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DOES POLLUTION DRIVE ACHIEVEMENT? THE EFFECT OF TRAFFIC POLLUTION ON ACADEMIC PERFORMANCE

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ABSTRACT

We examine the effect of school traffic pollution on student outcomes by leveraging variation in wind patterns for schools the same distance from major highways. We compare within-student achievement for students transitioning between schools near highways, where one school has had greater levels of pollution because it is downwind of a highway. Students who move from an elementary/middle school that feeds into a "downwind" middle/high school in the same zip code experience decreases in test scores, more behavioral incidents, and more absences, relative to when they transition to an upwind school. Even within zip codes, microclimates can contribute to inequality.

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I. Introduction

Over 6.4 million children attend public school within 250 meters of a major roadway (Kingsley et al., 2014), and nearly one in five schools that opened in the 2014-2015 school year were built near a busy road (Hopkins, 2017). Proximity to highways may make the land cheaper, but school districts and parents are often unaware of the health risks of highway pollution. Understanding the impact of traffic pollution in schools is critically relevant for social policy, but influences on academic achievement are largely absent from EPA estimates of the social costs of pollution.

There is relatively little research on how pollution exposure over primary and secondary school influences human capital accumulation. We attempt to build on earlier work by estimating the impact of attending a school with higher ambient pollution levels on the academic and behavioral outcomes of public school students. We use a novel identification strategy that leverages variation in pollution exposure caused by movement through the Florida school system as students transition from elementary to middle school or middle school to high school. We compare achievement in students transitioning between schools near highways, where one school has had greater levels of pollution because it is downwind of a highway, in models with zip code, grade, and student fixed effects.

A sizable literature in economics is interested in contemporaneous health- and mortality-related impacts of pollution.[1] Likewise recent evidence demonstrates that even mild early life

[1] A growing literature has linked air pollution to mortality among infants and the elderly (Anderson, 2015; Chay & Greenstone, 2003; Currie & Neidell, 2005; Deryugina, Heutel, Miller, Molitor, & Reif, 2016; Knittel, Miller, & Sanders, 2015), birth weight (Currie, Davis, Greenstone, & Walker, 2015; Currie & Walker, 2011), asthma attacks (Simeonova, Currie, Nilsson, & Walker, 2018), and bronchitis (Beatty & Shimshack, 2011), among other contemporaneous health shocks.

health shocks can substantially affect long-term outcomes,[2] but we know much less about how pollution exposure influences the years between early life and adulthood (Almond, Currie, & Duque, 2017). Additionally, while some recent research investigates how pollution exposure during gestation and early life affects later human capital outcomes (Almond, Edlund, & Palme, 2009; Bharadwaj, Gibson, Zivin, & Neilson, 2017; Black, Bütikofer, Devereux, & Salvanes, 2013; Persico, Figlio, & Roth, 2016; Sanders, 2012), little is known about medium-term, year-to-year health shocks during childhood and adolescence affect human capital formation and child development.

There are also a few studies that document how acute, short-term exposure to air pollution on testing days affects test score performance. For example, Marcotte (2017) used the variation in air quality on different testing days and found that children who took tests on worse days for pollen and fine airborne particulate matter had worse outcomes. Similarly, Roth (2016) found that pollution on testing days affected college students' performance in the United Kingdom, and Ebenstein, Lavy, & Roth (2016) found that pollution affected performance on high school exit exams in Israel. However, the present paper is the first to compare both year-to-year exposure to pollution, as well as exposure on the testing days.

To implement our natural experiment, we use a unique administrative dataset on the universe of public school students born in Florida from 1992-2002. We follow these students over time, observing rich information on their behavioral, demographic, and academic characteristics. We find that attending school where prevailing winds place it downwind of a nearby highway more than 60% of the time is associated with 0.040 of a standard deviation lower test scores, a 4.1

[2] For instance, early pollution exposure is related to the development of congenital anomalies (Currie, Greenstone, & Moretti, 2011), which affect outcomes long-term.

percentage point increase in behavioral incidents, and a 0.5 percentage point increase in the rate of absences over the school year, compared to attending a school upwind of a highway the same distance away.[3] Given the size and diversity of the state of Florida, we are also able to examine these impacts by race, socioeconomic status, and gender.

Our research design contrasts with an earlier literature that only either examined the influence of long-term in-utero exposure on test scores or the direct short-term effect of “day of test” exposure. This is the first paper to disambiguate the effects of acute exposure to pollution during testing days from medium-term exposure to pollution over a year. Along with Persico and Venator (2018), we are one of the first papers to estimate the impact of medium-term, year-to-year variation in pollution exposure on child achievement throughout childhood, and the first to do so using policy-generated moves through a school system as an identification strategy. Finally, we are the first paper to look at the causal impact on achievement of school districts locating schools downwind of major highways. Such policies expose students to higher levels of pollution, and we therefore shed light on policy implications related to school location decisions.

These contributions are relevant to broader discussions in the fields of health, inequality, and children. As Almond et al. (2017) point out in their recent literature review, even mild health shocks in early life can lead to substantial long-term negative outcomes, but we know substantially less about the intervening period between early life and adulthood. Likewise, most studies on pollution use larger geographic areas than the zip code level. Recent research suggests that there is significant within-commuting zone variation in intergenerational inequality (Rothstein, 2018),

[3] Behavioral incidents are teacher reported student behavior infractions. Most of the time (>95%) behavioral incidents result in suspension from school.

and small geographic variations in childhood pollution exposure could be one factor behind this pattern.

II. Background

A growing literature has linked pollution to mortality among infants and the elderly (Anderson, 2015; Chay & Greenstone, 2003; Currie & Neidell, 2005; Deryugina, Heutel, Miller, Molitor, & Reif, 2016; Knittel, Miller, & Sanders, 2015), asthma attacks (Simeonova, Currie, Nilsson, & Walker, 2018), and bronchitis (Beatty & Shimshack, 2011). Additionally, in-utero air pollution could affect human capital accumulation in childhood. Persico, Figlio and Roth (2016) find that in utero exposure to pollution is associated with lower birth weight, a higher likelihood of having a behavioral incident in school, and worse academic achievement. Several other studies find a similar relationship between in-utero exposure and later test scores (Almond et al., 2009; Bharadwaj et al., 2017; Black et al., 2013; Persico et al., 2016; Rau, Urzúa, & Reyes, 2015; Sanders, 2012). Many of these pollutants are extreme, including toxic waste sites (Persico et al., 2016; Rau et al., 2015), radioactive waste (Black et al., 2013), and nuclear fallout (Almond et al., 2009).

Much of this literature focuses on either the very young or the elderly. Younger populations are potentially of interest because investments in child health could result in greater later life productivity. While we know that early life health shocks can substantially affect long-term outcomes, we know very little about the years between early life and adulthood (Almond et al., 2017). A few exceptions include Aizer, Currie, Simon, and Vivier (2018), who find that early exposure to lead in preschool affects later test scores, Persico and Venator (2018), who find that being near an industrial plant harms tests scores and suspensions, and Simon (2016), who finds that early life exposure to cigarette smoke harms childhood health.

A few economists have focused on the effects of exposure to wind-based traffic pollution: Herrnstadt and Muehlegger (2015) argue that traffic pollution influences impulse control. They showed that short-term hourly variation in wind direction in Chicago lead to higher crime in areas downwind of highways than on the opposite upwind side. There is also some work on the prolonged impacts of traffic pollution. In a study similar to ours, Anderson (2015) documented that long-term exposure to being downwind of a highway was associated with higher mortality rates among the elderly, though housing characteristics were similar on either side of the road.

There is reason to believe that traffic pollution could be especially damaging during childhood because burning fossil fuels releases Polycyclic Aromatic Hydrocarbons (PAHs), carbon monoxide, and other toxicants. There are a growing number of epidemiological studies on how PAHs might harm child development, but most of the evidence of the effects of PAHs comes from in-vitro studies of embryonic rodent cells, which have shown that PAHs are potentially mutagenic (Lovasi et al., 2014; Margolis et al., 2016; Perera et al., 2009) or from associational studies that have found increased PAH exposure is associated with increased cases of asthma (Karimi, Peters, Bidad, & Strickland, 2015) and attention deficit hyperactivity disorder and learning disabilities (Abid, Roy, Herbstman, & Ettinger, 2014).

Likewise, pollution shocks during the school year could impede human capital formation through several channels. Health effects may reduce attendance. Currie and colleagues found that high levels of carbon monoxide were associated with reduced school attendance under a difference-in-differences strategy accounting for persistent school and year effects (Currie, Hanushek, Kahn, Neidell, & Rivkin, 2009). Ransom and Pope (1992) similarly found a relationship between pollution and school attendance, with more small particulate matter in the air associated with more absences. Second, early exposure could affect a child's development in ways that could persist even after the child is removed from a high-pollution environment. Finally, pollution could cause short-term cognitive and health disruptions in either children or teachers during the school day that could affect performance and accumulate over the course of the school year. There is growing evidence in the economic literature that pollution has short-term impacts on cognition, productivity, and behavior. Chang et al. (2016a, 2016b) use hourly variation to show that increased exposure to fine particulate matter decreases productivity per hour of pear packers and call center workers, while Archsmith, Heyes, and Saberian (2018) showed that baseball umpires make more mistakes on days with higher pollution.

School districts and parents are often unaware of the health risks of highway pollution, particularly because there are not many studies of the effects of air pollution from traffic on childhood health and achievement. In addition to shedding light on the causal relationship between traffic pollution in schools and child outcomes, this paper presents a timely evaluation of the effects of locating schools near highways.

III. Identification Strategy

Baseline Difference in Differences Design

Naïve correlations between air pollution and academic outcomes cannot be interpreted as causal because pollution exposure is not randomly assigned. To disentangle the effects of pollution exposure from other factors that could influence child outcomes, we follow children over time, and compare their outcomes as they transition from elementary/middle school to middle/high school when both schools are near a highway, but where some schools are upwind and others are downwind of the highway. By including individual, grade, year, and zip code fixed effects in our regression models, our strategy can be thought of as a type of difference-in-differences approach:

we compare within-child differences in an outcome before versus after changing schools for children who attend an upwind relative to downwind school in the same zip code.

We define a major highway as a US interstate or US highway and their immediate feeder routes.[4] Pollutants from car/truck exhaust can be blown hundreds of meters by the wind from such highways, particularly NO/NO_2 and ultrafine particles (UFP); the maximum distance we would expect pollutants to be blown is about 0.4 miles (Karner, Eisinger, & Niemeier, 2010).[5] In a supplementary analysis, we use EPA data to directly document that pollution is elevated downwind of major highways in Florida. We thus limit our sample to only schools within 0.4 miles from the highway to ensure that our treated and control schools are similar in unobservable characteristics that might differ between schools near and far from a highway. This is the same as the cutoff in Anderson (2015), who found similar housing prices on either side of highways in Los Angeles, while the downwind side of the highway had higher pollution and higher mortality among the elderly[6].

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[4] In our baseline specification we use FDOT shape files that have defined road segments along each highway. In a few cases, such road segments extend beyond the official designation to include main feeder roads that we also include as a "highway" in our sample. We get similar results when excluding these roads.

[5] A recent meta-analysis found that nitrogen oxide (NO and NO_2) blows up to 565 meters (0.35 miles) and ultrafine particles (UFP, defined as particulate matter 0.1 micrometers or less in diameter) blow up to 910 meters (0.57 miles) downwind (Karner, Eisinger, & Niemeier, 2010). Particulate matter 10 micrometers or less in diameter (PM_{10}) and ozone travel only 0.12 miles based on wind direction, while fine particular matter that is 2.5 micrometers or less in diameter ($PM_{2.5}$) does not vary substantially relative to background levels based on wind direction and distance from highway (Karner et al., 2010). Other studies find that traffic pollution potentially travels further when pushed by wind. Currie and Walker (2011) examined exposure within 1.12 miles, and recent work suggests that even 2 miles is possible in some cases (http://newsroom.ucla.edu/releases/air-pollution-from-freeway-extends-93857). We limit our analysis to 0.4 miles to remain conservative and to not compare schools near a highway to those that are further away.

[6] We also find null effects of wind direction on observable pollutants in our sample when we include pollutants more than 0.4 miles away in our sample.

We classify a school as downwind if the wind consistently blows across the highway and towards that school; we elaborate on the definition below. Figure 1 illustrates our analytical strategy. In Panel A, the bold gray line represents a major highway in an anonymized part of the state. The gray dots represent schools. If the dominant wind pattern blows east to west in this part of the state, schools to the left of the vertical major highway will be exposed to additional pollution. Schools to the right of the highway, though still exposed to similar traffic, noise,[7] or other characteristics that come with being proximate to a major highway, will receive substantially less pollution exposure. Students who attend a school upwind in, say, elementary school move to a new school when they switch from fifth to sixth grade. If that middle school is downwind of a major highway, that student is now treated, and the analysis compares their outcomes before and after treatment within the same zip code relative to students who move between schools and don't change their up/downwind status. Panel B of Figure 1 displays the distribution of interstates and US highways across Florida.

To implement this design, we limit the sample to just those students who either attend elementary school in fifth grade before moving to a middle school in sixth grade or those who attend a middle school in eighth grade and then move to a high school in ninth grade. The estimating equation is:

(1) $$Y_{igj} = \beta_0 + \beta_1 Downwind_{igj} + S_{gj}\omega + D_j\gamma + X_{ig}\rho + \theta_i + \tau_g + \delta_j + \varepsilon_{igj}$$

where $Downwind_{igj}$ is some measure of prevailing wind direction faced by school j attended by student i in grade g and β_1 is the coefficient of interest for the effect on some outcome (Y_{igj}) of being downwind. θ_i is an individual fixed effect to account for time-invariant student-level characteristics, τ_g is a grade fixed effect to account for any grade-specific effects, and δ_j is a zip-

[7] Noise from traffic pollution does not vary significantly with wind direction (Allen et al., 2009).

code level fixed effect to account for constant zip-code level characteristics in schools over time. Zip codes in Florida are typically small and subsume school districts[8], helping to absorb sorting by school district. The vector S_{gj} controls for time-varying school characteristics (percent Black, percent Hispanic, average maternal education by school, percent of children from married families, percent of teachers with a master's degree, school size in 100's of students, and the school's stability rate[9]). The vector D_j controls for two time-invariant school characteristics related to location: a vector of 0.1-mile-bin distance dummies measured from the nearest highway (0-0.1 miles, 0.1-0.2 miles, 0.2-0.3 miles, and 0.3-0.4 miles) and a linear control for number of highways within a one-mile radius.[10] The vector X_{it} controls for time-varying individual characteristics: free- and reduced-price lunch (FRL) status, year dummies, and an indicator for whether the student moved to a new school that year.[11] The coefficient β_1 on $Downwind_{igj}$ captures the differential change in test scores for a student who moves to a middle (high) school with a different prevailing wind direction relative to one who moves but whose school's wind direction does not change. In our baseline model we cluster all standard errors at the school level. [12]

The drawback of this approach is that we can only estimate effects for those who change their exposure status from fifth to sixth grade or eighth to ninth grade. We thus re-estimate equation (1) for all students in all grades and show these results in the Appendix. Here, the coefficient β_1 on

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[8] School districts in Florida are synonymous with counties.
[9] The stability rate is defined as the percentage of students in October who are still present in the February membership count.
[10] The count of roads provides an estimate of the density of roads in the area. Using the one-mile distance balances between not being collinear with number of nearest roads in our "downwind" model, with still capturing urban density.
[11] Our key coefficient therefore directly estimates the effect of moving downwind independent of the effect of moving.
[12] We show that this choice is robust to other reasonable clustering schemes in Appendix Table A5.

$Downwind_{igj}$ captures the change in test scores for a student who moves to any new school (for whatever reason) with a different prevailing wind direction relative to one who moves, but whose schools wind direction does not change.

We make two main identifying assumptions. First, we assume that after implementing our difference-in-differences model there are no factors other than differences in pollution levels that affect child outcomes when students transition to downwind schools. For example, any identification strategy that relies on student moves might be biased if families select into moving. All of our models employ student fixed effects to account for any constant student ability or other constant family characteristics. However, results would still be biased if students who will, for unobserved reasons, have lower test scores in a given year systematically move to downwind schools. To help avoid such potentially choice-driven moves, we focus on changes between schools that occur as part of the "policy-induced" transition of graduating from elementary schools that feed into a middle school or from middle schools that directly feed into high schools. These students did not choose to move when their trajectories were changing; instead, their move was determined by district policy. In addition, we test for sorting and school quality differences in several ways. For example, we show a balancing test in which we regress various school quality indicators on our main predictor variables. These results suggest that children who switch schools are switching to schools with similar characteristics as the ones they previously attended. We also perform a large number of additional tests for sorting into schools shown in section V.D and V.E below.

Second, we assume that in the absence of switching to a downwind or upwind school, other school switchers (to schools of the same downwind status) can serve as a valid counterfactual over the same time period. Estimations of equation 1 above will be biased if students who transition to/from a downwind school are on a different trajectory relative to their peers who did not make such a transition. We directly test for differential trends between treated and control students using an event study design. Because estimating event studies requires defining a discrete move from an upwind to a downwind school (or the reverse) and looking only at students who have non-missing test scores over a balanced panel, the samples and specifications are slightly different from our main model. We discuss our exact methodology for the event study in detail in the data appendix.

The treatment that we measure is a student attending a school that is downwind. This makes it difficult to separate the direct impact of individual level student pollution exposure from the impact of attending a school that has had longer-term high-level exposure to pollution. It is therefore important to interpret our baseline reduced form results as capturing the casual effect of both student pollution exposure and of attending a school that has had extended pollution exposure.

Finally, the results may be biased towards zero if exposure effects are long-lasting. For example, even after a student moves from a downwind school to an unexposed upwind school, the student might continue to have lower academic performance because of the permanent damage pollution might have done (e.g. if the student gets asthma, they will have it for life). This scenario would bias our estimates towards zero, so we will explore the differences in to-upwind versus to-downwind moves in detail below.

Downwind Status

Essential for the estimation of equation (1) above is that we assign prevailing wind direction to schools. We construct proxies of prevailing winds from high frequency, hourly wind data in 2010 using only hours that occur during the school day. At the hourly level, we define a school j as downwind of a given highway if the wind direction blows within 45 degrees of a ray running from the nearest point on the highway to the school.[13] That is, school *j* is downwind of the r^{th} nearest major highway segment in hour *h*, it would be considered downwind in that hour, as follows:

$$(2) \qquad Downdwind_{jrh} = \begin{cases} |ray_{jr} - winddirection_{jrh}| < 45° = 1 \\ |ray_{jr} - winddirection_{jrh}| \geq 45° = 0 \end{cases}$$

We proxy all other years of data with the 2010 data because the 2010 wind data has substantially more functioning wind monitors. There were many fewer wind monitors in the early years, so we lack the power to reliably use annual variation in wind direction. Further, there were many more anomalous and missing wind direction readings for the wind monitors that we did have in the earlier years, making us concerned that using this data will add significant noise to our estimates. Finally, wind monitors were being non-randomly added in geographic areas over time in a way that could be correlated with observed demographics in Florida. We are therefore concerned that using an unbalanced panel of wind monitor could introduce bias into our estimates. We do check, with the wind monitor data we have, that wind direction is consistent across years; for instance, the correlations between our annual wind direction measures in 2010 and 2012 is 0.81.

Some schools are near multiple major highways. Taking r = 1-5 highway segments, we take the maximum of $Downdwind_{jrh}$ to obtain $Downdwind_{jh}$, a measure of whether a school is downwind of at least one of the nearest five major highways in a given hour. We then collapse the data over the year to obtain $Downdwind_{j}$, which provides the percent of time a school is downwind from any nearby major highway over the course of the year. For our first measure of wind direction, we create a binary variable to delineate treated from non-treated schools, using a cutoff of 60% of time downwind. We originally chose the cutoff of 60% in our study to capture

[13] A road segment is a continuous portion of road with uniform characteristics as defined by the Florida Department of Transportation in their highway shape files.

schools that are downwind a large amount of the time and therefore get the most consistent exposure to pollution over the school day. Further, by focusing on schools that are downwind a high proportion of the time we make it more likely that students are regularly exposed throughout the day, as there is likely variation over the school day, depending on school and student schedules, in terms of when pollution matters the most for learning and cognition.[14] We test the robustness of this choice to other cutoffs empirically (see Figure 2) and find that outcomes are non-linear over percent of time downwind, with a drop in performance for schools downwind 60 percent of the time or more. From here on we refer to "downwind" as a school that is downwind 60% or more of the time and any other school as "upwind", unless we explicitly say otherwise.

Overall there are 59 downwind schools in our sample and 750 upwind schools. One concern is that we are comparing a large number of "control" schools to a relatively smaller number of treated schools. One way we address this concern is by showing a robustness test that limits the sample to "upwind" schools that are in the same zip code as the "downwind" schools. After removing the zip-codes that don't directly contribute to our identifying variation 25% of the schools in our sample are downwind (46 out of 187 schools), and our results are robust to this specification.

In addition, we also show all of our results using a continuous measure of wind exposure. We construct a variable that captures whether the average wind pattern blows directly at a school, directly away from a school, or in-between these extremes. Specifically, for each hour of observed

[14] Finally, 2010 is just one representative year, so focusing on schools that are downwind the majority of the time in 2010 makes it more likely that we are capturing prevailing winds. Further, as Figure A1 shows, there is fair amount of variation over time in wind direction and breaks from pollution exposure over the course of a day could provide respite. By focusing on schools that are downwind a high proportion of the time we make it more likely that students are regularly exposed throughout the day.

wind data, we calculate the difference in degrees between bearing from the school to the highway and the direction the wind is blowing at a school: $Intensity_{j1h} = |ray_{j1h} - winddirection_{j1h}|$. We only calculate this from the nearest highway (*r*=1), as there is no obvious way to measure intensity across multiple nearby highways like we do with downwind status. Because we do not average across multiple highways, when using wind intensity, we exclude parts of the road segment that go onto feeder routes in order to focus on only major US highway and interstates, meaning our N is smaller in this analysis. After calculating intensity within an hour, we take the average over all hours ($Intensity_{j1h}$) and transform this to equal zero when the average degree is directly away from a school (completely untreated by the wind) and one when the wind is always blowing directly towards a school. This measure has the advantage of capturing more information about wind direction and variation in how directly the wind is blowing at the school as a measure of treatment intensity.

IV. Data Description

Our sample contains the universe of students who were born in Florida in 1992-2002 and attended a Florida public school within 0.4 miles of a major US highway in 1996-2012. The data came from the Florida Department of Education (FDOE). This administrative data provides rich demographic characteristics and student-level outcomes not typically available in the literature. We exclude virtual academies where the physical location of a school is unrelated to student pollution exposure, as well as adult education centers, schools for troubled youths and teen parents, schools for children with disabilities, and juvenile justice centers. We link this student-level data to comprehensive data on school characteristics from the Florida School Indicator's Report (FSIR) and the National Center for Education Statistics (NCES), Florida highways shape files and traffic monitor data, and Florida wind monitor data.

Our primary outcome of interest is individual-level scores on the annual Florida Comprehensive Assessment Test (FCAT) in math and reading. Students took the FCAT in math and reading in grades 3 to 10 in 2001 through 2012, and we take the average of the two test scores.[15] We also examine two additional outcomes: whether the student was written up for a behavioral incident during the year and the annual absence rate for students on a zero to one scale. FDOE data includes individual-level characteristics such as race, ethnicity, gender, and free- or reduced-price lunch (FRL) eligibility.[16]

Highway Data

We link schools to the nearest major highway using road data from Florida Department of Transportation (FDOT), which maintains geo-coded files on the location and traffic density of large roads in Florida. We use the files from 2010, as there is little change in these roads from year to year. Each major highway is subdivided into smaller segments. The segment length varied from 74 feet to 29 miles, with a mean of 3.3 miles and a median of 2.0 miles. For matching roads to schools, we subdivide these road segments into a series of points that are a maximum of 0.1 miles apart. We match each school to its nearest five road segments using these points. Of the schools with at least one major highway within 0.4 miles, the average distance to the nearest road is 0.21 miles. Fifty three percent of those schools have only one major road within 0.4 miles, 24 percent have two, 10 percent have three, and the remaining 12 percent have four or more.

[15] Scores are standardized by year and grade at the state level for each test, with a mean of zero and a standard deviation of one, and we average the math and reading scores by year to create one summary measure of academic performance. We take the average of the two scores rather than estimating them separately to reduce noise and guard against type 1 error from multiple hypothesis testing. When looking at these outcomes separately they both follow the same overall pattern in our data.
[16] Additional information about the data sets and construction of variables is available in the data appendix.

The FDOT calculates estimated average annual daily traffic (AADT) for each road segment. These counts are an annual measure that does not provide specific details on average traffic counts over the school year or school day. Likewise, there is not enough year-to-year variation in traffic to leverage within road segment changes in annual average traffic volume over time. We instead use 2010 AADT to stratify our estimates by traffic volume, and we consider this to be a rough proxy of additional pollution exposure due to more heavily trafficked roads. For major highway segments, the AADT ranged from 1,150 cars per day to 306,000 cars per day. In our sample, the mean AADT of student's nearest road is 64,419 cars per day.

Wind Direction

To determine whether a school is downwind of a major highway, we use 2010 data from the U.S. Meteorological Assimilation Data Ingest System (MADIS), a part of the National Oceanic and Atmospheric Administration (NOAA). The 2010 data is the most complete year available that is within the time frame of education data. Each MADIS station includes wind readings once per minute, and we take the first observation per hour.[17] There are 1,029 stations in the state of Florida, and we connect each school to its nearest station and assign it that station's hourly wind data. We also match wind direction data to pollution monitor data which we discuss in detail in the data appendix. Across Florida winds vary substantially both within a 24 hour period and across geographic location (see Appendix Figure A1).

Descriptive Characteristics

Column 1 of Table 1 displays student-weighted average characteristics for all schools in Florida. Column 2 shows the same characteristics for all schools within 0.4 miles of a major highway, and Column 3 shows the average school characteristics for children who switch to

[17] We have also tried taking a random observation within the hour and the results are the same.

schools in sixth or ninth grade, for whom the downwind status of the school changes. Students attending schools within 0.4 miles of a highway are slightly more disadvantaged than children in Florida overall. They are more likely to have mothers who were not married at the time of birth, slightly more likely to be on free or reduced-price lunch, more likely to be Black, and less likely to be Hispanic. Overall, the children who switch to downwind or upwind schools are similar to other children attending schools within 0.4 miles of a highway on most characteristics, except for percent Hispanic, where they are more similar to the average for Florida.

V. Results

A. Main Results

Table 2 presents our main results. The sample is based on our preferred specification with policy-induced movers to middle school (grades 5-6) and high school (grades 8-9); a version with all students in all years is available in Appendix Table A1. The first row of Panel A is the estimated effect for students when they are in a school downwind of a major highway 60% or more of the time, relative to those same students when they are not. Panel B shows results using our continuous intensity measure, which we interpret as the estimated effect of changing to a school with wind blowing entirely upwind (equal to zero when the wind from the nearest road always blows directly away from the school) to entirely downwind (equal to one when the wind from the nearest road always blows directly towards the school).

The different specifications present broadly similar results: being downwind of a major highway is associated with lower average FCAT scores, a higher likelihood of having a behavioral incident, and a higher absence rate. Attending a school that is downwind of a major highway is associated with 0.04 standard deviation decrease in scores, relative to attending a school that is not. There is a 4.10 percentage-point increase in the likelihood of having a behavioral incident and a 0.54 percentage-point increase in the absence rate. Given that the average rate of absences in Florida schools is 5.6 percent, this is a 9.6 percent increase in the rate of absences from school. For the continuous measure, rotating wind such that a school is 10 percentage points "more" in the direction of the school is associated with a 0.014 standard deviation decrease in test scores. On this continuous measure, the effects are null for behavioral incidents and not statistically significant for rates of absence. Appendix Table A2 shows additional specifications for downwind status beginning only with a core set of fixed effects and controls, then gradually adding additional controls for school quality and demographic characteristics. If being downwind in our model was correlated to school characteristics due to student sorting or other reasons, we would expect the coefficient on downwind to change as we add these controls. We find similar results regardless of the specification.[18]

As discussed above, we chose the 60% cutoff for downwind status because we believe schools who experience particularly consistent wind pattern exposure over the school day are the ones most likely to show detectable effects on student outcomes.[19] Figure 2 directly tests this by presenting point estimates for average test scores using our main specification by the percent of time downwind, grouping schools into bins of downwind status: 0-20% of time downwind (the reference group), 20-30%, 30-40%, 40-50%, 50-60%, 60-70%, or more than 70% of the time. The

[18] We did this for mean intensity as well, and the results are similarly robust to including different controls. Due to the large number of results in the paper, this is available upon request.

[19] For example, more variable wind patterns provide more breaks from pollution exposure during the school day so that learning is less disrupted. Another possibility is that there is a tipping point over which pollution exposure matters for academic performance. Compounding both of these issues is that measurement error in capturing the prevailing wind direction could downwardly bias estimates, and we are less likely to be capturing prevailing winds at low levels of percent of time downwind.

effects are close to zero at low- to mid-levels of time spent downwind, while those schools downwind 60-70% or more than 70% of the year have larger negative effects on test scores.

The estimates based off of the policy-induced moves to middle/high school (Table 2) are somewhat larger than the magnitude of estimates using all students (Table A1), though the pattern of results is the same. Overall, our findings are consistent with moderately sized year-to-year effects of attending a school downwind on achievement. We discuss the economic significance of these magnitudes in the conclusion below. In the following sections, we use our preferred specification of using "policy-induced" moves unless otherwise stated.

A major concern with studies on pollution is that students will sort into schools, such that pollution is associated with poor performance but does not cause poor performance. However, there are many times where, within the same school district, students (or their parents) do not choose to move schools, but they instead moved into a new school due to district policy. Specifically, a student who graduates from elementary school (in grade 5) to middle school (in grade 6) will switch school locations. Without necessarily moving to a new home, some of these students move from an upwind to a downwind school, some move from a downwind to an upwind school, and some move within the same category. Therefore, we first test the validity of our results by showing an event study on the move from elementary to middle school. [20] This will make it transparent if those students who moved into a school with a different prevailing wind direction in

[20] We focus on the move to middle school first because it is a relatively transparent way of showing pre-trends for one of the major sources of policy-induced variation in the study. Further, there is a longer viable pre-period for this group due to a longer continuous period of elementary school than those moving from middle to high school. For the move from middle to high school there are fewer older students in the sample because tests end at grade 10, and they move more frequently, so we do not have enough statistical power to estimate an event study of substantial length on this move after balancing the sample. However, we do show an "all movers" event study in the appendix.

6th grade were on a different trajectory in achievement. Furthermore, the associated graphs help us understand how outcomes change relative to the timing of exposure to pollution.

Figure 3 focuses on two groups: those who move from a downwind elementary school to an upwind middle school from fifth to sixth grade ("To upwind") and those who move from an upwind elementary school to a downwind middle school from fifth to sixth grade ("To downwind"). We estimate the effects such that they are relative to grade 5. See the data appendix for more details on our event study methodology.

Several key patterns stand out. First, we see a relatively flat pre-trend in FCAT scores for both groups across grades 3-5. Second, scores drop sharply when students move to a downwind school in grade 6. Third, while there seems to be a slight increase in scores for students moving from a downwind to an upwind school, the impact is small and statistically insignificant. One explanation for this pattern is that the effects of pollution exposure may be persistent beyond the period of direct exposure. This would be the case if exposure to pollution in earlier grades has persistent effects on either cognition or skill acquisition that last even after pollution is alleviated. We also see a similar relatively flat pre-trend and sharp increase in behavioral incidents, with a more distinct effect of moving from downwind to upwind. Finally, the pre-period is mostly flat for percent of time absent, though there is a decline in absences in fifth grade followed by a sharp increase for those moving into a downwind school. We see a similar pattern if we instead use all students rather than our policy-induced movers (shown in appendix figure A2).[21]

[21] Appendix Figure A2 presents results for using variation from all moves for students who move from an upwind school (year -1) to a downwind school (year 0) in any grade (i.e., not only those students transitioning from elementary to middle school). Here, we see similar patterns for test scores and behavioral incidents. The pre-trends are slightly noisier but still relatively flat in the grades before the event with a sharp and persistent change in these outcomes as students move downwind. The pre-trends are not as flat for absences. We take these event studies as evidence

B. Annual versus Testing Week Pollution Exposure

Prior research finds that testing-day pollution exposure affects test performance (e.g., Ebenstein et al., 2016; Marcotte, 2017; Roth, 2016). In this section, we use our detailed wind data to assess this pattern, as well as test whether prevailing school year or testing week pollution better explains achievement outcomes. Though the designation of downwind status is static for each school for the annual variation, we can use the changing timing of the testing dates to examine whether testing-week-specific affects also drive results (Heissel & Norris, 2018). We do not show the same test on behavioral incidents or absence rate, as the test-week fluctuations should not change these annual measures.[22]

As in the main analysis, we use the 2010 data as a proxy for all years; that is, the annual exposure for a given school is the same across all years and variation comes from students moving across schools. We proxy testing week exposure using the 2010 wind data by creating a downwind measure based only on the specific two-week period of testing for each year.[23] Here, variation comes from both student moves and changes in the testing time. Not every school has wind data available to create this testing-year-specific downwind measure, so the N in this analysis is smaller than the main results.

Table 3 displays the results. Column 1 repeats the main specification on the subsample limited to schools with wind data available during the testing week. Column 2 instead only includes

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that differential trends between students who move downwind (or upwind) and those who do not change treatment status are not driving our results.

[22] We have examined these measures, and we find that test-week wind variation does not affect these outcomes after conditioning on annual variation, as would be expected. Results are available on request.

[23] While we get similar results using the annual data on wind patterns during testing weeks we are concerned about selection in where the wind monitors are set up over time, so we instrument one year of data over other years.

a measure of downwind status at the testing-week level. Finally, Column 3 includes both measures to test whether annual or testing week variation in pollution exposure more strongly predicts FCAT scores. We repeat this exercise for downwind status defined by being downwind 60% or more of the time (Panel A) and by our wind intensity measure (Panel B).

Focusing on Panel A, we replicate our finding that students in schools downwind 60% or more of the time over the course of the year have 0.04 standard deviations lower scores, relative to when they are in upwind schools. Moving to column 2, we find that attending a school that is downwind 60% or more during the testing week specifically leads to 0.02 standard deviations lower test scores, relative to testing weeks in other years when the student was not downwind. When we include both of these measures together, we find that the annual variation best predicts test score outcomes. Being downwind 60% or more of the time during the school year is associated with a 0.03 standard deviation decrease in test scores, while the testing-week-specific coefficient is small and statistically insignificant. In the intensity measure, the annual measure is almost twice the size of the test-week-specific measure of exposure. This suggests that continual exposure while students are learning has an impact that is two to four times greater than exposure on the day of the test.

C. Effects by Subgroup

We next examine several potential subgroups of interest. Different socioeconomic groups may have different access to resources to ameliorate the effects of pollution exposure such as academic help for more affluent students. Conversely, advantaged students are less likely to be exposed to pollutants at home, potentially leading to a larger marginal impact of attending a polluted school. Table 4 examines our preferred estimation for several subgroups: by race/ethnicity (White, non-Hispanic, Panel A; Black students, Panel B; Hispanic students, Panel C); by frequency that students identify as on free- or reduced-price lunch (always on FRL, Panel D; sometimes on FRL, Panel E; never on FRL, Panel F), and by gender (Panels G and H).

White, non-Hispanic students and Hispanic students have larger FCAT and absence responses to pollution, whereas Black students have larger behavioral incident results. The largest test score effects are for the never-FRL students, with lower effects for the always-FRL students. The sometimes-FRL students fall between these groups. There is no statistical effect on behavioral incidents for the never-FRL students. The behavioral effects are large and statistically about the same between the sometimes- and always-FRL students, though the sometimes-FRL estimate does not differ from zero. The absence rate effect is driven by the sometimes-FRL students.

There is no clear pattern of differences between boys and girls. Overall, these patterns suggest that the more-advantaged students are the most academically harmed by pollution exposure, while the less-advantaged are more likely to have behavioral incidents. While it is difficult to say for certain, this may be because disadvantaged students are already exposed to other sources of pollution.

D. Testing for Sorting into Schools

To test for sorting into schools, we first demonstrate that wind direction does not systematically predict school or student demographic characteristics. Figure 4 plots the relationship in raw means between the time a school spends downwind and several key school level characteristics. These figures show that spending more time downwind is not consistently associated with being negatively selected on observable socioeconomic demographic characteristics. If anything, being downwind a large amount of the time is associated with more students in married families and fewer black students, though the means are not typically statistically different from zero.

Table 5 shows a balancing test where we estimate equation 1 with various demographic characteristics as the outcome variable of interest regressed on our measures of downwind status. If within zip code sorting between schools is a problem after controlling for student fixed effects, we would expect it to be more of a problem in specifications where we leverage "any" move between schools rather than just the "policy generated" move to middle/high school. Therefore, we also show the balancing test in our supplementary specification where the coefficient on downwind status is identified off of "any" within student change. Overall the coefficients on downwind status in Table 5 are largely statistically insignificant, except for a few cases. This pattern is consistent with type 1 error. The coefficients are also of mixed signs relative to being associated with lower socioeconomic status characteristics. We also see no effect of wind status on the accountability grade Florida assigns the school (column 9). While attending a downwind school lowers test scores, the effects are not large enough to drive changes in high-stakes accountability tests: one of the key signals of school quality that families use. Finally, the coefficient on many of the most important covariates related to socioeconomic status are small and relatively precisely estimated. For example, in the "maternal education" regression the coefficient on being "downwind" is only .02 out of an average of around 12 years of mother's education. The lower bound of the 95% confidence interval suggests that at most being downwind decreases mother's education by a 0.1 of a year of education.[24]

The above test is consistent with sorting based on pollution being less of an issue with sorting into schools than residential sorting into neighborhoods. Selecting into schools based on

[24] Another key indicator of socioeconomic characteristics if the fraction of FRL students. Here the coefficient suggests that being downwind causes the percent of FRL students to decline by 1% (out of a mean of 67%). The standard errors are such that we can rule out that being downwind increases the percent of FRL students by more than 0.8%.

traffic pollution is also less likely than some other forms of pollution because small pollutants such as CO, UFP, and nitrogen oxides are not perceptible by human senses and are only detectable with scientific equipment. Larger, more perceptible particles do not disperse as far from highways. Finally, due to the coastal wind patterns and the peninsular shape of the state, prevailing winds tend to shift during the school day relative to the evening. Thus, even if a school is downwind over the course of a school day it does not necessarily mean the neighborhood it is located in itself is systematically downwind.

Zip code fixed effects help account for student sorting between zip codes. Our balancing test shows that within zip codes schools are similar based on observable demographic and quality characteristics, and the event study shows that treatment and control students are on comparable trajectories. That being said, we recognize that it is still possible that students could be sorting into schools or that prevailing wind direction could otherwise be endogenous, and we perform a number of tests to address this concern.

One serious remaining concern is that our results could be driven by within zip code sorting. We can formally test this by dropping all zip codes in which there are choices between elementary/middle/high schools in terms of being downwind 60% or more of the time. We begin by dropping all the control zip codes without at least one downwind school. Of the remaining we drop all those in which there are choices between elementary/middle/high schools that are both upwind and downwind. This limits the geographic coverage of our sample such that external validity is a concern, but an advantage of this approach is that now our results are exclusively identified off of cases where there is no room, within our observed sample, for within zip code sorting. Table 6 shows these results. The negative effects of attending a downwind school are larger than our baseline results and statistically significant, with a -0.08 standard devation impact on test scores. There are also larger effects on behavioral incidences and absences. However, the standard also errors are roughly double, making it unclear if the estimates are substantially different from our core results. Importantly, if within zip code sorting was driving our results we would expect to see smaller effects in this sample with few attendance choices.

In a related test, we drop all zip codes without at least one downwind school to address concerns that the "downwind more than 60% of the time" variable is comparing a large number of control schools to a small number of treated schools.[25] Results are in appendix Table 3 and are largely similar to our core results using downwind status. We also show our results are robust to dropping the most mobile students who we observe transitioning to schools between zip codes in Column 4 of Table 7, which we discuss in additional detail below.

E. Additional Robustness Checks

If our results are driven by traffic pollution, we would expect students to do worse if they are downwind of more heavily-trafficked roads. We operationalize this by examining the impact of being downwind of the road nearest to the school (r=1) in order to categorize schools by traffic volume. We then estimate our main model replacing the "downwind more than 60%" indicator with interactions between this indicator and three different AADT bins. We also include the un-interacted bins as controls.[26] Figure 5 plots the coefficients on these interactions. The estimates indicate that being downwind of the lower-traffic-volume roads has no statistical effect on FCAT scores: the point estimate is positive but statistically insignificant. The coefficient for being downwind of middle-traffic road is close to zero. There is a large effect of being downwind of the

[25] Once we drop these zip codes roughly 25% of the schools in the sample are downwind.

[26] The AADT bins we use are <50,000 average cars per day, 50,000-75,000 average cars per days, and >75,000 average cars per day.

highest-volume roads, and this effect statistically differs from the lowest-volume estimate (*p*-value of interaction=0.011). Overall, the main effects appear to be driven by the highest-trafficked roads.

We next perform a series of placebo tests to provide additional evidence that our results are not spurious. These placebo tests also guard against a related concern that, in spite of employing difference-in-differences, our estimates are somehow capturing the negative effects of changing schools.[27] Here we keep a students' timing of school changes the same but randomly assign downwind sixty percent of the time status and wind intensity at the school level.[28] We then re-run our primary specification with these placebo treatments. The results of this specification are presented in Table A3, and we find no statistically significant placebo effects.

Table 7 runs a number of additional robustness tests across our models using the average FCAT outcome to address a variety of concerns. The first column of Table 7 is a replication of the results from Table 2. The second column tests that noise or other highway related contaminants (such as kicked up dust) that travel short distances from highways due to wind direction are not driving the results. We do this by dropping schools within 0.3 miles of the highway. The results do not substantially change after dropping these schools. Column 3 presents results from a placebo test where we replace our "downwind" measure with an indicator variable equal to one if the wind is blowing parallel along the road segment sixty percent or more of the time. This should capture if there any effects related to strong prevailing winds in a location that is not directly associated with increased pollution exposure; however, the coefficient on test scores is small and not statistically significant.

[27] As another test against this concern we also tried controlling for "moving school" dummies up to three years out. Our results were robust to this specification.
[28] For wind intensity we draw from a uniform distribution. For downwind status we draw percent of time downwind from a uniform distribution and create an indicator for being downwind more than 60% of the time.

One worry with the analysis is that parents are moving their children in ways systematically related to achievement, even within the same school district. Though we do not know where students live, we know their school address, and in Column 4 we limit the sample to only students who stay in the same zip code in our observed data. Here, any differences cannot be driven by differential effects on cross-zip movers at any point through the end of high school. Here, we have lower power due to a lower N. The estimate for being downwind more than 60% of the time is larger in magnitude, while the estimate for the intensity measure is smaller.

Another concern with our analysis is that the long-run equilibrium of downwind schools is worse than in upwind schools, such that the downwind effect is actually a combination of pollution effects and negative peer effects. Although this would not change the policy implication that downwind schools are bad, it would be an important caveat in interpreting our results. We test this, as best as we can, by controlling for peer test scores as a "bad control". Specifically, when we add the average FCAT results for each school-year as a control in Column 5, the results do not change from the main specification, suggesting that it is pollution and not peer test scores that are driving our results.[29] Another point of evidence in support of this interpretation is that our estimates are roughly similar to estimates to pollution on test scores in other contexts (Marcotte, 2017; Persico & Venator, 2018).

As a final robustness check we examine different ways of clustering our standard errors. While we cluster our baseline results on school as the level of treatment, correlations in the error term across geography or over time could result in our estimated standard errors being too small. Appendix table A5 shows that our core results are robust to a range of different clustering schemes

[29] We recognize that average school-year FCAT is arguably an endogenous control, but felt reassured that including it here did not change our results.

for average FCAT. We have tried different types of clustering on the other outcomes, and they follow a similar pattern (results available upon request).

F. Pollution Estimates

So far we have focused on the reduced form effects of being downwind of a major highway. We can also approximately examine the first stage of pollution. We cannot directly apply our model to estimate pollution exposure because we cannot track changes in student-level exposure over time. Instead, we use hourly EPA pollution monitor and hourly MADIS wind data to examine how much pollution increases when the monitor is downwind of a highway in 2010. Our preferred specification uses month and site fixed effects, such that the effect is interpreted as the level of pollution for times when a monitor is downwind of a major highway, relative to times when the wind blows such that the same monitor is upwind. In appendix B we provide more details on this pollution data and on our exact estimating equation.

We do not have measures for ultrafine pollutants which are known to both affect cognition, health, and travel farther distances than heavier particles based on wind direction. However, we have data on several heavier particles (PM_{10}, CO, and NO_2) that we would expect to exhibit similar patterns with a smaller distance traveled (Karner et al., 2010). We take logs of these three pollutants so we can interpret the coefficient as percent changes.[30] We expect PM_{10} and CO to travel a maximum of about 0.12 miles, while NO_2 might travel up to 0.34 miles on the wind (Karner et al., 2010). We also examine a pollution index that normalizes each of these individual pollutants to have a mean of zero and a standard deviation of one over all pollution monitors, and then takes the simple average for each site-hour observation.

[30] We get similar results when we use levels instead of logs.

Table 8 presents the results. We include pollution monitors within 0.4 miles of a highway (Column 1) to match our main specification and pollution monitors within 0.1 miles (Column 2) to focus on the likely distance traveled of the particular pollutants we have available in the data. While Column 1 has more observations, we expect Column 2 to more consistently estimate these pollutants. The rows of the various pollution types include results of both being downwind (at a given site in a given hour), and by the downwind intensity measure (based on the difference in degrees in wind direction and monitor location in a given site and hour).

Broadly, across most measures, the table confirms the general pattern that being downwind increases pollution exposure. For instance, in the preferred 0.1 mile range, when a site is downwind of a major highway the pollution index increases by 0.187 standard deviations, relative to the hours of the day the site is not downwind. Moving from the wind blowing directly away from the monitor to directly at it in the wind intensity estimate increases pollution by 0.43 standard deviations. For the specific pollutants, PM_{10} increases by 11.2% when monitor is downwind of a major highway, CO increases by 8.9%, and NO_2 increases by a statistically insignificant 7.8%. The results are in the same direction but smaller when we expand the radius to 0.4 miles.

Very roughly, we approximate that downwind schools experience a 25% higher level of ambient traffic pollution in a day, relative to upwind schools.[31] We can combine our reduced form student achievement estimates with the estimated impacts of being downwind on pollution to derive a "two stage least squares" type of parameter. Scaling our preferred estimate of a policy-

[31] Students attending schools that are downwind 60% or more of the time are downwind on average 76% of the time or 6.08 hours of the school day, whereas other students are only downwind 2.16 hours (27% of the time). Therefore, "treated" students are downwind an average of 3.92 hours more than control students. Taking the pollution index measure of a 0.187 standard deviation increase in pollution, we calculate 0.187*3.92 = 0.73 standard deviations, or 25% of the pollution distribution applying the properties of a standard normal distribution.

induced move to a downwind school that has a 25% higher level of pollution, implies that increasing the ambient traffic pollution exposure of a school by 10% per day over the course of a school year causes students who attend this school to experience a 0.016 standard deviation decrease in test scores.[32] Similarly, a 10% increase in traffic pollution causes a 3.13 percentage point increase in behavioral incidents, corresponding to 14% of the mean. We can also approximate the additional exposure to ultrafine particulate matter using the atmospheric sciences literature. Based on estimates from the Karner et al. meta-analysis, schools downwind within 0.207 miles of a highway (the average for our sample) would experience an increase in ultrafine particulate matters that is 2.5 times the background levels.

VI. Conclusion

This is the first study, to our knowledge, to show negative academic effects of pollution related to traffic exposure during the school day. We leverage the microclimates that exist within zip codes and the policy-induced changes in school attendance for middle and high school to study how localized pollution exposure can harm school children. Using within-child variation in exposure, we show that children who move to a school downwind of a major highway have lower test scores and a higher likelihood of behavioral incidents and missing school than when those same children attended schools with similar characteristics that were not downwind of a major highway. The effects are larger for more heavily-trafficked roads, and the effects appear to last even after the child moves away from a downwind school. This suggests that once damage from pollution is done, even during middle childhood, it might persist, potentially affecting outcomes far into the future.

[32] Calculated by dividing a 0.040 standard deviation decrease in test scores and a 25 percent increase in pollution and then multiplying by 0.10.

In addition, the magnitude of these effects are substantively important, especially when one considers that 6.4 million children (or about 12.6 percent of public and secondary school students) attend school within 250 meters of a major roadway. To put this in context, Chetty, Friedman and Rockoff (2014) find that a one standard deviation improvement in teacher quality increased test scores by 0.1 standard deviations. This suggests that removing exposure to local highway pollution would increase test scores as much as increasing teacher quality by 40 percent of a standard deviation. Our findings are about one fifth of the magnitude of the Tennessee STAR experiment (Krueger, 1999), which found that reducing class sizes from 22 to 15 students increased test scores by about 0.2 standard deviations.

We can also use our estimates to evaluate the academic impact of environmental regulations that have decreased traffic emissions by applying our estimate that a 10% decrease in traffic pollution leads to a 0.016 standard deviation increase in scores. The EPA estimates increased auto and truck regulations as part of the Clean Air Act reduced traffic emissions by 70% between 1970 and 2015 (EPA, 2015), which implies a large 0.11 standard deviation increase in test scores.[33] These estimates would suggest that the reductions in traffic pollution over the past three decades are on par with major education interventions in a way that has not been catalogued by EPA welfare estimates.

There is reason to believe that our estimates are a lower bound on the true effects of highway pollution. For instance, our study's findings are identified from children who attended school within 0.4 miles of a major road for at least two school years. While that includes about

[33] See https://www.epa.gov/clean-air-act-overview, last accessed on 7/23/2018. While we believe this provides one application for understanding our estimates, there are some caveats to interpreting our results in this way. Our parameter is estimated off of our specific natural experiment and more research would be needed to understand how to apply this more broadly.

36% of our study population in Florida, we do not include effects for children who move from schools very far from a major highway to being downwind of such a road. Conceivably, such children are exposed to less ambient pollution when they are farther away from roads, so the change in pollution exposure may be related to even larger effect sizes for them. However, selection issues prevent us from exploring this possibility further. We note, however, that our estimates show negative effects for all students. In addition, our results will be biased towards zero if the effects of pollution exposure are long-lasting. Then, even after a student moves from a downwind school to an unexposed upwind school, the student might continue to have lower academic performance.

Our results also imply several important policy lessons. First, districts may want to consider the benefits of placing schools away from major highways. Districts may be unable to move already-existing schools, but compensatory measures such as air filtration systems may reduce the amount of in-school pollution exposure for schools located near highways (South Coast Air Quality Management District, 2013). Schools downwind of a major highway are not the only ones exposed to pollution, so these measures may be beneficial for schools in polluted areas more broadly. Finally, recent work by Chetty et al. (2014) suggests that there is a massive amount of heterogeneity across cities in intergenerational mobility. However, there is reason to consider that even within zip codes there are forces that create unequal outcomes due to, for example, the placement of schools. More broadly, pollution exposure is not evenly distributed across the socioeconomic spectrum. Given that low-income and minority students are more likely to be exposed to pollution and live near major roads, our demonstrated relationship between pollution and academic achievement may provide insight into why academic achievement gaps persist in the United States.

References

Abid, Z., Roy, A., Herbstman, J. B., & Ettinger, A. S. (2014). Urinary polycyclic aromatic hydrocarbon metabolites and Attention/Deficit Hyperactivity Disorder, learning disability, and special education in U.S. children aged 6 to 15. *Journal of Environmental and Public Health*, *2014*.

Aizer, A., Currie, J., Simon, P., & Vivier, P. (2018). Do low levels of blood lead reduce children's future test scores? *American Economic Journal: Applied Economics*, *10*(1), 307–341.

Allen, R. W., Davies, H., Cohen, M. A., Mallach, G., Kaufman, J. D., & Adar, S. D. (2009). The spatial relationship between traffic-generated air pollution and noise in 2 US cities. *Environmental Research*, *109*(3), 334–342.

Almond, D., Currie, J., & Duque, V. (2017). *Childhood Circumstances and Adult Outcomes: Act II* (Working Paper No. 23017). National Bureau of Economic Research.

Almond, D., Edlund, L., & Palme, M. (2009). Chernobyl's subclinical legacy: Prenatal exposure to radioactive fallout and school outcomes in Sweden. *The Quarterly Journal of Economics*, *124*(4), 1729–1772.

Anderson, M. L. (2015). *As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality* (SSRN Scholarly Paper No. ID 2663236). Rochester, NY: Social Science Research Network.

Archsmith, J., Heyes, A., & Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*.

Beatty, T. K. M., & Shimshack, J. P. (2011). School buses, diesel emissions, and respiratory health. *Journal of Health Economics*, *30*(5), 987–999.

Bharadwaj, P., Gibson, M., Zivin, J. G., & Neilson, C. (2017). Gray matters: Fetal pollution exposure and human capital formation. *Journal of the Association of Environmental and Resource Economists*, *4*(2), 505–542.

Black, S. E., Bütikofer, A., Devereux, P. J., & Salvanes, K. G. (2013). *This Is Only a Test? Long-Run Impacts of Prenatal Exposure to Radioactive Fallout* (Working Paper No. 18987). National Bureau of Economic Research.

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016a). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, *8*(3), 141–169.

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016b). *The Effect of Pollution on Worker Productivity: Evidence from Call-Center Workers in China* (Working Paper No. 22328). National Bureau of Economic Research.

Chay, K. Y., & Greenstone, M. (2003). The Impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics*, *118*(3), 1121–1167.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). The long-term impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *104*(9), 2633–2679.

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, *129*(4), 1553–1623.

Currie, J., Davis, L., Greenstone, M., & Walker, R. (2015). Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings. *American Economic Review*, *105*(2), 678–709.

Currie, J., Greenstone, M., & Moretti, E. (2011). Superfund cleanups and infant health. *American Economic Review*, *101*(3), 435–441.

Currie, J., Hanushek, E. A., Kahn, E. M., Neidell, M., & Rivkin, S. G. (2009). Does pollution increase school absences? *The Review of Economics and Statistics*, *91*(4), 682–694.

Currie, J., & Neidell, M. (2005). Air pollution and infant health: What can we learn from California's recent experience? *The Quarterly Journal of Economics*, *120*(3), 1003–1030.

Currie, J., & Walker, R. (2011). Traffic congestion and infant health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, *3*(1), 65–90.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2016). *The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction* (Working Paper No. 22796). National Bureau of Economic Research.

Ebenstein, A., Lavy, V., & Roth, S. (2016). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, *8*(4), 36–65.

EPA. (2015, February 27). Overview of the Clean Air Act and Air Pollution [Collections and Lists].

Heissel, J. A., & Norris, S. (2018). Rise and shine: The effect of school start times on academic performance from childhood through puberty. *Journal of Human Resources*, *53*(4), 957–992.

Herrnstadt, E., & Muehlegger, E. (2015). *Air Pollution and Criminal Activity: Evidence from Chicago Microdata* (Working Paper No. 21787). National Bureau of Economic Research.

Hopkins, J. S. (2017). *The invisible hazard afflicting thousands of schools*. Center for Public Integrity.

Karimi, P., Peters, K. O., Bidad, K., & Strickland, P. T. (2015). Polycyclic aromatic hydrocarbons and childhood asthma. *European Journal of Epidemiology*, *30*(2), 91–101.

Karner, A. A., Eisinger, D. S., & Niemeier, D. A. (2010). Near-roadway air quality: Synthesizing the findings from real-world data. *Environmental Science & Technology*, *44*(14), 5334–5344.

Kingsley, S. L., Eliot, M., Carlson, L., Finn, J., MacIntosh, D. L., Suh, H. H., & Wellenius, G. A. (2014). Proximity of US Schools to Major Roadways: a Nationwide Assessment. *Journal of Exposure Science & Environmental Epidemiology*, *24*(3), 253–259.

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2015). Caution, drivers! Children present: Traffic, pollution, and infant health. *The Review of Economics and Statistics*, *98*(2), 350–366.

Krueger, A. B. (1999). Experimental estimates of education production functions. *The Quarterly Journal of Economics*, *114*(2), 497–532.

Lovasi, G. S., Eldred-Skemp, N., Quinn, J. W., Chang, H., Rauh, V. A., Rundle, A., … Perera, F. P. (2014). Neighborhood social context and individual polycyclic aromatic hydrocarbon exposures associated with child cognitive test scores. *Journal of Child and Family Studies*, *23*(5), 785–799.

Marcotte, D. E. (2017). Something in the air? Air quality and children's educational outcomes. *Economics of Education Review*, *56*, 141–151.

Margolis, A. E., Herbstman, J. B., Davis, K., Thomas, V. K., Tang, D., Wang, Y., … Rauh, V. A. (2016). Longitudinal effects of prenatal exposure to air pollutants on self-regulatory capacities and social competence. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *57*(7), 851–860.

Perera, F. P., Li, Z., Whyatt, R., Hoepner, L., Wang, S., Camann, D., & Rauh, V. (2009). Prenatal airborne polycyclic aromatic hydrocarbon exposure and child IQ at age 5 years. *Pediatrics*, *124*(2), e195–e202.

Persico, C., Figlio, D., & Roth, J. (2016). *Inequality Before Birth: The Developmental Consequences of Environmental Toxicants* (Working Paper No. 22263). National Bureau of Economic Research.

Persico, C., & Venator, J. (2018). *The Effects of Local Industrial Pollution on Students and Schools* (Working Paper No. 3218789). Social Science Research Network.

Ransom, M. R., & Pope, C. A. (1992). Elementary school absences and PM10 pollution in Utah Valley. *Environmental Research*, *58*(1), 204–219.

Rau, T., Urzúa, S., & Reyes, L. (2015). Early exposure to hazardous waste and academic achievement: Evidence from a case of environmental negligence. *Journal of the Association of Environmental and Resource Economists*, *2*(4), 527–563.

Roth, S. (2016). *The Contemporaneous Effect of Indoor Air Pollution on Cognitive Performance: Evidence from the UK I Benefited from Comments and Suggestions*. Zurich: IZA Conference on Labor Market Effects of Environmental Policies.

Rothstein, J. (2018). *Inequality of Educational Opportunity? Schools as Mediators of the Intergenerational Transmission of Income* (Working Paper No. 24537). National Bureau of Economic Research.

Sanders, N. J. (2012). What doesn't kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *Journal of Human Resources*, *47*(3), 826–850.

Simeonova, E., Currie, J., Nilsson, P., & Walker, R. (2018). *Congestion Pricing, Air Pollution and Children's Health* (Working Paper No. 24410). National Bureau of Economic Research.

South Coast Air Quality Management District. (2013). *Final 2012 Air Quality Management Plan*. Diamond Bar, CA: South Coast Air Quality Management District. Retrieved from

Tables

Table 1: Characteristics of children within 0.4 miles of a highway

	(1) All children born in Florida	(2) All children attending school within 0.4 miles of a highway	(3) Children who change downwind status as they switch schools in 6th or 9th grade within 0.4 miles of a highway
School size (in 100s)	9.59	8.79	9.53
Percent of teachers with an MA degree	0.315	0.314	0.308
Percent of time free or reduced price lunch	0.517	0.590	0.604
Stability rate	0.940	0.935	0.931
Percent black	0.224	0.330	0.360
Percent Hispanic	0.240	0.206	0.252
Average maternal education	12.37	12.15	12.20
Percent mothers who are married	0.643	0.549	0.536
N Students	1,682,489	628,356	8,908

Notes: Observations are at the student-school-grade level. Column 1 are the means for children who moved from a school upwind to downwind at least once; column 2 shows means for children attending school within 0.4 miles of a highway; and column 3 shows means for children who switch downwind status as they change schools in 6th or 9th grade (downwind status changes) within 0.4 miles of a highway. Standard deviations are below means in parenthesis.

Table 2: Impact of attending school downwind

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
Panel A: Downwind more than 60% of the time			
Downwind more than 60%	-0.0400**	0.0410**	0.0054*
	(0.0167)	(0.0184)	(0.0028)
Observations	273,592	237,987	234,907
N students	107,635	94,464	93,385
Mean of outcome	0.0189	0.143	0.056
Panel B: Wind intensity			
Mean intensity, 0.1=10% from upwind	-0.1368***	-0.0015	0.0110
	(0.0491)	(0.0549)	(0.0082)
Observations	234,323	203,425	200,995
N students	92,788	81,264	80,388
Mean of outcome	0.0189	0.143	0.056

Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time or an intensity variable that increases by 0.1 if the wind blows 10 percentage points more directly at the school, on average. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade.

$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Annual versus testing week variation on average FCAT

	(1) Annual variation	(2) Test-week variation	(3) Annual and test-week variation
	Panel A: Downwind more than 60% of the time		
Annual	-0.0408**	NA	-0.0348*
	(0.0183)		(0.0194)
Testing week	NA	-0.0157*	-0.0116
		(0.0087)	(0.0092)
Observations	218,397	218,397	218,397
N Students	87,009	87,009	87,009
	Panel B: Wind intensity		
Annual	-0.1549**	NA	-0.1164*
	(0.0569)		(0.0586)
Testing week	NA	-0.0720**	-0.0572*
		(0.0229)	(0.0235)
Observations	190,444	190,444	190,444
N Students	75,965	75,965	75,965

Notes: Each row within a panel shows results from a different regression where average FCAT is the dependent variable. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Panel A examines pollution exposed using the 60% or more definition of downwind; Panel B uses the wind intensity measure. Column (1) runs the main specification on the subsample with wind data available during the testing week, but defines downwind at the annual level. Column (2) defines downwind at the testing-week level. Column (3) includes both measures to test whether annual or testing week variation in pollution exposure more strongly predicts FCAT scores. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade.

$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Effects by demographic subgroups

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
	Panel A: White, non-Hispanic students		
Downwind more than 60%	-0.0838***	0.0434*	0.0237***
	(0.0267)	(0.0242)	(0.0061)
	Panel B: Black non-Hispanic students		
Downwind more than 60%	-0.0030	0.0567**	0.0007
	(0.0184)	(0.0260)	(0.0112)
	Panel C: Hispanic students		
Downwind more than 60%	-0.0492**	0.0248	0.0110**
	(0.0229)	(0.0235)	(0.0049)
	Panel D: Always FRL students		
Downwind more than 60%	-0.0237	0.0422**	0.0094
	(0.0166)	(0.0197)	(0.0062)
	Panel E: Sometimes FRL students		
Downwind more than 60%	-0.0384	0.0481	0.0225***
	(0.0237)	(0.0309)	(0.0082)
	Panel F: Never FRL students		
Downwind more than 60%	-0.0777**	0.0163	0.0030
	(0.0306)	(0.0122)	(0.0042)
	Panel G: Girls		
Downwind more than 60%	-0.0356**	0.0491**	0.0141***
	(0.0160)	(0.0214)	(0.0045)
	Panel H: Boys		
Downwind more than 60%	-0.0449***	0.0341**	0.0126*
	(0.0171)	(0.0164)	(0.0069)

Notes: The panel indicates the subgroup stratified on. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a grade-moved indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. $^{*}p < 0.1$ ** $p < 0.05$, *** $p < 0.01$

Table 5: Balancing test

	(1) School size (in 100s)	(2) School stability	(3) Fraction teachers with master's degree	(4) Fraction FRL students	(5) Mean years of mothers' education by school	(6) Fraction black by school	(7) Fraction mothers married at birth by school	(8) Fraction Hispanic by school	(9) School Accountability Grade
Panel A: Main Specification Movers to Middle/High School									
Downwind more than 60%	-0.1332	-0.0013	-0.0096	-0.0115	0.0278	0.0070	-0.0041	0.0101	0.0438
	(0.7228)	(0.0052)	(0.0164)	(0.0098)	(0.0743)	(0.0107)	(0.0048)	(0.0181)	(0.1327)
Observations	284,508	284,508	284,508	284,508	284,508	284,508	284,508	284,508	273,294
N students	111,623	111,623	111,623	111,623	111,623	111,623	111,623	111,623	107,727
Downwind intensity	4.9441*	-0.0025	-0.0920*	-0.0261	0.1248	-0.0167	-0.0118	-0.0139	-0.4799
	(2.6077)	(0.0285)	(0.0486)	(0.0344)	(0.1690)	(0.0334)	(0.0201)	(0.0357)	(0.5462)
Observations	243,694	243,694	243,694	243,694	243,694	243,694	243,694	243,694	233,485
N students	96,287	96,287	96,287	96,287	96,287	96,287	96,287	96,287	92,584
Panel B: Balancing Test on "All Moves"									
Downwind more than 60%	-0.3528	0.0006	-0.0119	-0.0100	0.0373	0.0105	-0.0037	0.0053	0.0447
	(0.6003)	(0.0051)	(0.0166)	(0.0088)	(0.0596)	(0.0096)	(0.0047)	(0.0142)	(0.1090)
Observations	1,141,297	1,141,297	1,141,297	1,141,297	1,141,297	1,141,297	1,141,297	1,141,297	1,107,536
N students	337,228	337,228	337,228	337,228	337,228	337,228	337,228	337,228	330,034
Downwind intensity	4.0820*	-0.0014	-0.0596	-0.0427	0.0875	-0.0266	-0.0127	-0.0026	-0.2385
	(2.3678)	(0.0274)	(0.0410)	(0.0288)	(0.1580)	(0.0272)	(0.0184)	(0.0312)	(0.4117)
Observations	1,012,079	1,012,079	1,012,079	1,012,079	1,012,079	1,012,079	1,012,079	1,012,079	978,578
N students	304,375	304,375	304,375	304,375	304,375	304,375	304,375	304,375	296,584

Notes: Each row and column shows results from a different regression. Rows include downwind defined as an indicator variable for whether a student is in a school that is downwind of a major highway at least 60% of the time and the downwind intensity measure where an increase of 0.1 indicates a school is 10 percentage points more downwind. Each column uses a different variable as an outcome to verify that treatment status is not related to observable characteristics. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, and distance from nearest highway dummies. The models also include the school-level characteristics, whether the student was on FRL that year, and school demographic characteristics, except when that variable is the outcome. Standard errors clustered on school are in parentheses. Panel A uses only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade. Panel B includes all students and moves.

$^{*}p < 0.1$ ** $p < 0.05$, *** $p < 0.01$

Table 6: Test for school sorting: including only zip codes without school choices near a highway

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
Panel A: Downwind more than 60% of the time			
Downwind more than 60%	-0.0822**	0.1629***	0.0156**
	(0.0346)	(0.0288)	(0.0052)
Observations	8,335	7,497	7,412
N Students	5,922	5,440	5,383
Panel B: Downwind intensity			
Mean intensity, 0.1=10% from upwind	-0.8553**	1.5993***	0.1498**
	(0.3390)	(0.3036)	(0.0529)
Observations	8,335	7,497	7,412
N Students	5,922	5,440	5,383

Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time or an intensity variable that increases by 0.1 if the wind blows 10 percentage points more directly at the school, on average. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade, only in zips where there is no "choice" on which type of school (upwind/downwind) a student attends in a given grade.
$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Additional robustness and validity tests for average FCAT

	(1) Baseline model	(2) Drop schools <0.3 miles from highways	(3) Parallel wind placebo	(4) Drop students changing school-zips, grades 5-10	(5) Controlling for average FCAT by school
Panel A: Downwind more than 60% of the time					
Downwind more than 60% of the time	-0.0400**	-0.0359**	NA	-0.0782***	-0.0387**
	(0.0167)	(0.0167)		(0.0245)	(0.0163)
Observations	273,592	230,653		53,662	273,592
N Students	107,635	92,965		20,614	107,635
Panel B: Downwind intensity					
Mean intensity, 0.1=10% from upwind	-0.1368***	-0.1499***	NA	-0.1149	-0.1396***
	(0.0491)	(0.0527)		(0.0712)	(0.0486)
Observations	234,323	196,027		48,392	234,323
N Students	92,788	79,524		18,552	92,788
Panel C: Winds blow parallel 60% of the time					
Winds blow parallel 60% of the time	NA	NA	-0.0012	NA	NA
			(0.0134)		
Observations			230,653		
N Students			929,65		
Baseline model	Yes	No	No	No	No
Drop schools <0.3 miles from highways	No	Yes	No	No	No
Parallel wind placebo	No	No	Yes	No	No
Drop students changing school-zips, grades 5-10	No	No	No	Yes	No
Controls for school-level FCATs	No	No	No	No	Yes

Notes: Each column and row represents results from a different regression with average FCAT as the dependent variable. Column 1 replicates our results from table 2. Column 2 drops schools within 0.3 miles of a road. Column 3 is a placebo test replacing our wind exposure measure with winds blowing parallel to the highway 60% of the time or more as the variable of interest. Column 4 drops any student whose school changes zip codes in grades 5 through 10. Column 5 adds controls for school-level FCATs. Otherwise, the regression includes all of the controls in our baseline models. Standard errors clustered on school in parentheses. $^{*}p < 0.1$ ** $p < 0.05$, *** $p < 0.01$

Table 8: Pollution and Wind Direction

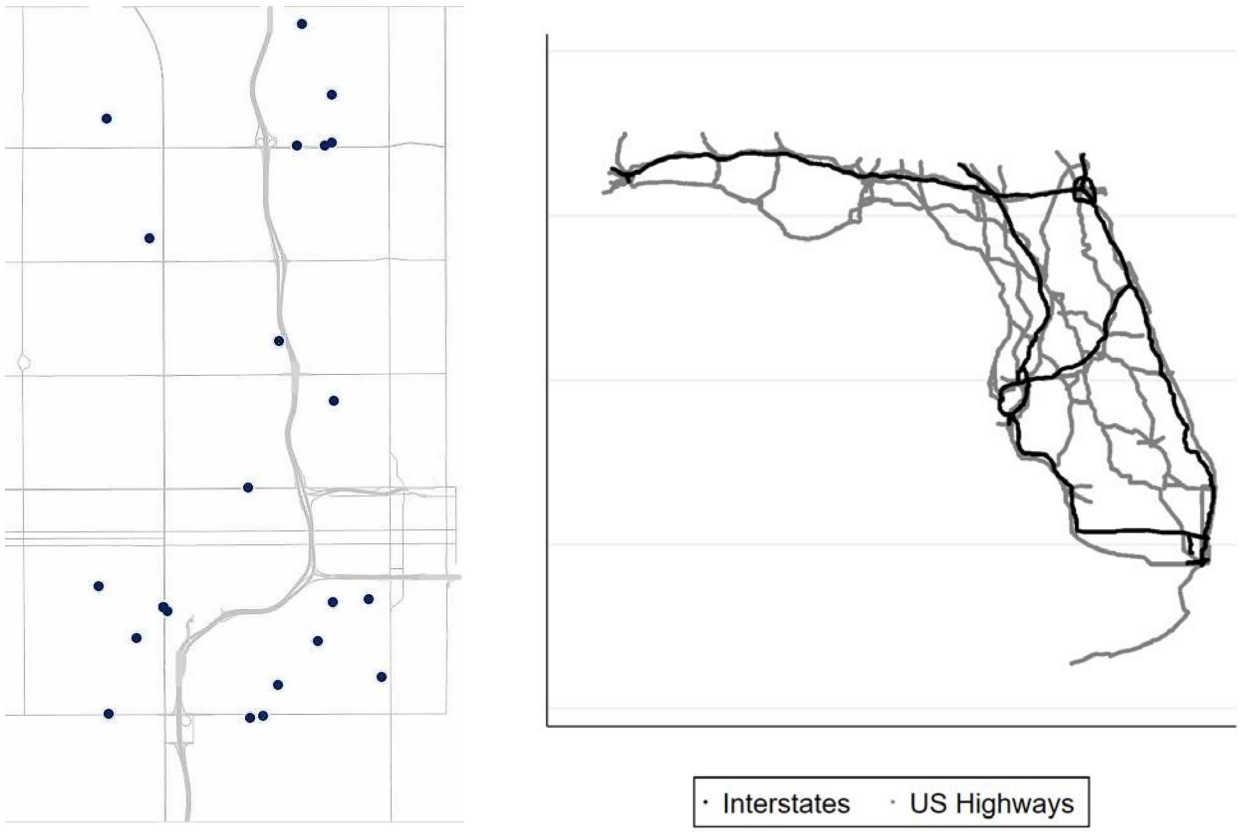
	(1) Monitors within 0.4 miles of road	(2) Monitors within 0.1 miles of road
	Outcome 1: Pollution index	
Downwind	0.043**	0.187***
	(0.022)	(0.039)
Mean intensity, 0.1=10% from upwind	0.060	0.433***
	(0.038)	(0.060)
# of Observations	36,979	11,505
	Outcome 2: Log PM_{10}	
Downwind	0.023	0.112***
	(0.019)	(0.031)
Mean intensity, 0.1=10% from upwind	0.034	0.270***
	(0.034)	(0.045)
# of Observations	13,244	5,520
	Outcome 3: Log CO	
Downwind	0.049**	0.089**
	(0.021)	(0.035)
Mean intensity, 0.1=10% from upwind	0.083**	0.175***
	(0.034)	(0.066)
# of Observations	13,966	2,777
	Outcome 4: Log NO_2	
Downwind	0.047	0.078
	(0.035)	(0.089)
Mean intensity, 0.1=10% from upwind	0.106*	0.641***
	(0.063)	(0.169)
# of Observations	5,805	590
Month FE	Yes	Yes
Site FE	Yes	Yes
Total # of monitors	15	5

Notes: The data used in this table is 2010 hourly MADIS wind monitor data merged with hourly pollution monitor data for all monitors within 0.4 miles of a highway. Each row and column shows results from a different regression. Downwind is an indicator for the pollution monitor being downwind in that hour. Intensity is the direction the wind is blowing in that hour normalized to be 1 when blowing directly at the monitor and zero when blowing directly away. Within 0.4 miles there are five PM10 monitors, three NO_2 monitors, and seven CO monitors. Within 0.1 miles there are two PM_{10} monitors, two CO monitors, and one NO_2 monitors. Standard errors (in parentheses) are clustered at the site-date level.

Figures

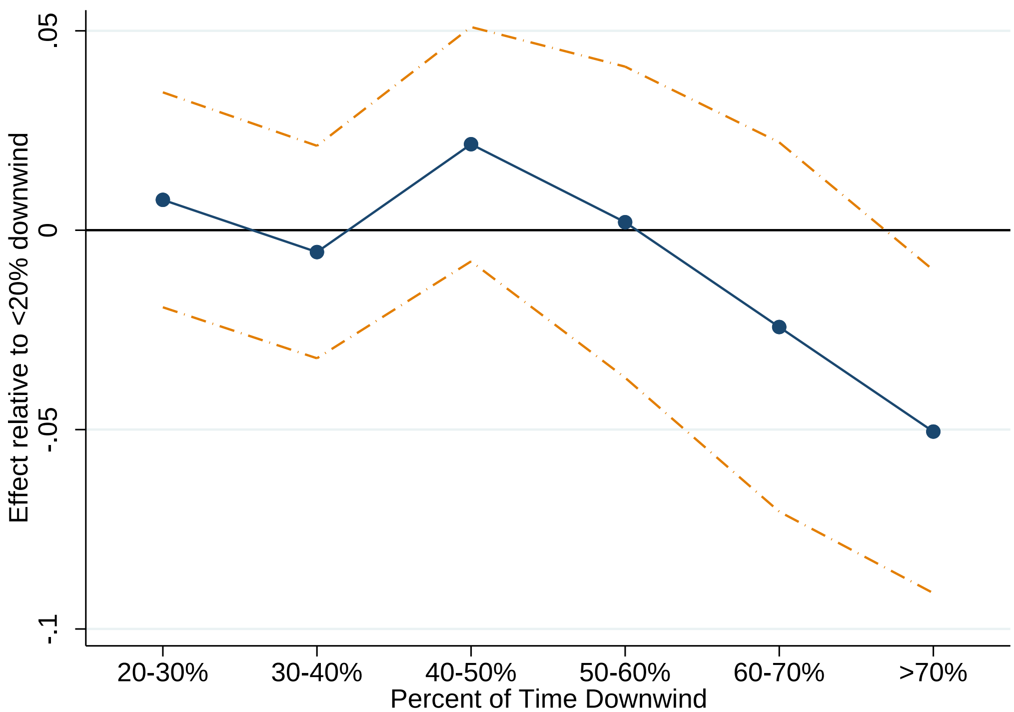
Figure 1: Identification of upwind and downwind schools

Panel A Panel B



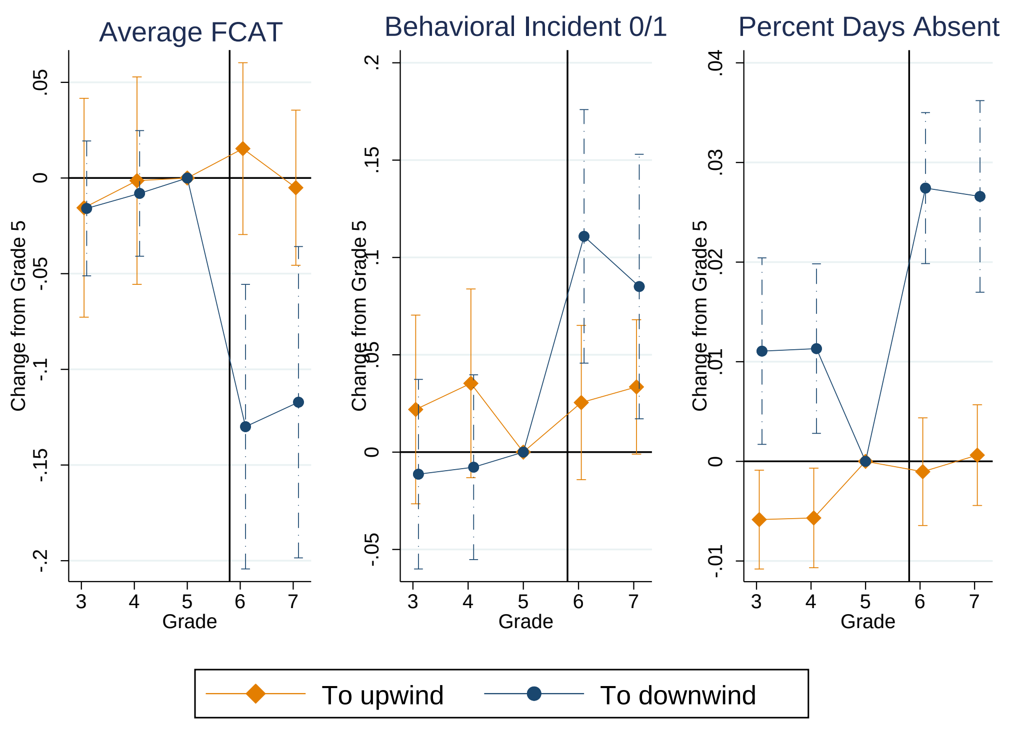
Notes: Panel A is an anonymized map of a portion of Florida that shows the relationship of some of the schools in our sample (the blue dots) relative to a major highway (the solid grey lines). Panel B is a map created from the Florida Department of Transportation shape files showing the interstates (in black) and US highways (in gray) in Florida, which we define as "major highways" for the purpose of our research design.

Figure 2: Effects by percent of time downwind



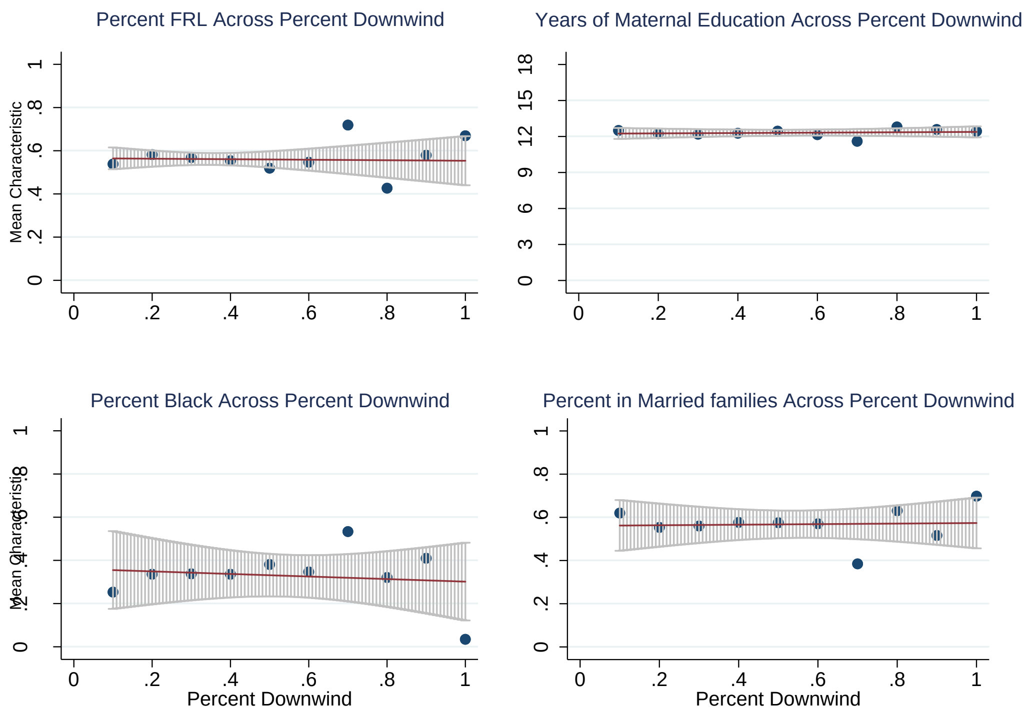
Notes: This figure shows the effect of percent of time downwind relative to a major highway on average FCAT for those moves generated by a "policy-induced" move to middle or high school. Each point plots the coefficient on a dummy for that bin of percent of time downwind. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a grade-moved indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year.

Figure 3: Sixth grade move event study by mover type



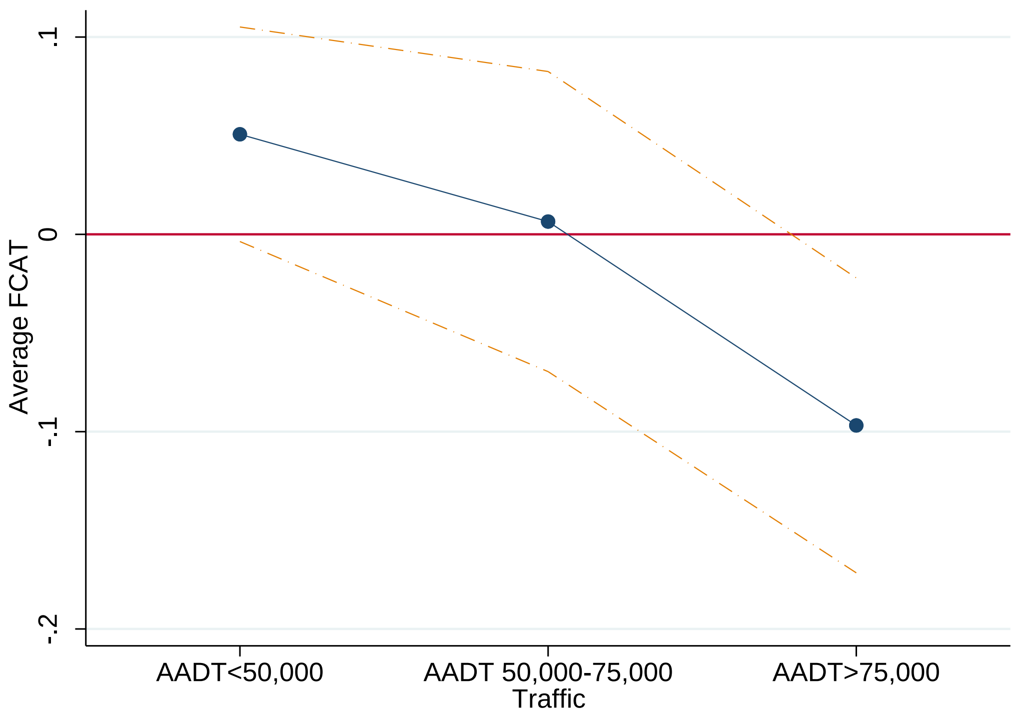
Note: This figure shows the effect of a "policy-induced" move out of fifth grade of a student transitioning either to or from a school that is downwind more than 60% of the time. The Y-axis plots interactions between being in a given grade and the type of mover. Being a student who does not switch wind status is the excluded group to avoid collinearity with the student fixed effects. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a year-mover indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. See the text for more details.

Figure 4: School demographics over percent of time downwind



Notes: This figure plots mean demographic characteristic for each school in our sample relative to its percent of time the school spent downwind of nearby highways. We fit a line to the data (the red lines), and plot its associated standard errors. Percent time spent downwind is based on 2010 wind monitor data matched with school location relative to the five nearest major highways.

Figure 5: Effects of being downwind 60% of the time by traffic



Notes: This figure shows how our estimates vary based on the effect of being downwind of the closest road segment with varying levels of average annual daily traffic (AADT) counts. AADT data comes from 2010 FDOT traffic monitor data. The Y-axis plots the coefficients on the interaction between being downwind of a road segment with the stated AADT bin. This model include AADT bin dummies, grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a grade-moved indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade.

APPENDIX: FOR ONLINE PUBLICATION

A: Additional Tables and Figures

Table A1: Impact of attending school downwind, all students

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
	Panel A: Downwind more than 60% of the time		
Downwind more than 60%	-0.0168	0.0384**	0.0092***
	(0.0143)	(0.0188)	(0.0035)
Observations	1,094,430	961,448	953,242
N Students	325,737	291,499	289,507
	Panel B: Mean intensity		
Mean intensity, 0.1=10% from upwind	-0.0874*	0.0673	0.0011
	(0.0499)	(0.0489)	(0.0076)
Observations	970,244	853,134	846,304
N Students	293,916	263,163	261,380

Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time or an intensity variable that increases by 0.1 if the wind blows 10 percentage points more directly at the school, on average. Sample includes all students in all years.

$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table A2: Effects under various models

	(1) Controlling for only distance, number of roads and changing schools	(2) Controlling for only distance, number of roads, changing schools, and school quality measures	(3) Main specification
	Panel A: Average FCAT		
Downwind more than 60%	-0.0371**	-0.0370**	-0.0400**
	(0.0166)	(0.0174)	(0.0167)
Observations	274,148	273,592	273,592
N students	107,841	107,635	107,635
	Panel B: Behavioral incident (0/1)		
Downwind more than 60%	0.0413**	0.0424**	0.0410**
	(0.0184)	(0.0189)	(0.0184)
Observations	238,546	237,987	237,987
N students	94,655	94,464	94,464
	Panel C: Rate of absence		
Downwind more than 60%	0.0053*	0.0053**	0.0054*
	(0.0028)	(0.0027)	(0.0028)
Observations	235,454	234907	234907
N students	94,464	93,573	93,573

Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies. Column 2 additionally controls for other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. The final column is our primary specification and additionally controls for school demographic characteristics. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time. Sample includes only students in the years of policy-induced moves in grades 5, 6, 8, and 9.

$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table A3: Robustness to dropping zip codes without at least one downwind school

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
Downwind more than 60%	-0.0460**	0.0385**	0.051
	(0.0172)	(0.0186)	(0.0034)
Observations	16829	14912	14687
N Students	7050	6293	6216

Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade.

$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Table A4: Placebo test – random assignment of wind direction

	(1) Average FCAT	(2) Behavioral incident (0/1)	(3) Rate of absence
	Panel A: Downwind more than 60% of the time		
Downwind more than 60%	0.0016	-0.0012	0.0005
	(0.0020)	(0.0020)	(0.0003)
Observations	276,905	240,951	237,845
N Students	108,686	95,439	94,352
	Panel B: Mean intensity		
Mean intensity, 0.1=10% from upwind	0.0039	-0.0006	0.0005
	(0.0033)	(0.0032)	(0.0005)
Observations	276905	240,951	237,845
N Students	108,686	95,439	94,352

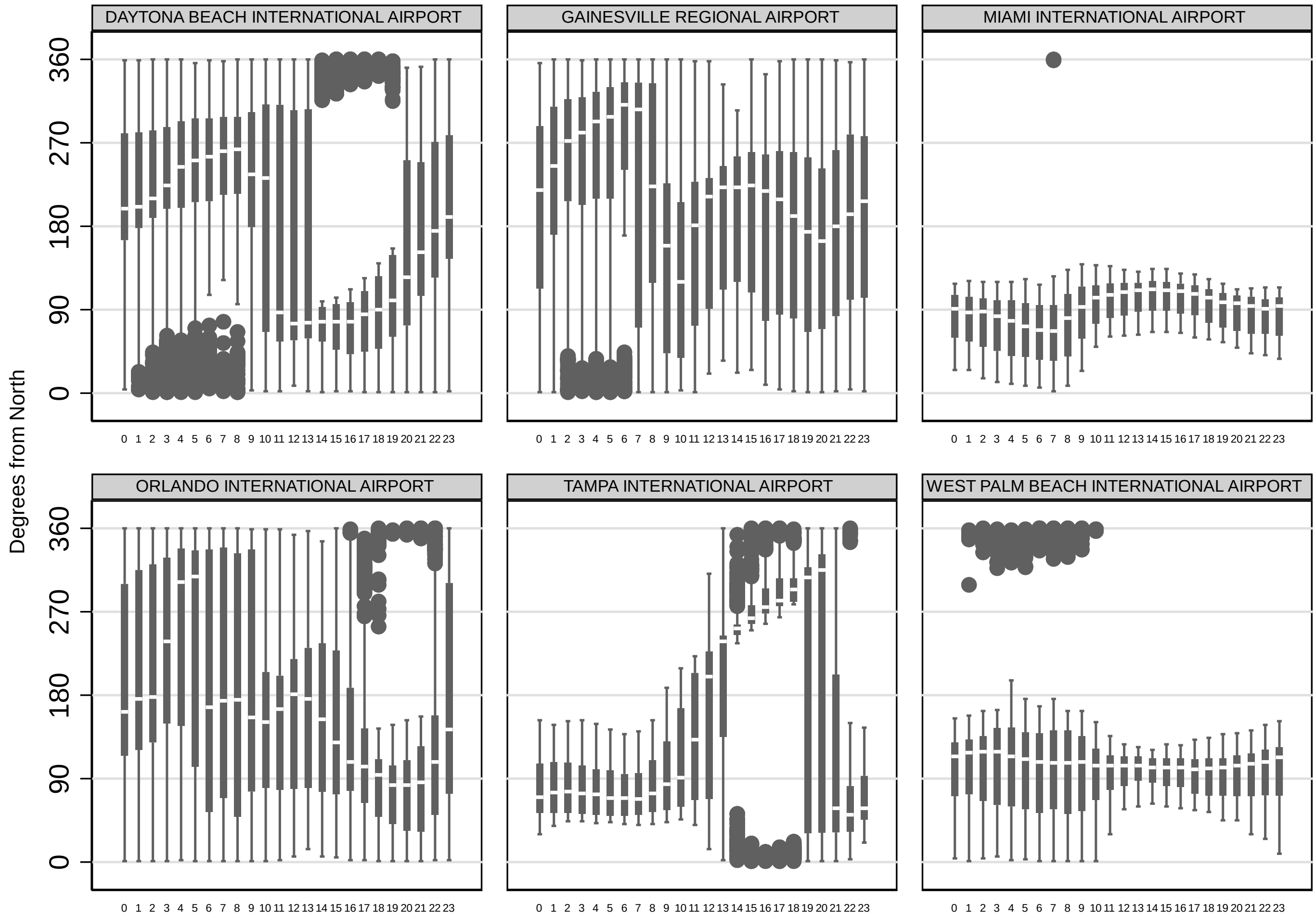
Notes: Each column and row represent results from a different regression. All random variables are assigned using a uniform distribution. For the "Downwind more than 60%" rows we randomly assign % of time downwind between zero and one, and then create an indicator for being downwind more than 60% of the time. For "intensity" we randomly assign each school an average wind intensity level. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a year-mover indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. $^{*}p < 0.1$ $^{**} p < 0.05$, $^{***} p < 0.01$

Table A5: Robustness to Clustering: Average FCAT

Clustering Scheme:	(1) School	(2) Student	(3) School & Student	(4) Zip code & Student
		Panel A: Downwind more than 60% of the time		
Downwind more than 60%	-0.0400** (0.0167)	-0.0400*** (0.0086)	-0.0400*** (0.0141)	-0.0400* (0.0207)
		Panel B: Mean intensity		
Mean intensity, 0.1=10% from upwind	-0.1368*** (0.0491)	-0.1368*** (0.0195)	-0.1368*** (0.0402)	-0.1368*** (0.0455)
Cluster on School	Yes	No	No	No
Cluster on Student	No	Yes	No	No
Cluster on School and Student	No	No	Yes	No
Cluster on Student and Zip code	No	No	No	Yes

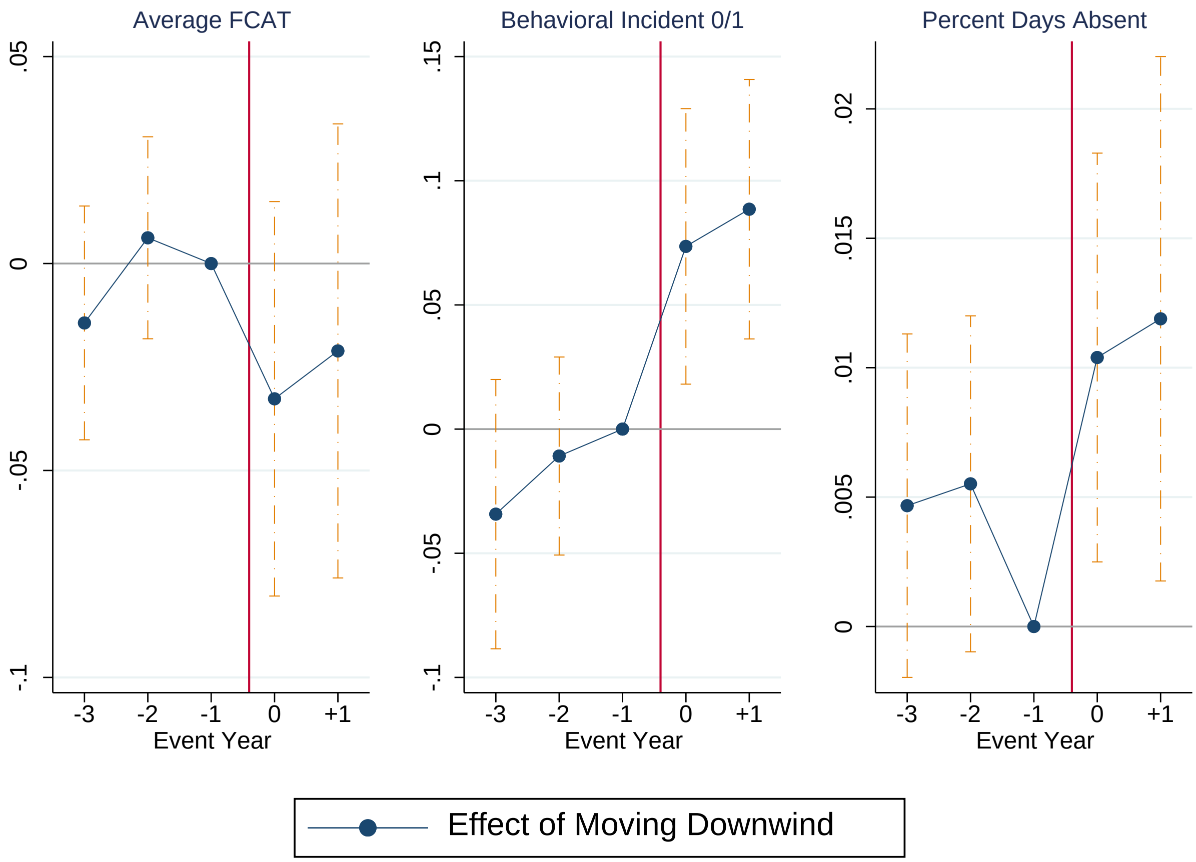
Notes: Each row and column shows results from a different regression. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, a grade-moved indicator, the number of highways within a mile, distance from nearest highway dummies, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year. Standard errors clustered on school are in parentheses. Coefficients of interest are an indicator variable for whether a student's school was downwind 60% or more of the time or an intensity variable that increases by 0.1 if the wind blows 10 percentage points more directly at the school, on average. All models are estimated using only the "policy-induced" moves to middle/high school by dropping "K through 12" schools and limiting the sample only to students who change schools from fifth to sixth or eighth to ninth grade.
$^{*}p < 0.1$ $^{**}p < 0.05$, $^{***}p < 0.01$

Figure A1. Wind direction across Florida



Note: This figure depicts a series of box plots representing the distribution of wind directions throughout the day over a year for wind monitors in different geographic locations in Florida. The x-axes are hours in the day and the y-axes are wind direction in degrees from north for the direction the wind is blowing at each hour. The grey dots represents outliers. This figure is constructed from NOAA (MADIS) wind data from 2010.

Figure A2: Event student for all students, relative to year of the move



Notes: This figure plots coefficients from an event study where the event is any move to a school that is downwind more than 60% of the time. The X-axis charts "event time" in grades relative to the move. The Y-axis plots coefficients of the effect of being in the given event year on the given outcome. All models include grade fixed effects, zip code fixed effects, student fixed effects, year fixed effects, distance from nearest highway dummies, a grade-moved indicator, the number of highways within a mile, school demographic characteristics, other school-level characteristics (percent of teachers with a master's degree, size, and stability rate), and whether the student was on FRL that year.

B: Data Appendix:

FCAT scores are standardized by year and grade at the state level for each test, with a mean of zero and a standard deviation of one, and we average the math and reading scores by year to create one summary measure of academic performance. We decided to average reading and math to create an aggregate measure of student achievement that reduces noise and the likelihood of type 1 error due to multiple hypothesis testing. That being said, we have also looked at these scores independently and find that they follow a similar pattern.

We construct the rate of absences variable by dividing the number of days absent by the number of days in the school year.

The longitudinally-linked data follow students over time so long as they remain in the Florida public school system. The FDOE conducts the longitudinal matching process. About 90% of students are matched year-to-year by social security number, and any remaining students are matched by name and birthday. This matching process contains a small number of errors likely caused by multiple students with similar names or birthdays. To account for this, we ran a specification in which we exclude students who move backwards more than two grades, fail and then skip a grade, have a change in birthday, or change gender from year-to-year. In total, these deletions amount to about 5% of the original dataset. We lose few students in the longitudinal analysis; among students who took the third grade FCAT before 2009, we observe 90% taking an FCAT the following year and over 80% taking an FCAT five years later.

School Characteristics

School location data come from the 2010 National Center for Education Statistics data, which provides the latitude and longitude of every school in the United States. We use 2010 as a standard year due to slight variations in the reported locations of schools over time. Data on school characteristics comes from the Florida School Indicators Report (FSIR), which is released annually by the Florida Department of Education. This data includes percent of teachers with a master's degree, school size, school stability rate, school racial demographics and a variety of other school characteristics. Maternal education by school and percent of married mothers by school were calculated based on Florida vital statistics data that was aggregated at the school level.

Event Study Methodology

The event study regressions include all the same variables as in our primary specification (equation 1). However, when estimating event studies we need to take into account two specific issues that arise in our context: 1) many students move multiple times such that there is not always one treatment occurrence per student. 2) treatment comes from both moving to upwind and moving to downwind: while these estimates are averaged together in our regression model we need to estimate them separately to show distinct patterns in the event study. Students who never change treatment status are left in the reference group in both event study models.

The "move to middle school" event study design (figure 3) resolves these issues by only focusing on moves from fifth to sixth grade. We only include those student who we observe continuously between third and sixth grade, dropping students who attended K through 12 schools, and who moved between an upwind and downwind school before 6^{th} grade. Because of missing data, sample sizes become much smaller if we try to extend the event study beyond 7^{th} grade. We simplify the "All mover" event study (Appendix Figure A4) by just looking at downwind moves. Here we define a qualifying event as a student who we observe for five years, and who we observe for at least three years before and three years after a move. We include all students with a qualifying event in the sample as well as students who never change downwind status. We drop students who changed to downwind status without meeting the standard for a “qualifying event” or who had more than one qualifying event (in practice very few students had more than one qualifying event).

Wind Direction, and Traffic Pollution Model

To estimate the relationship between pollution and wind direction we use high frequency 2010 MADIS and EPA data at the hourly level. We limit our sample to all monitors within 0.4 miles of a major highway (or 0.1 miles in some specifications). As with measuring downwind status, we only use wind and pollution data during the school day. We then estimate the following regression:

$$P_{idh} = \gamma_0 + \gamma_1 Downwind_{idh} + \varphi_i + \varepsilon_{idh}$$

Where P_{idh} is a measure of pollution for monitor i during day d and in hour h. $Downwind_{idh,}$ is one of two measures of wind direction within that day and hour. First we use an indicator for the wind blowing within 45 degrees of a ray running from the nearest point on the highway to the pollution monitor. The second measure is the difference in degrees between bearing from the monitor to the highway and the direction of the wind at which the wind is blowing at a school: $Intensity_{idh} = |ray_{idh} - winddirection_{idh}|$, normalized to be 1 when blowing directly at the monitor and zero when blowing directly away. Both of these measures are hourly level analogues of our two measures of downwind status discussed in section III of the main text. φ_i is a vector of monitor specific fixed effects. We control for month fixed effects in order to account for seasonal differences in pollution and wind direction. Within 0.4 miles there are five PM10 monitors, three NO_2 monitors, and seven CO monitors. Within 0.1 miles there are two PM_{10} monitors, two CO monitors, and one NO_2 monitors. We cluster all models at the monitor site-day level (we do not have enough monitors to cluster at the monitor level). The majority of wind monitors do not measure the same pollutant. One of the 15 total wind monitors measures both PM10 and N02, and another measures both PM10 and CO.