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Something in the air? Air quality and children's educational outcomes

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ABSTRACT

Poor air quality has been shown to harm the health and development of children. Research on these relationships has focused almost exclusively on the effects of human-made pollutants, and has not fully distinguished between contemporaneous and long-run effects. This paper contributes on both of these fronts. Merging data on ambient levels of human-made pollutants and plant pollen with detailed panel data of children beginning kindergarten in 2010, I study the relationship between poor air quality on achievement in early grades. I also provide tentative estimates of the effects of air quality in the first years of life on school-readiness. I find that students score between 1 to 2 percent lower on math and reading scores on days with high levels of pollen or fine airborne particulate matter, and that asthmatic students score about 10 percent lower on days with high levels of ozone. I find suggestive evidence that poor air quality during early childhood negatively affects school readiness.

Economists have done a substantial amount of research linking poor air quality to health and developmental outcomes for children. This research has mostly 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 impacts of ambient pollution on acute health episodes or cognitive performance later in life. In this paper, I contribute to 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 estimate effects of exposure to air pollution and pollen early in life on school readiness, and the effects of exposure while in school on achievement. To both of these ends, I 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 academic outcomes I combine data on daily ambient pollution and pollen levels in nearly 20 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 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 measures of math and reading skills. Further, the date on which ECLS-K students are tested is recorded, so that I can know the ambient levels of pollution and pollen when students were tested as well as the period leading up to the test.

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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 employ a standard human capital model common to the health literature to illustrate the pathways through which poor air quality could affect children's performance in school,[2] and derive testable hypotheses. I next describe the data and empirical models used to address these questions about short and long-run effects of exposure. Because I have panel data, inference principally comes from variation in within-student exposure to threats to air quality. However, since school readiness is measured by tests administered at a point in time, for that outcome I exploit variation in exposure due to month of birth for matriculating kindergartners within each school setting. Further, because the relationship between air quality and weather is well established, I illustrate the importance of controlling for weather conditions.

This paper contributes to an emerging literature on the role of air quality and the development and academic achievement of children. Understanding the implications of air quality on educational achievement is vital for assessing the full costs of human made pollution, as well as estimating the benefits and implications of policies to limit exposure to threats to air quality or limit the affects of exposure. These include policies to treat acute symptoms of affected children, such as subsidies for asthma or allergy treatments. More broadly this literature is beginning to shed light on the role of indoor air quality in schools on student achievement (Stafford, 2015). Better understanding how environmental threats to air quality affect outcomes within schools is relevant for understanding if air conditioning and other aspects of the conditions of schools shape trends in achievement, both in the aggregate and for students in resource-poor districts.

1. 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 are borne over a long time horizon for children relative to adults. Children are more susceptible to harm, in part, because physiologic development *in utero* and early infancy is especially rapid - so any factors inhibiting this process can disrupt normal development (Gluckman, Hanson, Cooper, & Thornburg, 2008; U.S. EPA, 2013; and Currie, Joshua, Jamie, & Neidell, 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 (Schwartz, 2004; U.S. EPA, 2013).

Indeed, the impact of poor air quality has been found to effect health *in utero* and in early childhood. Exploiting variation in air pollution due to the implementation of the Clean Air Acts and the recession of the early 1980 s, Chay and Greenstone (2003a and b, 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 affects child health via birth weight. Currie, Neidell, and Schmieder (2009) illustrate that variation in exposure to carbon monoxide among pregnant women affects birth weight for their children. Birth weight is a well-known indicator of myriad long-term developmental outcomes. For example, using administrative data on birth and school records in Florida and identifying off of birth weight differences between twins, Figlio, Guryan, Karbownik, and Roth (2014) find that birth weight effects on cognitive performance in school are "essentially constant through the school career…" of children. Bharadwaj et al (2014) find evidence that in utero exposure to carbon monoxide in Santiago Chile is associated with lower 4th grade test scores. Two studies linking exposure to air pollution to lower performance on high school tests (Sanders, 2012) and earnings in adulthood (Isen, Rossin-Slater, and Walker, 2014) provide further reduced form evidence consistent with this 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 & Neidell, 2013) and airport traffic in California (Schlenker & Walker, 2016).

The 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, 2009). However, 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 (Lavy, Ebenstein, & Roth, 2014). While the importance of this link has yet to be established, it is clear that high levels of pollutants can cause breathing problems and asthma attacks and thereby inhibit performance. For example, Graff Ziven and Neidell (2013) and Chang, Zivin, Gross, and Neidell (2014) illustrate that poor air quality lowers productivity of piece rate daily farm workers and produce packers, respectively. Two studies most relevant to this paper are, Lavy et al. (2014) and Stafford (2015). Lavy and his colleagues 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.[3] Stafford (2015) examines performance on Texas's standardized math and reading tests before and after school renovations that improve indoor air quality and finds substantial improvements in test scores following renovations to remediate mold or improve ventilation.

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 (Meltzer et al., 2012).[4] 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 mucous membrane (Janeway, Travers, & Walport, 2001). These are the common symptoms of seasonal allergic rhinitis (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

[2] The seminal work on this area is by Grossman (1972). For relevant extensions and discussion of this context, see Currie et al. (2014).

[3] A distinct but related literature in development economics has established a link between extreme weather events in utero and early childhood on health and education outcomes in developing countries in Africa and Asia. The mechanisms at play are thought to include fetal origins, malnutrition, and increased exposure to indoor pollution from heating and cooking during cold/wet weather. See for example, Alderman et al (2006); Groppo and Kraehnert (2016); and Deuchert and Felfe (2015).

[4] 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).

response to allergens affects cognitive function is through effects on sleep. A very common problem suffered by those with allergies is interrupted sleep and daytime somnolence (Santos, Pratt, Hanks, McCann, and Craig (2006)). Beyond this, cytokines and 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 (Dowlati et al. (2009); Kronfol and Remick (2000)).

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.[5] 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 was 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.

In this paper, I extend previous work in this area by providing the first evidence on the impact of air quality on early childhood cognitive functioning using panel data and an identification strategy that relies on within-student variation. Further, by linking individual data to local air quality this paper also expands on previous work by examining the importance of exposure accumulated over childhood separate from exposure at the time of testing.

2. Conceptual model

As is clear from previous work, poor air quality can affect children's cognitive performance 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. To clarify the mechanisms though which air quality could affect health and functioning via long-term development, 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 measures health in periods p and s.
- E measures exposure to air of poor quality in respective periods.
- F is a vector of time invariant family characteristics, including genetic and family environment factors.
- C measures cognitive ability in each period.

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.[6] 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:

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

This makes clear that air pollution and pollen can affect cognitive functioning of school-aged children both through long-term effects and limitations due to ambient exposure. First, in early childhood, exposure to low-quality air can harm health, thereby limiting early cognitive development - a determinant of cognitive ability at later ages. Poor air quality in early childhood can affect early childhood health, and through that channel health later on, which is an input into cognitive skill in school age. Ambient exposure is a second pathway through which poor quality air can limit cognitive performance for school-aged children by limiting health contemporaneously.

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 reduced form approaches.

In this paper, I employ panel data that offers some hope for providing insight into the patterns at play here. But, the data I employ provides very limited data on child health, so I cannot sort out the effects of poor air quality during early childhood on health versus cognitive development. However, I am able to use data over the course of childhood to assess whether poor air quality affects children's reading and math readiness when the show up at kindergarten. I then use data on ambient air quality during kindergarten through second grade to test for contemporaneous effects over and above the long-term effects of earlier exposure.

3. Data and methods

To study the relationship between air quality and cognitive performance of children, I combine data from a variety of sources.

[5] For example, Wilken et al. (2002) randomly divided subjects with SAR into a group exposed to pollen and a control group, and 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.

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

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. Finally, I merge in data on weather conditions from the National Climatic Data Center. The resultant data set makes it possible 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.[7] 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. 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 is not available. 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.[8] Since these periods are either seven or eight days in length, I refer to them as weeks, below.

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 source of error, despite the 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 & Faber, 2012). Nonetheless, measurement error is surely an issue. To the extent that air quality is not a factor in determining inter-county moves, then this measurement error would merely be a source of attenuation bias for the estimates of threats to air quality on school readiness. However, if better-informed or wealthier families are more attuned to threats from pollution, measurement error may be systematically related to student or school factors associated with achievement. The fact that all models control for student/family attributes and school fixed effects helps limit this threat. Nonetheless, this potential measurement error suggests that the models of lifetime exposure estimated here should be viewed as suggestive, rather than causal.

For the ECLS-K:2011 data I restrict my analyses to children residing in a county with air quality monitors for pollutants and atmospheric pollen. In each of these counties, I am able to measure levels of ozone and airborne particulate matter (APM2.5).[9] I also use measures of ambient pollen, as grains recorded per cubic meter of air in a 24-hour period. The dependent variables are grade-specific standardized measures 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, Lê, Nord, & Sorongon, 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.

3.1. Empirical models

Central to the problem of estimating the relationship between environmental exposure and child outcomes is the endogeneity of exposure. Since exposure cannot be randomized, researchers typically exploit natural experiments. In this context, a common strategy is to compare pre- and post-exposure differences in outcomes for one group to unexposed comparison groups over the same periods. This is the spirit of the estimation strategy I employ to study the effects of exposure to high levels of pollution and pollen among school aged children. To estimate the relationship between ambient air quality and children's performance in school, 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 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 I can also control for location 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: 1) control for local economic conditions, and 2) estimate models that controls for student fixed effects. The model takes the following form:

$$\ln(y)_{ialt} = a + b_1 X_{it} + b_2 L_t + b_3 \ln(P)_{ialt} + b_4 W_{ialt} + \alpha_i + \gamma_l + \phi_t + g_{at} + \varepsilon_{ialt} \quad (1)$$

where y_{ialt} is a measure of achievement for student i in assessment/subject a in location l, at time t; X_{it} is a vector of family and student characteristics pertinent to test performance for student i at time t; L_t is a measure of the characteristics of the county in which the student lived in year t; P_{ialt} is a vector of measures of ambient pollution and pollen at the location/time when the student took assessment a; W_{ialt} measured weather conditions at the time a student took an assessment; α_i is a student-specific intercept, γ_l is a location/site fixed effect, ϕ_t is a year/season fixed effect measuring the year in school and semester (Fall/Spring) of the test, and; g_{at} is a grade-year-subject fixed effect. I also estimate models that allow for site specific linear trends, rather than common year fixed effects.

Identification of the impact of decrements in air quality on test performance comes from changes over time in test scores for exposed students, net of average student characteristics that may be

[7] 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.

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

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

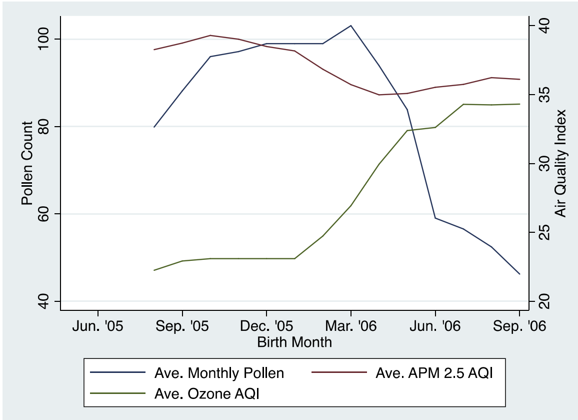

Fig. 1. Air quality in first year of life, by month of birth: salt lake city, UT
Note: See text for definitions.

correlated with exposure. The identifying assumption is that *ex ante* test score growth is not correlated with factors that shape changes in exposure to pollutants and pollen. Because air quality is a measure for a community not an individual student, standard errors are clustered at the monitoring site level.

Estimating the impact of lifetime exposure to pollution and pollen on school readiness cannot rely on a similar within-student strategy, since the outcome is a math or reading assessment administered once, at the start of kindergarten. Rather, I estimate the impact of early exposure by estimating the relationship between cumulative exposure from birth, on math and reading assessments administered to students at the start of kindergarten. The model is:

$$\ln(\mathrm{y})_{ialt} = a + b_1 X_{it} + b_2 L_t + b_3 \ln(P)_{ialt} + b_4 \sum_{t=0} P_{ialt} + b_5 W_{ialt} + \alpha_i + \gamma_l + \phi_t + g_{at} + \varepsilon_{ialt} \quad (2)$$

Model (2) differs from Model (1) because of the absence of a student fixed-effect, and in that the variable of interest is 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. Variation in air quality comes from within location variation in the levels of pollution and pollen to which students are exposed based on their birthdays. The identifying variation relied on here can be seen by recognizing that sample students are a cohort, all entering kindergarten in the same year. If all children live in the same county from birth to kindergarten entry, then the differences in exposure to air pollution and pollen, conditional on age, is driven by intertemporal variation in air quality in the year when the cohort was born, along with the timing of a child's birth. So, if an area experienced a spring of unusually poor air quality, children born in winter would be exposed to different levels of air pollution than the children born in summer.

Consider an example to help make this more transparent, in Fig. 1. The figure graphs average air quality during the first year of life for children who would enroll in kindergarten in 2010-11 in Salt Lake City, Utah, by their month of birth. Children born in the fall and winter of 2005 were exposed to higher average pollen levels than children born in late spring and summer of 2006. So, children born in December 2005 were exposed to an average pollen count of about 100 g/m^3 per month over the first 12 months of their lives – a level classified as high in standard air quality ratings – while those born after the heavy pollen season of spring 2006 were exposed to about half that much pollen. Conversely, children born in the summer of 2006 were exposed to higher levels of ozone during their first year, since they experienced portions of two summers by their first birthday. It is this variation, rather than within-student differences I use to identify the effects of early/lifetime exposure on math and reading readiness at the start of kindergarten. The assumption here is that timing of birth, and the within-site variation in air quality in 2005 and 2006 compared to other years has no effect on readiness. Buckles and Hungerman (2013) have illustrated that the fertility behavior of relatively educated, older women trying to conceive is different from younger, less educated women, resulting in seasonal patterns in the maternal characteristics of newborn infants. This is a potentially threat to validity for using month of birth as an instrument, common in research on topics like academic red-shirting. Here, however, this is less of a concern since the identifying assumption is that weekly patterns of air pollution within a site during the birth year are exogenous. This would hold even if there are average month of birth differences in student characteristics, as long as the variation in air quality driving the estimates is due to as good as random site-specific differences in inter-temporal air quality patterns during the birth year.[10]

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 = 1450.

4. 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 are Hispanic children. This is likely the consequence of selecting only ECLS-K:2011 sample members who live in sites where air quality data are available. Notably, these sites include areas with disproportionately high Hispanic populations, including large metropolitan areas in California and Texas. 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.[11] 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.[12]

4.1. 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

[10] In the aggregate, monthly variation in air quality does not mirror the well-established relationship between age and school-readiness. See Fig. A1 for the patterns of math/reading scores by month of birth for the estimation sample.

[11] Digest of Education Statistics, Table 204.10: http://nces.ed.gov/programs/digest/d13/tables/dt13_204.10.asp.

[12] Digest of Education Statistics, Table 202.20: http://nces.ed.gov/programs/digest/d14/tables/dt14_202.20.asp.

Table 2
Mean test scores and air quality measures by assessment period.

Assessment period	Variable	Mean	Std. Dev
Fall of Kindergarten	Math score	32.5	11.81
	Reading score	48.27	12.61
	Pollen count	116.33	236.5
	PM 2.5 AQI	9.49	3.65
	Ozone AQI	30.93	9.37
Spring of Kindergarten	Math score	46.28	12.34
	Reading score	61.98	14.85
	Pollen count	571.63	857.34
	PM 2.5 AQI	35.58	11.97
	Ozone AQI	37.93	7.29
Fall of 1st Grade	Math score	54.53	14.41
	Reading score	71.08	16.66
	Pollen count	104.55	165.17
	PM 2.5 AQI	42.24	10.89
	Ozone AQI	34.58	12.9
Spring of 1st Grade	Math score	68.07	15.3
	Reading score	85.5	15.91
	Pollen count	451.83	821.57
	PM 2.5 AQI	38.97	13.37
	Ozone AQI	40.06	8.48
Fall of 2nd Grade	Math score	72.41	15.01
	Reading score	88.87	14.16
	Pollen count	130.3	182.11
	PM 2.5 AQI	38.4	8.42
	Ozone AQI	32.98	7.81
Spring of 2nd Grade	Math score	81.71	13.74
	Reading score	96.87	12.6
	Pollen count	701	1226.7
	PM 2.5 AQI	36.03	10.79
	Ozone AQI	38.01	5.29

those subjects at a point in time, as well track growth over time. Hence, mean scores increase with age, and changes are measures of relative growth.[13] There are larger increases in scores on 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 positively skewed 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 dependent variables and measures of air quality into logs for the regression analyses.

4.2. Early Childhood Exposure and Test Scores

In Table 3, I present estimates of the relationship between ambient air quality during reading and math assessments. All models include child, time and location fixed effects, as described in Model 1, above. By focusing on within-site variation in air quality the results in Table 3 are robust to any metropolitan differences in air quality, amenities and infrastructure, and to parental sorting that might be related to children's academic achievement.

The first two columns do not control for weather conditions (temperature and precipitation) during the testing period, while the second two columns include controls for weather. The results in Table 3 are consistent with a number of well-known patterns in educational outcomes. Poor and minority children score lower on both math and reading assessments. For example, I estimate children from poor families score about 9 percent lower on math assessments and approximately 8 percent lower in reading. Further, girls in these early grades score higher than comparable boys on reading assessments.

The results also suggest negative relationships between threats to air quality and student performance in school. In the first two columns, when no controls for temperature and precipitation are included, students perform relatively poorly on math assessments when levels of ambient pollen and ozone are high, and poorly on reading assessments on days of high levels of APM2.5 and ozone. Recall that measures of air quality are in log form, so the coefficients approximate elasticities. So each 1 percent increase in ambient pollen levels is associated with about a 0.007 percent reduction in performance on reading and math assessments. 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 0.7 percent. The relationships between APM2.5 and ozone levels are larger in magnitude. For example, each percent increase in these air quality indices reduces reading performance of elementary school children by about 0.02 percent. So, increasing APM2.5 from an average day (25) to one with unhealthy air (above 50), would be expected to decrease performance on reading assessments by 2 percent.

The addition of controls for daily high temperature and precipitation illustrates two important aspects of the relationship between air quality and performance on cognitive tasks: Weather conditions can have their own effects, and can explain some of the relationship observed for air quality. The relationship between pollen and APM2.5 are both reduced modestly when weather conditions are included, while the relationship between ozone and test performance observed in the first panel is entirely explained by weather. This is due to a significant negative relationship between daily high temperature and test performance, and the strong positive relationship between ozone and high temperature. One potential explanation is that in schools without air conditioning, high temperatures make test taking difficult on their own, and this effect is more important than any net ozone effect. The same is not true for pollen and particulate matter: Regardless of weather conditions, these threats to air quality lower students' performance on math and reading assessments, respectively.

In columns 5 and 6, I present estimates of models that control for underlying changes in student test scores using site-specific linear trends along with common year/season fixed effects. The effects of ambient pollen on math achievement and APM2.5 on reading achievement are essentially unchanged from the previous specification controlling for underlying year/season effects as common shifters. The robustness of the estimates to different approaches to modeling underlying time/aging effects suggests that within-site variation in air quality is effectively unrelated to other factors that might be changing in a city/area that may shape math and reading achievement patterns for young children.

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

[13] For details, see https://nces.ed.gov/ecls/assessments2011.asp.

Table 3
Air quality and performance on math and reading assessments in elementary school.

VARIABLES	Outcome					
	Math (1)	Reading (2)	Math (3)	Reading (4)	Math (5)	Reading (6)
Pollen	−0.007**	−0.001	−0.006**	−0.002	−0.005**	−0.001
	(0.0023)	(0.0025)	(0.0025)	(0.0026)	(0.0022)	(0.0029)
APM2.5 AQI	−0.001	−0.022*	0.001	−0.017**	0.001	−0.020**
	(0.011)	(0.012)	(0.0099)	(0.0066)	(0.011)	(0.0077)
Ozone AQI	−0.034**	−0.022***	−0.009	−0.009	0.007	0.006
	(0.0139)	(0.0068)	(0.0145)	(0.0098)	(0.008)	(0.011)
High Temperature (C°)			−0.004***	−0.0018**	−0.004***	−0.0017**
			(0.001)	(0.001)	(0.001)	(0.001)
Precipitation			−0.0001	0.00002	−0.0001	0.00002
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age (in months)	0.086***	0.041***	0.084***	0.040***	0.082***	0.045***
	(0.012)	(0.012)	(0.0082)	(0.012)	(0.009)	(0.011)
Age^2	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0003***	−0.0001***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00003)	(0.00003)
Two Parents?	0.017*	−0.005	0.017*	−0.002	0.012	−0.006
	(0.0078)	(0.0073)	(0.0078)	(0.012)	(0.008)	(0.008)
Observations	5451	5443	5451	5443	5451	5443
R-squared	0.877	0.870	0.878	0.870	0.880	0.872
Number of Children	1450	1450	1450	1450	1450	1450
Child FE?	Yes	Yes	Yes	Yes	Yes	Yes
Site FE?	Yes	Yes	Yes	Yes	Yes	Yes
Period FE?	Yes	Yes	Yes	Yes	Yes	Yes
Site Trends?	No	No	No	No	Yes	Yes

All models, control for family composition and poverty status, child gender, race and ethnicity, and percent of students in grade who are eligible for free or reduced price meals, as described in Model 1.
Robust standard errors (clustered on site) in parentheses.
* $p<0.1$
** $p<0.05$,
*** $p<0.01$,

obvious marker for sensitivity to changes in air quality. In Table 4, I present results of Model 1, restricting the analysis to children with an asthma diagnosis, as reported by their parents. Table 4 also presents basic demographic characteristics of this subset of children. Comparing the top panel with overall sample means illustrates that asthma is more common among boys and children from single parent families, and somewhat less common among Hispanic children.[14]

The bottom panel (B) of Table 4 presents estimates of the effect of declining air quality on reading and math assessment scores for children with a history of asthma. Notable here is that compared to the full sample, there is a large effect of ozone air quality on test performance for asthmatic students. For these students, the effects of ozone swamp any other air quality (or weather) effects. Ozone typically is found to have especially harmful effects for those with asthma, because is it not water-soluble and can build up in and inflame lung tissue. In the clinical medical literature ozone is identified as the most important pollution trigger for acute asthma attacks. For example, in *Lancet*, McConnell et al. (2002) report that in a study of more than 3500 children, ozone was the only air pollutant associated with asthma risk.

4.3. Lifetime exposure and school readiness

I next turn to operationalizing model 2, which includes measures of lifetime exposure to pollen, fine airborne particulate matter, and ozone. Recall 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. Since all models control for age (in months), variation is driven by patterns of air quality during 2004-2005, when this cohort was born.

In Table 5, I present results for estimates of Model 2. The dependent variables are measures of reading and math skills at the start of kindergarten and the measures of lifetime exposure are standardized (normal) here, since the units of measure of pollen and APM2.5 and ozone are different and are summed over multiple periods. The impact of ambient air quality on school readiness is somewhat different from the patterns of air quality on within-student test performance, in Table 3. While changes in performance from assessment to assessment were smaller for students tested on days with high levels of particulate matter (pollen and APM2.5), there is limited evidence that pollen or APM2.5 at the start of kindergarten negatively affect performance. Reading scores are lower on days with relatively high pollen, but APM2.5 has no similar effect.

While ambient air quality appears to have little effect on school readiness, lifetime exposure to pollen has significant negative effects on reading and math ability at the start of kindergarten: a standard deviation increase in pollen levels leads to a decrease of more than 20% in performance on the start-of-kindergarten reading and math assessments. Exposure to ozone and APM2.5 over the course of childhood does not appear to have similarly harmful effects on math and reading abilities at the start of kindergarten.

Finally, in Table 6 I make use of the fact that air quality is known before, during and after students take math and reading assessments. Using this information, I can assess whether air quality in advance of testing has lingering effects over and above contemporaneous effects. Further, air quality measured after testing periods should have no effects, and hence provide a falsification check on the main results. I attempt to limit the impact of serial correlation within a site by using air quality measured two weeks before and after a test week. The results in Table 6 are from

[14] This measure is as reported by parents.

Table 4
Effects of air quality on test scores among children with asthma.

Panel A: Characteristics of Asthmatic Students

Variable	Mean	Std. Dev.
Female(0/1)	0.355	0.479
Black (0/1)	0.151	0.358
Hispanic (0/1)	0.235	0.424
Poor (0/1)	0.167	0.373
Two Parents (0/1)	0.544	0.498

Panel B: Estimates of Air Quality Effects on Test Scores

Variable	Outcome:			
	Math	Reading	Math	Reading
Pollen	-−0.002	−0.0002	−0.001	−0.0004
	(0.0023)	(0.0047)	(0.0025)	(0.0049)
APM2.5 AQI	−0.011	−0.044*	−0.001	−0.044**
	(0.0247)	(0.0222)	(0.030)	(0.018)
Ozone AQI	−0.131**	−0.065**	−0.113**	−0.068***
	(0.051)	(0.0257)	(0.042)	(0.0196)
High Temperature (C°)			−0.0034*	0.0001
			(0.0002)	(0.001)
Precipitation (x100)			0.000	0.005
			(0.0002)	(0.02)
Age (in months)	0.091***	0.031	0.090***	0.032
	(0.019)	(0.022)	(0.02)	(0.022)
Age^2	−0.0000***	−0.000	−0.0000***	−0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Two Parents?	0.009	0.0002	0.006	−0.0005
	(0.023)	(0.012)	(0.023)	(0.026)
Observations	842	843	842	843
R-squared	0.884	0.856	0.885	0.856
Number of Children	230	230	230	230
Child FE?	Yes	Yes	Yes	Yes
Site FE?	Yes	Yes	Yes	Yes
Period FE?	Yes	Yes	Yes	Yes

All models, control for family composition and poverty status, child gender, race and ethnicity, and percent of students in grade who are eligible for free or reduced price meals, as described in Model 1.
Robust standard errors (clustered on site) in parentheses.
* $p<0.1$
** $p<0.05$,
*** $p<0.01$,

models including site, year, and child fixed effects, and can be compared to the main results (columns 3 and 4) in Table 3, which found negative effects of pollen on math and APM2.5 on reading. The results in Table 6 suggest that the impact of pollen on math scores may be driven by lingering effects of exposure during the weeks leading up to testing. Controlling for pollen levels before and after testing dates, I find the effect of pollen levels two weeks prior to testing has negative effects on math achievement, and the point estimate is

The relationship between APM2.5 on reading scores identified in Table 3 does not seem to be driven by prior exposure. Rather, the point estimate (-0.014) of the impact of fine particulate matter AQI on reading is quite similar to the preferred estimate (-0.017) from Table 3. However, the contemporaneous estimate here is not significant because the addition of pre/post measures inflates standard errors. The magnitude of the effect of ozone in the weeks after testing is slightly larger than the effect during the testing week. Recall that for the full sample (i.e. not restricted to asthmatic students) the results in Table 3 indicated no negative effects of ozone on math or reading scores. In any case, there is no evidence in Table 6 that air quality measured after testing weeks affects math or reading scores.

5. Conclusions

Economists have advanced our understanding of the effects of air quality on human health and development. Recent work in this area has examined the effects of air quality on children's performance in school. This paper provides the first evidence on this topic using panel data and an identification strategy relying on within-student variation. Secondly, by linking individual data to local air quality, I provide insight into the relative importance of exposure accumulated over childhood separate from exposure at the time of testing.

Using data on academic skills between the ages of 5 to 8 years old, I find evidence that math and reading achievement are inhibited by diminished air quality due to pollen and fine airborne particulate matter, respectively. For students with a history of asthma, as reported by a parent, I find large negative effects of ozone on math and reading achievement. The magnitudes of the estimated effects of poor air quality on children's performance on cognitively demanding tasks are substantively important. Students score between 1 to 2 percent lower on math and reading scores on days with high levels of pollen or APM2.5 compared to days when they are low. For ozone, the effect on math and reading performance for students with a reported history of asthma are much larger: If tested on days with high levels of ozone, asthmatic students score about 10 percent lower on reading and math assessments than if they'd been tested on a day with low ozone.

In addition to contemporaneous effects, I find substantial negative effects of lifetime exposure to pollen on math and reading ability at the start of kindergarten. Indeed, a one standard deviation increase in lifetime pollen exposure decreases performance on both assessments of math and reading readiness by

Table 5
Air quality and math and reading school readiness.

Variable	Outcome	
	Math	Reading
Pollen (at test)	0.001	−0.018**
	(0.0125)	(0.0072)
APM2.5 (at test)	−0.010	−0.025
	(0.0263)	(0.0226)
Ozone (at test)	0.061	0.040
	(0.0717)	(0.0690)
High Temperature (C°)	−0.001***	−0.000
	(0.0003)	(0.0002)
Precipitation	−0.000	0.000
	(0.0003)	(0.0003)
Pollen (Lifetime)	−0.202***	−0.201***
	(0.0452)	(0.0239)
APM2.5 (Lifetime)	0.064	0.050
	(0.0691)	(0.0387)
Ozone (Lifetime)	−0.073	-0.044
	(0.1058)	(0.0687)
Female	0.001	0.036***
	(0.0241)	(0.0098)
Black	−0.113***	−0.036
	(0.0252)	(0.0273)
Hispanic	−0.199***	−0.102***
	(0.0340)	(0.0243)
Age (in months)	0.022***	0.011***
	(0.0021)	(0.0012)
Child Poor?	−0.099**	-0.075**
	(0.0407)	(0.0315)
Two Parents?	0.101**	0.070***
	(0.0355)	(0.0146)
% Receiving FARM	−0.003***	−0.002***
	(0.0006)	(0.0003)
Observations	1070	1070
R-squared	0.349	0.255
Site FE?	Yes	Yes
Period FE?	Yes	Yes

All models, control for family composition and poverty status, child gender, race and ethnicity, and percent of students in grade who are eligible for free or reduced price meals, as described in Model 2.
Robust standard errors (clustered on site) in parentheses.
** $p<0.05$
*** $p<0.01$,

Table 6
Air quality around test dates and math and reading scores.

Variable	Outcome	
	Math	Reading
Pollen (at test)	0.0001	−0.002
	(0.0028)	(0.0032)
Pollen (2 weeks before test)	−0.009***	0.001
	(0.0016)	(0.0022)
Pollen (2 weeks after test)	−0.001	0.0001
	(0.0024)	(0.0021)
APM2.5 (at test)	−0.001	−0.014
	(0.012)	(0.008)
APM2.5 (2 weeks before test)	−0.001	0.008
	(0.011)	(0.013)
APM2.5 (2 weeks after test)	−0.003	−0.01
	(0.01)	(0.01)
Ozone (at test)	0.003	−0.007
	(0.014)	(0.011)
Ozone (2 weeks before test)	−0.027	0.01
	(0.022)	(0.015)
Ozone (2 weeks after test)	−0.033	0.001
	(0.027)	(0.019)
Child FE?	Yes	Yes
Site FE?	Yes	Yes
Period FE?	Yes	Yes

All models, control for family composition and poverty status, child gender, race and ethnicity, and percent of students in grade who are eligible for free or reduced price meals, and weather conditions, as described in Model 1.
Robust standard errors (clustered on site) in parentheses.
* $p<0.1$,
** $p<0.05$
*** $p<0.01$,

20 percent. This is an effect size of 0.5, and large by the standards of school based interventions. If one uses the rule-of-thumb estimate of a 1 standard deviation for a typical student's learning gain over the course of a school year, high levels of pollen exposure can mean children start kindergarten about half a year behind. This magnitude is not surprising in light of the large clinical literature on pollen exposure and child learning, discussed above and high childhood seasonal allergy rates. There is also clinical evidence suggesting pollen exposure affects child cognitive development (Simons, 1996).

Distinguishing between the impacts of ambient air quality and long-term exposure 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. Further, contemporaneous effects can more readily be ameliorated, for example by spending less time out of doors in advance of cognitively demanding tasks or scheduling those tasks to avoid poor air quality days. If effects are due to extended exposure, this suggests the mechanism could be inhibited development or learning, and avoidance would be relatively costly.

Better understanding the relative impacts 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 improve student performance on assessments by improving air quality and possibly by encouraging effective treatment for sensitive groups.

The case for expanding treatment is strongest for students with asthma. I find the largest negative effects of poor air quality on school performance for this group. Evidence from the medical and public health literature already indicates substantial long-term benefits and cost savings for school-based interventions to diagnose and treat asthma. For example, Tai and Base (2011) estimate that the benefits of school-based health clinics in reducing hospitalization and other immediate health costs of asthma, as well as improved mortality and work productivity are more than four times larger than their costs. The possibility of preventing additional costs due to limited educational achievement for asthmatic students would be further justification for subsidies to improve diagnosis and treatment for children.

The results here provide less clear evidence about the value of treatment to non-asthmatic students for air-quality induced disorders like seasonal allergies. The observational data used here provides no information about whether students suffered from or were treated for seasonal allergies. Further, while clinical studies overwhelmingly find seasonal allergy symptoms negatively impact cognitive functioning (e.g., Bender, 2005; Druce, 2000; and Fineman, 2002), medical treatments do not offer much protection (Bender, 2005, and Kay, 2000).

While the current results provide mixed support for expanding treatment for conditions exacerbated by poor air quality, they provide unequivocal evidence of the value of limiting exposure to air pollution and pollen. 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 a source for socio-economic disparities in the education. Schools

Fig. A1. Math/reading scores at start of kindergarten by month of birth. Air quality in first year of life, by month of birth: salt lake city, UT

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.

A potential limitation of the current paper is the use of community level measures of air quality to measure the environment of students sitting in classrooms in the surrounding community. One reason for this is that at least in some schools, children are tested in classrooms equipped with air-conditioning, where closed windows and air filtration improves air quality. This is not necessarily a limitation here, since human adaptation to air quality is relevant for understanding effects on cognitive functioning. A different problem is due to the fact that air quality varies over time and space, so levels of daily average air quality recorded at monitoring site are likely to mis-measure the levels of exposure in the community. Any measurement error would result in attenuation bias, suggesting the estimates here are lower bounds.

Appendix

See Fig. A1.

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