollution and pollen on children's performance on cognitive tests I estimate a series of regression models of grade-specific measures of math and reading performance on measures of exposure to air pollution and pollen. Control variables include measures of the student's

[5] APM2.5 is a measure of fine micro particles (less than 2.5 micrometers in diameter).

family's composition, income, employment at that time as well as student demographics, and measures of his or her school's socioeconomic and demographic profile. Because students are clustered in schools we can also control for school fixed effects. To limit threats to internal validity that might arise if students living in areas with poor air quality also are different in unobservable ways I will: 1) control for local economic conditions, and 2) estimate models that controls for student fixed effects. The models take the following forms:

(1) $$\ln{(y)}_{iat} = a + b_1 X_i + b_2 L_t + b_3 \ln{(P)}_{iat} + s_i + g_{at} + \varepsilon_{iat}$$

(2) $$\ln{(y)}_{iat} = a + b_1 X_i + b_2 L_t + b_3 P_{iat} + b_4 \sum_{t=0}^{t-1} \ln{(P)}_{iat} + g_{at} + \varepsilon_{iat}$$

where y_{iat} is a measure of achievement for student *i* in assessment/subject *a* at time *t*; X_i is a vector of family and student characteristics pertinent to test performance for student *i*; L_t is a measure of the characteristics of the county in which the student lived in year *t*; P_{iat} is a vector of measures of ambient pollution and pollen on the date *t* when the student took the assessment *a*; g_{at} is a grade-year-subject fixed effect. Model (2) differs from model (1) by including a measure of cumulative pollution and pollen levels during each month of student i's childhood in the county in all months prior to assessment. Variously, b_3 and b_4 are the coefficient vectors of interest: measuring contemporaneous and cumulative effects of air quality on cognitive performance, respectively. In estimation below, I estimate the models in level and growth form. As is common in the empirical literature, the identification here comes from arguably exogenous variation in exposure to threats to air quality.

Results:

In Table 1, I present descriptive information about the ECLS-K:2011 sample. The demographic characteristics for the sample are unremarkable; with the exception of the high proportion (30.8%) of sample children is Hispanic children. This is likely the consequence of selecting only ECLS-K:2011 sample members who live in cites where air quality data are available. Notably, these cites include areas with disproportionately high Hispanic populations, including San Jose, San Diego, Atlanta, Houston and Dallas. Nonetheless, the mean rate of FARM eligibility in sample students' schools is 42.4 percent, essentially identical to the national average of 42% at the time.[6] For the ECLS-K:2011 sample, the mean percent of minority students in sample members' schools is 53.46 percent. This compares to a rate of 58 percent of all kindergarten students who are black and Hispanic in 2013 reported by the NCES.[7]

Air Quality Variation:

In Table 2, I present descriptive statistics for mean performance on math and reading assessments administered during each round of the ECLS-K:2011, along with measures of air quality during the week of testing. The math and reading scores summarize performance on assessments designed to measure children's skills in those subjects at a point in time, as well track growth over time. Hence, mean scores increase with age, and changes within assessments are measures of relative growth.[8] Interestingly, there are relatively large increases in scores on

[6] Digest of Education Statistics, Table 204.10:
http://nces.ed.gov/programs/digest/d13/tables/dt13_204.10.asp
[7] Digest of Education Statistics, Table 202.20:
http://nces.ed.gov/programs/digest/d14/tables/dt14_202.20.asp
[8] For details , see https://nces.ed.gov/ecls/assessments2011.asp

assessments between Fall and Spring within a grade compared to the change observed from Spring to Fall, especially for math. This is consistent with summer learning loss.

Table 2 also provides some insight into seasonal variation in air quality. Most notably, Spring is a period with substantially higher levels of ambient pollen. It is also clear that the mean is not fully informative as a measure of pollen levels, as the maxima during Spring are quite high. While pollen is clearly seasonal, other threats to air quality are less so. Only in the case of ozone AQI does it appear that Spring is associated with lower air quality. Ozone levels increase with heat and are especially high in summer. The mean air quality indices for fine particulate matter, and ozone are in the 30s and 40s. Note that these indices increase as air quality worsens, and measures over 50 are where initial warnings for sensitive groups are issues. Importantly, the distributions of ambient pollen levels are highly skewed (e.g. skewness = 11.9), and the metrics differ between pollen levels and the AQI indices. Because of both the different metrics and the skewed distribution of pollen levels, I transform all measures of air quality into logs for the regression analyses, as are the dependent variable.

Figures 2-4 provide further insight into variation in different threats to air quality over time, as well as across cities where the ECLS-K:2011 sample resides. Figure 2 is a scatterplot of mean levels of ambient pollen during the week of the ECLS-K:2011 assessments. The y-axis of the figure is logarithmically scaled, because of the substantial positive skew. To help interpret the scatterplot, when pollen counts exceed 90 grains/m^3 pollen levels are classified as high under the commonly used Padgett rating system (and extreme when counts exceed 1,500). Clearly, pollen levels are typically higher in Spring than Fall, and there is substantial variation at the time of testing across cities. Important for my identification strategy is the within-city variation. Because of the density, it can be hard to discern levels, but interesting types of cities emerge. Some cities, such as Houston, have high levels of ambient pollen in both Fall and Spring, though both vary. Other cities, like the New York City boroughs have trace amounts of pollen (<10) in the Fall, but very high levels in some Springs. Other cities vary at lower levels: Salt Lake City varies from levels that would be rated as moderate to only one year with high levels, while San Diego varies from very low to low levels.

Figures 3 and 4 are plots of the variation in fine particulate matter and ozone levels (respectively) during the assessments across the cities where ECLS-K:2011 children reside. These differ from Figure 2 only in that the y-axis is not logged. Both figures suggest some seasonality: the variance of particulate matter and the mean of the ozone air quality index are higher during Spring. As in Figure 2, some cities experience larger intertemporal changes in levels of air quality.

Regression Analyses:

In Table 3 I present select results of a naïve model of the relationship between ambient air quality during reading and math assessments. While this model includes basic controls for student and school characteristics, variation in air quality over space is assumed here to be orthogonal to other factors that could influence student math and reading achievement. Regional and metropolitan differences in air quality and amenities or infrastructure, along with parental sorting all make this a dubious assumption.

In Table 4, I present results of models that move beyond controlling for basic demographic characteristics by including child, time and location fixed effects, as described in model 1, above. The table is divided into two panels: The top panel includes results for the full all ECLS-K:2011 rounds, while the bottom panel includes results only for the four rounds wherein the full sample was assessed. This restriction drops data from the Fall 1st and 2nd grade rounds, since only a subset of the sample was tested. The point estimates are nearly identical in both panels, but unsurprisingly the standard errors in the second panel are somewhat larger. The results in Table 4 suggest that increases in ambient pollen decrease performance on math assessments, but not on reading. There is weaker evidence that human-made air pollutants affect test-performance. Performance on reading assessments declines as the air quality index for fine particulate worsens, though this is significant at only 10%.

To interpret the magnitude of these coefficients, recall, the dependent and key independent variables are in log form, so they approximate elasticities. In the case of pollen, performance reading and math assessment declines by 0.008 percent for each 1 percent increase in ambient pollen levels. At the mean, 1 percent is about 3.5 to 4 g/m^3. To make the magnitude of this effect interpretable, a 100 percent increase in pollen levels (i.e. from trace amounts to the mean) would be associated with a decrease in performance on math and reading assessments in late elementary and middle school by about 0.8 percent.

The results in Table 4 are estimates of average effects of diminished air quality for all students. Of course, some students are more affected by changes in air quality, and these averages conflate larger effects of vulnerable groups with null or negligible effects for others. While the ECLS-K:2010 has limited information about child health, parents are asked if their children have ever been diagnosed with asthma – an obvious marker for sensitivity to changes in air quality. In Table 5 I present results of Model 1, restricting the analysis to children with an asthma diagnosis, as reported by their parents. Table 5 also presents basic demographic characteristics of this subset of children. The top panel illustrates that asthma is more common among boys and black children.

The bottom panel (B) of Table 5 presents estimates of the effect of declining air quality on reading and math assessment scores for children with a history of asthma. For these students, allergens are associated with declining performance on both reading and math assessments. These effects are larger in magnitude than those estimated on the full sample of students. The point estimates for the impact of declining air quality indices for fine particulate matter and ozone are also larger than observed for the full sample. However, standard errors are a good bit larger because of the restricted sample size. Only in the case of ozone on math assessments is the coefficient significant.

Heretofore, I have not made use of the fact that air quality data is available not only for the time of the ECLS-K:2011 assessments, but also before and after. I make use of this in two ways: First, by re-estimating model 1, but including measures of air quality two weeks before and two weeks after assessment dates, and; Second, by estimating model 2, including measures of lifetime exposure to threats to air quality.

Air Quality Before/After Assessments:

Including measures of air quality before and after assessment dates is useful for at least two reasons. First, it is possible that the effect of exposure to air of poor quality on cognitive functioning is not immediate. Rather, it could be that diminished air quality affect learning, not contemporaneous performance on cognitively demanding tasks. If so, the results in Table 4 could be picking up lagged effects. Second, by including measures of air quality after assessments are over serves as an obvious falsification test: We shouldn't expect exposure in the future to affect test scores today. Indeed, if air quality after-the-fact affected test scores we would worry that other factors were linked to both levels of exposure and performance in school.

In Table 6 I present results of the re-estimation of model 1 including measures of the average air quality during the week that began 14 days and ended 7 days *before* the assessment week, and during the week that began 7 days and ended 14 days *after* the assessment week. Choosing pre/post periods that were more than a week from the assessment limits overlap/error with the contemporaneous air quality measures. For pollen, it appears that higher levels both during and two weeks prior to assessments limit student performance in math, while the effects on reading are only contemporaneous. If air quality in advance of tests limits learning, this suggests that inhibiting learning before testing is relatively important in math. Among human-made pollutants, only for ozone is there evidence of effects of exposure before the test date. Interestingly for ozone, the effects of air quality before and during testing are in opposite directions, essentially nullifying one another.

In all cases in Table 6, there is no evidence that air quality after testing is completed has any bearing on math or reading scores. This provides reassurance about the identification strategy here.

Lifetime Exposure:

I next turn to operationalizing model 2, which includes measures of lifetime exposure to pollen, fine airborne particulate matter, sulfur dioxide and ozone. I do not include sulfur dioxide because few sites reported this measure during the early childhood of the sample. An important limitation of the lifetime measure is that I assume children do not move between birth and enrollment in kindergarten. This is necessary because the ECLS-K provides information on residence only at the time of the initial survey and all follow-ups. The implication of this is that variation in lifetime exposure comes entirely from differences in exposure within a site. And, since the sample is a cohort entering kindergarten during the Fall of 2010, the variation is entirely due so variation in air quality during the first year of life. To see this, note that all children in the same area were exposed to the same ambient air in 2010. This is true for 2009, 2008, and so on. Only during the year when the cohort was born was there variation in levels of exposure, driven by the timing of birth (and gestation). Since all models control for age (in months), variation is driven by patterns of air quality during 2004-2005, when this cohort was born.

Finally, since there is no variation within student, I estimate the impact of lifetime exposure on math and reading performance as a growth model, including lags of previous performance as controls. This is not ideal, since it requires that all effects of lifetime exposure operate to impede learning after a student starts school, and ignores early losses.

In Table 7 I present results for estimates of model 2, controlling for lifetime exposure. In all cases, the contemporaneous effect of exposure on achievement growth is large, relative to the estimates from model 1. This is consistent with the possibility that high rates of contemporaneous exposure are correlated with factors that might otherwise improve learning gains, and are themselves correlated with the overall level of air pollution. These might include levels of economic activity and population density. Only in the case of pollen do I find evidence of deleterious effects of exposure during early childhood.

Conclusions:

In this paper I have attempted to add to our understanding of the effects of air quality on human health and development, by incorporating data on an important natural threat with data on human-made pollutants. Using data on academic skills as they develop between the ages of 5 to 8 years old, I find the strongest evidence that math achievement in particular is inhibited by diminished air quality. In particular high levels of ambient pollen limit performance and growth on math assessments administered during the first three years of elementary school. I find weaker evidence that fine airborne particulate matter and ozone limit math or reading achievement.

A second objective of the current paper was to distinguish between the impact of ambient air quality and long-term exposure. This distinction matters because it is suggestive of mechanisms, and potentially solutions. If all effects are contemporaneous, the impact of diminished air quality is most likely due to impermanent, mild respiratory distress or discomfort. If effects are due to extended exposure, this suggests the mechanism could be inhibited development or learning.

On balance, I have found little evidence that the impact of air quality operates through long-term exposure. This finding is both unexpected and provisional. Exposure to pollution, including air pollution, is known to have substantial negative consequences for fetal and neo-natal development. Since the variation exploited here occurs in the first year of life, one would expect impacts on math and reading competency. However, a limitation of the research design here is that the outcome of interest is learning after the age of five. So, while I find that early exposure to air pollution and pollen does not diminish the rate of learning after five, I cannot say that it has no effect on the math and reading ability of children at the point when they start school. Exploring this margin is an important next step.

Better understanding the relative importance of long-term and ambient exposure is important for determining what to do about threats to air quality as they affect children's academic growth. Of course, any negative effects are cause to limit exposure. An important lesson of the current finding is that limiting exposure in school settings, and treating children for the symptoms of exposure are of real importance. Performance on school-based tests is used to allocate resources to schools and to track students within schools. An obvious implication is that schools can reduce noise in the measures they use for these decisions by improving air quality and encouraging inexpensive and effective treatment for pollen allergies.

The implications of these findings raise a more fundamental concern, however. Since ambient air quality in school settings is best controlled via air conditioning, and diagnosis and treatment for allergies requires access to health care, air quality may serve as an additional source of growing disparities in the education. Schools in low-income areas are often relatively old, and less likely to be equipped with air conditioning. And, poor students are less likely to receive diagnosis and treatment for health problems.

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Figure 1

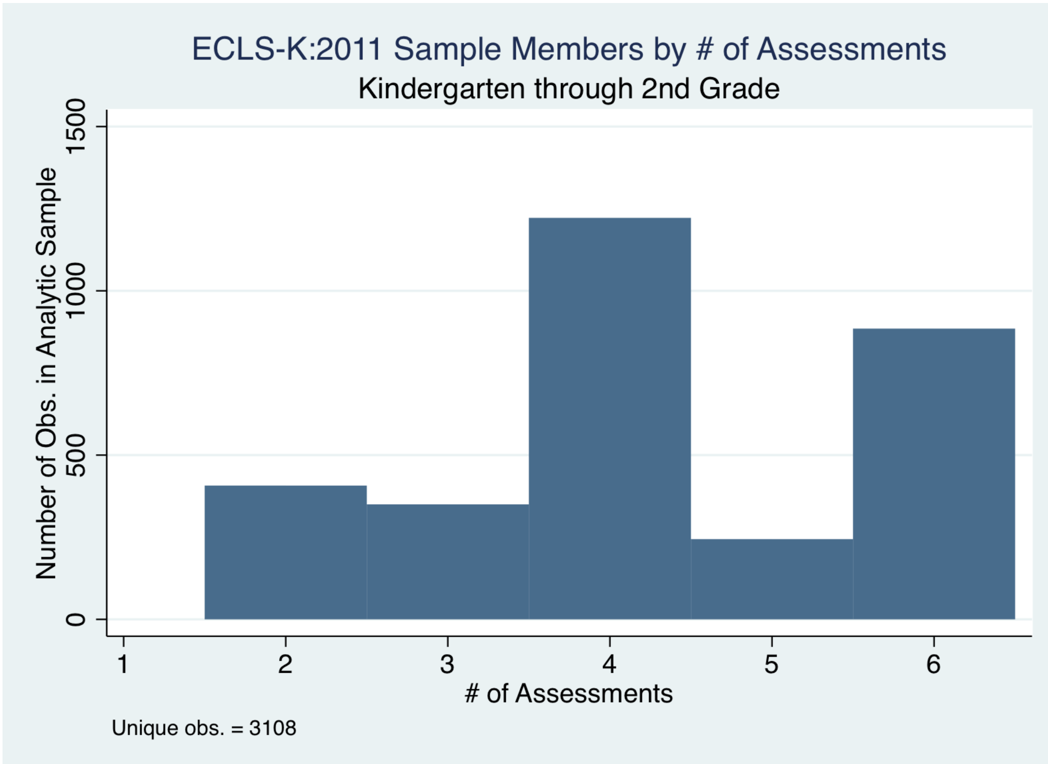

Figure 2

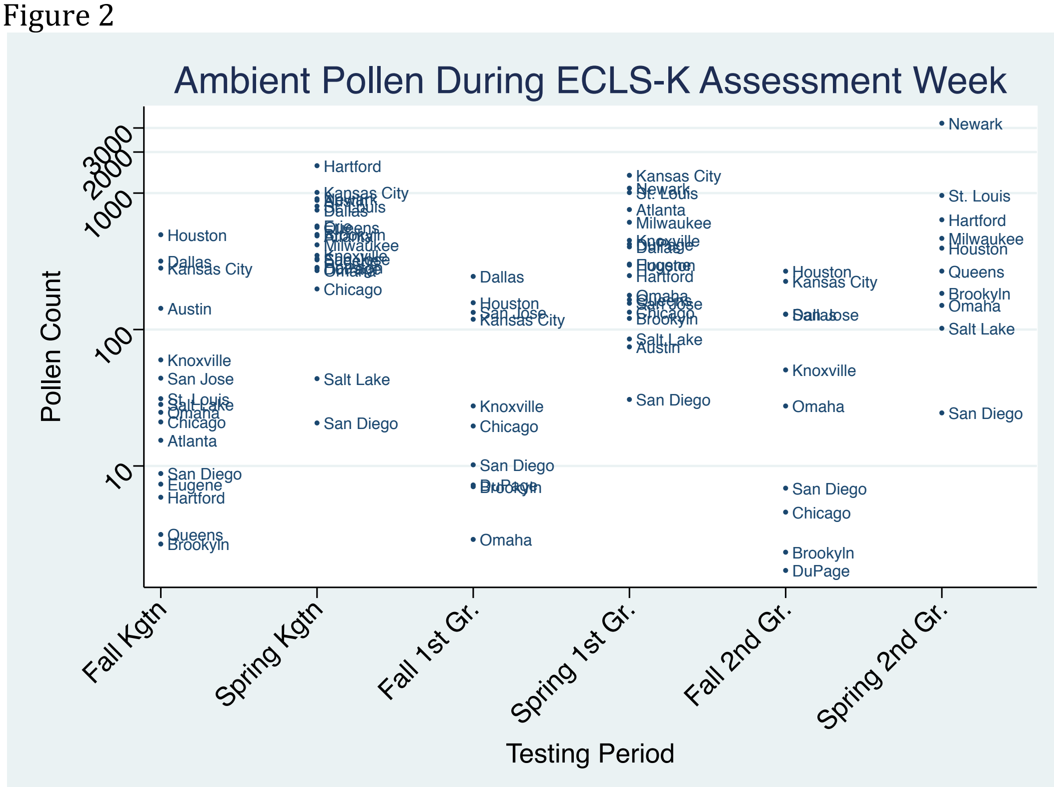

Figure 3

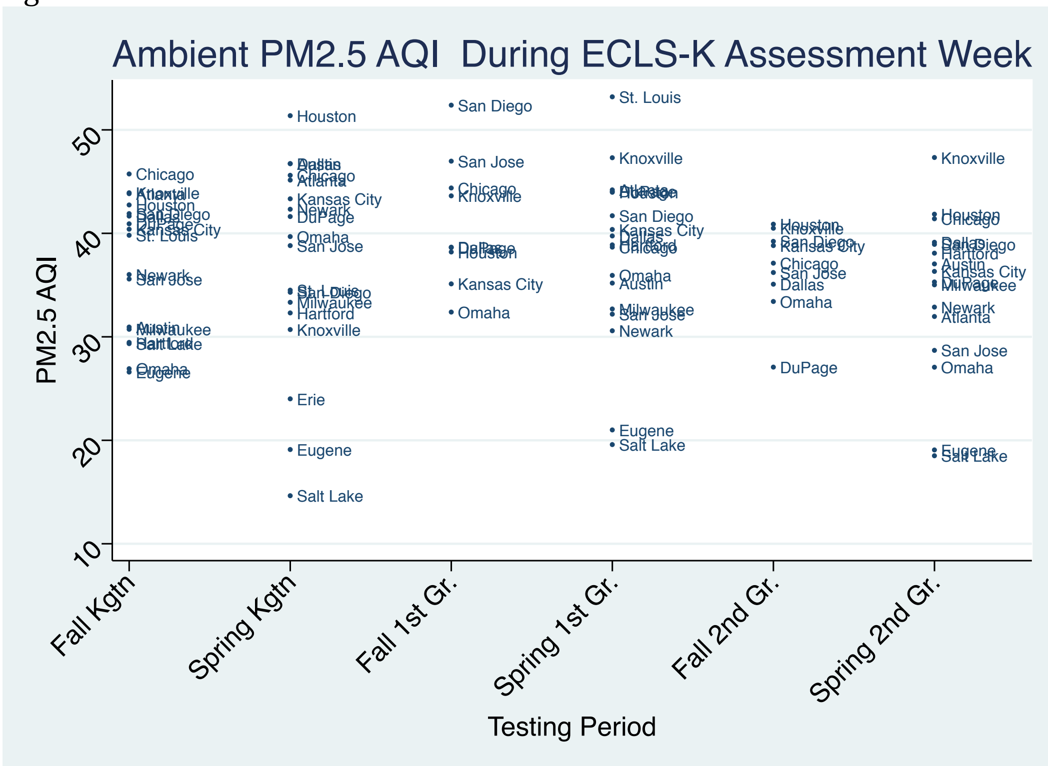

Figure 4

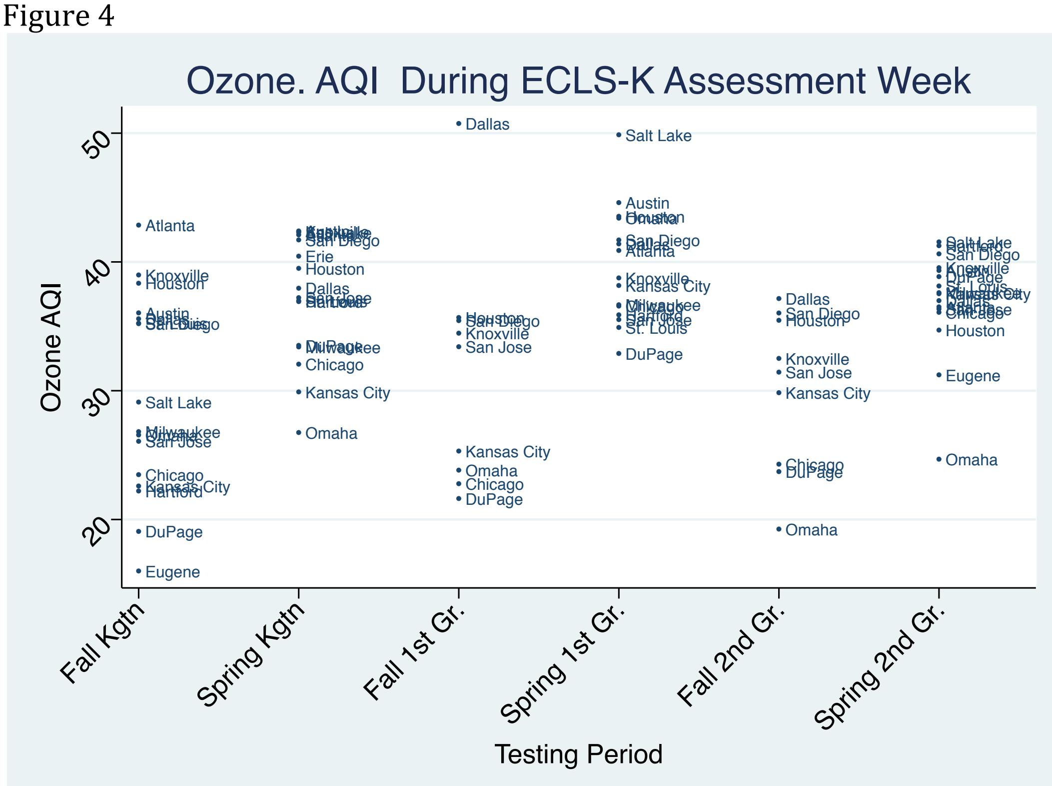

Table 1

Descriptive Statistics for ECLS-K 2011 Sample

	Mean	St. Dev.
Female (0/1)	0.499	0.5
Black (0/1)	0.152	0.359
Hispanic (0/1)	0.32	0.466
White (0/1)	0.412	0.492
Age (in months)	81.01	11.57
Child's Family Poor? (0/1)	0.261	0.44
# of Siblings	1.53	1.14
Private School? (0/1)	0.122	0.327
Live with Two Parents? (0/1)	0.724	0.447
Age of Primary Household Head	35.75	6.69
Pct of Students in School FARM eligible	42.4	31.36
n	13,282	

Table 2

Mean Test Scores and Air Quality Measures by Assessment Period

Assessment period	Variable	Mean	Std. Dev	Min	Max
Fall of Kindergarten	Math score	32.5	11.81	7.4	77.7
	Reading score	48.27	12.61	25.5	99.6
	Pollen count	116.33	236.5	0	1369.5
	PM 2.5 AQI	9.49	3.65	1.8	30.9
	Ozone AQI	30.93	9.37	5.6	63.5
	SO2 AQI	6.9	5.01	0.4	22.3
Spring of Kindergarten	Math score	46.28	12.34	11.1	88.8
	Reading score	61.98	14.85	26.83	108.4
	Pollen count	571.63	857.34	0.9	3822
	PM 2.5 AQI	35.58	11.97	10.5	76.1
	Ozone AQI	37.93	7.29	18.5	90.5
	SO2 AQI	1.41	1.55	0.2	9.9
Fall of 1st Grade	Math score	54.53	14.41	17.4	108.7
	Reading score	71.08	16.66	34.9	113.5
	Pollen count	104.55	165.17	0	628
	PM 2.5 AQI	42.24	10.89	8	75.8
	Ozone AQI	34.58	12.9	13.8	78.7
	SO2 AQI	4.74	4.66	0	20.3
Spring of 1st Grade	Math score	68.07	15.3	16.5	109.5
	Reading score	85.5	15.91	31.5	115.8
	Pollen count	451.83	821.57	8.3	5312
	PM 2.5 AQI	38.97	13.37	11.8	93.5
	Ozone AQI	40.06	8.48	20.2	77.2
	SO2 AQI	3.32	3.42	0	17
Fall of 2nd Grade	Math score	72.41	15.01	19.2	106.3
	Reading score	88.87	14.16	49.8	116.4
	Pollen count	130.3	182.11	0	864.2
	PM 2.5 AQI	38.4	8.42	14.9	74
	Ozone AQI	32.98	7.81	13.4	54.3
	SO2 AQI	3.39	3.96	0	23.4
Spring of 2nd Grade	Math score	81.71	13.74	14.8	106.6
	Reading score	96.87	12.6	49.8	116.4
	Pollen count	701	1226.7	1	7746.2
	PM 2.5 AQI	36.03	10.79	12	65.8
	Ozone AQI	38.01	5.29	24	55.9
	SO2 AQI	2.77	3.52	0	17.9

Table 3

Naive Estimates of Ambient Air Quality and Test Scores

	Reading		Math	
Female (0/1)	0.043	***	0.004	
	0.008		0.015	
White (0/1)	-0.026		-0.032	
	0.018		0.017	
Black (0/1)	-0.019		-0.062	**
	0.016		0.028	
Hispanic (0/1)	-0.082	***	-0.125	***
	0.016		0.024	
Age (in months)	0.006	***	0.014	***
	0.001		0.002	
Child Poor (0/1)	-0.072	***	-0.092	***
	0.013		0.018	
Private School (0/1)	0.037		0.046	
	0.023		0.031	
Father present	0.037	**	0.067	**
	0.016		0.032	
Mother's age	0.001		0.001	
	0.001		0.001	
Pct. FARM eligible	-0.001	***	-0.0015	***
	0.0002		0.0005	
Pollen during assessment	-0.01	**	-0.012	*
	0.005		0.006	
PM2.5 AQI during assesement	-0.007		-0.001	
	0.017		0.021	
Ozone AQI during assessment	0.031		0.011	
	0.031		0.051	
SO2 AQI during assessment	-0.003		0.002	
	0.008		0.008	
R^2	0.676		0.665	

Omitted race category is Asian/other

*** Sign. at 1% level.
** Sign. at 5% level.
* Sign. at 10% level.

Table 4
Child Fixed Effects Estimates of Air Quality and Test Scores

	Reading		Math	
All Periods				
Pollen during assessment	-0.002		-0.008	***
	0.002		0.003	
PM2.5 AQI during assesement	-0.024	*	-0.016	
	0.014		0.012	
Ozone AQI during assessment	-0.003		-0.011	
	0.011		0.017	
SO2 AQI during assessment	0.006		0.001	
	0.004		0.006	
Restricting to Full-Sample Periods				
Pollen during assessment	-0.002		-0.008	***
	0.002		0.003	
PM2.5 AQI during assessment	-0.032		-0.019	
	0.022		0.018	
Ozone AQI during assessment	-0.002		0.009	
	0.015		0.031	
SO2 AQI during assessment	0.003		-0.005	
	0.005		0.007	

*** Sign. at 1% level.
** Sign. at 5% level.
* Sign. at 10% level.

Table 5
Air Quality and Test Scores Among Student with Asthma

Panel A: Characteristics of Asthmatic Students

Variable	Mean	Std. Dev.
Female (0/1)	0.406	0.491
Black (0/1)	0.173	0.378
Hispanic (0/1)	0.328	0.469

Panel B: Fixed Effects Est. of Air Quality on Test Scores

	Reading		Math	
All Periods				
Pollen during assessment	-0.009	**	-0.012	***
	0.003		0.003	
PM2.5 AQI during assessment	-0.039		-0.019	
	0.048		0.034	
Ozone AQI during assessment	-0.036		-0.085	**
	0.026		0.032	
SO2 AQI during assessment	0.009		0.006	
	0.005		0.009	

*** Sign. at 1% level.
** Sign. at 5% level.
* Sign. at 10% level.

Table 6
Test Scores and Air Quality Before, During and After Assessment Dates

	Reading		Math	
Pollen:				
During assessment	-0.009	***	-0.008	***
	0.0053		0.003	
Two weeks before assessment	-0.002		-0.011	***
	0.003		0.002	
Two weeks after assessment	0.001		-0.001	
	0.003		0.006	
PM2.5 AQI:				
During assessment	-0.033	*	-0.022	
	0.019		0.014	
Two weeks before assessment	0.01		-0.004	
	0.018		0.013	
Two weeks after assessment	-0.009		-0.001	
	0.011		0.01	
Ozone AQI:				
During assessment	0.01		0.041	**
	0.026		0.02	
Two weeks before assessment	-0.017		-0.052	***
	0.011		0.016	
Two weeks after assessment	-0.011		-0.044	
	0.025		0.028	
SO2 AQI:				
During assessment	0.006		0.006	
	0.004		0.006	
Two weeks before assessment	0.005		-0.002	
	0.006		0.006	
Two weeks after assessment	0.003		0.007	
	0.005		0.004	

*** Sign. at 1% level.
** Sign. at 5% level.
* Sign. at 10% level.

Table 7
Test Scores and Air Quality: Contemporaneous and Lifetime Exposure

	Reading		Math	
Pollen:				
During assessment	-0.033	***	-0.026	***
	0.007		0.006	
Lifetime exposure	0.0004		-0.034	***
	0.059		0.039	
PM2.5 AQI:				
During assessment	0.007		-0.038	*
	0.018		0.021	
Lifetime exposure	-0.131		-0.026	
	0.122		0.09	
Ozone AQI:				
During assessment	-0.084	**	0.027	
	0.033		0.03	
Lifetime exposure	-0.029		-0.032	
	0.136		0.071	

*** Sign. at 1% level.
** Sign. at 5% level.
* Sign. at 10% level.