Severe Air Pollution and School Absences: Knowledge For International Knowledge Workers

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April 13, 2018

Abstract

Air pollution may impede high-skill workers from taking up short or long-term residence in the developing world, for professional or personal advancement. Indeed, this is revealed in the US State Department's monitoring of PM2.5 in many cities globally. Despite knowledge worker mobility being key to the modern global economy, we know little about the daily functioning of these families. We assess one source of friction by examining how PM2.5 affects attendance at international schools in north China. Pollution sensitivity is stronger among US/Canadian/European than Chinese, and among children who miss school the most, but overall is modest compared to estimates for the US. Using school absence patterns as a window into short-run health and behavior, our study suggests that high-income, highly educated families find ways to adapt, likely by moving life indoors, even if temporary residence in China comes at the expense of long-term health.

Keywords: Air pollution, school absences, international knowledge worker, defensive expenditure, particulate matter, longitudinal study, heterogeneous effects, human capital, developing country, environmental justice, distributed lags, instrumental variables, thermal inversions

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1 Introduction

Consider a highly skilled couple with young children, living in a rich country and facing the opportunity to transfer to the developing world, for professional or personal advancement. Aware of the routinely severe ambient air pollution in typical host cities (Van Mead, 2017), from Beijing to Calcutta to Dhaka, a pressing question on the couple's minds is likely to be: To what extent will air pollution act as an impediment to my child attending school or to the family's activities more generally, whether due to higher rates of sickness from exposure or to actions taken to avoid exposure? To our knowledge, there is no systematic evidence on this question. The question matters more broadly given that the international mobility of knowledge workers and the investments they enable are key inputs to the modern global economy (OECD, 2008; Freeman, 2010; UNCTAD, 2013; Thomas, 2014).

Our window into this question is to examine school attendance and how this responds to particle pollution in a sample of 6,500 children of all ages enrolled at three international schools in a major urban center in north China. Enjoying high education and incomes, these families typically have access to substantial defensive capital, including air filtering systems at home, school, work and car. To add perspective, annual tuition reaches one quarter of a million Chinese Yuan, or about US$ 40,000, per child. In terms of income and education, correlates of health status, our population is quite homogeneous.

We gained access to individual-level attendance records over multiple years, jointly covering 2008 to 2014, allowing us to control for potential confounds and sources of variability, including seasonality, weather and unobserved heterogeneity. During this period, daily PM2.5 (particulate matter of diameter up to 2.5 micrometers) concentrations measured at the US embassy at most 20 km from each school averaged 98 $\mu g/m^3$. This mean level is eight times the primary one-year average National Ambient Air Quality Standard (NAAQS) of 12 $\mu g/m^3$ set by the US Environmental Protection Agency.[1] That the US State Department monitors PM2.5 in several cities in the developing world underscores

[1] Particle levels stand out when comparing air quality in developing versus rich nations. Lelieveld et al. (2015) estimates that outdoor PM2.5 causes 3.2 million premature deaths globally each year, compared with 0.14 million from ozone, an oxidizing agent and very different pollutant formed under radiation and heat that has been studied in US settings (e.g., Graff Zivin and Neidell, 2012; Deschenes et al., 2017).

both the impediment to knowledge worker mobility (US citizens in this case) and the relative threat posed by particles (other pollutants are not monitored). We observe students' nationalities, both foreign and Chinese, and the time since first enrolling at the school which, for most children in the sample, may be a reasonable proxy for their time of residence in China. We are thus able to look for heterogeneous responses of absences to short-run variation in PM2.5 across nationality, duration at the school, student age, calendar year (should awareness of PM2.5 and its health impact have shifted), and among children who vary widely in their overall levels of absenteeism (irrespective of reason).

Beyond reporting Ordinary Least Squares (OLS) fixed-effects estimates, our favored Two-Stage Least Squares (2SLS) approach allows for measurement error in PM2.5 exposure as well as unobserved determinants of student absences that may drive or correlate with PM2.5 levels. Our 2SLS estimates are based on the exclusion restriction that atmospheric ventilation conditions, which fluctuate from day to day, induce absences only indirectly, by shifting PM2.5, and this exogenous PM2.5 component then drives absences. Previous research has adopted designs using the degree of atmospheric stagnation to infer the causal impact of air pollution on economic outcomes, both in China and elsewhere (Ransom and Pope, 2013; Hanna and Oliva, 2015; He et al., 2018b). We provide visual in-sample evidence of how atmospheric ventilation drives the build-up and removal of particles, such as a layer of hot air that stations over the metropolis, trapping emissions close to the surface, until the thermal inversion lifts a few days later.

We do find that international school absences in this severely polluted Chinese city respond to short-run fluctuation in PM2.5. The occurrence of severe PM2.5 on the day before—defined here as a 24-hour mean above 200 μg/m^3—raises the probability of an absence by 0.93 percentage point, or +15% relative to an absence rate of 6.2 in every 100 enrolled student by school day observations in the sample.[2] Hales et al. (2016) conjecture "that absolute values of PM2.5 (may) matter more in determining school absences than do fluctuations from mean PM2.5 levels" (p.11), and thus it is conceivable that the routinely high PM2.5 already contributes to some absenteeism beyond the variation we pick up.[3] In

[2]Here we report 2SLS estimates, which tend to be double their OLS counterparts.

[3]The 5th percentile of the daily PM2.5 distribution over our sample period is (a high) 17 μg/m^3.

our setting, an overall absence rate of 6 percent is higher than the 4 to 5 percent reported for school children in Utah Valley and Texas (Ransom and Pope, 1992; Currie et al., 2009), but lower than the 10 percent reported for Salt Lake City, where PM2.5 averages 10 μg/m^3 (Hales et al., 2016).[4] Besides, our students often take trips abroad and may skip school on days shortly before or after vacations. Our favored estimation sample drops any second and subsequent adjacent absence days within the same absence spell by a student, in order to examine the likely single decision behind the absence spell. (Other studies have access only to aggregate absences, so are unable to do this.) Pollution-induced absence spells include both remedial responses and averting behavior. For example, students may stay at home to recover from sickness or to avoid going outdoors as well as, in this high-income population, travel out of north China to escape a multi-day bout of severe pollution. Beyond student absences and human capital formation, the data more generally provide insight on how air quality impacts these families' lives. We estimate that severe PM2.5 on the day before a school day increases the probability that an absence spell is initiated by 0.43 percentage point, that is, an 11% increase relative to a sample mean of 3.8 percent.

We specify models with richer lag structures that allow more prolonged PM2.5 exposure to explain the absence decision, beyond simply PM2.5 on the day before or early morning of the school day. Biological effects may not be manifested in the form of an absence immediately, much as an avoidance trip's departure from the city may lag high PM2.5 by a few days. Distributed lag models with up to 14 days of delay yield estimated cumulative PM2.5 effects that grow with the number of lags.[5] In a model with cubic functions of daily PM2.5 in each of the 14 days preceding a school day, a large and infrequent shift in the pollution dose from 100 to 200 μg/m^3 sustained over an entire fortnight raises the probability that an absence spell is initiated by about 0.8 percentage point, or +20% relative to the sample mean of 3.8 percent (a risk ratio of 1.2).

We further find that Chinese nationals display lower absence responses to PM2.5 than US/Canada/Europe nationals.[6] The sensitivity of absences to PM2.5 is stronger among

[4]In our sample, absenteeism is lowest among nationals of Japan, Korea and Singapore.

[5]Zanobetti et al. (2003) find that models considering only immediate exposure to particle pollution, as opposed to more prolonged exposure over several weeks, underestimate the mortality response.

[6]It is conceivable that family experience and culture play a role in avoidance behavior (as in fertility and

children who exhibit higher absenteeism overall, particularly those in the top quintile of the distribution of individual absence rates over the 6,500 sampled students. Our data uniquely allow us to track a student as she grows or as her duration at the school increases. We find a U-shaped absence response to PM2.5 over age, though of marginal significance. The PM2.5-absence response does not vary with the time of residence in China, as proxied by the time since first enrolling at the school. We find no evidence that these international children's sensitivity evolves, by which they would acclimatize, or grow weaker.

On a positive note, combining the empirical PM2.5 variation in this city with our estimated responses reveals that severe PM2.5 explains only a fraction of one percentage point of the overall 4 percent absence incidence. Only for the most sensitive subgroup does severe PM2.5 explain one percentage point.[7] In our setting, the share of absences explained by shifts in ambient air quality is not large relative to estimates from aggregate data for the US. Ransom and Pope (2013) find that PM10 in Utah Valley "caused 2.25 percent of students to be absent on the average day... roughly *half* of the total rate of absenteeism" (p.14, emphasis added).[8] Currie et al. (2009) estimate a 0.8 percentage point reduction in absences for El Paso in 2000/01, a year with lower CO levels compared to 1986, when CO exceeded the NAAQS on 16 days. Hales et al. (2016) study Utah absences over a later period than in their seminal work, finding that "a 100 μg/m^3 increase in 7-day moving average PM10 is associated with a 10% to 15% increase in absences" (p.11)—a response that is still higher but closer to what we find. Currie et al. (2009) helpfully review the previous literature, which typically regresses school- or grade-level absence counts or rates on one or two pollutant levels (PM10, CO, ozone, NOx), finding mostly positive associations—and often of large magnitudes.[9]

We emphasize that the implications of our study go beyond the absenteeism of a narrow

work outcomes, e.g., Fernandez and Fogli (2006)) an aspect that has not been studied. Our multinational sample concurrently experiences the same environment and enjoys similar income and schooling.

[7] For example, the incidence of absences in the top quintile of the student absenteeism distribution is predicted to fall from 9.0% to 8.6%, i.e., by 0.4 percentage point, if we truncate the right tail of the 24-hour PM2.5 distribution at 200 μg/m^3 (corresponding to an 11% density). Similarly, predicted absences in this group fall by 1.2 percentage point if we truncate the PM2.5 distribution at 100 μg/m^3 (a 40% density).

[8] PM10, that includes and is usually double PM2.5, averages 45 μg/m^3 in the 1985-1991 Utah sample.

[9] Table 1 in Currie et al. (2009) summarizes the sample, method and findings in Ransom and Pope (1992), Makino (2000), Chen et al. (2000), Gilliland et al. (2001), and Park et al. (2002). Romieu et al. (1992) examine ozone-related absences in a panel of 111 preschoolers in Mexico City over three months.

group of children of high-income international workers residing in north China. Poor air quality (primarily from airborne particles) is observed across developing-world cities and is conceivably a key impediment to attracting skilled labor, of high value to the host economies that compete with employers in the rich world. The principals we met with described enquiries from prospective parents, whether Europeans investing in their careers or Chinese returning to their home country, who were concerned that their children, and thus themselves, would not function well in such a degraded ambient environment. The highly educated parents wished to know whether the defensive capital (air-conditioning and windows that shut properly) and procedures (pollution thresholds for outdoor play) that were in place provided protection to their children. Examining the absences of such children thus tells us about how attractive economic hubs in the developing world can be to high-skill workers typically with young families. The effect of air pollution on these families' daily routines may be a major impediment, and our study offers unique insight into this aspect of international knowledge worker mobility.

Our paper makes several contributions over the extant literature linking student absences to air pollution. It is the first study to offer a window into the daily functioning of a group of young, high-income and mostly rich-country nationals being subjected to a developing nation's urban air, often for the first time. The media has covered the cost to skilled families of adapting to China's air (Mangin, 2014; Wong, 2015; Liu, 2017; Mullin, 2017). In its mission to protect US citizens, the US State Department seems to agree, by measuring and reporting—in real time and at considerable cost—PM2.5 in cities across Bangladesh, China, Colombia, India, Indonesia, Vietnam, and others. Our study is the first to examine a child by day panel for a sizable population over multiple years, to consider a PM2.5 range that is most relevant to developing countries, and to allow a plausible lag structure. Like Ransom and Pope (2013), our approach adopts credible exclusion restrictions based on daily atmospheric ventilation conditions that critically determine local air quality and yet do not respond to anthropogenic activity.

School attendance is a key input to the production of human capital (Grossman and

Kaestner, 1997; Gottfried, 2014). Beyond children's health,[10] our paper contributes to our understanding of the location decisions, human capital formation, and coping strategies by high-skill households in the many polluted cities of the developing world. Our finding that despite the excess pollution the absentee response is not excessive relative to what the literature finds for the US suggests that high-income families from mostly rich countries, stationed temporarily in developing-world megacities, find ways to adapt. For example, moving life indoors and staying inside air-conditioned spaces at home, school, and car, may partly be protective of one's health, even if temporary residence in north China comes at the expense of long-term health, a topic that remains open for research.

Related health literature. A literature, mostly in epidemiology, examines the relationship between acute exposure to air pollution and public health outcomes, for which data are collected via encounters with health suppliers or vital records. When it comes to more subtle manifestations of morbidity that do not lead to health encounters, the evidence is more sparse. Recent studies by economists have examined the causal effect of short-run pollution exposure on medication purchases (Deschenes et al., 2017), hours worked (Hanna and Oliva, 2015; Aragon et al., 2018) and productivity while at work (Graff Zivin and Neidell, 2012; Chang et al., 2016b,a; He et al., 2018b). Unlike us, studies have typically had to rely on aggregate data, rather than individual-level panels, or examined rich-world settings, where pollutant concentrations in ambient air are much lower than in developing countries, particulate matter in particular.[11]

2 Institutional background and data

Origin of student attendance records. In 2013, we contacted the principals of 16 international schools located in a Chinese city that is routinely exposed to severe PM2.5

[10] Currie et al. (2009) cite the "lack of health measures that capture the range of morbidities purportedly related to pollution" (p.693). Ransom and Pope (2013) argue that absences are "a measure of children's health and morbidity that is more sensitive than the extreme measures of hospitalization or death" (p.2).

[11] Exceptions are studies examining worker or household-level panels in China and Peru (Chang et al., 2016a; He et al., 2018b; Aragon et al., 2018). Given their developing country setting, these three studies focus on particulate matter. Lines of enquiry relating air pollution to morbidity include households' avoidance behavior to mitigate health damage (Moretti and Neidell, 2011), and the short-run impact of pollution on test scores, which may operate through morbidity (Ebenstein et al., 2016; Ham et al., 2014).

pollution. These schools cater largely to the international community and, to a lesser extent, to Chinese families that have some international connection, such as families that have lived outside China. We explained that we were interested in studying the effect of air pollution on student absences at several international schools and that, in view of the topic's sensitivity, the addressee's school would be anonymized were it ultimately included in our sample. Such data might inform on possible adaptation by children (and their families) of varying nationalities to a new and polluted environment, starting from the day they first enroll at the school. Among the 16 schools that we contacted, principals at seven schools agreed to meet with us. Ultimately, longitudinal student-level attendance records were shared by three of these schools.[12]

Variation in absence rates and absence inequality. A key aspect of the attendance data is its longitudinal structure and high frequency. Since we follow the same student day by day, we can control for individual heterogeneity and seasonality. The periods of observation for the three schools are: (1) September 2008 to June 2014, (2) April 2010 to December 2014, and (3) April 2013 to June 2014. The schools vary in size, with median enrollment across days in each school sample of: (1) 1,541, (2) 1,056, and (3) 284 students. Each of the three schools caters to children of all ages, from 3 to 19 years.

In terms of student nationality, rich countries grouped by continent—US/Canada, Europe, Japan/Korea/Singapore—each account for at least one-third of enrollment for at least one school, e.g., at one school, US/Canada accounts for one-third of enrollment and Europe accounts for another one-third of students. Chinese nationals account for 7% to 20% of the student body at each school. For each school sample, the median enrollment duration among departing students is about two years, with the 10th percentile below one year and the 90th percentile above four years (see Figure A.1(b)). Due to the high turnover, the number of students in the combined sample (henceforth, sample) is 6,545.

We take the schools' published calendars and validate these against observed attendance records. We define a school day as a day in which a given school was in session. This is invariably a weekday, Monday to Friday, during the academic year from August

[12]The initial contact letters as well as the non-disclosure agreements we signed, with the addressee and school details omitted, are available from the authors.

to June/July, excluding winter and summer vacations, breaks of three or more successive weekdays, and short holidays of one or two successive weekdays. As labeled here, breaks include the extended National Day and Spring Festival (Chinese New Year) celebratory periods, whereas short holidays include "staff professional development" and "parent-teacher conference" days and the one or two-day Mid Autumn and Dragon Boat Festivals.

Table 1 reports summary statistics across enrolled student by school day (henceforth, student-day) observations. The sample consists of 2.5 million student-day pairs. Compared to the absence rate for nationals of Japan/Korea/Singapore, at 4.7% of student-days, absenteeism is 31% and 51% higher for nationals of Europe, at 7.1%, and the US/Canada, at 6.1%, respectively. Perhaps surprisingly, the absence rate for Chinese nationals, at 7.2%, is similar to that of Europeans.

Since adjacent school days of absence by a same student are usually triggered by a single choice or shock, such as health and travel, we will focus our analysis on how pollution exposure may trigger the decision to initiate a spell of consecutive absence days. If we exclude the second and subsequent adjacent absence days of every student absence spell from the sample, keeping the first day of each absence spell as well as all student-day observations of attendance, then absences account for 4.0% of student-day observations.

To illustrate, say that the sample consisted merely of one student and 10 consecutive school days, Monday to Friday of week 1 and Monday to Friday of week 2. If the student were absent on Thursday and Friday of week 1 (or, similarly, Friday of week 1 and Monday of week 2), then the "raw" absence rate would be 2/10. Excluding the second day of the absence spell—say that it was triggered by the single decision to travel over an extended weekend—the "spell-adjusted" absence rate would be 1/9. It is the influence of acute exposure to particle pollution on initiating absence spells that we will examine.[13]

Figure 1 summarizes how (raw) absence rates vary over time and across children. For every day in the sample, when at least one school is in session, we compute the proportion of enrolled students who are absent. Panel (a) shows a right-skewed distribution of the aggregate absence rate over 1,234 days. The median day exhibits an absence rate of 5.8%,

[13] For perspective, the sample contains 165,698 student-day absences and 97,164 absence spells. 70% of absence spells last one day, 15% last two (school) days, and 6% last three days.

and days in the 10th and 90th percentiles experience absence rates of 3.8% and 10.5%. The day-to-day variation in absenteeism is important to our empirical strategy. Our task is to uncover to what extent this temporal variation is driven by variation in concurrent and recent exposure to ambient PM2.5, once we account for other time-varying determinants.

Individual heterogeneity is another key feature of the data. For every child, we divide the child's overall number of days absent by the number of school days in the sample during which she was enrolled. This would be 2/10 in the preceding example. Panel (b) shows a right-skewed distribution of the individual absence rate over 6,545 students. The median student is absent on 5.1% of days. Some students exhibit a significantly higher absence rate than others. Fixing enrollment, the top 10% of absentees account for 35% of aggregate absences, with a mean absence rate of 23%. Such absence inequality has not been documented and may have long-lasting effects on human capital accumulation.

For each child, we also divide the number of school days while enrolled in the sample by her number of absence spells; this would be 9 school days/absence spell for the single student in the example. Figure 1(c) shows there is much cross-sectional variation in this school days/absence spell statistic. In-sample enrolled days are low for some students since they enrolled at the school near the end of the sample period. It is also plausible that some families leave China earlier than anticipated due to difficulty adapting to the polluted environment. Figure A.1(a) reports the distribution across students of school days in the sample; one academic year consists of just under 200 school days. Figure A.2 shows that students with short duration in the sample or at the school, in panels (a) and (b) respectively, are associated with higher absence rates.

Figure 2 considers several time-varying drivers of absences, factors that we control for in our empirical model. There are non-monotonic relationships between absenteeism and age, in panel (a), and day of the week, in panel (b). The absence rate is lower at age 8-10 years compared to younger and older students. The absence rate is higher on Mondays and Fridays compared to midweek. A weekend effect may partly be driven by activities that compete with school, such as trips. Panel (c) shows the effect of (pre-determined) vacations and breaks on surrounding school days. Absence rates tend to increase in the five days leading up to a vacation/break, and decrease in the five days following a vacation/break, likely due in part to students taking off early for a trip out of town (e.g., to their home country) or returning late.[14] Patterns in the data assure us of their high quality.

Panel (d) reports a seasonal pattern for absenteeism, with lower absence rates around August/September, as the academic year is off to a start, and in May, typically the last full month of the academic year, compared to more absences in December through February.[15] Many students travel abroad over the winter vacation and may depart before school closes in December or return after school reopens in January. Since newly enrolled students are often being introduced to a type of urban environment that is foreign to them, we separately plot absence rates over the calendar months in a student's first year of enrollment versus subsequent years. We find little variation along this margin—if anything, absences appear slightly lower during a student's first year.

Particle pollution, weather and atmospheric ventilation. As a proxy for severe air pollution, we obtained PM2.5 mass concentrations measured every hour by the US State Department on the rooftop of the US embassy located in the city that hosts the schools over the 2008 to 2014 sample period. This outdoor air monitoring site is located no more than 20 km from the three schools. The schools informed us that most students live within 10 km of the school, likely due in part to the state of road congestion in major Chinese cities (Viard and Fu, 2015; Gu et al., 2017). Alternative PM2.5 measurements at Chinese Ministry of Environmental Protection (CMEP) sites across the city, available only from 2013, show tight spatial correlation not only across CMEP sites but also with US embassy records in the overlapping period. Specifically, in 2013 and 2014 the correlation coefficient between (24-hour) PM2.5 at the US embassy and the average for CMEP sites is a very high 0.97.[16] This speaks to the importance of regional atmospheric ventilation shocks,

[14] Similarly, absences increase in the days leading up to, and decrease in the days following, a short holiday. Further, official public holidays on which a school is in session (22 days in the sample) shift absences (up by two-thirds). While schools may not follow the official public holiday calendar, children can be impacted by it if parents' employers adopt this calendar, inducing travel. For example, the government decreed that the Monday and Tuesday prior to 2013's Labor Day, on a Wednesday, were public holidays. Although all three schools were in session on the Monday and Tuesday, absences were high.

[15] Hales et al. (2016) report similar weekly and annual patterns for elementary school absence counts in Utah, speaking to the quality of our micro data. We also observe more absences on colder winter days.

[16] Andrews (2008) and Ghanem and Zhang (2014) consider manipulation of pollution readings published by the Chinese authorities, but in preceding years.

discussed below, that govern the dispersion of pollutants and are plausibly exogenous to unobserved determinants of absences. As attested by local and foreign media coverage, fluctuation in PM2.5 severity is a citywide—not a neighborhood—phenomenon.

For the same-day air quality as a potential shifter of absences, we take the PM2.5 reading at 6 am, prior to classes starting. To allow for more prolonged pollution exposure, over up to the 14 preceding calendar days, to explain absence, we aggregate the one-hour PM2.5 readings into daily 24-hour averages. In specifications with up to 14 days of lagged exposure, we discard up to 14 days from the first school day after vacations, as students may have been out of town and we are unable to assign lagged exposure. Figure 3(a) shows wide variation in daily PM2.5 over the sample period. There is substantial density beyond 100 μg/m^3, and even beyond 200 μg/m^3. In panel (b), variation up to 400 μg/m^3 remains even after regressing daily PM2.5 on month-of-year fixed effects and day-of-week fixed effects. Pollution is not exclusively a winter phenomenon: PM2.5 averages 88 μg/m^3 between April and September. Panel (c) reports the distribution of the absolute change in daily PM2.5 from one day to the next, where the median shift is a high 37 μg/m^3 (the 75th percentile is 68 μg/m^3). Table 1 shows that much variation also remains even as we aggregate PM2.5 over consecutive days, e.g., the 7-day and the 14-day averages have ranges of 25-346 and 34-270 μg/m^3, respectively.

We obtained weather conditions at ground level, compiled by NASA for the sampled city and period, namely, 3-hour readings for temperature, relative humidity and precipitation. We control for these variables in our student absence equations, as such weather conditions may shift absences directly (Section 3). Compared to the magnitude of PM2.5 shocks from one day to the next, Figure A.3 suggests that weather is more persistent, with median shifts in daily mean ambient temperature and relative humidity from one day to the next of 1.2 °C and 7.7%, respectively.[17]

Ventilation conditions in the lower atmosphere for a reference location 19 km from the US embassy are available from NOAA. We observe 12-hour readings (8 am and 8 pm

[17]This feature, coupled with the weather controls that we add directly to our estimating equation, suggests that ambient weather is unlikely to confound our inference of the impact of PM2.5 on absences. Taking longer two-day differences, the median absolute shift is 51 μg/m^3, 1.8 °C and 11% for 24-hour mean PM2.5, temperature and relative humidity, respectively.

local time) of vertical thermal gradients and horizontal wind speed and direction. Beyond the OLS estimates that we provide, our 2SLS estimates allow for measurement error in students' pollution exposure, as well as time-varying omitted correlates or determinants of student absences, including emissions from road traffic. In such specifications, we instrument for measured PM2.5 using PM2.5 variation induced by atmospheric ventilation shocks, as proxied by temperature-altitude gradients and wind conditions.

Figure 3's three last panels report on the strength of the atmospheric ventilation instruments. The plots show (all variables are daily means) PM2.5 against: (d) the temperature difference from ground level to a pressure point of 1000 mb, (e) the temperature difference from 1000 to 925 mb, and (f) ground-level wind speed. Again, we partial out confounding systematic seasonal and weekly variation from each series. Positive and steeper temperature gradients with altitude (e.g., a layer of hot air stationed overhead that traps pollutants close to the ground, where they are emitted), as well as lower wind speeds (e.g., still air), are strongly associated with a deterioration in air quality, as indicated by higher fine particle levels. The 2SLS identifying assumption is that day-to-day shifts in ventilation, both vertical (thermal inversions set in and lift) and horizontal (wind changes in intensity and direction), do not affect absences directly or correlate with unobserved determinants of absences.

3 Empirical model

An observed absence decision for child i on school day t can be described by a latent utility model, where the utility from not attending school is:

$$y_{it}^{*} = \alpha_0 + Z_t\beta + W_t\alpha_1 + X_{it}\alpha_2 + \alpha_i + \alpha_t + \epsilon_{it} \quad (1)$$

and binary variable A_{it} (denoting absence) is 1 if and only if $y_{it}^{*} > 0$. Row vector Z_t of pollution variables includes concurrent exposure (e.g., PM2.5 at 6 am of school day t) and, more generally, lagged-day exposure, Z_{tp}, where $p = 0, 1, ..., P$ indexes the lag in calendar days relative to t, starting with $p = 0$, the period concurrent to school day t, and $P \geq 0$. For example, a model with $P = 1$ restricts only prior-day (and same-day) pollution to influence absences. Z_{tp} can be a non-parametric or parametric function of exposure, e.g., a dummy for PM2.5 above a threshold, or a cubic function of PM2.5.[18]

Vector W_t consists of concurrent weather covariates, namely, ground-level temperature, relative humidity and rain.[19] W_t can affect both direct and opportunity costs of attending school. For instance, cold and rain may raise the effort required to get out of bed and commute to school, including through any health channels. At the same time, bad weather can reduce the value of outdoor activities that may compete with school. Following Section 2, X_{it} captures time-varying student-level determinants or correlates of absences, such as granular age bins and functions of time since first enrolling at the school, e.g., indicators for the student's first two semesters of enrollment. Student fixed effect α_i captures the unobserved characteristics that affect an individual's utility from not attending school. To account for systematic annual and weekly cycles and other time-varying drivers of absences, vector α_t includes year-month (month-of-sample) fixed effects and day-of-week fixed effects (this includes an indicator for public holidays when the student's school was in session). To capture travel ahead of, or extended beyond, longer periods in which school closes, α_t further includes indicators for each of the five school days that lead up to, or that follow, a winter or summer vacation or a break.[20]

We then estimate a linear probability model of student absences:

$$P(A_{it} = 1) = \alpha_0 + Z_t\beta + W_t\alpha_1 + X_{it}\alpha_2 + \alpha_i + \alpha_t + \epsilon_{it} \tag{2}$$

Distributed lag structure for PM2.5 exposure. Following a literature in epidemiology (Zanobetti et al., 2002, 2003), we estimate models with distributed lag structures increasing from $P = 1$ to $P = 14$ days prior to the observed student absence decision, to capture the cumulative impact from more prolonged exposure to particle pollution.

[18] Other pollutants such as CO, NOx or ozone are not available over the sample period, but in our setting PM2.5 dominates the official Air Quality Index (AQI). The interpretation we offer is that of PM2.5 as a wider "indicator" (Dominici et al., 2010) of the severity of atmospheric pollutants, including ultrafine particles (PM 0.01 to 0.1) that are not routinely monitored in China or even the US (He et al., 2018a).

[19] We include linear and quadratic terms for: the 24-hour means of temperature, humidity and rain on the previous day $t-1$, and 6 am readings for these variables on day t. We further include indicators for any rain on day $t-1$ and rain at 6 am on day t. In a robustness test, we model temperature in bins.

[20] These indicators can be interacted with nationality. We further add indicators for each of the two school days that lead up to, or that follow, a short holiday (one or two successive weekdays without school).

For example, in a model in which P PM2.5 covariates enter linearly, we estimate $1+P$ parameters β_p in (2), and report the cumulative shift in the probability of absence from a given PM2.5 increase sustained in each of $1+P$ concurrent and lagged days of exposure, $\sum_{p=0}^{P}\beta_p$. This model is the unconstrained distributed lag, UDL(P). Although serial correlation in Z can make estimation of the individual β_p challenging, the cumulative effect can be precisely estimated (Wooldridge, 2015, p.316).

Alternatively, in a polynomial distributed lag PDL(P,Q) model, the $1+P$ coefficients on the lag structure are disciplined according to a smooth polynomial function of degree $Q<P$, such that the exposure coefficients satisfy $\beta_p=\sum_{k=0}^{Q}\eta_k p^k$, $p=0,1,...,P$, where η_k are parameters constraining the β_p. As an alternative to UDL models, we estimate PDL($P,2$) models constraining the β_p to follow a quadratic, and find a similar cumulative impact $\sum_{p=0}^{P}\beta_p$. Constraining the shape of variation in the lagged dose-response coefficients may improve precision relative to the UDL, at the expense of minimal bias (Schwartz, 2000). For comparison, in studies of daily aggregate elementary school absences, Ransom and Pope (2013) specify 7-day lagged averages for PM10 (and CO) as the measure of exposure, whereas Gilliland et al. (2001) allow acute pollution effects to be distributed over up to 30 days.

Endogenous PM2.5 exposure. Besides OLS, we estimate models by 2SLS to alleviate concern that PM2.5 exposure is measured with error, leading to attenuation bias, or endogenous.[21] The exclusion restriction is that ventilation in the lower atmosphere, V, only affects absences through its effect on air pollution. Specifically, V includes the atmospheric thermal gradients and surface wind speed and direction variables reported in Table 1. To account for the build-up of particles when ventilation is poor, we include an indicator for wind speed less than 1 m/s interacted with each of three indicators denoting inversions in the three layers closest to the surface.[22] Such variables are key determinants

[21]For instance, unobserved shifts in the value of activities that compete with school, a popular concert say, might raise absences as well as traffic congestion and emissions, leading to upward bias. Similarly, shocks to road congestion might raise vehicle emissions and absences.

[22]For continuous variables, we include squares. We include 24-hour mean ventilation conditions on the day and in each of the two prior days (or, for sensitivity, one prior day). Ransom and Pope (2013) use a "clearing index which measures the level of ventilation or air movement in the atmosphere...defined as mixed layer depth...times the wind speed" (p.7); a day is "stagnant" when the clearing index on the day and the two prior days stays below a threshold.

of PM2.5 and are unlikely to correlate with unobserved absence shocks, ϵ_{it}. Recall from Figure 3 that PM2.5 is higher the less negative (or more positive) is the temperature-altitude gradient, since warmer air overhead traps PM2.5 that is emitted or formed near the ground, and similarly when the air is still and horizontal ventilation is poor. We use ventilation V to form an instrument, $\hat{Z}$, for measured 24-hour PM2.5, Z, by fitting:

$$Z_t = \delta_0 + V_t\delta_1 + \delta_t + \nu_t, \tag{3}$$

where δ_t are time fixed effects (year-month, day-of-week) and (3) is implemented on daily observations t between August 2008 and December 2014.

To be clear, (3) is not the first-stage equation. This ventilation-pollution model produces fitted values $\hat{Z}$ that, together with covariates in the absences model (2) such as weather (W_t), student age (X_{it}) and fixed effects, comprise our first stage.[23] With regard to the exogeneity of wind speed (a component of V) and thus of $\hat{Z}$, the routinely mild wind in our setting,[24] while clearing the atmosphere, is unlikely to impact behavior. In a robustness test, we add wind speed to other ambient weather conditions (temperature, humidity and rain) that are allowed to affect absences directly.

4 Pollution's effect on international children's lives

We first examine the relationship between absences on a given school day and PM2.5 levels on the day before, and then subsequently enrich the lag structure of the model to allow for more prolonged PM2.5 exposure to explain absences. We obtain our preferred estimation sample from the original student-day observations as follows. For each school by age group pair (three schools each with preschool, primary, middle and high school divisions, totaling 12 pairs), we compute the fraction of students absent on each school day. Observations pertaining to a school day in which the student's school-division specific absence rate exceeds 30% are dropped from the estimation sample, since the very high absence rate is

[23]Isen et al. (2017) instrument for pollution using fitted pollution, imputed from a policy rather than atmospheric intervention. An alternative to instrumenting for Z using V-induced $\hat{Z}$ is to use V. Results should be similar in linear models such as ours (Angrist and Krueger, 2001), as we confirm (Table 6).

[24]Wind speeds in Chicago and Los Angeles average, respectively, 4.6 m/s and 3-4 m/s compared to 2.0 in our sample (Herrnstadt and Muehlegger, 2015; Anderson, 2016).

likely due to recording error. This drops only 0.7% or 17,547 out of 2,528,567 observations in the original sample.[25] We further exclude the second and subsequent adjacent absence days for every observed student absence spell in the original sample, since these follow-on absence days typically stem from the same decision that drove the first absence day in the spell, for example, health or travel, including remedial or defensive responses to pollution. We examine spell-adjusted absences, where an absence is the first school day of an absence spell. We show that estimates are fairly robust to keeping 62,504 observed second and subsequent absence days within absence spell in the estimation sample; intuitively, effects are higher.[26] The estimation sample consists of 2,448,516 observations.

Table 2 estimates linear probability model (2) of student absences and, as alternative measures of immediate exposure to severe PM2.5, considers: (columns 1 and 2) an indicator that daily mean PM2.5 on the day before the absence decision exceeded 200 $\mu g/m^3$; (column 3) a count of the days in which daily mean PM2.5 exceeded 200 $\mu g/m^3$ in the three days prior to the absence decision (zero, one, two or three); (column 4) a linear spline function of daily mean PM2.5 on the day before the absence decision; and (columns 5 to 7) a quadratic function of daily mean PM2.5 on the day before the absence decision. In column 1, severe PM2.5 on the day before, defined here as a mean above 200 $\mu g/m^3$, raises the probability that an absence spell is initiated by a precisely estimated 0.20 percentage point. Relative to a sample mean of 3.83 percent, this is a 5.2% increase (0.2/3.83). In column 2, we instrument for the severe PM2.5 dummy using fitted ventilation-induced PM2.5 and its square.[27] We obtain a 2SLS estimate of the effect of severe PM2.5 that is about double the OLS estimate. The occurrence of severe PM2.5 yesterday raises the probability that an absence spell is initiated today by 0.43 percentage point, i.e., an 11% increase relative to a sample mean of 3.83 percent. Again, the exclusion restriction is that absences respond to atmospheric thermal gradients and surface wind only indirectly, through these variables' effect on particle levels. A higher absence response estimated by

[25] Figure 1(a) shows low density already at an absence rate of 20%. Table 5 shows that estimates are robust to: not dropping observations on these very high absence days, or instead to only dropping observations pertaining to days in which the absence rate exceeds 50%.

[26] Gilliland et al. (2001) examine "incident" (first-day) absences as opposed to "prevalent" absences.

[27] This is conventional 2SLS (Angrist and Pischke, 2009), with the first-stage a linear regression of the severe PM2.5 dummy on fitted ventilation-induced PM2.5 and its square (and exogenous covariates).

2SLS compared to OLS, as in column 2 versus column 1, is a result we obtain throughout.

Consistent with column 1, column 3 reports OLS estimates that each additional severe PM2.5 day in the preceding three days raises the incidence of absences by 0.13 percentage point. Thus, for example, the incidence of severe PM2.5 in all three preceding days raises the probability that an absence spell is initiated today by 0.39 percentage point, or 10% of the sample mean. A higher estimated absence response on allowing sustained PM2.5 exposure to drive absences, as in column 3 versus column 1 (0.13×3 versus 0.20), is another result we obtain throughout.

Column 4 reports OLS estimates of a linear spline function of prior-day PM2.5, with three knots set at 50, 100 and 200 μg/m^3. Perhaps surprisingly, the likelihood that an absence spell is initiated falls as prior-day PM2.5 increases over the 50 to 100 μg/m^3 range, only to grow as prior-day PM2.5 increases beyond 100 μg/m^3. To illustrate the point estimates, a shift from 50 to 100 μg/m^3 lowers the absence incidence by $0.43 \times (100 - 50)/100 = 0.22$ percentage point; a shift from 100 to 200 μg/m^3 raises the absence probability by $0.16 \times (200 - 100)/100 = 0.16$ percentage point. One interpretation is that on "blue sky days" when air quality is relatively good, say, below 50 μg/m^3, students are more likely to skip school to go to the park or to run errands outdoors.[28] A non-monotonic absence response, by which absences initially fall as pollution rises from low levels to subsequently rise, as in column 4, is yet another result we obtain throughout.

The non-linearity in the pollution-absence relationship in our setting can be seen directly in the data, in Figure 4: in panels (a) to (c) we document the incidence of absences over prior-day PM2.5 bins of width 20 μg/m^3, i.e., 0-20, 20-40, etc. We plot the proportion of students initiating an absence spell both in the original sample, as well as in the estimation sample that excludes observations jointly yielding school-division absence rates over 30%. We also show alternative bins of width 30 μg/m^3. The absence incidence falls over the first several bins and then rises. To highlight variation in the 50-100 μg/m^3 range, panels (d) to (f) show the proportion of students initiating an absence spell against

[28] Shi and Skuterud (2015) find employees in Canada calling in sick when weather is of high recreational quality. Also see Connolly (2008). Wong (2013) cites a senior at a local high school in north China: "The days with blue sky and seemingly clean air are treasured, and I usually go out and do exercise."

percentiles of the PM2.5 distribution. Moreover, panels (g) to (i) of Figure 4 show percentiles of the PM2.5 distribution after partialling out co-variation with all the other absence shifters in the model (e.g., weather W_t, time fixed effects α_t).

The parametric specification in columns 5 to 7, in which we include both linear and quadratic terms in prior-day PM2.5, similarly yields a non-monotonic pollution-absence relationship, e.g., OLS estimates in column 5. Comparing column 6 to column 5, estimated coefficients on prior-day PM2.5 change little if we include the same-day PM2.5 reading at 6 am, a few hours before classes start, to the model of absences. This specification, which has a falsification test flavor, suggests that the decision to miss school is taken prior to 6 am on the same day, for example, on the evening before the school day. Again, the 2SLS estimate of the absence response is about double the OLS estimate as PM2.5 becomes increasingly severe (column 7 versus column 5).[29]

We also observe that the share of absence spells lasting one day grows as the severity of pollution increases. For example, take the distribution of the past-three-day severe PM2.5 count over all student-day observations (with year and month-of-year partialled out) and compare the duration of absence spells initiated in the top decile of this PM2.5 distribution compared to those initiated in the bottom decile. One-day absences account for 73% of absence spells initiated under severe PM2.5 compared to 63% of absence spells initiated under lower pollution. We tentatively interpret this evidence as being consistent with a compositional change in absences, toward shorter pollution-induced (biological or behavioral) absences as PM2.5 rises relative to longer predetermined absences.

In sum, Table 2 shows that the estimated student absence response to PM2.5 is: (i) stronger if one allows for endogenous PM2.5 exposure, e.g., due to attenuation bias, (ii) stronger if one allows for a more delayed response than the day (or a few hours) before the school day, and (iii) non-monotonic, at least over the initial range of PM2.5 variation in our urban China setting where skies are routinely *not* blue.

Heterogeneity and robustness. Table 3 implements the 2SLS estimator of the prior-day severe PM2.5 dummy (as in Table 2, column 2) on separate subsamples based

[29]We instrument for PM2.5 and its square using fitted ventilation-induced PM2.5 and its square.

on: (column 1) the time elapsed since first enrolling at the school, with the first and second semesters of enrollment jointly accounting for 32% of student-day observations; (column 2) academic year, with school days in the 2012/13 and subsequent years accounting for 43% of observations; (column 3) nationality group; (column 4) age group; and (column 5) quintile of the distribution of individual absence rates across the 6,545 students in the sample (Figure 1(b)), i.e., over 80th percentile absentee, 60th to 80th percentile, etc.[30] As a measure of individual vulnerability in general, Currie et al. (2009) state that "there is a long tradition of using absence from school to define disability among children" (p.684).

As a less flexible alternative to Table 3's subsample analysis, Table 4 reports on 2SLS regressions implemented on the full sample but now interacting the prior-day severe PM2.5 dummy with nationality group or with absenteeism quintile. We instrument for the severe PM2.5 measure and its interactions with levels and corresponding interactions of fitted ventilation-induced PM2.5 and its square. As further sensitivity analysis, we specify the past-three-day severe PM2.5 count as an alternative measure of pollution severity. We also show OLS estimates.

Estimates for all implementations in Tables 3 and 4 suggest that Chinese nationals display lower absence responses to PM2.5 than US/Canada nationals. We reject equal responses for these two nationality groups with a p-value of 0.009 (Table 4, column 2). Both flexible and less-flexible implementations indicate that the sensitivity of absences to severe PM2.5 is stronger among students who exhibit higher absenteeism overall. The estimated coefficient on the severe PM2.5 dummy increases as we separately consider subsamples of children in higher absenteeism quintiles (Table 3, column 5). Similarly, estimates on the severe PM2.5 $\times$ absenteeism quintile interactions increase in the absenteeism quintile (Table 4, column 4). A child in the highest absenteeism quintile is 1.3 percentage point more likely to initiate an absence spell on the school day following a severe PM2.5 day compared to a child in the lowest quintile. To check whether this result may be driven in part by students with short duration in the sample, who tend to be absent more (Figures A.1

[30] Column 5 uses an endogenous variable to stratify the sample. The purpose is descriptive. Moreover, we show below that PM2.5 explains a small share of overall absenteeism. Findings are similar if we correct for age before grouping students by overall absenteeism quintile.

and A.2), we re-estimated Table 4, column 4's specification on a subsample restricted to students with over 200 school days (about one academic year) of observation. This shrinks the number of children from 6,545 to 4,390. Estimates on the severe PM2.5 $\times$ absenteeism quintile interactions (not shown for brevity) are very similar to those reported in Table 4, where the sample included the short-duration students.

Moreover, Table 3 provides weak evidence that the sensitivity of absences to severe PM2.5 is lower: (i) in the first semester of enrollment compared with subsequent semesters (column 1), and (ii) among students aged 5 to 12 years compared with younger and older children (column 4). However, differences are not statistically significant. Figure 5 plots the heterogeneous absence response to PM2.5 by nationality group, age group and absenteeism quintile estimated in Table 3.

Tables 5, 6 and A.1 show several robustness tests: (i) varying the estimation sample, e.g., not dropping the very high absence days, not dropping the second and subsequent absence day within absence spell, restricting to students with over 200 school days; (ii) varying the set of controls, e.g., controlling for temperature with granular bins 3 °C wide, adding week-of-year dummies for finer seasonal controls, interacting year-month fixed effects with school-division fixed effects; and (iii) varying the set of excluded instruments. In particular, keeping all days of an extended absence raises estimates; keeping the very high absence days lowers estimates, as does specifying granular temperature bins.

More prolonged pollution exposure. We now enrich the lag structure of our model of PM2.5 as a driver of absences. Importantly, 24-hour PM2.5 fluctuates substantially from day to day (the 75th percentile is a 68 μg/m^3 swing) and there is large variation in exposure even as we aggregate over several days (the 7-day average ranges from 25 to 346 μg/m^3). Table 7 and Figure 6 report cumulative effects of past P days of PM2.5 on the decision to initiate an absence spell, for alternative: distributed lag models (lagged exposure coefficients disciplined or not); PM2.5 measures (non-parametric or parametric); identifying restrictions (all measured PM2.5 variation or only that induced by atmospheric ventilation); and estimation samples (full sample or specific to child's nationality or overall absenteeism level). Consistent with the above findings, estimated responses are generally higher under 2SLS than OLS, higher as we allow a longer delay up to a fortnight (fixing the average dose over the lags), higher for US/Canada (and Europe) than for Chinese nationals, and higher for students who generally miss school the most.

Panels A and C of Table 7 specify daily lags of severe particle pollution, each lag characterized by a dummy indicating 24-hour PM2.5 in excess of 200 μg/m^3. A large shift in exposure over the preceding week, from 0 to 7 days of severe PM2.5, raises the incidence of absences by: 1.14 percentage point in the full sample (panel A, right and Figure 6(b), row/horizontal axis marked $P = 7$); 1.17 percentage point among US/Canada nationals (panel C, left); and 2.50 percentage points for children in the top quintile of the absenteeism distribution (panel C, right).[31]

To quantify the empirical importance of PM2.5 fluctuations around a severe threshold at explaining absences overall, we can take each estimated model and predict absences in the counterfactual scenario that 24-hour PM2.5 were not to exceed 200 μg/m^3. Mechanically, we set the severe PM2.5 dummy to zero once the model has been estimated. We find that in-sample severe PM2.5 variation explains considerably less than one percentage point (one-quarter) of student absences in the overall population. An alternative definition of severe PM2.5, using a threshold of 100 rather than 200 μg/m^3 for each lagged day, yields similar estimates (panel D versus panel C).

Panel B of Table 7 specifies daily lags of 24-hour PM2.5, its square and its cube. A sizable shift in week-long exposure, from 100 to 200 μg/m^3 sustained over 7 days, raises the probability that an absence spell is initiated by 0.98 percentage point (panel B, right and Figure 6(f), row/horizontal axis marked $P = 7$).[32] Taking each estimated model and predicting aggregate absences under the counterfactual scenario that the 24-hour PM2.5 distribution were truncated at 100 μg/m^3, close to the sample mean, we again find that in-sample severe PM2.5 variation explains less than one percentage point of overall student absences. Mechanically, we replace 24-hour PM2.5 above 100 μg/m^3 by 100 μg/m^3 once

[31] 2SLS estimates based on a UDL(7). Figure 6(d) reports on an alternative quadratic PDL(7,2).

[32] 2SLS estimates based on a quadratic PDL(7,2). The caption to the table or figure describes how the lagged exposure coefficients are disciplined, as well as the functional form of the excluded instruments. Denoting 24-hour PM2.5 in daily lag p of school day t by Z_{tp}, and using β_{1p}, β_{2p} and β_{3p} to denote the coefficients on Z_{tp}, its square Z^2_{tp} and its cube Z^3_{tp}, the cumulative effect of the 100 to 200 μg/m^3 shift in week-long exposure is calculated as $\sum_{p=1}^{7}(200-100)\beta_{1p} + (200^2-100^2)\beta_{2p} + (200^3-100^3)\beta_{3p}$.

the model has been estimated.

5 Discussion

We find that the severity of particle pollution drives school absences in a 1,234-school day panel of 6,545 high-income students attending international schools in north China. A 2SLS model with 7 lagged days of exposure indicates that the incidence of absences is 1.1 percentage point higher in the wake of daily PM2.5 exceeding 200 μg/m^3 *seven* days in a row compared to a less polluted week in which daily PM2.5 remains below 200 μg/m^3 throughout (95% CI = [0.7,1.5]). A model with a smoother cubic PM2.5 specification, also allowing up to 7 days of delay and identification similarly based on exogenous shifts in atmospheric ventilation, indicates that raising the preceding week's dose from a constant 100 μg/m^3 to a constant 200 μg/m^3—still a sizable variation in the sustained dose—raises the absence incidence by 0.6 percentage point (95% CI = [0.3,0.9]).

Such illustrative responses of +1.1 and +0.6 percentage point, amounting to +30% and +15% over a sample mean absence incidence of 3.8 in every 100 school days, are significant. However, when paired with empirically observed short-run PM2.5 fluctuation, and despite PM2.5 fluctuating widely within season in the sampled location,[33] particle pollution still explains only 0.1 to 0.2 absence among 3.8 overall absences per 100 school days. It is possible that the generally high levels of ambient PM2.5 in north China (the 5th percentile is 17 μg/m^3) already raise the baseline absence rate, as conjectured by Hales et al. (2016). We note, however, that absenteeism in our sample lies within the range reported for the US. The absence response we estimate from short-run variation in pollution is modestly sloped compared to estimates at sustained lower concentrations encountered in the US, which is consistent with the "supralinearity" hypothesis for the concentration-response function (Pope et al., 2015). Perhaps the main reason explaining the moderate absence response to the excessive pollution, first documented here, is that the affluent population we examine is *largely able to adapt*, for example, by shifting life indoors, behind windows that shut properly and where air is sucked in through air conditioners and

[33]For example, the median two-day difference in daily 24-hour PM2.5 is 51 μg/m^3 (note 17).

filters.[34] Other than—or because of—life shifting away from outdoor air, daily routines appear quite normal when viewed from the window of school absences.

The heterogeneity that we uncover is revealing. The lower absence response to PM2.5 that we estimate among Chinese nationals (9% of the sample) compared to the majority share of US, Canadian and European citizens, is consistent with longer-run adaptation, since the degraded environment may be more familiar to Chinese children's physiology as well as parental behavior. We do not find differential sensitivity of absences to PM2.5 over time of residence in China, as proxied by time of enrollment at the school. The pattern is also consistent with compensatory inter-temporal reallocation of schooling. Western parents may tolerate higher absenteeism during their temporary residence in China in anticipation of a near-term return to a less polluted home-country environment, whereas Chinese parents view residence in a polluted environment as less temporary. We also observe a markedly stronger absence response to PM2.5 among students who generally miss school the most. We view this pattern as being consistent with the epidemiological literature that broadly finds health outcomes to be driven in large part by chronically unhealthy individuals in the population (Pope and Dockery, 1992; Peters et al., 1997).

Excluding days surrounding vacations and breaks, the in-sample absence incidence in January is 4.2% compared with 3.2% in May and 2.9% in September. North China's January is colder, drier and tends to be more polluted than May or September. An extreme environment might call for extreme measures, such as expanding the winter vacation by six weeks until Chinese New Year in early February, for most students to remain in their home countries, and instead shorten the long summer vacation, when environmental quality in north China is relatively higher. The policy might abate absences to the tune of one school day for every three students each year (6 weeks $\times$ 5 school days/week $\times$ 0.01). While such a school policy is unlikely to be popular in the west, and such avoidance unaffordable among low-income children, the policy and the avoidance it enables might be welcomed by the informed, affluent and adaptive transnational families studied here.

[34]For example, see the "Q&A on air quality" posed by TimeOut (2015) nine international schools in Beijing, surveying air quality controls that are in place, including thresholds for outdoor play.

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Table 1: Descriptive statistics

Variables	N	Mean	Std.dev.	Min.	Max.
Enrolled student is absent on school day (yes=1)...	2,528,567	0.066	0.248	0.000	1.000
...& National of US/Canada (yes=1)	620,852	0.061	0.240	0.000	1.000
...& National of Europe (yes=1)	778,501	0.071	0.257	0.000	1.000
...& National of Japan/Korea/Singapore (yes=1)	448,206	0.047	0.212	0.000	1.000
...& National of China (yes=1)	231,037	0.072	0.259	0.000	1.000
...& National of other countries (yes=1)	423,363	0.074	0.262	0.000	1.000
...& First year of enrollment (yes=1)	801,706	0.067	0.250	0.000	1.000
...& Not the 2nd or subsequent day of absence spell (yes=1)	2,460,033	0.040	0.195	0.000	1.000
Number of days since first enrolling at school (days)	2,513,076	852.69	820.62	0.00	5387.00
First 180 days of enrollment (yes=1)	2,513,076	0.18	0.39	0.00	1.00
181 to 360 days from first enrolling (yes=1)	2,513,076	0.14	0.34	0.00	1.00
Academic year 2012/13 onward (yes=1)	2,528,567	0.43	0.49	0.00	1.00
National of US/Canada (yes=1)	2,501,959	0.25	0.43	0.00	1.00
National of Europe (yes=1)	2,501,959	0.31	0.46	0.00	1.00
National of Japan/Korea/Singapore (yes=1)	2,501,959	0.18	0.38	0.00	1.00
National of China (yes=1)	2,501,959	0.09	0.29	0.00	1.00
National of other countries (yes=1)	2,501,959	0.17	0.37	0.00	1.00
Age (years)	2,518,364	11.13	4.10	1.00	21.00
Student over 12 years old (yes=1)	2,518,364	0.40	0.49	0.00	1.00
Particle pollution, Z					
PM2.5 concentration, daily 24-hour mean (μg/m^3)	2,172	98.04	75.91	2.92	568.57
PM2.5 concentration, 6 am reading (μg/m^3)	2,105	95.46	82.42	2.00	532.00
PM2.5 concentration, prior 2 days' mean (μg/m^3)	2,145	98.09	67.22	8.96	492.41
PM2.5 concentration, prior 7 days' mean (μg/m^3)	2,022	98.52	44.54	25.29	345.95
PM2.5 concentration, prior 14 days' mean (μg/m^3)	1,870	98.84	33.77	34.36	270.49
Weather, W					
Temperature at the surface (daily 24-hour mean, °C)	2,327	11.47	11.66	-18.19	33.21
Relative humidity at the surface (daily 24-hour mean, %)	2,327	49.52	19.30	0.00	100.15
Precipitation at the surface (daily 24-hour mean, mm/hour)	2,327	0.06	0.26	0.00	4.69
Any precipitation on the day (yes=1)	2,327	0.17	0.37	0.00	1.00
Atmospheric ventilation, V					
Temperature difference (°C) for increasing altitudes at standard atmospheric pressure levels					
...from surface to 1000 mb	2,326	0.30	1.41	-3.50	7.25
...from 1000 to 925 mb	2,327	-3.26	1.78	-6.50	7.70
...from 925 to 850 mb	2,327	-3.97	1.91	-7.00	9.15
...from 850 to 700 mb	2,327	-8.93	3.20	-15.70	5.25
...from 700 to 500 mb	2,327	-15.40	2.83	-25.30	-4.80
Wind speed at the surface (daily 24-hour mean, m/s)	2,326	2.04	1.07	0.00	9.00
Wind direction at the surface (all hours from a given direction=1)					
...from North	2,327	0.32	0.30	0.00	1.00
...from East	2,327	0.24	0.30	0.00	1.00
...from South	2,327	0.27	0.28	0.00	1.00
...from West	2,327	0.16	0.23	0.00	1.00

Notes: An observation is a student by school day pair (student-day for short) or, for pollution, weather and atmospheric ventilation variables, a day. The periods of observation for the three schools, all located in the same city, are: (1) September 2008 to June 2014, (2) April 2010 to December 2014, and (3) April 2013 to June 2014. The sample period for environmental data is August 18, 2008 (14 days prior to September 1, 2008) to December 31, 2014.

Table 2: Student absences and concurrent pollution: **Non-parametric and parametric** PM2.5 specifications estimated by **OLS or 2SLS**

PM2.5 specification: (Dependent variable is 1 if absence spell is initiated)	(1) Severe prior day **OLS**	(2) Severe prior day **2SLS**	(3) Severe past 3 d **OLS**	(4) Spline function **OLS**	(5) Quadr. prior day **OLS**	(6) W/ 6 am same day **OLS**	(7) Quadr. prior day **2SLS**
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.20***	0.43***					
	(0.05)	(0.10)					
Count of past 3 days PM2.5>200 μg/m^3			0.13***				
			(0.02)				
Prior-day PM2.5 3-50 μg/m^3 ($\times$100)				-0.07			
				(0.16)			
Prior-day PM2.5 50-100 μg/m^3 ($\times$100)				-0.43***			
				(0.10)			
Prior-day PM2.5 100-200 μg/m^3 ($\times$100)				0.16***			
				(0.06)			
Prior-day PM2.5 200-569 μg/m^3 ($\times$100)				0.14***			
				(0.05)			
Prior-day PM2.5 ($\times$100 μg/m^3)					-0.24***	-0.28***	-0.55***
					(0.05)	(0.05)	(0.09)
Prior-day PM2.5 squared					0.08***	0.08***	0.18***
					(0.01)	(0.01)	(0.03)
Same-day PM2.5 ($\times$100 μg/m^3, 6 am)						0.02	
						(0.05)	
Same-day PM2.5 squared (at 6 am)						0.01	
						(0.01)	
Flexible weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student age bins (width 1 year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for first 2 semesters of enrollment	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days around vacation/break	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days around short holiday	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,297,246	2,291,723	2,244,876	2,297,246	2,297,246	2,245,573	2,291,723
Number of students	6,439	6,439	6,439	6,439	6,439	6,439	6,439
Number of regressors	118	118	118	121	119	121	119
R-squared (within)	0.006	0.006	0.006	0.006	0.006	0.006	0.006
First-stage F-statistic		405,262					116,615
Mean value of dependent variable (%)	3.83	3.83	3.83	3.83	3.83	3.83	3.83

Notes: The sample consists of all students enrolled at three international schools in a major city of China, over a combined period from September 2008 to December 2014. An observation is a student by school day. The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise; the estimation sample thus excludes the second and subsequent adjacent absence days within each observed absence spell. We also drop observations pertaining to a school day in which the student's school-division specific absence rate exceeds 30%. OLS estimates or 2SLS estimates, where we instrument for measured PM2.5 (both non-parametric and parametric specifications) using PM2.5 fitted by atmospheric ventilation conditions (note 22) and the square of these ventilation-induced fitted values. Weather controls are flexible functions of temperature, relative humidity and rain observed on the previous day and at 6 am on the day (note 19). Standard errors, in parentheses, are clustered by student. Alternative standard errors, with two-way clustering by student and by school-age-day, are slightly larger. ***Significant(ly different from zero) at (the) 1% (level), **at 5%, *at 10%.

Table 3: Student absences and concurrent pollution: A non-parametric PM2.5 specification with **heterogeneous effects**, estimated by 2SLS flexibly by subsample

Coefficient on prior-day PM2.5 > 200 μg/m^3 (yes=1). Standard error in parentheses.					
Restrict estimation to subsample defined on:	(1) Time since first enrolling	(2) Academic year	(3) Nationality	(4) Age	(5) Absenteeism quintile
First 180 days of enrollment	0.34 (0.21)				
Mean value of DV (%)	3.70				
181 to 360 days from first enrolling	0.57** (0.25)				
Mean value of DV (%)	3.70				
Over 360 days from first enrolling	0.43*** (0.12)				
Mean value of DV (%)	3.89				
Academic year 2011/12 or before		0.58*** (0.13)			
Mean value of DV (%)		3.75			
Academic year 2012/13 onward		0.30** (0.15)			
Mean value of DV (%)		3.92			
Nationals of US/Canada			0.54*** (0.19)		
Mean value of DV (%)			3.86		
Nationals of Europe			0.54*** (0.18)		
Mean value of DV (%)			3.98		
Nationals of Japan/Korea/S'pore			0.34* (0.19)		
Mean value of DV (%)			2.96		
Nationals of China			-0.14 (0.33)		
Mean value of DV (%)			4.12		
Nationals of other countries			0.41 (0.26)		
Mean value of DV (%)			4.20		
Students aged up to 4 years				0.41 (0.59)	
Mean value of DV (%)				5.58	
Students aged 5 to 8 years				0.05 (0.18)	
Mean value of DV (%)				3.03	
Students aged 9 to 12 years				0.24 (0.15)	
Mean value of DV (%)				2.71	
Students aged 13 to 16 years				0.72*** (0.19)	
Mean value of DV (%)				4.24	
Students aged 17 years and over				1.04*** (0.37)	
Mean value of DV (%)				7.01	
Students in absenteeism quintile 1					0.10 (0.13)
Mean value of DV (%)					1.05
Students in absenteeism quintile 2					0.15 (0.15)
Mean value of DV (%)					2.11
Students in absenteeism quintile 3					0.52*** (0.20)
Mean value of DV (%)					3.28
Students in absenteeism quintile 4					0.55** (0.24)
Mean value of DV (%)					4.74
Students in absenteeism quintile 5					0.96*** (0.36)
Mean value of DV (%)					8.96

Notes: The table shows estimates for 20 2SLS regressions, separately implemented on subsamples defined on: (1) the time elapsed since first enrolling at the school, (2) academic year, (3) nationality, (4) age, and (5) overall absenteeism quintile. An observation is a student by school day. The dependent variable (DV) is 1 if the student initiates an absence spell on the day, and 0 otherwise. Controls include flexible weather controls, student age bins (width 1 year), bins for first 2 semesters of enrollment (except in column 1), student fixed effects, year-month fixed effects, day-of-week fixed effects, bins for days around vacations/breaks, and bins for days around short holidays. Other notes to Table 2 apply. For brevity, we omit the number of observations, the number of regressors and other regression statistics. ***Significant at 1%, **at 5%, *at 10%.

Table 4: Robustness to estimating non-parametric specifications for prior-day PM2.5, that allow for heterogeneous effects, on the **full sample** (OLS or 2SLS)

Interaction with PM2.5	Nationality		Absenteeism quintile			
(Dependent variable is 1 if absence spell is initiated)	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.22**	0.63***	-0.13**	0.10		
	(0.10)	(0.18)	(0.06)	(0.11)		
... × national of US/Canada	0.10	-0.02				
	(0.13)	(0.20)				
... × national of Europe	-0.05	-0.26				
	(0.12)	(0.20)				
... × national of Japan/Korea/Singapore	-0.04	-0.39*				
	(0.13)	(0.20)				
... × national of China	-0.31*	-0.63**				
	(0.17)	(0.26)				
... × student in absence rate quintile 2			0.16*	0.05		
			(0.08)	(0.12)		
... × student in absence rate quintile 3			0.16*	0.22		
			(0.09)	(0.15)		
... × student in absence rate quintile 4			0.53***	0.31*		
			(0.11)	(0.17)		
... × student in absence rate quintile 5			0.91***	1.29***		
			(0.16)	(0.24)		
Count of past 3 days PM2.5>200 μg/m^3					0.00	0.17*
					(0.03)	(0.09)
... × student in absence rate quintile 2					0.06*	0.01
					(0.04)	(0.06)
... × student in absence rate quintile 3					0.05	0.09
					(0.04)	(0.08)
... × student in absence rate quintile 4					0.15***	0.13
					(0.05)	(0.09)
... × student in absence rate quintile 5					0.44***	0.65***
					(0.07)	(0.12)
Observations	2,274,381	2,268,906	2,297,246	2,291,723	2,244,876	2,239,353
Number of students	6,267	6,267	6,439	6,439	6,439	6,439
Mean value of dependent variable (%)	3.83	3.83	3.82	3.83	3.83	3.83

Notes: The table takes the non-parametric PM2.5 specifications implemented on the full sample in Table 2 and interacts PM2.5 with either the student's nationality group, in columns 1 and 2, or the student's overall absenteeism quintile, in columns 3 to 6. The reference category is a National of other countries, in columns 1 and 2, or the first absenteeism quintile, in columns 3 to 6. An observation is a student by school day. The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Controls include flexible weather controls, student age bins (width 1 year), bins for first 2 semesters of enrollment, student fixed effects, year-month fixed effects, day-of-week fixed effects, bins for days around vacations/breaks, and bins for days around short holidays. Other notes to Table 2 apply. For brevity, we omit the number of regressors and other regression statistics. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

Table 5: Robustness to sample, based on a non-parametric specification for prior-day PM2.5 estimated by OLS or 2SLS

Robustness test	Baseline Table 2 Col. 1 & 2	(1) Full sample	(2) Drop zero absence days	(3) Drop > 50% absence days	(4) Students > 200 days	(5) Drop first month enroll	(6) Drop IB exam period	(7) All days of absence spell
Panel A: Estimation by **OLS**								
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.20***	0.16***	0.17***	0.20***	0.17***	0.20***	0.20***	0.26***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Observations	2,297,246	2,307,672	2,280,228	2,304,386	2,051,556	2,205,419	2,261,478	2,354,948
Number of students	6,439	6,439	6,439	6,439	4,347	6,408	6,439	6,439
R-squared (within)	0.006	0.007	0.006	0.007	0.006	0.006	0.006	0.009
Mean value of dependent variable (%)	3.83	3.93	3.86	3.88	3.82	3.86	3.82	6.18
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.43***	0.29***	0.43***	0.38***	0.41***	0.44***	0.42***	0.93***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.14)
Observations	2,291,723	2,302,149	2,274,705	2,298,863	2,046,331	2,199,956	2,255,955	2,349,223
Number of students	6,439	6,439	6,439	6,439	4,347	6,408	6,439	6,439
R-squared (within)	0.006	0.007	0.006	0.007	0.006	0.006	0.006	0.009
First-stage F-statistic	405,262	410,890	387,408	410,331	509,611	401,972	409,248	439,081
Mean value of dependent variable (%)	3.83	3.93	3.86	3.88	3.82	3.86	3.82	6.18
Number of regressors	118	118	118	118	118	118	118	118
Flexible weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student age bins (width 1 year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for first 2 semesters of enrollment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days around vacation/break	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days around short holiday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimates for 7 OLS regressions in Panel A and 7 2SLS regressions in Panel B. The point of departure are the OLS and 2SLS specifications of Table 2, columns 1 and 2, reproduced in the leftmost column. An observation is a student by school day. Relative to the baseline specification: Column 1 does not drop observations pertaining to days with school-division specific absence rates in excess of 30%. Column 2 drops observations pertaining to days with zero school-division specific absences. Column 3 drops observations pertaining to days with school-division specific absence rates only in excess of 50% (not 30%). Column 4 drops students with no more than 200 school days of enrollment in the sample. Column 5 drops observations pertaining to students' first 30 days of enrollment at the school. Column 6 drops observations pertaining to students aged at least 17 years and the month of May, when International Baccalaureate exams are held. Column 7 keeps the second and subsequent absence days within absence spell in the estimation sample. The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise—except in column 7, where the dependent variable is 1 if the student is absent on the day, irrespective of whether initiating or continuing an absence spell, and 0 otherwise. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

Table 6: Other robustness tests, based on a quadratic specification for prior-day PM2.5 estimated by OLS or 2SLS

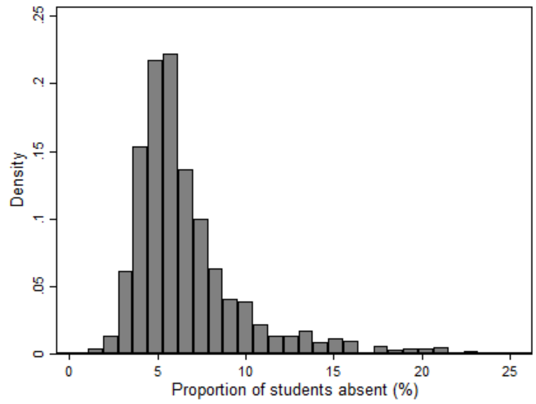
Robustness test		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Alternative controls W_t or α_t					Alternative instruments	
	Table 2 Col. 5 & 7	Temperature bins (3 °C)	Include week	Year-month × school-divis.	Trend × school-divis.	Include wind speed	$\hat{Z}$ w/o wind dir.	V, not V-induced $\hat{Z}$
Panel A: Estimation by **OLS**								
Prior-day PM2.5 ($\times 100\ \mu g/m^3$)	-0.24***	-0.25***	-0.21***	-0.24***	-0.16***	-0.24***		
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)		
Prior-day PM2.5 squared	0.08***	0.08***	0.06***	0.08***	0.04***	0.08***		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		
Observations	2,297,246	2,297,246	2,297,246	2,297,246	2,297,246	2,294,750		
R-squared (within)	0.006	0.008	0.008	0.008	0.006	0.006		
Mean value of dependent var. (%)	3.83	3.83	3.83	3.83	3.83	3.83		
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 ($\times 100\ \mu g/m^3$)	-0.55***	-0.48***	-0.53***	-0.53***	-0.63***	-0.50***	-0.59***	-0.47***
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.11)	(0.10)	(0.12)
Prior-day PM2.5 squared	0.18***	0.16***	0.15***	0.18***	0.18***	0.16***	0.20***	0.17***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Observations	2,291,723	2,291,723	2,291,723	2,291,723	2,291,723	2,291,723	2,291,723	2,294,741
R-squared (within)	0.006	0.008	0.008	0.008	0.006	0.006	0.006	0.006
First-stage F-statistic	116,615	112,437	92,954	116,108	110,519	60,549	95,746	47,189
Mean value of dependent var. (%)	3.83	3.83	3.83	3.83	3.83	3.83	3.83	3.83
Number of regressors	119	131	163	567	85	120	119	119
Flexible weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student age bins (width 1 year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for first 2 semesters of enroll.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes			Yes	Yes	Yes
Week-of-year fixed effects			Yes					
Year-month by school-division				Yes				
Quadratic trend by school-division					Yes			
Month-of-year fixed effects					Yes			
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days about vac./break/hol.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimates for 4 OLS regressions in Panel A and 7 2SLS regressions in Panel B. The point of departure are the OLS and 2SLS specifications of Table 2, columns 5 and 7, reproduced in the leftmost column. An observation is a student by school day. The number of students is 6,439 in all regression samples. Relative to the baseline specification: Column 1 replaces prior-day 24-hour mean ambient temperature and its square, included in W, by ambient temperature bins of width 3 °C (see note 19). Column 2 includes 51 week-of-year fixed effects. Column 3 interacts year-month fixed effects with school by division indicators. Column 4 replaces year-month fixed effects with a quadratic trend interacted with school by division indicators, as well as 11 month-of-year fixed effects. Column 5 includes prior-day 24-hour mean wind speed as an absence shifter (dropping wind speed from the exclusion restrictions). Column 6 drops wind direction when fitting ventilation-induced PM2.5, $\hat{Z}$. Column 7 instruments for measured PM2.5 using ventilation conditions on the day, V, rather than fitted values for ventilation-induced PM2.5, $\hat{Z}$. The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

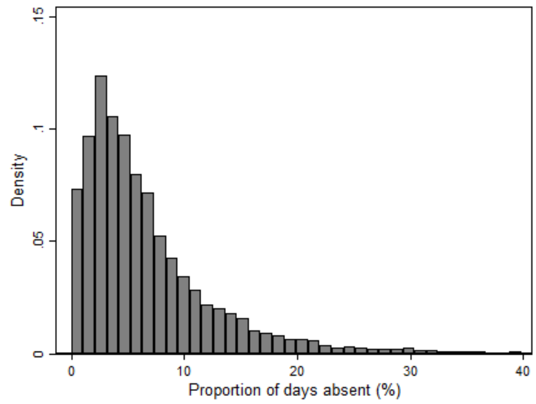
Table 7: Student absences and more prolonged pollution exposure: Non-parametric and parametric PM2.5 specifications, with P daily lags, estimated by OLS or 2SLS

Panel A: 24-h PM2.5 > 200 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)									
Lags in	OLS				2SLS				
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	2,297,246	0.20	(0.05)	-0.02 pct pt	2,294,741	0.57	(0.12)	-0.07 pct pt
3	2,232,217	0.45	(0.07)	-0.05 pct pt	2,226,694	0.89	(0.13)	-0.10 pct pt
5	2,152,799	0.48	(0.09)	-0.06 pct pt	2,147,276	1.24	(0.17)	-0.15 pct pt
7	2,090,242	0.45	(0.10)	-0.05 pct pt	2,079,629	1.14	(0.20)	-0.13 pct pt
9	2,019,035	0.70	(0.12)	-0.08 pct pt	2,003,332	0.89	(0.21)	-0.10 pct pt
11	1,961,415	1.09	(0.14)	-0.13 pct pt	1,943,169	1.19	(0.23)	-0.14 pct pt
13	1,905,311	1.25	(0.15)	-0.15 pct pt	1,884,494	1.34	(0.24)	-0.16 pct pt
Panel B: 24-h PM2.5, PM2.5 squared, PM2.5 cubed (each lag) & Constrained exposure coefficients, PDL($P, 2$)								
Lags in	OLS				2SLS			
model, P	Observations	Cumulative effect 100→200 μg/m^3		Absence counterf.: Truncate 100 μg/m^3	Obser-observ.	Cumulative effect 100→200 μg/m^3		Absence counterf.: Truncate 100 μg/m^3
3	2,238,487	0.21	(0.04)	-0.07 pct pt	2,232,964	0.73	(0.13)	-0.19 pct pt
5	2,170,142	0.34	(0.05)	-0.10 pct pt	2,164,619	0.73	(0.12)	-0.21 pct pt
7	2,108,047	0.37	(0.07)	-0.10 pct pt	2,097,434	0.59	(0.15)	-0.14 pct pt
9	2,024,965	0.45	(0.08)	-0.12 pct pt	2,009,262	1.08	(0.19)	-0.21 pct pt
11	1,976,146	0.48	(0.09)	-0.14 pct pt	1,957,900	0.33	(0.22)	-0.12 pct pt
13	1,920,944	0.61	(0.11)	-0.18 pct pt	1,900,127	0.90	(0.30)	-0.23 pct pt
Panel C: 24-h PM2.5 > 200 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)								
Lags in	2SLS: US/Canada nationality subsample				2SLS: 5th absenteeism quintile subsample			
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	563,855	0.69	(0.24)	-0.08 pct pt	367,307	1.34	(0.44)	-0.16 pct pt
3	545,265	0.94	(0.27)	-0.11 pct pt	357,393	2.46	(0.46)	-0.28 pct pt
7	508,177	1.17	(0.41)	-0.14 pct pt	333,932	2.50	(0.70)	-0.31 pct pt
13	458,450	1.69	(0.50)	-0.20 pct pt	303,045	2.48	(0.85)	-0.31 pct pt
Panel D: 24-h PM2.5 > 100 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)								
Lags in	2SLS: US/Canada nationality subsample				2SLS: 5th absenteeism quintile subsample			
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	563,855	0.15	(0.15)	-0.06 pct pt	367,307	0.39	(0.28)	-0.16 pct pt
3	545,265	0.45	(0.22)	-0.19 pct pt	357,393	1.40	(0.37)	-0.57 pct pt
7	508,177	0.99	(0.29)	-0.40 pct pt	333,932	2.15	(0.48)	-0.88 pct pt
13	458,450	2.33	(0.45)	-0.94 pct pt	303,045	3.40	(0.76)	-1.39 pct pt

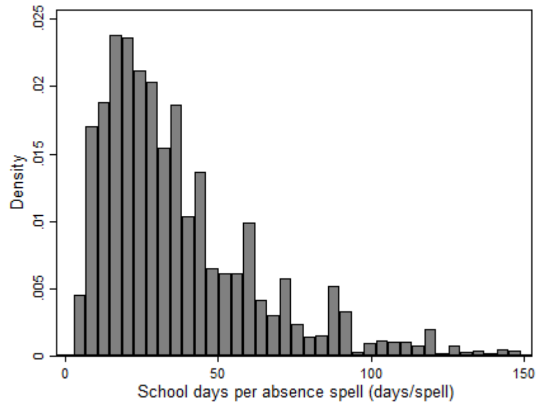
Notes: The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Distributed lag models, estimated by OLS or 2SLS (as labeled), include P lags of the daily PM2.5 measure given by: (panels A and C) 1 if the respective 24-hour PM2.5 > 200 μg/m^3 and 0 otherwise; (panel D) 1 if the respective 24-hour PM2.5 > 100 μg/m^3 and 0 otherwise; and (panel B) the respective concentration, its square and its cube. In the cubic PM2.5 specification of panel B, we constrain the P coefficients on the PM2.5 lags to follow a quadratic, the P coefficients on the squared PM2.5 lags to follow another quadratic, and the P coefficients on the cubed PM2.5 lags to follow yet another quadratic. Panels C and D restrict the 2SLS estimation sample to nationals of US/Canada or to students in the top absenteeism quintile (as labeled). An observation is a student by school day. All controls and notes reported in Table 2 apply (the cubic PM2.5 specifications additionally includes cubes of fitted ventilation-induced PM2.5). For brevity, we omit the number of regressors and other regression statistics. Standard errors (SE) are in parentheses. ***Significant at 1%, **at 5%, *at 10%.



(a) Absence rates, over school days

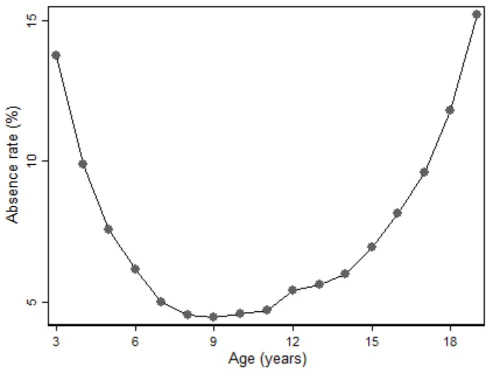


(b) Absence rates, across individual students

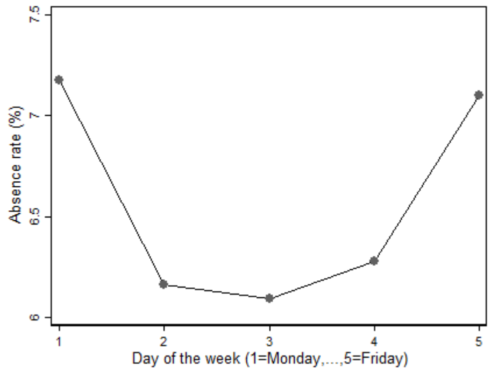


(c) School days per absence spell, across students

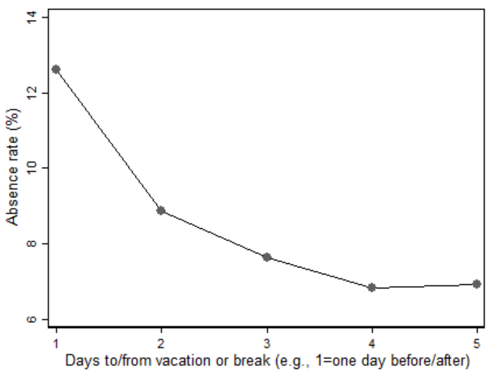
Figure 1: Distribution of absence rates: (a) over school days, and (b) across individual students in the sample (shown up to 40% for better visualization). Panel (c) reports the distribution across individuals of the ratio of a student's total school days to total absence spells (shown up to 150 days/absence spell). An observation is: (a) a school day, and (b), (c) an enrolled student.



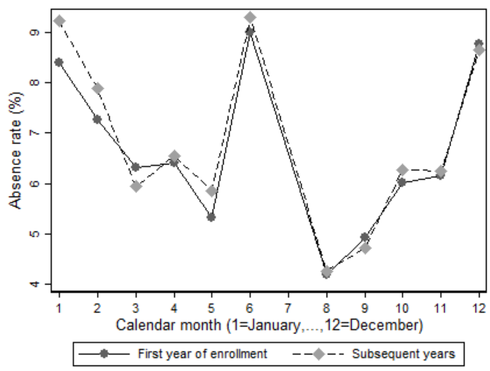
(a) By student age



(b) By day of the week

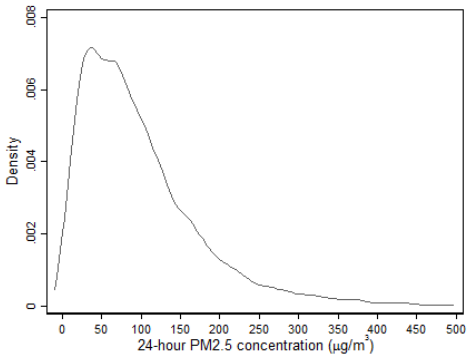


(c) By days to/from vacation or break

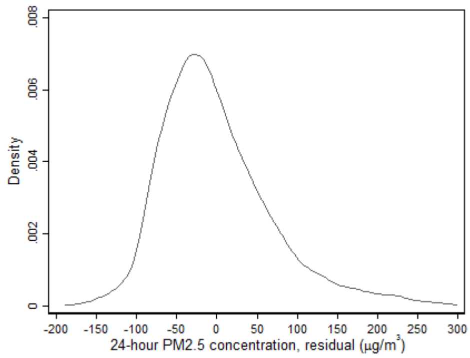


(d) By calendar month, by year of enrollment

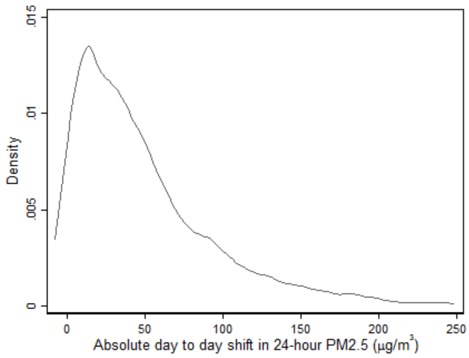
Figure 2: Absence rates over student-days in the sample: (a) by student age, (b) by day of the week, (c) by the number of days leading up to, or following, a vacation or break, and (d) by calendar month. In panel (d), we separately plot absence rates over the calendar months in a student's first year of enrollment versus subsequent years.



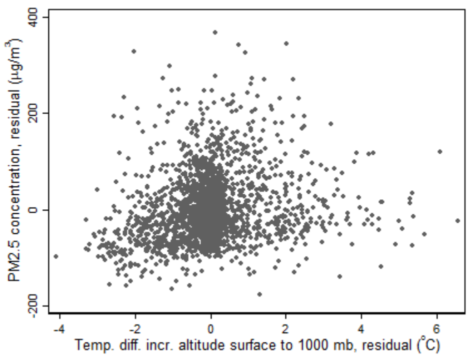
(a) PM2.5 distribution



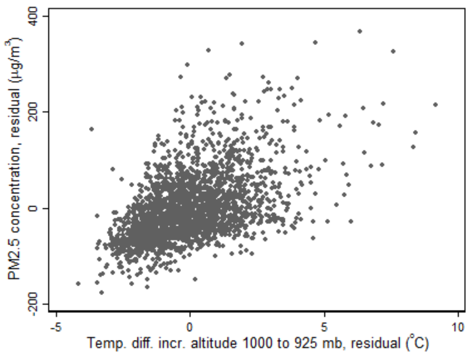
(b) PM2.5 distribution: Deaseasoned



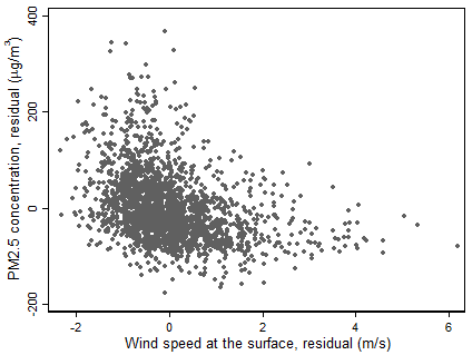
(c) Day to day shift (up or down) in PM2.5



(d) PM2.5 & temp. inversion layer 1

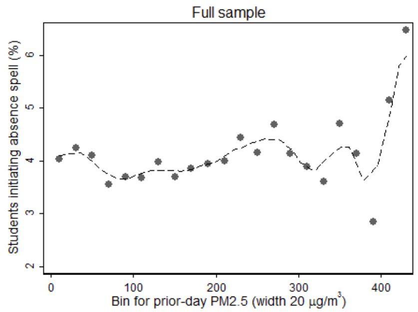


(e) PM2.5 & temp. inversion layer 2

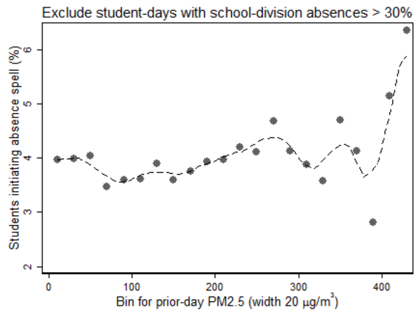


(f) PM2.5 & wind speed

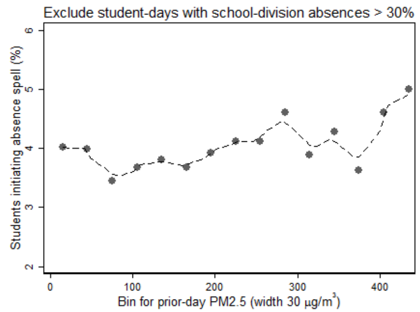
Figure 3: Variation in 24-hour mean PM2.5 concentration (μg/m^3) in the sample: (a) PM2.5 distribution (shown up to 500 μg/m^3 for better visualization); (b) residual PM2.5 distribution, once systematic temporal variation (year-month and day-of-week) is partialed out (shown up to 300 μg/m^3); (c) distribution of the absolute shift in PM2.5 from one day to the next (shown up to 250 μg/m^3); (d) to (f) residual PM2.5 against residual temperature gradients in the lower atmosphere (°C from ground-level to 1000 mb equivalent altitude, and from 1000 to 925 mb), and residual wind speed (m/s). An inversion describes a *positive* temperature-altitude gradient in the raw (non-deseasoned) series.



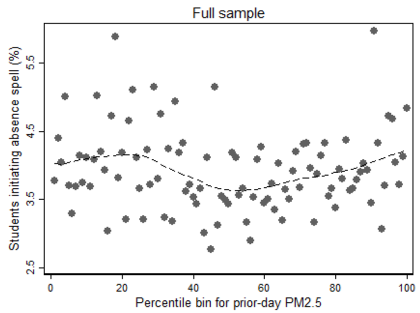
(a) PM bin 20 μg/m^3 wide, orig. sample



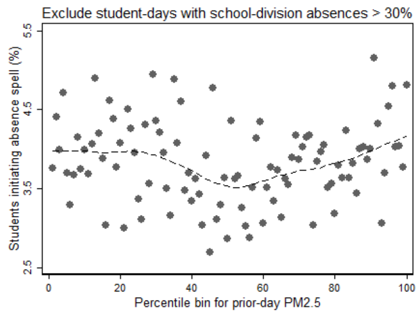
(b) PM bin, $\leq$30% absence days



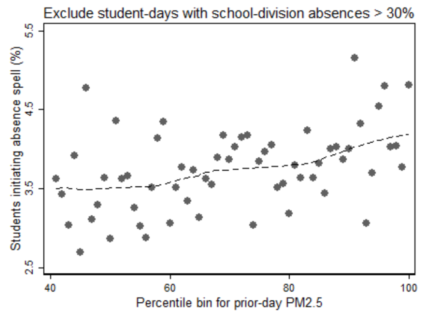
(c) PM bin 30 μg/m^3 wide



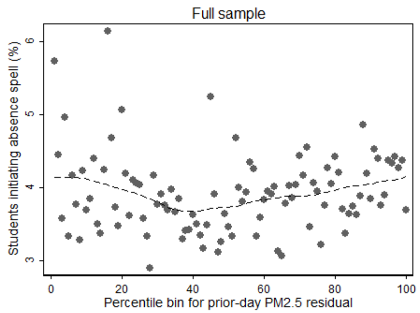
(d) Percentile PM, orig. sample



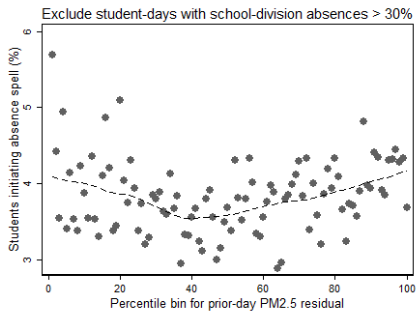
(e) Percentile PM, $\leq$30% absence days



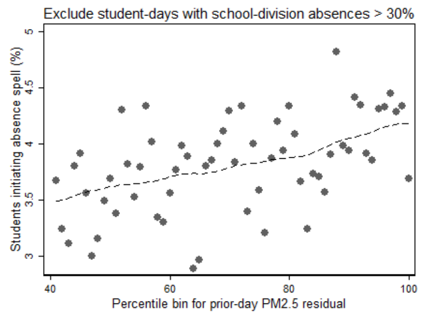
(f) Percentile PM, 40 to 99



(g) P'tile PM resid., orig. sample

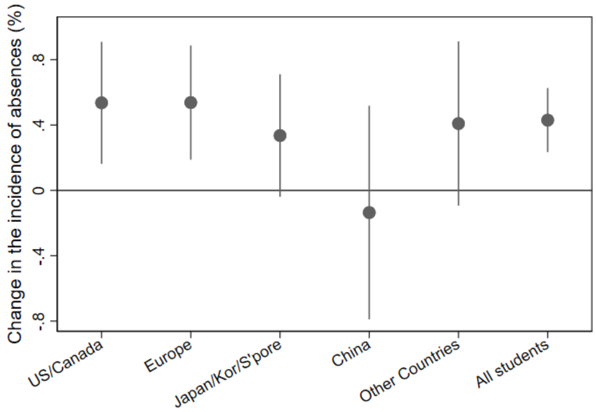


(h) P'tile PM res., $\leq$30% absence days

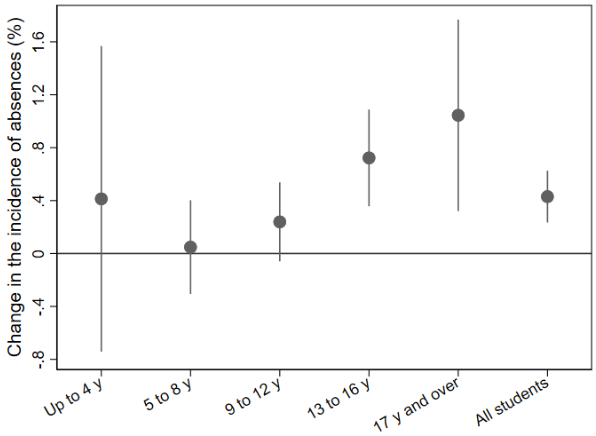


(i) P'tile PM resid., 40 to 99

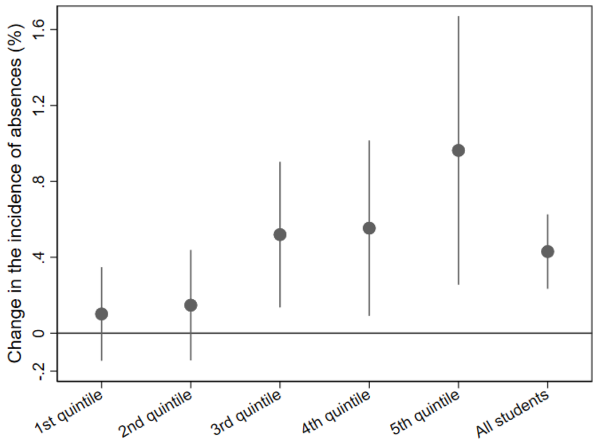
Figure 4: A non-linear pollution-absence relationship in the aggregated data. Panels (a) to (c) show, for the original sample or the estimation sample without high absence days, the proportion of students initiating an absence spell against prior-day PM2.5 bins of width 20 (or 30) μg/m^3, labeled at the bin midpoint. Panels (d) to (f) show the incidence of absences against prior-day PM2.5 percentiles. Panels (g) to (h) partial out co-variation with other absence shifters in the model prior to taking PM2.5 percentiles.



(a) Heterogeneous effects over nationality

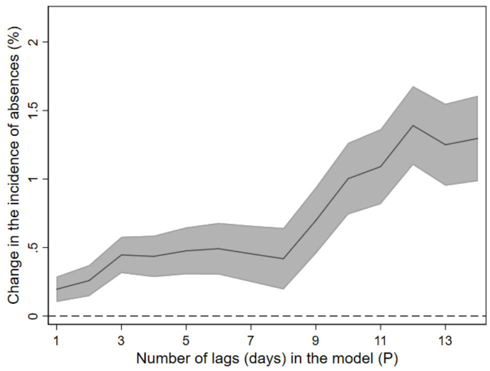


(b) Heterogeneous effects over age

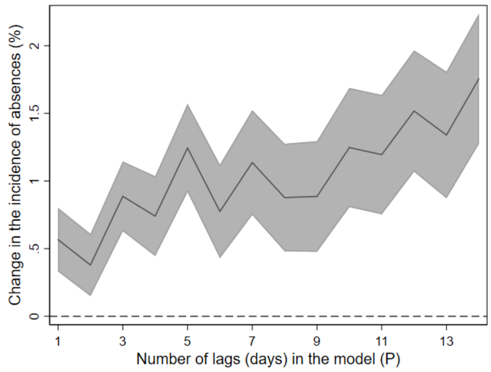


(c) Heterogeneous effects over absenteeism quintile

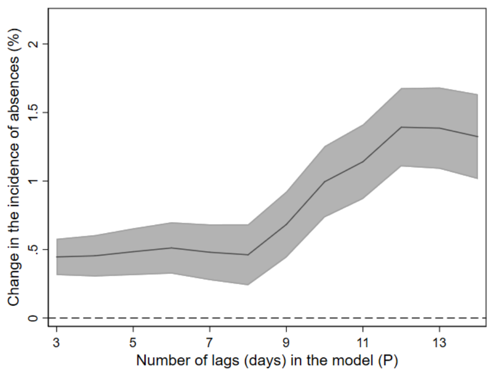
Figure 5: Heterogeneous sensitivity of absences to concurrent pollution: (a) by student nationality, (b) by student age, and (c) by student absenteeism quintile. 95% confidence intervals on the effect of severe PM2.5 (defined as prior-day 24-hour mean $> 200\ \mu g/m^3$) on the probability that an absence spell is initiated. Source: 2SLS estimates implemented separately by subsample, reported in columns 3 to 5 of Table 3; 2SLS estimate implemented on the full sample, reported in column 2 of Table 2.



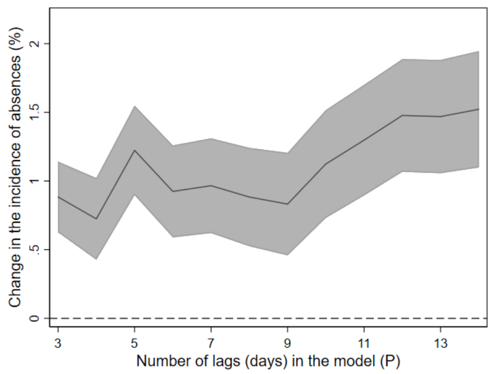
(a) Severe PM2.5, UDL(P), OLS



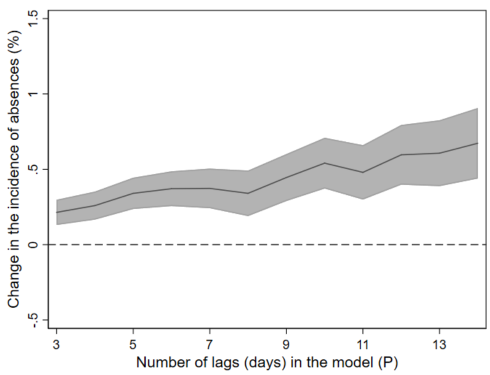
(b) Severe PM2.5, UDL(P), 2SLS



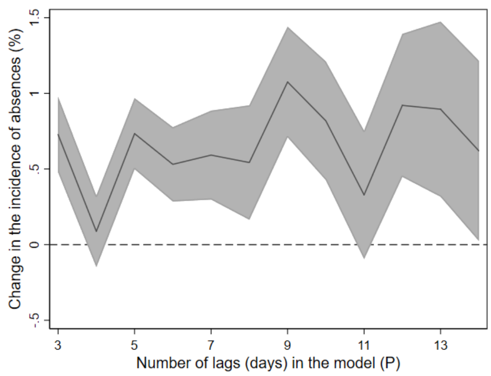
(c) Severe PM2.5, PDL($P,2$), OLS



(d) Severe PM2.5, PDL($P,2$), 2SLS



(e) Cubic PM2.5, PDL($P,2$), OLS



(f) Cubic PM2.5, PDL($P,2$), 2SLS

Figure 6: Cumulative impact of more prolonged PM2.5 exposure on the probability that an absence spell is initiated. Panels (a) to (d) show estimates, for a severe PM2.5 dummy (24-hour mean > 200 μg/m^3) specification, of the cumulative effect on absences from P preceding days of severe PM2.5, relative to zero days of severe PM2.5. Panels (e) and (f) show estimates, for a cubic PM2.5 (24-hour mean, its square, its cube) specification, of the cumulative effect on absences from shifting PM2.5 on each of the P preceding days from 100 to 200 μg/m^3. Panels (a) and (b) (resp., panels (c) to (f)) implement unconstrained UDL(P) (resp., quadratic PDL($P,2$)) distributed lag models. For the cubic PM2.5 specification, the PDL($P,2$) constrains the P coefficients on the PM2.5 lags to follow a quadratic, the P coefficients on the squared PM2.5 lags to follow another quadratic, and the P coefficients on the cubed PM2.5 lags to follow yet another quadratic. Distributed lag models in panels: (a), (c) and (e) are estimated by OLS; (b), (d) and (f) are estimated by 2SLS. In each panel, we implement a different distributed lag model as we raise P along the horizontal axis. Point estimates and 95% confidence intervals are shown. All controls and notes reported in Table 2 apply (the cubic PM2.5 specification additionally includes cubes of fitted ventilation-induced PM2.5).

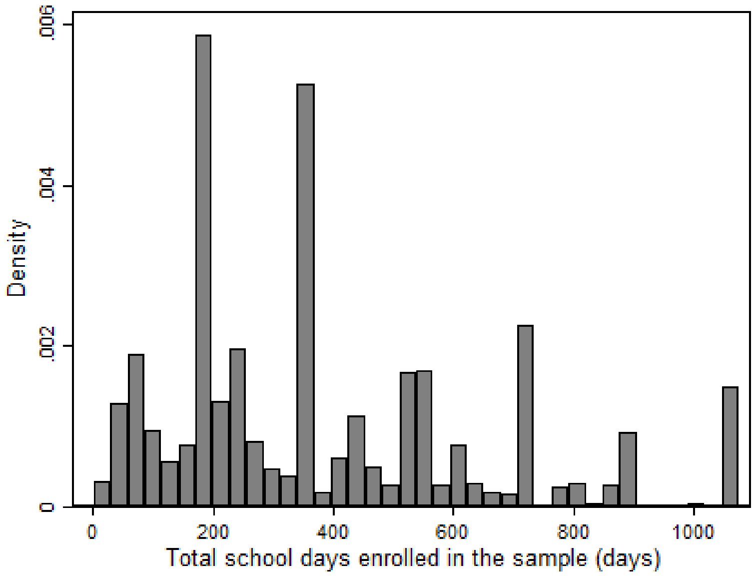
A Appendix

Table A.1 reports additional robustness tests, as explained in the text. The figures that follow provide further description of the data, and are referenced in the text.

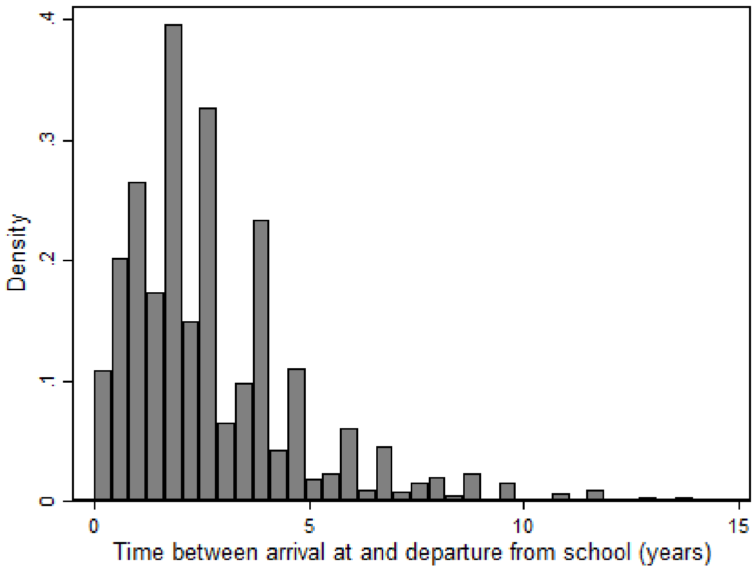
Table A.1: Other robustness tests, based on a non-parametric specification for prior-day PM2.5 estimated by OLS or 2SLS

Robustness test		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Alternative controls W_t or α_t					Alternative instruments	
	Table 2 Col. 1 & 2	Temperature bins (3 °C)	Include week	Year-month × school-divis.	Trend × school-divis.	Include wind speed	$\hat{Z}$ w/o wind dir.	$\hat{Z}$ with 1-d lag for V
Panel A: Estimation by **OLS**								
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.20***	0.18***	0.20***	0.20***	0.12***	0.20***		
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)		
Observations	2,297,246	2,297,246	2,297,246	2,297,246	2,297,246	2,297,246		
R-squared (within)	0.006	0.006	0.006	0.008	0.006	0.006		
Mean value of dependent var. (%)	3.83	3.83	3.83	3.83	3.83	3.83		
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 > 200 μg/m^3 (yes=1)	0.43***	0.24**	0.40***	0.45***	0.18**	0.47***	0.33***	0.44***
	(0.10)	(0.11)	(0.10)	(0.10)	(0.09)	(0.09)	(0.11)	(0.10)
Observations	2,291,723	2,291,723	2,291,723	2,291,723	2,291,723	2,293,228	2,291,723	2,293,228
R-squared (within)	0.006	0.008	0.008	0.008	0.006	0.006	0.006	0.006
First-stage F-statistic	405,262	413,522	532,716	395,259	675,901	261,523	291,175	420,690
Mean value of dependent var. (%)	3.83	3.83	3.83	3.83	3.83	3.83	3.83	3.99
Number of regressors	118	130	162	566	84	119	118	118
Flexible weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student age bins (width 1 year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for first 2 semesters of enroll.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes			Yes	Yes	Yes
Week-of-year fixed effects			Yes					
Year-month by school-division				Yes				
Quadratic trend by school-division					Yes			
Month-of-year fixed effects					Yes			
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bins for days about vac./break/hol.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimates for 5 OLS regressions in Panel A and 7 2SLS regressions in Panel B. The point of departure are the OLS and 2SLS specifications of Table 2, columns 1 and 2, reproduced in the leftmost column. An observation is a student by school day. The number of students is 6,439 in all regression samples. Relative to the baseline specification: Column 1 replaces prior-day 24-hour mean ambient temperature and its square, included in W, by ambient temperature bins of width 3 °C (see note 19). Column 2 includes 51 week-of-year fixed effects. Column 3 interacts year-month fixed effects with school by division indicators. Column 4 replaces year-month fixed effects with a quadratic trend interacted with school by division indicators, as well as 11 month-of-year fixed effects. Column 5 includes prior-day 24-hour mean wind speed as an absence shifter (dropping wind speed from the exclusion restrictions). Column 6 drops wind direction when fitting ventilation-induced PM2.5, $\hat{Z}$. Column 7 includes 24-hour mean ventilation conditions on the day and one preceding day (not two) when fitting ventilation-induced PM2.5, $\hat{Z}$ (see note 22). The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

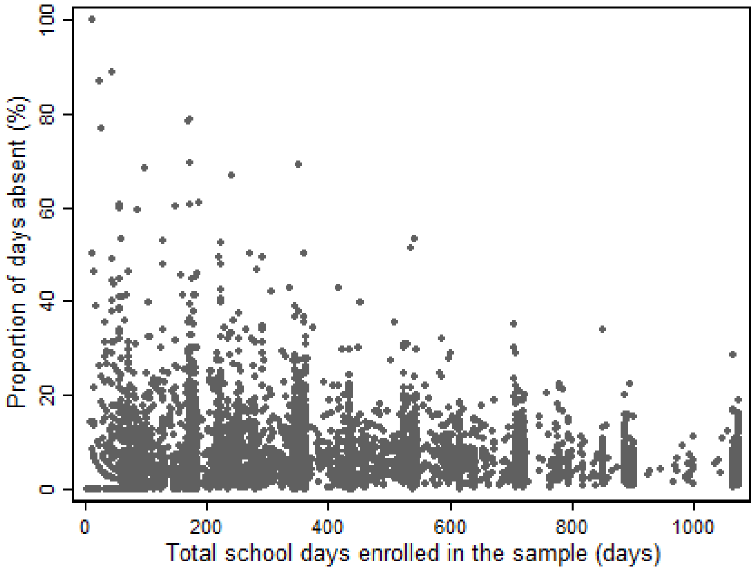


(a) Days enrolled in the sample, across students

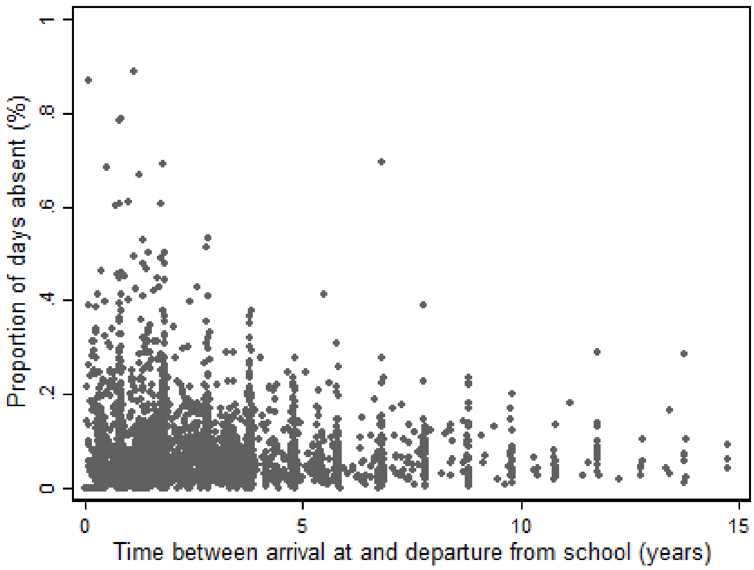


(b) Total duration at the school, across departed students

Figure A.1: Distribution of enrollment across students: (a) school days observed in the sample, and (b) time from student's arrival at the school to departure from the school. An observation is: (a) an enrolled student, and (b) an enrolled student who departed in-sample.

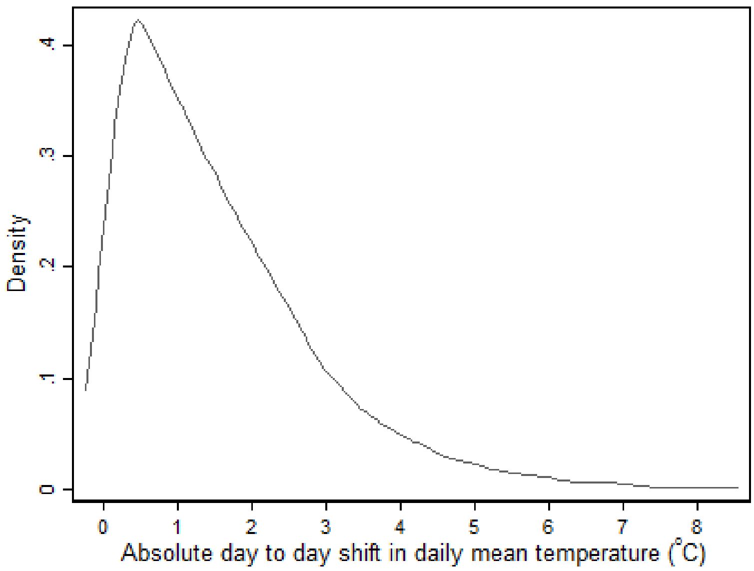


(a) Absence rate & days enrolled in the sample, across students

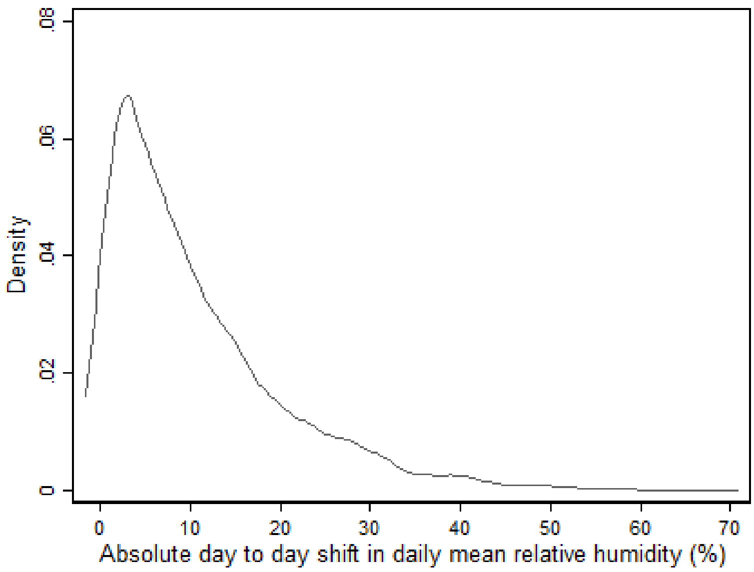


(b) Absence rate & duration at the school, across departed students

Figure A.2: A student's overall absence rate (as in panel (b) of Figure 1) against enrollment, as measured by: (a) school days observed in the sample, and (b) time from student's arrival at the school to departure from the school. An observation is: (a) an enrolled student, and (b) an enrolled student who departed in-sample.



(a) Day to day shift (up or down) in ground temperature



(b) Day to day shift (up or down) in ground humidity

Figure A.3: Ground-level weather conditions persist from one day to the next. Distribution of the absolute shift in daily mean ambient: (a) temperature, and (b) relative humidity, from one day to the next. We partial out systematic temporal variation (year-month and day-of-week), though doing so makes little difference.