The Effects of Daily Air Pollution on Students and Teachers

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Abstract

Recent empirical research shows that air pollution harms student test scores and attendance and increases office discipline referrals. However, the mechanism by which air pollution operates within schools to negatively affect student and teacher outcomes remains largely opaque. The existing literature has primarily focused on the effects of prolonged exposure to pollution on end-of-year test scores or total absence counts. We examine how ambient air pollution influences student-by-day and teacher-by-day outcomes, including absences and office discipline referrals, using daily administrative data from a large urban school district in California between 2003 and 2020. Using wind direction as an instrument for daily pollution exposure, we find that a 10 $\mu g/m^3$ increase in daily PM2.5 causes a 5.7% increase in full-day student absences and a 28% increase in office referrals in a three-day window. Importantly, the effects are driven by low-income, Black, Hispanic, and younger students. In addition, over three days, a 10 $\mu g/m^3$ increase in daily PM2.5 causes a 13.1% increase in teacher absences due to illness. Our research indicates that decreasing air pollution in urban areas could enhance both student and teacher attendance, and minimize disruptive behavior in educational settings.

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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 and Mandic 2017). Furthermore, in 2016, nearly 22 percent of all public schools were within one mile of a Toxic Release Inventory (TRI) facility, which represents one type of industrial plant releasing air pollution. While recent evidence shows that exposure to high levels of air pollution negatively affects students' health (Brook et al. 2010; Jassal, Bakman, and Jones 2013; Roy et al. 2011), behavior, test scores, and attendance (Currie et al. 2009; Heissel, Persico, and Simon 2022; Persico and Venator 2021), little is known about the mechanisms through which air pollution operates within schools to harm students' academic performance.

The existing literature has largely focused on the aggregate effects of prolonged exposure to pollution on one-off measures of achievement such as end-of-year test scores or absence counts, largely due to data constraints. We address this gap in the literature by evaluating how daily variation in ambient air pollution affects student-by-day and teacher-by-day outcomes. Using a comprehensive dataset from a large urban school district in California, we analyze daily elementary and secondary school student absences, student office discipline referrals, and teacher absences. Adopting the methodology of Deryugina and colleagues (2019), we use daily wind direction as an instrument for PM2.5 exposure, conditional on school, grade, month-year, and day of the week fixed effects. Our instrumental variables strategy addresses measurement error in pollution and reduces concerns about endogeneity by using daily pollution induced by fluctuations in wind direction to estimate the effects of pollution on student and teacher outcomes.

We find that a 10 μg/m^3 increase in daily PM2.5 is associated with a 0.0045 increase in full-day student absences over the three days starting from the day of higher air pollution and continuing through the following two days, which is a 5.7% increase above the mean. In addition, we find a 0.0018 increase in office discipline referrals, which is a 28% increase above the mean. In addition, a 10 μg/m^3 increase in daily PM2.5 causes a 0.0168 increase in days of teacher absences for illness and personal leave, which represents an increase of 13% above the mean. We also find a dose-dependent relationship between air pollution and absences, with days in which the Air Quality Index (AQI) is above 100 having the largest effects for both students and teachers. More importantly, Black, Hispanic, low-income, and younger children demonstrate higher susceptibility to the effects of air pollution. These findings align with the mounting evidence that pollution disproportionately affects low-income and racial or ethnic minority groups (Currie et al. 2009; Mohai et al. 2011), reinforcing the need for targeted, evidence-based policy interventions.

Understanding the relationship between daily air pollution and student outcomes, including absences and office discipline referrals, is important for three reasons. First, the consequences of daily variation in ambient air quality might be masked by more persistent place-based effects or the research designs used in studies that rely on annual data. This lack of knowledge, and of the mechanisms through which pollution hinders learning, prevents schools from proactively or reactively responding to high-pollution days. Second, the impact of pollution on limiting students' academic achievement and increasing absences and behavioral issues in schools may exacerbate racial and socio-economic educational disparities and contribute to the school-to-prison pipeline (Christle, Joliyette, and Nelson 2005). By understanding the complex interplay between pollution, absences, and disciplinary referrals, educators and policymakers could develop strategies to address these issues, thereby helping to prevent students from being pushed out of the educational system. Finally, understanding the specific mechanisms through which pollution affects attendance could lead to more effective strategies for increasing attendance and, in turn, enhancing student achievement. As attendance is an essential input to educational success, student absenteeism is associated with both short- and long-term cognitive performance and academic achievement, including test scores, grade repetition, high school competition, and college enrollment (Almond, Edlund, and Palme 2009; Gershenson, Jacknowitz, and Brannega 2017; Liu, Lee, and Gershenson 2021; Marcotte 2017; Mohai et al. 2011; Pischke 2007).

Air pollution not only affects students but also significantly impacts teachers, making it essential to examine the relationship between daily air pollution and teacher absences. While understanding teacher well-being is important on its own, examining the relationship is important for three main reasons. First, air pollution impacts teacher absences and creates a ripple effect on student achievement, as teacher absences can disrupt the quality of instruction, leading to negative educational outcomes for students (Miller, Murnane, and Willett 2008). Second, as public sector employees, the impact of air pollution on teacher absences provides valuable insights into labor force participation and productivity in the public sector. Third, these factors deserve deeper attention because they can limit the economic mobility of the most vulnerable and contribute to perpetuating societal inequality. By quantifying the impact of air pollution on both students and teachers, school districts and policymakers can develop targeted interventions to mitigate these effects and improve overall educational outcomes.

II. Background

In the 2021–22 school year, nearly 15 million students, approximately 31 percent of students in the United States, missed 10 percent or more of school (Balfanz 2024). There is broad consensus that student absences negatively impact numerous measures of student performance in various educational settings. Student attendance plays a critical role in shaping immediate and future educational outcomes for both students and their schools. The detrimental effects of absences, manifesting in lower test scores, graduation rates, and college enrollment, not only affect academic performance but also limit broader future opportunities for students (Alexander, Entwisle, and Olson 2007; Aucejo and Romano 2016; Azevedo et al. 2021). Consequently, thirty-six states and the District of Columbia use chronic absenteeism, or missing 10 percent of school days within one academic year, in their accountability systems as a way to measure school quality (Jordan and Miller 2017).

Beyond impacting academic achievement, absences from school also pose significant sociological risks, often leading to behaviors that may result in disciplinary actions among students. Unexcused absences are of particular concern because they may indicate delinquency (Attwood and Croll 2006), and student misbehavior further reinforces academic risks, school disengagement, and truancy (Gottfried 2009; Hancock and Zubrick 2015). Additionally, student absences are associated with risky behaviors such as tobacco, alcohol, and drug use, which can lead to office referrals, suspensions, and even expulsions (Hallfors et al. 2002; Henry and Huizinga 2007).

These school discipline practices are worth considering because of their potentially negative effect on student outcomes and their reciprocal effects on the learning environment of the school population (Luiselli et al. 2005). Office discipline referrals often precede exclusionary discipline actions, such as suspensions and expulsions (Skiba et al. 2002; Skiba and Rausch 2006). While teachers and principals may utilize exclusionary discipline to create a safer learning environment, this practice can also exacerbate the school-to-prison pipeline. Suspended students are more likely to receive low test scores, miss school, drop out of school, be incarcerated, and come into contact with the juvenile justice system (Bacher-Hicks, Billings, and Deming 2019;

Sorensen, Bushway, and Gifford 2022). Furthermore, the negative effects of suspensions extend beyond the suspended students, as exposure to suspensions can also hinder the academic achievement of their peers (Lacoe and Steinberg 2019). In U.S. public schools, minority students are more frequently subjected to exclusionary discipline practices (Liu, Hayes, and Gershenson 2024; Shi and Zhu 2022; Fenning and Rose 2007). This tendency is compounded in schools serving socioeconomically disadvantaged students, where a more punitive approach is often adopted toward absences and misbehavior (Leung-Gagné et al. 2022).

Student absences and office discipline referrals also create spillover effects for parents. When children are absent from school due to illness, parents are frequently obliged to miss work (Neuzil, Hohlbein, and Zhu 2002). Additionally, the parents' workplace performance tends to decline when their children are frequently ill, as they have limited opportunities for physical and psychological recovery (Grzywacz et al. 2005). The consequences of student absences are wide-ranging, affecting not only classroom participation and academic outcomes, such as test scores, graduation, and dropout rates, but also parent's ability to work and maintain consistent employment.

Beyond student absences, extensive research indicates that teacher absences significantly affect student achievement, further complicating the educational landscape. Teacher absences can hinder student academic performance because substitute teachers may not be as effective, resulting in less learning and a decrease in student's motivation to attend school (Duflo, Hanna, and Ryan 2012; Herrmann and Rockoff 2012). Using data from elementary school teachers in an urban school district, Miller, Murnane, and Willett (2008) find that increased teacher absenteeism reduces math achievement. Similarly, Clotfelter, Ladd, and Vigdor (2009) use data from North Carolina to confirm the negative impact of teacher absences on student achievement. When regular teachers are absent, schools must hire substitute teachers, who may not have the same qualifications, experience, or effectiveness to provide instruction. This decline in instructional effectiveness poses a significant challenge, particularly for schools serving economically disadvantaged children in under-resourced environments (Liu, Loeb, and Shi 2022).

Student and teacher absences are significant determinants of academic achievement. To develop policies to address student and teacher absences, it is crucial to identify and understand the contributing factors. A growing body of research links air pollution to student absences. One of the earliest studies by Ransom and Pope (1992) finds that an increase in PM10 exposure in Utah Valley from 1986 to 1987 is associated with increased elementary school student absences. Building on this work, Currie and colleagues (2009) use data from 1996 to 2001 from a large school district in Texas and find that carbon monoxide increases student absences. Similarly, Liu and Salvo (2017) report that in China, an increase in PM2.5 is associated with higher absences among students from wealthy countries. Chen, Guo, and Huang (2018) further support these findings, showing that air pollution in China contributes to absences among local students due to health concerns.

In addition to absences, recent research indicates that air pollution contributes to behavioral issues, including disruptive and aggressive behavior (Heissel, Persico, and Simon 2022; Lu et al. 2018; Bondy, Roth, and Sager 2020; Herrnstadt et al. 2021; Burkhardt et al. 2020; Berman et al. 2019). Air pollution is associated with cellular inflammation, oxidative stress, and small blood vessel occlusion, all of which can increase the likelihood of mistakes, aggressive behavior, and criminal activity (Rammal et al. 2008; Calderón-Garcidueñas et al. 2015; Haynes et al. 2011; Younan et al. 2018; Hernstadt et al. 2021). Pollution can also penetrate the brain and potentially influence students’ behaviors (Gładka, Rymaszewska, and Zatoński 2018).

Building upon the expansive literature reviewed above, our paper makes several contributions to the study of air pollution's effects on students and teachers. First, our instrumental variables specification limits the impact of measurement error in pollution and reduces any remaining endogeneity concerns by using daily pollution induced by fluctuations in wind direction to provide direct and highly variable dispersal of pollutants over a district's population. Second, our detailed data provide additional information on the reasons for absences and the types of incidents resulting in a behavioral referral, allowing for a closer examination of how air pollution affects the behavior of elementary, middle, and high school students. Finally, we examine the impacts of environmental pollution on human capital using data on daily teacher absences. While a growing body of literature identifies links between air pollution and worker productivity (Graff Zivin and Neidell 2012; Chang et al. 2016; Chang et al. 2019) or absences (Holub, Hospido, and Wagner 2021), the majority of studies focus on private sector employees, particularly those working outdoors. By examining the effects of air pollution on teachers, we make a novel contribution to the literature on the relationship between environmental factors and human capital.

III. Data

A. Student Absences, Student Referrals, and Teacher Absences

We use rich longitudinal administrative data from a large urban California school system, spanning the 2002-2003 to the 2019-2020 school years and covering all K-12 students. To identify the relationships between pollution, absences, and referrals, we compile three datasets: (1) student absences from 2003-2013, (ii) student referrals from 2017-2020, and (iii) teacher absences from

2012 to 2018.[1] Our student-level and teacher-level data are novel since they are at the daily level and include the reasons for absences and referrals.

For instance, the reasons for student referrals are classified into eleven categories, such as violence, substance misuse, interpersonal offenses, and disruption. This categorization enables us to examine the effects of pollution on different types of student referrals. Because suspensions can occur much later than the behavior resulting in an office discipline referral, we use referrals rather than suspensions in this paper (Liu, Hayes, and Gershenson 2024). In addition, since suspensions may be applied differentially across racial and socioeconomic groups, we believe referrals serve as better indicators of behavior than suspensions.

Similarly, the data on teacher absences includes reasons for absences, including illness, personal or emergency leave, professional development, and other administrative reasons. The student absence data, however, only label absences as excused or unexcused without providing details reasons. As a result, we combine excused and unexcused absences to examine overall student absences. The data also contain sociodemographic information at the individual level, which allows us to control for observable variables and conduct a heterogeneity analysis.

However, there are a few caveats. First, due to the implementation of a new system for recording student absences in 2014, we limit our analysis of student absence data to the period before 2014. Second, data on teacher absences are only available for the years between 2012 and 2018. Finally, valid referral data are only available beginning in 2017. Consequently, the datasets for student absences, teacher absences, and student referrals each cover slightly different periods.

B. Air Pollution

[1] In this context, all years refer to school years. For example, 'student absences from 2003-2013' spans from the 2002-2003 school year to the 2012-2013 school year. Similarly, 'student referrals from 2017-2020' and 'teacher absences from 2012 to 2018' also represent school years, not calendar years.

We use daily county-level PM2.5 data for 2003 to 2020 from the US Environmental Protection Agency (EPA) Air Quality System (AQS). This dataset provides hourly average concentrations of PM2.5 in micrograms per cubic meter at the pollution monitor level. We then link these pollution monitors to the nearest school using inverse distance weighting. While this in situ ground-based monitoring network offers precise measurements at specific locations, it presents spatial gaps in accurately assessing pollution exposure over broader geographic areas, such as counties (Al-Hamdan et al. 2014). Moreover, in compliance with the Clean Air Act's National Ambient Air Quality Standards (NAAQS), local governments often place monitors in areas with lower levels of pollution (Grainger and Schreiber 2019). This strategic placement, along with the tendency of polluters to increase emissions during non-monitoring periods (Zou 2021), leads to measurement error. This error arises when the pollution levels recorded at the monitor sites do not reflect the actual exposure experienced by individuals in surrounding areas.

To mitigate the limitations of ground-level air monitoring networks, we integrate them with satellite data from remote sensing systems (Al-Hamdan et al. 2009). Specifically, we complement the EPA data with satellite-derived PM2.5 estimates from the Centers for Disease Control and Prevention (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) database for 2003 to 2011. In our analysis, which covers 3,287 days from 2003 to 2011, we identify 177 days with missing PM2.5 levels from EPA ground monitors and replace these with corresponding satellite data from the CDC. The CDC, in collaboration with the National Aeronautics and Space Administration (NASA), employs a regional surfacing algorithm by Al-Hamdan et al. (2009) that generates daily PM2.5 estimates for counties, including those with limited or no monitoring networks. This algorithm creates spatial grids with a 10-kilometer resolution across the 48 contiguous states and the District of Columbia. The inputs for this algorithm consist of both ground-based EPA PM2.5 measurements and NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) aerosol optical depth (AOD) readings (CDC 2023). For more information about these data, please refer to our data appendix.

C. Meteorological Conditions

We obtain wind direction and wind speed data from the North American Regional Reanalysis (NARR), a dataset that the National Centers for Environmental Prediction (NCEP) produces with high resolution and frequency, collected eight times daily. Focusing on atmospheric and land surface hydrology, NARR incorporates data from various sources, including rawinsondes carried by weather balloons, dropsondes dropped from aircraft, pibals (pilot balloons), aircraft readings, surface observations, and geostationary satellites (Mesinger et al., 2006). The model operates with a 32-km grid and 45 atmospheric layers, dividing the surface area into 32 km x 32 km grid cells and the atmosphere into 45 layers from the Earth's surface upward.

In the NARR model's 32-by-32 kilometer grid, wind conditions are recorded as two vector pairs: the *u-component* for the east-west direction and the *v-component* for the north-south direction, each aligning parallel to the x- and y-axes, respectively. The process of determining wind direction begins with interpolating daily estimates of the u and v components at each wind monitor. Next, we calculate wind direction using the inverse trigonometric formula: $direction = arctan\ (\frac{v}{u})$. The arctan2 function, commonly found in many programming languages, helps us adjust for the quadrant by identifying whether the u and v components are positive or negative. Finally, we convert the angle from radians to degrees, making it easier to interpret. Wind direction is defined as the origin from which the wind blows. For example, a "north wind" refers to wind blowing from the north. In meteorological terms, a wind direction of 0 degrees indicates wind coming from the north and heading south. Furthermore, we calculate the average daily wind speed using the formula: $speed = \sqrt{u^2 + v^2}$.

Our daily county-level temperature and precipitation data come from the National Oceanic and Atmospheric Association (NOAA). We supplement our daily measures of temperature and precipitation with Deryugina and colleagues (2019) data, which is based on the Parameter-elevation Regressions on Independent Slopes Model (PRISM). PRISM performs climate-elevation regressions for each cell in the digital elevation, model, utilizing data from approximately 13,000 surface stations for precipitation and 10,000 for temperature to ensure spatial accuracy in data quality (Daly et al. 2008). Additionally, we collect daily cloud cover data from NARR, focusing on total cloud coverage for the entire atmosphere, reported as a percentage.

D. Descriptive Statistics

Table 1 presents summary statistics for our three primary estimation samples: student absences (2003-2013), student referrals (2017-2020), and teacher absences (2012-2018). The student absences sample consists of 126,105 unique students with an average of 5.17 absences per student-year. In the student referrals sample, we identify 72,305 unique students, with an average of 0.31 referrals per student. The teacher absences sample includes 4,771 unique teachers, with an average of 8.20 absences per teacher-year. In both the student absences and referrals samples, Hispanic and Asian students represent the majority, accounting for over 60 percent of the student population. In contrast, the teacher sample is predominantly White, constituting 47.5%, followed by 21.3% Asian, 14.1% Hispanic, and 5.1% Black teachers. The mean daily PM2.5 concentration in the student absences sample is 11.04 $\mu g/m^3$, with a standard deviation of 7.51. For the student referrals and teacher absences samples, measured in a later period, the mean daily PM2.5 concentrations are lower at 9.70$\mu g/m^3$ and 9.17$\mu g/m^3$, respectively. Table 1 also provides the percentage of gender distribution, special education learners, English language learners, and the total number of schools in the study.

Panel A of Figure 1 depicts the average of PM2.5 levels and student absences by weekday for the 2003–2013 school years. The data reveals that average PM2.5 concentrations are lowest on Tuesdays and steadily increase toward Fridays. Notably, the pattern of student absences aligns with pollution trends over the days of the week, indicating a potential lagged effect. Specifically, student absences are at their lowest on Wednesdays and rise toward the end of the week. Panel B of Figure 1 shows the daily variation in PM2.5 over our entire time period from 2002-2019. The figure shows that increases or decreases of 10 μg/m^3 or more from day to day are very common. Panel C of Figure 1 presents average daily PM2.5 concentrations for the calendar years 2003–2019, which exhibit a downward trend.

IV. Empirical Strategy

To estimate the effect of pollution on students and teachers, we begin by estimating the following model:

$$(1)\ Y_{igsdmy} = \beta\, Pollution_{igsdmy} + X'_{igsdmy}\gamma + \theta_d + \varphi_{my} + \phi_s + \tau_g + \varepsilon_{igsdmy},$$

where Y_{igsdmy}, is the three-day cumulative count of our outcome variables for individual *i* in grade *g* at school *s* on day *d* in month *m* and year *y*. Our outcome variables include days of student absences, student office disciplinary referrals, and teacher absences. Aggregating these outcomes over three days accounts for potential lagged effects from exposure to high PM2.5 levels (Deryugina et al. 2019). If high air pollution on Monday makes a student sick on Tuesday or Wednesday, our model will capture this effect. $Pollution_{igsdmy}$ is the daily average PM2.5 concentration (μg/m^3), and β is the parameter of interest.

To flexibly control for weather conditions, we create deciles of average daily temperature, precipitation, wind speed, and cloud coverage. Since the dependent variable is a three-day total—summing the count on day *d* and the following two days—we include two leads of weather deciles to ensure that our parameter of interest does not capture the effects of weather conditions over the following two days. We also include interactions between temperature and precipitation over a three-day window, allowing the effect of temperature to vary with precipitation, and vice versa. In addition to weather confounders, we control for students-level characteristics (race, gender, and special-needs status) and neighborhood-level characteristics (income level). The term X_{igsdmy} is a vector of these weather and sociodemographic controls, accounting for individual and time-varying conditions potentially correlated with both pollution and outcomes.

Furthermore, our estimates also include school (ϕ_s), grade (τ_g), day of the week (θ_d), and month-by-year (φ_{my}) fixed effects. School fixed effects capture any time-invariant, school-level differences in pollution and the outcome variables. The grade fixed effects control for differences across grade levels that might affect pollution exposure or outcomes. Day of the week fixed effects account for any routine weekday variations, while month-by-year fixed effects control for time-varying shocks or seasonal patterns that could affect pollution and stdduent and teacher outcomes across all schools within each specific month and year. In summary, these fixed effects enable us to make within-school and within-grade comparisons over time, adjusting for potential seasonal and weather patterns. Finally, we cluster stand errors at the school level to account for potential correlations within the same school.

Despite these controls and fixed effects, ordinary least squares (OLS) estimates of equation (1) are prone to bias if PM2.5 is measured with error. For example, ground monitor-level air pollution data may fail to capture true population-level exposures because monitors can be strategically placed in less polluted areas (Grainger and Schreiber 2019), polluters may strategically alter emissions when monitoring occurs (Zou 2021), and spatial-temporal coverage is limited (Al-Hamdan et al. 2009). Although we complement EPA ground-level monitor data with CDC-NASA satellite data, endogeneity from local economic activities and inherent measurement errors persist, as fixed monitoring sites cannot fully capture how air quality varies across space and time.

Consider a hypothetical district where the population is evenly dispersed around a central pollution source. The direction of the wind determines which part of the district experiences pollution exposure—a dynamic not fully captured by a single monitor. Specifically, when the wind blows from north to south, the schools in the south of the district face higher pollution as they are downwind of the pollution source. Conversely, when the wind blows from south to north, the schools in the north face higher pollution. In this scenario, only half of the district is exposed to high pollution levels, while the other half remains relatively unaffected. This variation can lead to an attenuated or null estimated effect, potentially biasing the results.

To address this classical measurement error problem, we complement our baseline OLS with instrumental variables (IV) strategy following Deryugina and colleagues (2019). This approach utilizes daily changes in wind direction as an instrument for pollution exposure, exploiting the natural variation in pollution driven by wind patterns. This method is particularly effective because it operates independently of the placement of pollution monitors, capturing the effects of nonlocal pollution sources that impact larger geographic areas more uniformly. Wind not only disperses pollutants within a district but also transports air pollution from external sources into the district. PM2.5 is often carried over substantial distances by wind (Borgschulte, Molitor, and Zou 2020; Deryugina et al. 2019) and poses a widespread threat to public health, irrespective of its origin. Focusing on daily changes in wind direction, we introduce an exogenous source of within-district variation in pollution levels. We estimate the following model:

$$(2)\ Pollution_{igsdmy} = \beta Winddirection_{igsdmy}^{90b} + X'_{igsdmy}\gamma + \theta_d + \varphi_{my} + \phi_s + \tau_g + \varepsilon_{igsdmy},$$

$$(3)\ Y_{igsdmy} = \beta \widehat{Pollution}_{igsdmy} + X'_{igsdmy}\gamma + \theta_d + \varphi_{my} + \phi_s + \tau_g + \varepsilon_{igsdmy}.$$

Equation (2) is the first stage in our two-stage least squares (2SLS) estimation strategy. Here, $Winddirection_{igsdmy}^{90b}$ is a set of binary variables equal to one if the daily average wind direction in our district falls within the relevant 90-degree interval [90b, 90b + 90) and zero otherwise. The omitted category is the interval [0,90), where *b* ranges from 1 to 3. As in equation (1), we include the same weather and sociodemographic controls (X'_{igsdmy}) along with the same fixed effects and cluster stand errors at the school level. The second stage is shown in equation (3), where $\widehat{Pollution}_{igsdmy}$ is the fitted value from the first stage. The outcome Y_{igsdmy} again represents either the three-day cumulative count of student absences, office discipline referrals, or teacher absences for individual *i* in grade *g* at school *s* on day *d* in month *m* year *y*. Our primary specification spans three days to account for the short-term displacement of absences or referrals.

Although our preferred specification uses three-day aggregate counts of absences or referrals in levels, Appendix Tables A4 and A5 present results when applying the inverse hyperbolic sine (IHS) transformation. The HIS transformation, defined as $\text{asinh}(x) = \log(x + \sqrt{x^2+1})$, is particularly useful for handling the large number of zeros in our outcome variables while normalizing the data. The effect of a 1 μg/m^3 increase in PM2.5 on absences or referrals is given by β. Because we use the IHS transformation, β is adjusted by $\beta^* \sqrt{1 + \frac{1}{y^2}}$. This is an important adjustment in this context to account for the large number of zeros for both the absence and referral outcomes, which results in a low dependent variable mean.

The key identifying assumptions of our instrumental variable strategy are that (1) wind direction causes variation in daily concentrations of PM2.5, and (2) wind direction affects student absences, teacher absences, and student referrals only through its influence on air pollution. By utilizing daily wind direction that occurs outside of our school district as an instrument for pollution, we can potentially eliminate measurement errors in daily pollution exposure (Szpiro, Sheppard, and Lumley 2011). In the United States, there are numerous large point sources of pollution, including wildfires, power plants, and factories. These pollution sources tend to cluster together in specific geographic regions (Filonchyk and Peterson 2023) leading to district-wide contamination when the wind comes from a polluted direction.

Figure 2 visually depicts a strong first-stage relationship between daily wind direction and PM2.5 concentrations, using estimates from equation (2). Pollution levels in our district tend to be higher when the wind direction is between the southeast (135 degrees) and southwest (225 degrees). In Table A1 of the Appendix, we provide coefficients for each wind direction dummy variable, where the interval [0,90) is omitted. Furthermore, the robustness of the first stage is evident from the large F-statistic of 14,989 observed in the student absences sample.

V. Results

A. Student Absences and Behavioral Referrals

Panel A of Table 2 shows results from our reduced form estimates of PM2.5 on the three-day cumulative number of student absences and disciplinary referrals. Specifically, the outcome aggregates the day of pollution exposure and the following two days. As shown in Column 1 of Panel A, a 10 $\mu g/m^3$ increase in daily PM2.5 is associated with a 0.0011 decrease in daily full-day absences. Contrary to student absences, we find a modest increase in the likelihood of having any disciplinary referral (column 2) and referrals due to drug, walkouts, skipping class, and other reasons (column 5). These referrals often result in suspensions or other disciplinary actions. Nonetheless, OLS estimates are subject to bias, especially if pollution is measured with error or if unobserved factors correlate with both pollution and student outcomes. To address this concern, we employ an instrumental variables strategy.

Panel B of Table 2 presents the results from our primary wind IV specification. As shown in Columns 1 and 2, a 10 μg/m^3 increase in daily PM2.5 causes a 0.0045 increase in full-day student absences over the three days starting from the day of higher air pollution and continuing through the following two days, which is a 5.7% increase above the mean. In addition, we find a 0.0018 increase in office discipline referrals, which is a 28% increase above the mean. Furthermore, higher air pollution increases referrals for violent behavior (column 3) and for defiance and interpersonal conflict (column 4). These results align with the literature on pollution and crime, which suggests that air pollution increases violent behavior (Burkhardt et el. 2019; Burkhardt et al. 2020; Berman et al. 2019; Baryshnikova, Davidson, and Wesselbaum 2019). We also find that PM2.5 exposure elevates the likelihood of referrals due to drug use, walkouts, or skipping school, indicating a broad link between air pollution and higher-risk behaviors.

Because different students might be treated differently for a variety of reasons, in Panel C of Table 2 we present 2SLS estimates that add student fixed effects. The findings are nearly identical to the results in our primary specification. In Table A2, we confirm that these findings remain consistent when using Poisson regression, and in Table A4, we also show similarly robust pattern when using the IHS transformation of the outcome instead of the level of the outcome variables.

When comparing the OLS and IV estimates in Panels A and B of Table 2, we observe a sign change from negative to positive for student absences. This pattern is similar to the findings of Deryugina and colleagues (2019), where the sign changed from negative to positive when comparing OLS to the IV estimates for three-day hospitalization rates. This shift suggests that OLS estimation suffers from bias due to endogeneity and measurement error. For example, neighborhood sorting might be a concern. If there is negative selection into neighborhoods with poor air quality (Hausman and Stolper 2020), this could create a spurious correlation between pollution, absences, and referrals. However, it is unlikely that this sorting occurs on a daily basis in response to wind direction.

To further investigate, we also examine one-day, two-day, and four-day models in Table A3 of the Appendix. This analysis allows us to evaluate the impact of contemporaneous PM2.5 exposure on student absences and referrals across various time windows. The findings indicate both immediate and lagged effects of air pollution. Specifically, the two-day model exhibits a stronger influence on absences compared to the primary three-day model, suggesting a more immediate influence of pollution on student attendance. In contrast, referrals show a sustained positive and statistically significant impact in both the three-day and four-day models, indicating a more prolonged effect of pollution on student behavior.

To determine whether contemporaneous pollution exposure or pollution exposure in previous weeks drives the results, we also conduct an event study in Figure 3 that uses weekly averages of PM2.5 in the weeks leading up to the reference day. We include 4 weeks of lags of weekly average PM2.5 in addition to estimating the effects of pollution on the week of an absence or disciplinary referral in school (in week 0), predicted by wind direction.[2] Only pollution in the preceding week has a noticeably large positive effect on absences or disciplinary referrals. We

[2] While a regression using daily pollution is closer to our main specification, using weekly pollution allows us to present results showing the effects of pollution farther back in time more easily.

take this as suggestive evidence that the effect of air pollution on absences and student behavior is due to contemporaneous exposure, rather than exposure to pollution in previous weeks.

B. Heterogeneity in the Effects of Pollution

Next, we explore whether pollution affects different demographic groups in different ways. Different socioeconomic groups might have varying access to resources that can mitigate the effects of pollution. For instance, students from affluent backgrounds might have the means to install air purifiers at home or reside further from pollution sources. Conversely, students from less advantaged backgrounds may experience higher pollutant exposure at home, potentially leading to a smaller marginal impact of attending a school in a polluted area. Given the disproportionate exposure to pollution exposure experienced by communities of color and low-income households (Banzhaf, Ma, and Timmins 2019; Persico, Figlio, and Roth 2016), we examine the results by student-level characteristics, including race, gender, and special needs status. Table 3 presents IV estimates for each subgroup, with column headers reporting the outcome variables.

Panels A through C of Table 3 report the three-day cumulative full-day student absences and referrals for White, Black, and Hispanic. While air pollution increases student absences across all racial-ethnic groups, the effects are the largest for Black students. Specifically, a 10 $\mu g/m^3$ increase in daily PM2.5 leads to a 0.0157 increase in full-day absences for Black students, representing a 9.6% increase above the mean. Similarly, we find substantial effects on school discipline for Black and Hispanic students: a 10 $\mu g/m^3$ increase in daily PM2.5 increases any referrals by 18% (0.0054) and referrals due to violence by 32% above the mean (0.0028) for Black students. These findings imply that differential pollution exposure might explain some of the disproportionalities in disciplinary outcomes by race.

Panels D and E of Table 3 show the effect of PM2.5 on student absences and referrals for female and male students. While the overall pattern is similar for both groups, girls are more likely to be absent due to pollution, whereas boys show slightly larger effects on referrals from exposure to pollution. Moreover, Panel F indicates that pollution significantly affects students with special needs. A 10 $\mu g/m^3$ increase in daily PM2.5 is associated with a significant 4.6% (0.0061) increase in student absences and a 25.2% (0.0042) increase in any referrals for students with special needs. These patterns suggest that socioeconomically disadvantaged students are more likely to be absent and receive office disciplinary referrals when air pollution is high, which exacerbates underlying inequalities.

We further examine whether certain school-level characteristics make some groups more vulnerable to pollution than others. Table 4 provides our preferred estimates for various subgroups based on school-level characteristics, specifically income (schools in the lowest, middle, and highest income tertiles) and school level (elementary, middle, and high schools).[3] Panels A, B, and C of Table 4 show that students in the lowest- and middle-income tertiles are more adversely affected than those in the highest-income tertile. Specifically, a 10 $\mu g/m^3$ increase in daily PM2.5 raises student absences by 7.8% (0.658) in the middle income tertile schools, compared with only 0.42% (0.0302) in the highest income tertile schools. We also find much larger effects on referrals, and especially referrals due to violent behavior, in schools serving lower-income populations. For students in the poorest schools, a 10 $\mu g/m^3$ increase in daily PM2.5 causes an increase in referrals of 37% and an increase in referrals due to violence of 42%. This pattern aligns with broader socioeconomic and environmental disparities, wherein lower-income students often reside in neighborhoods experiencing higher levels of air pollution (Houston et al. 2004; Hanna 2007),

[3] Please note that we estimated these results after collapsing the data to the day, school and grade level, so the means are higher in this table.

which then might translate into higher levels of behavioral issues. However, even the highest income schools see increases in violence with increases in air pollution: a 10 $\mu g/m^3$ increase in daily PM2.5 raises referrals by 18% and referrals due to violence by 60% above the mean (0.0514).

In Panels D, E, and F of Table 4, we report the effect of air pollution on student absences by school level. The largest effects on both absence and referral occur among middle school students. A 10 $\mu g/m^3$ increase in daily PM2.5 is associated with a significant 1.3335-day increase in absences and a significant 0.4983 increase in any referrals for middle-school students, a 31.5% increase. Overall, the findings in Table 3 and Table 4 underscore the complexity of the interaction between environmental conditions, student demographics, school characteristics, and educational outcomes. These results have significant implications for residential segregation and environmental justice, as non-White, special needs, and low-income students are more vulnerable to the harmful effects of pollution than others.

C. Teacher Absences

Numerous studies elucidate the impact of air pollution on children's health (Currie and Walker 2011) and academic outcomes (Almond, Edlund, and Palme 2009). However, there is less work on how air pollution affects adult health and subsequent workplace absences. We employ our same three-day primary specification to assess the effect of air pollution on teacher absences. Both OLS and IV estimates are presented in Table 5. Column 1 encompasses all reasons for absences, including personal leave, professional development or permission days, and other administrative leave. Column 2 shows the result for teacher absences due to illness or personal leave. In the context of teacher absences, it is important to note that 'personal leave' is often used interchangeably with sick leave. Consequently, we include personal leave in our analysis of teacher absences due to illness.

Panel A of Table 5 presents the OLS estimates, which all display a positive relationship. The coefficients for any teacher absences and absences due to illness or personal leave are positive and statistically significant. Specifically, a 10 μg/m^3 increase in daily PM2.5 is associated with a 2.4% increase in any teacher absences and a 3.1% increase in teacher absences due to illness or personal leave.

Panel B of Table 5 presents the IV estimates from our primary specification. We find that a 10 μg/m^3 increase in daily PM2.5 is associated with a 0.0168-day increase in teacher absences due to illness or personal leave, which is an increase of 13.1%. This increased effect size suggests that the OLS approach could underestimate the actual impact of air pollution on teacher absences. As expected, there is no relationship between pollution and administrative leave. The estimates in Panel C add teacher fixed effects, and the results are nearly identical. This again suggests that wind direction is a good instrument for pollution exposure for estimating the effects of pollution on human health and behavior.

Our findings confirm the adverse effects of air pollution on teacher absences, potentially through health-related issues. These findings have important implications not only for teacher well-being and job satisfaction but also for educational continuity. Teacher absences, exacerbated by high pollution levels, potentially disrupt student learning and negatively affect student outcomes, highlighting the broader consequences of air pollution for the education system.

D. *Additional Threats to Internal Validity*

We next explore whether there is a dose-dependent relationship between air pollution levels and student absences, student referrals, and teacher absences. We would expect that people exposed to higher levels of pollution would have more illness and absences from school, as well as disciplinary referrals. To evaluate this, we compare each of the outcome variables for different

AQI bins: 0-24, 25-49, 50-99, and over 100, using the 0-24 range as the reference group. Panels A through D of Figure 4 illustrate the non-linear impact of air pollution on student absences, any student disciplinary referral, student referrals due to violence, and teacher absences due to illness or personal leave. Our findings reveal a significant increase in student absences, referrals, and teacher absences on days with an AQI exceeding 100, confirming the non-linear effects of air pollution on these outcome variables.

Table 6 presents results from various alternative specifications. One potential issue is the presence of common shocks that could affect particular cohorts. In Column 1 of Table 6, we include school-by-grade and grade-by-year fixed effects to control for school-by-grade-specific shocks and common shocks affecting cohorts, respectively. Additionally, we include day-year fixed effects to account for any common seasonal variation in absences to our main instrumental variables specification.

Next, we estimate the elasticity of student absences, referrals, and teacher absences with respect to air quality in column 2 of Table 6. Elasticity is a useful measure to demonstrate how responsive the outcome variables are in response to changes in air pollution. We calculate elasticity by taking the log of average daily PM2.5 concentrations and applying the IHS transformation to the three-day cumulative counts of outcome variables. The estimated elasticity reported in Column 2 of Panel A, for example, shows that a 100% increase in average daily PM2.5 leads to a 6.69% increase in full-day student absences.

Finally, given that absences and referrals are relatively rare daily outcomes, we test the robustness of our results by aggregating the data to the weekly-individual level for student absences, referrals, and teacher absences. Column 3 of Table 6 reports an IV specification that uses the number of days the wind blows from a polluted direction within a week as an instrument for weekly average pollution exposure.[4] Our estimates indicate that a 10 μg/m^3 increase in weekly PM2.5 increases student absences by 100% (0.13533) and any referrals by 182% (0.01780) above the mean. While marginally significant, a 10 μg/m^3 increase in weekly PM2.5 also increases teacher absences by 69% (0.15391) above the mean. These findings suggest that exposure to pollution may have cumulative effects over time.

VI. Conclusion

This is the first study to our knowledge to use daily data to investigate how pollution affects student and teacher behavior in schools. Using changes in daily wind direction as an instrument for daily air pollution exposure, we find that a 10 μg/m^3 increase in daily PM2.5 leads to a 5.7% increase in full-day student absences and a 28% increase in disciplinary referrals for suspension over the three days including and following the day of higher air pollution. In addition, we find that a 10 μg/m^3 increase in daily PM2.5 causes a 13% increase in teacher absences for illness or personal leave.

To put these results in context, we performed a Back of the Envelope (BOE) calculation. Our results suggest that a 10 μg/m^3 increase in PM2.5 over the school year would result in an additional 4.87 days absent per student, or 355,647 absences across the district.[5] In addition, Liu, Lee, and Gershenson (2021) find that missing one additional class in middle and high school leads to 0.3-0.4% of a standard deviation lower test scores. This implies that a 10 μg/m^3 increase in PM2.5 over the school year would result in about 2% of a standard deviation lower test scores

[4] We define the 0-90 degree quadrant, which is equivalent to a Northeasterly wind, as the polluted direction for all the outcomes.

[5] A 10 μg/m3 increase in PM2.5 is associated with a .013533 increase in absences * 36 weeks in the school year = 4.87 more absences per year per child. The district contains about 73,000 children * 4.87 days absent per child * 36 weeks per school year.

from increased absences alone.[6] While this is a relatively modest effect on test scores, it is not the only way pollution might operate to reduce test scores. Previous work has found that exposure to increased pollution during the school year leads to 2-4% of a standard deviation lower test scores (Persico and Venator 2021; Heissel, Simon and Persico 2022), suggesting that the reduction in test scores reflects a combination of factors, including student absences, suspensions, and teacher absences.

We also demonstrate that there are disparate effects of air pollution based on race, income, and age. First, Black, Hispanic, and low-income students are more likely to be absent from school or receive a disciplinary referral when PM2.5 increases. This may be because low-income, Black, and Hispanic children are disproportionately exposed to environmental pollution and are less able to avoid exposure to pollution. In particular, referrals for violent offenses are significantly larger on days with higher pollution. Given that low-income and minority students are more likely to be exposed to pollution and live near sources of pollution, the relationship between pollution and student behavior may provide insight into why academic achievement gaps persist in the United States.

Analyzing the effects of air pollution on student and teacher absences and student discipline with daily data is critical, as it can lead to improved intervention strategies in schools. Given the disproportionately severe impact of absenteeism and suspensions on socioeconomically disadvantaged students, it is even more important to understand how pollution affects the functioning of schools and student behavior. Understanding how air pollution affects school functioning is also important for policy, especially as schools are considering implementing air

[6] Assuming 4.87 days absent translates into roughly 5 classes missed over the school year. Liu, Lee and Gershenson (2021) find that 10 missed classes translates into a 4% of a standard deviation drop in test scores, so 5 classes would be a 2% of a standard deviation drop in test scores. Note that this paper uses the same data, so the estimates are exactly right.

purification interventions in the wake of the COVID-19 pandemic. This lack of knowledge, and of the mechanisms through which pollution hinders learning, prevents schools from proactively or reactively responding to high-pollution days. Pollution-induced increases in school absences and disciplinary issues may intensify racial and socioeconomic disparities in educational outcomes, contributing to the school-to-prison pipeline. These effects can hinder the economic advancement of the most disadvantaged populations and perpetuate broader societal inequalities.

In addition to understanding the true costs of pollution, our work contributes to a growing literature on air pollution and education by elucidating some important mechanisms through which pollution affects test scores and other educational outcomes, as well as the teacher labor supply. Policymakers could consider improving school ventilation using High-Efficiency Particulate Air (HEPA) filters to mitigate these risks. This approach is particularly crucial in schools serving socioeconomically disadvantaged and younger students, providing a strong rationale for increased support to reduce educational inequality. Furthermore, our findings imply that reducing air pollution in metropolitan areas may effectively improve student and teacher attendance and decrease disruptive behavior in schools, which are all likely to increase student achievement.

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Tables

Table 1: Descriptive Statistics of Students in the Sample

	(1) Student Absences Sample, 2003-2013	(2) Student Referrals Sample, 2017-2020	(3) Teacher Sample, 2012-2018
Percent White	0.117	0.118	0.475
Percent Black	0.129	0.072	0.051
Percent Hispanic	0.236	0.293	0.141
Percent Asian	0.396	0.326	0.213
Percent Highest Income Tertile	0.247	0.300	
Percent Middle Income Tertile	0.244	0.298	
Percent Lowest Income Tertile	0.254	0.301	
Percent Female	0.483	0.481	0.679
Percent Male	0.517	0.519	0.321
Percent Special Education	0.091	0.13	
Percent English Language Learner	0.368	N/A	
Average Number of Absences per Student-Year	5.168		
	[8.383]		
Average Number of Referrals per Student-Year		0.314	
		[1.992]	
Average Number of Absences per Teacher-Year			8.197
			[8.988]
Average Daily PM2.5 Concentration	11.045	9.696	9.167
	[7.510]	[11.885]	[6.094]
Number of Unique Students/Teachers	126105	72305	4771
Total Number of Schools	126	149	127

Notes: This table presents statistics across three samples. The unit of observation is individual-by-day. Column (1) reports the sample mean with standard deviations in brackets for the student absences sample from 2003-2013. Column (2) reports the sample mean with standard deviations for the student referrals sample from 2017-2020. Colum (3) reports the sample mean with standard deviations for the teacher absences sample from 2012-2018. All years refer to school years.

Table 2: Three-Day OLS and IV Estimation of Effect of PM 2.5 on the Number of Student Absences and Referrals

		Student Referrals			
	(1) Full-Day Student Absences	(2) Any Referrals	(3) Violence	(4) Defiance & Interpersonal	(5) Drug, Walkout, Skip & Other
Panel A: OLS Estimates					
Average daily PM2.5 (in 10 $\mu g/m^3$)	-0.00113***	0.00010*	0.00001	0.00006	0.00007**
	(0.00038)	(0.00006)	(0.00004)	(0.00004)	(0.00003)
Panel B: IV Estimates					
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.00452***	0.00184***	0.00053***	0.00104***	0.00050***
	(0.00164)	(0.00037)	(0.00015)	(0.00024)	(0.00018)
First-Stage F-Statistic	22,549	921,779	921,779	921,779	921,779
Panel C: IV Estimates with Student FE					
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.00502***	0.00183***	0.00053***	0.00104***	0.00051***
	(0.00159)	(0.00037)	(0.00015)	(0.00024)	(0.00018)
Mean of Outcome	0.07870	0.00651	0.00186	0.00371	0.00197
First-Stage F-Statistic	22,811	932,656	932,656	932,656	932,656
Observations	23,705,108	16,611,767	16,611,767	16,611,767	16,611,767

Notes: This table reports the effect of PM2.5 on student absences and student referrals. Panel A reports OLS estimates using the number of three-day cumulative counts of daily full-day student absences and different types of disciplinary referrals as an outcome. Panel B reports IV estimates using the number of three-day cumulative counts of daily full-day student absences and different types of disciplinary referrals as an outcome. Panel C reports Three-day IV estimates with student fixed effects. Column (1) shows the results of full-day absences; Column (2) shows the results for any referrals; Column (3) shows the results of student referrals due to violence; Column (4) shows the results of student referrals due to defiance and interpersonal offense; and Column (5) shows the results of student referrals due to drug, walkout, skip, and other reasons. All regressions for student absences and referrals include school, grade, month-year, day-of-week fixed effects (FEs), student characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The student characteristics include gender, race, income, special education, and English language learner (ELL) status. It is important to note that information on ELL status is not available throughout the sample period for student referrals. Therefore, we control for student characteristics, excluding ELL status, in the student referrals sample. Standard errors are clustered at the school level and are in parentheses. * p < .1, ** p < .05, *** p < .01

Table 3: Heterogenous Effects by Student-Level Characteristics

	(1) Full-Day Absences	(2) Any Referrals	(3) Referrals due to Violence
Panel A: White Students			
Average daily PM2.5 (in 10 μg/m^3)	0.00853* (0.00440)	0.00101* (0.00053)	0.00005 (0.00025)
Mean of Outcome	0.09814	0.00233	0.00073
Observations	2,422,776	1,991,598	1,991,598
Panel B: Black Students			
Average daily PM2.5 (in 10 μg/m^3)	0.01569*** (0.00481)	0.00538** (0.00208)	0.00281** (0.00125)
Mean of Outcome	0.162685	0.03023	0.00873
Observations	2,328,958	1,158,147	1,158,147
Panel C: Hispanic Students			
Average daily PM2.5 (in 10 μg/m^3)	0.00688*** (0.00236)	0.00354*** (0.00085)	0.00084*** (0.00030)
Mean of Outcome	0.11287	0.00913	0.00230
Observations	5,591,144	4,743,334	4,743,334
Panel D: Girls			
Average daily PM2.5 (in 10 μg/m^3)	0.00508*** (0.00178)	0.00136*** (0.00039)	0.00029** (0.00014)
Mean of Outcome	0.07862	0.00374	0.00081
Observations	11,550,024	8,010,340	8,010,340
Panel E: Boys			
Average daily PM2.5 (in 10 μg/m^3)	0.00400** (0.00181)	0.00229*** (0.00050)	0.00075*** (0.00025)
Mean of Outcome	0.07878	0.00909	0.00283
Observations	12,155,084	8,601,427	8,601,427
Panel F: Special Needs Students			
Average daily PM2.5 (in 10 μg/m^3)	0.00611*** (0.00276)	0.00417*** (0.00115)	0.00124*** (0.00046)
Mean of Outcome	0.13107	0.01657	0.00513
Observations	2,578,465	2,500,364	2,500,364
Panel G: Non-Special Needs Students			
Average daily PM2.5 (in 10 μg/m^3)	0.00434** (0.00167)	0.00141*** (0.00030)	0.00040*** (0.00013)
Mean of Outcome	0.07231	0.00473	0.00127
Observations	21,126,643	14,111,403	14,111,403

Notes: This table reports the effect of PM2.5 on the number of three-day cumulative student absences and referrals based on student-level characteristics. Each panel indicates the subgroup stratified on. Column (1) displays the results for full-day student absences; Column (2) displays the results for any referrals; and Column (3) displays the results for referrals due to violence. All regressions include school, grade, month-year, day-of-week FEs, student

characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The student characteristics include gender, race, income, special education, and English language learner (ELL) status. Note that the information on ELL status is not available throughout the sample period of student referrals. Thus, we control for student characteristics, excluding ELL status, in the student referrals sample. Standard errors are clustered at the school level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Heterogenous Effects by School-Level Characteristics

	(1) Full-Day Absences	(2) Any Referrals	(3) Referrals due to Violence
Panel A: Schools in the Lowest Income Tertile			
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.24498 (0.27004)	0.24311*** (0.08915)	0.07998** (0.03165)
Mean of Outcome	8.16709	0.64401	0.18798
Observations	95,029	56,283	56,283
Panel B: Schools in the Middle-Income Tertile			
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.65807*** (0.24795)	0.34323*** (0.09121)	0.02842 (0.02458)
Mean of Outcome	8.38978	0.78256	0.18843
Observations	94,928	56,355	56,355
Panel C: Schools in the Highest Income Tertile			
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.03022** (0.01431)	0.09079** (0.04137)	0.05139* (0.02597)
Mean of Outcome	7.06931	0.22400	0.08545
Observations	95,552	56,269	56,269
Panel D: Elementary Schools			
Average daily PM2.5 (in 10 $\mu g/m^3$)	0.43653*** (0.08238)	0.05283** (0.02186)	0.01770* (0.01010)
Mean of Outcome	6.11970	0.29083	0.14856
Observations	205,473	125,891	125,891
Panel E: Middle Schools			
Average daily PM2.5 (in 10 $\mu g/m^3$)	1.33347*** (0.35723)	0.49827*** (0.16215)	0.16616** (0.06643)
Mean of Outcome	12.3222	1.58326	0.33137
Observations	39,847	29,704	29,704
Panel F: High Schools			
Average daily PM2.5 (in 10 $\mu g/m^3$)	-0.71410 (0.59576)	0.25328*** (0.07700)	0.04756** (0.01983)
Mean of Outcome	12.35765	0.60189	0.05589
Observations	40,445	40,685	40,685

Notes: This table reports the effect of PM2.5 on the number of three-day cumulative student absences and referrals based on school-level characteristics. Each panel indicates the subgroup stratified on. Column (1) displays the results for full-day student absences; Column (2) displays the results for any referrals; and Column (3) displays the results for referrals due to violence. All regressions include school, grade, month-year, day of week FEs, school characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The school characteristics include race, gender, income, special education, and English language learner (ELL) status. Note that the information on ELL status is not available throughout the sample period of student referrals. Thus, we control for student characteristics, excluding ELL status, in the student referrals sample. Standard errors are clustered at the school level and are in parentheses.

* p < .1, ** p < .05, *** p < .01

Table 5: Three-Day OLS and IV Estimation of Effect of PM 2.5 on the Number of Teacher Absences

	(1) Any Absences	(2) Illness/Personal Leave	(3) Other Administrative Leave
Panel A: OLS Estimates			
Average daily PM2.5 (in 10 μg/m^3)	0.00501*** (0.00165)	0.00399*** (0.00121)	0.00041 (0.0000)
Panel B: IV Estimates			
Average daily PM2.5 (in 10 μg/m^3)	0.00672 (0.00955)	0.01679** (0.00644)	0.00054 (0.00138)
First-Stage F-Statistic	63,853	63,853	63,853
Panel C: IV Estimates with Teacher FE			
Average daily PM2.5 (in 10 μg/m^3)	0.00671 (0.00956)	0.01678** (0.00645)	0.00054 (0.00138)
Mean of Outcome	0.20709	0.12801	0.00747
First-Stage F-Statistic	63,623	63,623	63,623
Observations	1,339,633	1,339,633	1,339,633

Notes: This table reports the effect of PM2.5 on teacher absences. Panel A reports OLS estimates using the number of three-day cumulative counts of teacher absences by different reasons shown in each column. Panel B reports IV estimates using the number of three-day cumulative counts of teacher absences. Panel C reports three-day IV estimates with teacher fixed effects. Column (1) presents the results for any kind of teacher absences, which include sick leave, personal leave, professional development or permission days, other administrative leave, and other absences not covered in the list. Columns (2)-(4) show the results for different types of teacher absences. Column (2) shows the results for teacher absences due to illness or personal leave/emergency; Column (3) shows the results for absences due to professional development or permission days; Column (4) shows the results for other administrative leave. Other administrative leave includes bereavement, jury duty, administrative leave, legal purposes, and military leave. All teacher absences regressions include school, teacher's teaching grade, month-year, day-of-week fixed effects (FEs), teacher characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The teacher's characteristics include gender and race. Standard errors are clustered at the school level and are in parentheses.
* p < .1, ** p < .05, *** p < .01

Table 6: IV Results for Alternative Specifications

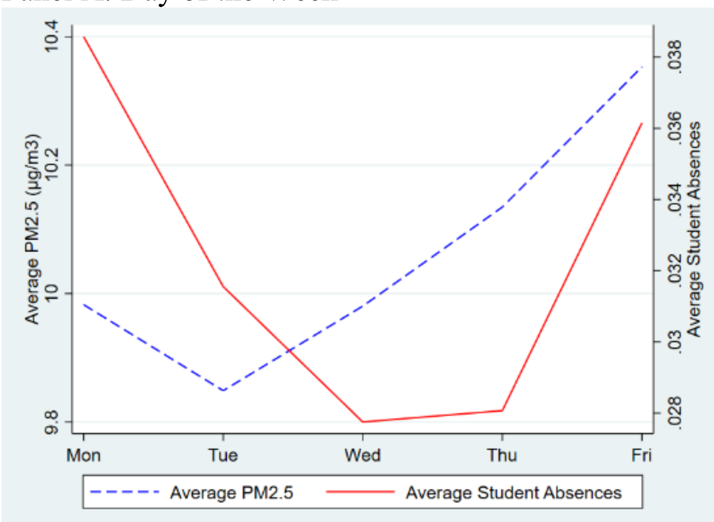
	(1) Using School-Grade, Grade-Year, and Day-Year FEs	(2) The Elasticity of Absences/Referrals with Respect to Air Quality	(3) Weekly Outcomes
Panel A. Full-Day Student Absences			
Average daily PM2.5 (in 10 μg/m^3)	0.00419***	0.669***	0.13533***
	(0.00149)	(0.240)	(0.02070)
Mean of outcome	0.07870	0.0623	0.135257
First-Stage F statistic	31,657	17,360	1647
Observations	23,705,108	23,705,108	16,840,908
Panel B. Any Student Referrals			
Average daily PM2.5 (in 10 μg/m^3)	0.00153***	2.073***	0.01780**
	(0.00034)	(0.612)	(0.00840)
Mean of outcome	0.0065	0.0055	0.009789
First-Stage F statistic	1,842,209	212,054	84
Observations	16,611,767	16,611,767	6,579,666
Panel C. Student Referrals Due to Violence			
Average daily PM2.5 (in 10 μg/m^3)	0.00041***	2.440***	0.00706***
	(0.00013)	(0.871)	(0.00182)
Mean of outcome	0.0019	0.0016	0.002774
First-Stage F statistic	1,842,209	212,054	84
Observations	16,611,767	16,611,767	6,579,666
Panel D. Teacher Absences due to Illness/Personal Leave			
Average daily PM2.5 (in 10 μg/m^3)	0.01562**	1.550***	0.15391*
	(0.00629)	(0.317)	(0.07917)
Mean of outcome	0.1281	0.0996	0.222416
First-Stage F statistic	66,926	270,006	7,989
Observations	1,339,633	1,339,633	530,443

Notes: This table reports the effect of PM2.5 on the number of three-day cumulative counts on student absences, referrals, and teacher absences. Panels A, B, C, and D report the results on full-day student absences, any student referrals, referrals due to violence, and teacher absences, respectively. Each column represents the results of a different specification. Column (1) presents the results of our primary specification with school-grade, grade-year, and day-year FEs. Column (2) presents the estimated elasticity. Regressions in Columns (1) and (2) include school, grade, month-year, day-of-week FEs, individual characteristics, deciles of average temperature, precipitation, wind speed, cloud cover, and interactions of temperature and precipitation over the three days. Column (3) examines weekly aggregates and reports the effect of the number of days the wind blows from the polluted direction on our outcome variables. The unit of analysis is at the individual-weekly level. The regression control for school, grade, year FEs, individual characteristics, deciles of average temperature, precipitation, wind speed, cloud cover, and interactions of temperature and precipitation. Standard errors are clustered at the school level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

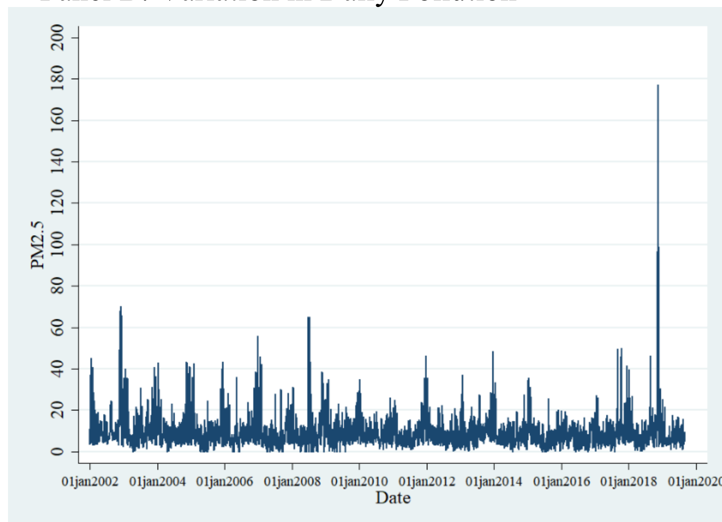
Figures

Figure 1: Average Pollution Experienced by Day of the Week and Year

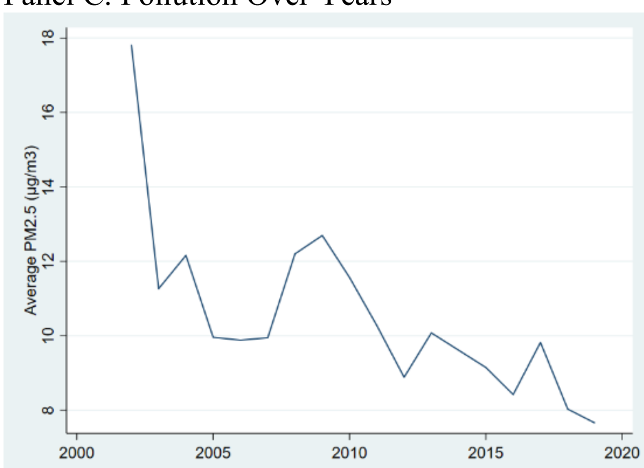
Panel A. Day of the Week



Panel B: Variation in Daily Pollution

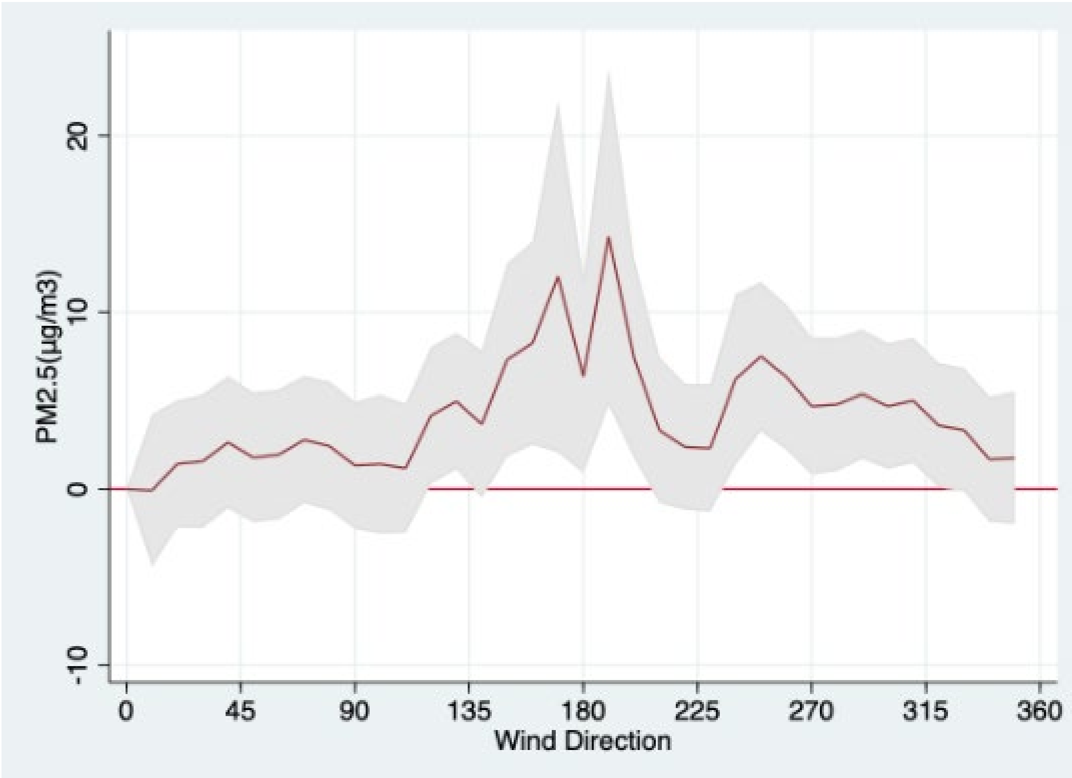


Panel C. Pollution Over Years



Notes: Panel A depicts the average level of PM2.5 concentrations experienced by day of the week from 2003 to 2019, along with the average student absences on a given day of the week from 2003 to 2013. We produce Panel A by averaging PM2.5 concentrations and full-day student absences by day of the week. Panel B displays the average daily PM2.5 concentrations during our sample periods.

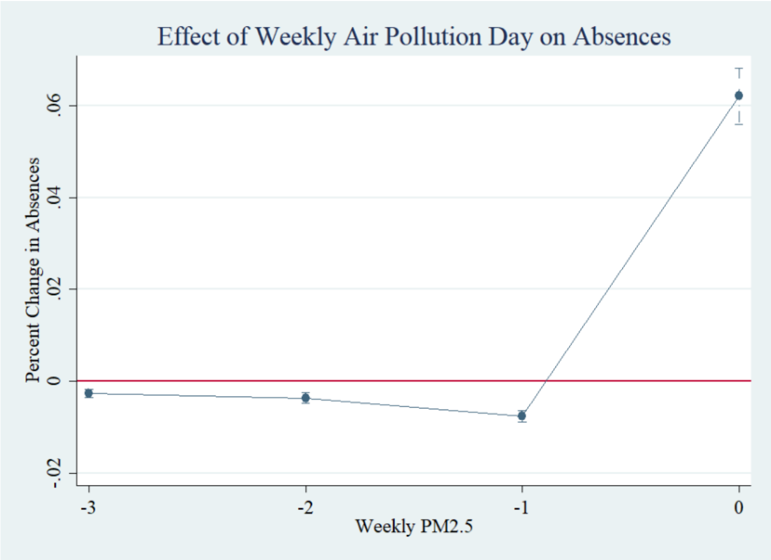
Figure 2: Wind Direction and PM2.5 concentrations for Our District in CA



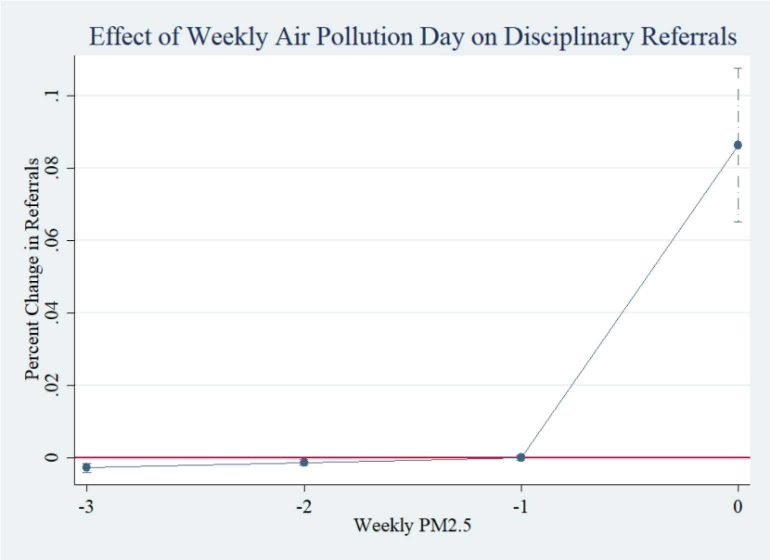
Notes: This figure depicts our district's first stage for our student absences sample from school the 2003–2013 school years. As depicted, high PM2.5 concentrations are associated with winds from the southeast (135 degrees) and southwest (225 degrees). Controls include month-by-year, day of the week fixed effects (FEs), deciles of average temperature, precipitation, wind speed, cloud cover, and interactions between temperature and precipitation. The grey areas are the 95% confidence intervals.

Figure 3: Event Study of Weekly Air Pollution on Absences and Disciplinary Referrals

Panel A. Student Absences (2003–2013)



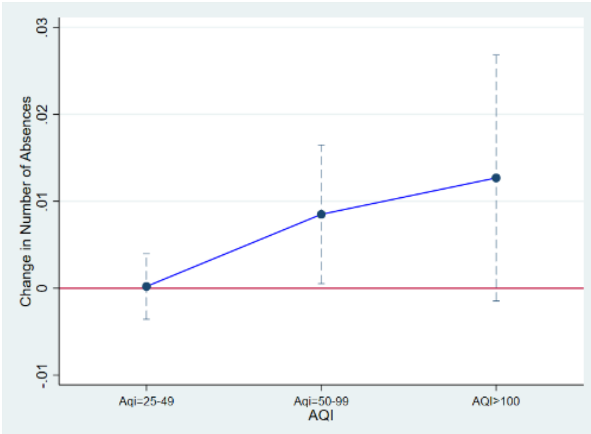
Panel B. Any Disciplinary Referrals (2017–2020)



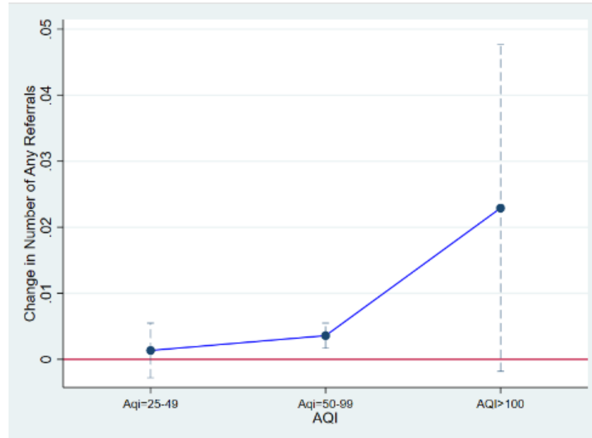
Notes: Panel A of Figure 3 depicts an event study of the effect of weekly PM2.5 on the number of weekly absences over weeks of exposure using the number of times the wind blew from the polluted direction in the past week as an instrument for weekly PM2.5. Panel B depicts the same event study with disciplinary referrals as the outcome. We control for school, grade, and year fixed effects, as well as deciles of average weekly temperature, precipitation, and wind speed, and student characteristics, including gender, race, income, special education, and English language learner status. The dashed vertical lines indicate the 95% confidence intervals, based on standard errors clustered at the school level.

Figure 4: Effect of Air Pollution on Student and Teacher Absences and Student Referrals by the Amount of Pollution

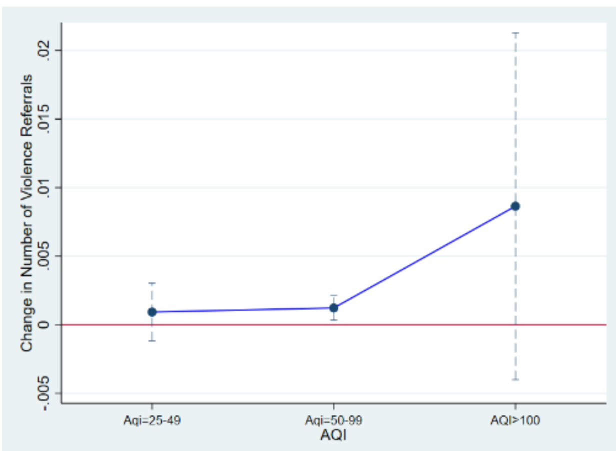
Panel A. Student Absences (2003–2013)



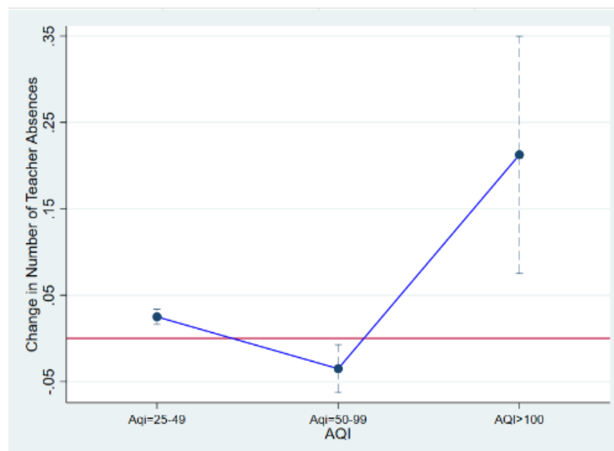
Panel B. Any Referrals (2017–2020)



Panel C. Violence Referrals (2017–2020)



Panel D. Teacher Absences – Illness/Personal Leave (2012–2018)



Notes: These figures plot the non-linear effects of air pollution on the number of three-day cumulative outcome variables. The omitted category is an AQI of less than 25. We use daily wind direction as an instrument for PM2.5 and control for include school, grade, month-year, and day-of-week fixed effects, as well as deciles of average temperature, precipitation, wind speed, cloud cover, interactions of temperature and precipitation over the three days, and student characteristics, including gender, race, income, special education, and English language learner status. The dashed vertical lines indicate the 95% confidence intervals, based on standard errors clustered at the school level. Panels A, B, C, and D show the effects of air pollution on student absences, any student referrals, student referrals due to violence, and teacher absences due to illness or personal leave, respectively.

ONLINE APPENDIX

A. Data Appendix: Meteorological Data

MODIS, an instrument aboard NASA's Terra and Aqua satellites (King et al. 2013), plays a crucial role in measuring AOD, which quantifies the concentration of aerosol particles in an atmospheric column extending from the Earth's surface to its uppermost layer (Al-Hamdan et al. 2009). However, the use of this dataset comes with certain caveats. First, the accuracy of AOD retrievals depends on surface reflectance. While accuracy is higher over dark, low-reflectance surfaces, such as vegetated areas or remote oceans, it diminishes over bright surfaces like deserts or urban landscapes with complex materials (Gupta et al. 2016). This raises concerns about potential biases in PM2.5 data retrieved from remote sensing in our urban California school district study sample due to these surface differences.

To address these concerns, we compute the mean absolute difference of PM2.5 concentrations between ground-based EPA observations and CDC-NASA satellite data, finding a mean absolute difference of 3.45 $\mu g/m^3$ with a standard deviation of 3.88. When converted to the Air Quality Index (AQI), this 3.45 $\mu g/m^3$ difference equates to an AQI of 14, a relatively minor variation within the 0-500 AQI range, where values above 100 are typically considered unhealthy for sensitive groups. The moderately strong correlation coefficient of 0.75 between these two sources also suggests a significant alignment.

Another caveat in utilizing MODIS AOD satellite remote sensing data is its difficulty in incorporating meteorological factors (Al-Hamdan et al. 2014). Given that AOD is a columnar measurement, it is hard to provide information about the distribution or movement of aerosols at different atmospheric layers, which are influenced by various weather factors. To account for this issue, we collect additional weather variables, including temperature, precipitation, wind speed, and cloud coverage, and integrate them into our regression analysis. Consequently, our combined EPA AQS and CDC-NASA satellite dataset for 2003–2011 represents a comprehensive set of pollution data. For the years 2012 to 2020, we rely exclusively on EPA AQS data.

APPENDIX REFERENCES

Gupta, P., R. C. Levy, S. Mattoo, L. A. Remer, and L. A. Munchak. 2016. "A Surface Reflectance Scheme for Retrieving Aerosol Optical Depth over Urban Surfaces in MODIS Dark Target Retrieval Algorithm." *Atmospheric Measurement Techniques* 9(7):3293-308.

King, M. D., S. Platnick, W. P. Menzel, S. A. Ackerman, and P. A. Hubanks. 2013. "Spatial and Temporal Distribution of Clouds Observed by MODIS Onboard the Terra and Aqua Satellites." *IEEE Transactions On Geoscience and Remote Sensing* 51(7):3826-52.

Online Appendix Tables

Table A1: First Stage Effects of Daily Wind on Daily Pollution

	PM2.5 Concentration		
Binned Wind Direction	(1) Student Absences Sample	(2) Student Referrals Sample	(3) Teacher Sample
Angle range 90-180	5.4929***	3.7040***	3.0940***
	(0.0403)	(0.0078)	(0.0077)
Angle range 180-270	4.7481***	3.3518***	1.8210***
	(0.0492)	(0.0054)	(0.0248)
Angle range 270-360	2.3617***	5.4235***	1.8950***
	(0.0160)	(0.0056)	(0.0090)
First-Stage F-Statistic	14989	921767	63853
Observations	26,628,985	16,611,767	1,339,633

Notes: This table reports our first stage, which shows the association between daily wind direction and daily PM2.5 concentrations. Column (1), Column (2), and Column (3) present our first-stage results for student absences, student referrals, and teacher absences samples, respectively. Angle range 90-180, angle range 180-270, and angle range 270-360 are a set of binary variables equal to one if the daily average wind direction in our district falls within the 90-degree interval [90, 180), [180, 270), and [270, 360), respectively. The omitted category is the interval [0, 90). The regressions include month-year and day of the week fixed effects, deciles of average temperature, precipitation, wind speed, cloud cover, and interactions of temperature and precipitation over the three days. Standard errors are in parentheses.

* p < .1, ** p < .05, *** p < .01

Table A2: The Effects of Pollution on Student and Teacher Behavior using Poisson Regression (IV)

	(1) Teacher absences - Illness/Personal Leave	(2) Full-Day Student Absences	(3) Any Referrals	(4) Referrals due to violence
Average daily PM2.5 (in μg/m^3)	0.011965** (0.005151)	0.005586*** (0.001768)	0.031482*** (0.004594)	0.029517*** (0.008001)
Mean of outcome	0.12802	0.078756	0.007146	0.007398
First-Stage F-statistic	28,807	13,102	257,636	257,636
Observations	1,339,633	23,705,108	16,611,767	16,611,767

Notes: This table reports the effect of PM2.5 on student and teacher absences and student referrals using Poisson regression. Column (1) shows the results of teacher absences due to illness or personal leave/emergency full-day absences; Column (2) shows the results of full-day student absences; Column (3) shows the results for any referrals; Column (4) shows the results of student referrals due to violence. The teacher absences regression includes school, teacher's teaching grade, month-year, day-of-week fixed effects (FEs), teacher characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The teacher's characteristics include gender and race. All regressions for student absences and referrals include school, grade, month-year, day-of-week FEs, student characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The student characteristics include gender, race, income, special education, and English language learner (ELL) status. It is important to note that information on ELL status is not available throughout the sample period for student referrals. Therefore, we control for student characteristics, excluding ELL status, in the student referrals sample. Standard errors are clustered at the school level and are in parentheses. * p < .1, ** p < .05, *** p < .01

Table A3: One-Day, Two-Day, Three-Day, and Four-Day IV Estimation of Effect of PM2.5 on the Number of Student Absences and Referrals

		Referrals		Teacher Absences	
	(1) Full-Day Student Absences	(2) Any Referrals	(3) Violence	(4) Any Absences	(5) Illness/Personal Leave
Panel A. One-Day IV Estimates					
Average daily PM2.5 (in 10 μg/m^3)	0.00164***	-0.00008	-0.00002	-0.00333	-0.00441*
	(0.00042)	(0.00009)	(0.00006)	(0.00303)	(0.00233)
Mean of Outcome	0.02783	0.02135	0.00605	0.07009	0.04743
First-Stage F-Stat	15,298	276,894	276,894	48,464	48,464
Observations	42,362,584	29,570,082	29,570,082	2,371,959	2,371,959
Panel B. Two-Day IV Estimates					
Average daily PM2.5 (in 10 μg/m^3)	0.00621***	0.00009	0.000010	-0.01255*	-0.00695
	(0.00100)	(0.00020)	(0.00009)	(0.00694)	(0.00584)
Mean of Outcome	0.05326	0.0043	0.0012	0.13893	0.08753
First-Stage F-Stat	10,830	260,352	260,352	72,152	72,152
Observations	32,867,128	22,991,819	22,991,819	1,848,055	1,848,055
Panel C. Three-Day IV Estimates					
Average daily PM2.5 (in 10 μg/m^3)	0.00452***	0.00184***	0.00053***	0.00672	0.01679**
	(0.00164)	(0.00037)	(0.00015)	(0.00955)	(0.00644)
Mean of Outcome	0.07870	0.00651	0.00186	0.20709	0.12801
First-Stage F-Stat	22,549	932,656	932,656	63,853	63,853
Observations	23,705,108	16,611,767	16,611,767	1,339,633	1,339,633
Panel D. Four-Day IV Estimates					
Average daily PM2.5 (in 10 μg/m^3)	0.00209	0.0159***	0.0190***	0.02734**	0.03467***
	(0.00163)	(0.0050)	(0.0068)	(0.01062)	(0.0863)
Mean of Outcome	0.10609	0.0072	0.0021	0.27766	0.17494
First-Stage F-Stat	63,086	1671743	1671743	356,186	356,186
Observations	14,962,590	10,589,499	10,589,499	851,761	851,761

Notes: This table reports the effect of PM2.5 on student absences, referrals, and teacher absences across various time windows. Panel A presents instrumental variable (IV) estimates using the number of one-day counts of daily student absences, referrals, and teacher absences as the outcome. Panels B, C, and D report the IV estimates based on the number of two-day, three-day, and four-day cumulative counts for student absences, referrals, and teacher absences. Column (1) shows the results of full-day absences. Columns (2) and (3) show the results of any referrals and student referrals due to violence. Columns (4) and (5) present the results of any teacher absences and teacher absences due to illness or personal leave. All regressions include school, grade, month-year, day-of-week fixed effects FEs, individual characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature. The student characteristics include gender, race, income, special education, and English language learner (ELL) status. The teacher's characteristics include gender and race. Standard errors are clustered at the school level and are in parentheses. * p < .1, ** p < .05, *** p < .01

Table A4: Three-Day OLS and IV Estimation of Effect of PM 2.5 on the IHS Transformation of Student Absences and Referrals

		IHS Student Referrals			
	(1) IHS Full-Day Student Absences	(2) Any Referrals	(3) Violence	(4) Defiance & Interpersonal	(5) Drug, Walkout, Skip & Other
Panel A: OLS Estimates					
Average daily PM2.5 (in 10 μg/m^3)	-0.012***	0.015*	0.006	0.017	0.035**
	(0.004)	(0.009)	(0.019)	(0.010)	(0.014)
Panel B: IV Estimates					
Average daily PM2.5 (in 10 μg/m^3)	0.054***	0.277***	0.283***	0.281***	0.267***
	(0.019)	(0.055)	(0.079)	(0.063)	(0.089)
First-Stage F-Statistic	22549	921,750	921,750	921,750	921,750
Panel C: IV Estimates with Student FE					
Average daily PM2.5 (in 10 μg/m^3)	0.056***	0.276***	0.281***	0.280***	0.266***
	(0.007)	(0.036)	(0.069)	(0.047)	(0.066)
Mean of Outcome	0.062	0.006	0.002	0.032	0.017
First-Stage F-Statistic	1,275,257	933,250	933,250	933,250	933,250
Observations	23,705,108	16,611,767	16,611,767	16,611,767	16,611,767

Notes: This table reports the effect of PM2.5 on the IHS transformation of student absences and student referrals. Panel A reports OLS estimates using the number of three-day cumulative counts of daily full-day student absences and different types of disciplinary referrals as an outcome. Panel B reports IV estimates using the three-day cumulative counts of daily full-day student absences and different types of disciplinary referrals as an outcome. Panel C reports three-day IV estimates with student fixed effects. Column (1) shows the results of full-day absences; Column (2) shows the results for any referrals; Column (3) shows the results of student referrals due to violence; Column (4) shows the results of student referrals due to defiance and interpersonal offense; and Column (5) shows the results of student referrals due to drug, walkout, skip, and other reasons. All regressions for student absences and referrals include school, grade, month-year, day-of-week fixed effects (FEs), student characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The student characteristics include gender, race, income, special education, and English language learner (ELL) status. It is important to note that information on ELL status is not available throughout the sample period for student referrals. Therefore, we control for student characteristics, excluding ELL status, in the student referrals sample. Standard errors are clustered at the school level and are in parentheses. * p < .1, ** p < .05, *** p < .01

Table A5: Three-Day OLS and IV Estimation of Effect of PM 2.5 on the IHS Transformation of Teacher Absences

	(1) IHS Any Absences	(2) IHS Illness/Personal Leave	(3) IHS Other Administrative Leave
Panel A: OLS Estimates			
Average daily PM2.5 (in 10 μg/m^3)	0.025*** (0.008)	0.029*** (0.009)	0.042 (0.035)
Panel B: IV Estimates			
Average daily PM2.5 (in 10 μg/m^3)	0.017 (0.044)	0.124** (0.049)	0.069 (0.168)
First-Stage F-Statistic	63,853	63,853	63,853
Panel C: IV Estimates with Teacher FE			
Average daily PM2.5 (in 10 μg/m^3)	0.017 (0.032)	0.124*** (0.041)	0.069 (0.176)
Mean of Outcome	0.1643	0.0996	0.0055
First-Stage F-Statistic	63,623	63,623	63,623
Observations	1,339,633	1,339,633	1,339,633

Notes: This table reports the effect of PM2.5 on teacher absences. Panel A reports OLS estimates using the IHS transformation of three-day cumulative counts of teacher absences by different reasons shown in each column. Panel B reports IV estimates using the IHS transformation of three-day cumulative counts of teacher absences. Panel C reports three-day IV estimates with teacher fixed effects. Column (1) presents the results for any kind of teacher absences, which include sick leave, personal leave, professional development or permission days, other administrative leave, and other absences not covered in the list. Columns (2)-(4) show the results for different types of teacher absences. Column (2) shows the results for teacher absences due to illness or personal leave/emergency; Column (3) shows the results for absences due to professional development or permission days; Column (4) shows the results for other administrative leave. Other administrative leave includes bereavement, jury duty, administrative leave, legal purposes, and military leave. All teacher absences regressions include school, teacher's teaching grade, month-year, day-of-week fixed effects (FEs), teacher characteristics, deciles of average temperature, precipitation, wind speed, and cloud cover, and interactions of temperature and precipitation over the three days. The teacher's characteristics include gender and race. Standard errors are clustered at the school level and are in parentheses.

* p < .1, ** p < .05, *** p < .01