Severe Air Pollution and School Absences: Longitudinal Data on Expatriates in North China

Haoming Liu[1] and Alberto Salvo[*2]

[1]*Department of Economics, National University of Singapore, and IZA*
[2]*Department of Economics, National University of Singapore*

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Abstract

Little is known about how children of high-income expatriate families, often from rich nations, adapt to temporary residence in a severely polluted city of the developing world. We use a six-year panel of 6,500 students at three international schools in a major city in north China to estimate how fluctuation in ambient PM2.5 over the preceding fortnight impacts daily absences. Our preferred estimates are based on the exclusion restriction that absences respond to atmospheric ventilation such as thermal inversions only through ventilation's effect on particle levels. A large and rare 100 to 200 $\mu g/m^3$ shift in average PM2.5 in the prior week raises the incidence of absences by 1 percentage point, about one-quarter of the sample mean. We find stronger responses for US/Canada nationals than among Chinese nationals, and among students who generally miss school the most. Overall responses are modest compared to the effect on absences from more moderate in-sample variation in pollution estimated for the US using aggregate data. Using school absence patterns as a window into short-run health and behavior, our study suggests that high-income families find ways to adapt, likely by moving life indoors, even if temporary residence in north China comes at the expense of long-term health.

Keywords: School absences, air pollution, particulate matter, PM2.5, acute exposure, longitudinal study, heterogeneous effects, thermal inversions, atmospheric ventilation, environmental health, environmental damage, environmental valuation, avoidance behavior, distributed lags, instrumental variables

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1 Introduction

A large 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, including emergency room visits, hospital admissions, mortality and neonatal health. 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., 2016), productivity while at work (Graff Zivin and Neidell, 2012; Chang et al., 2016b,a; He et al., 2017), and student absences (Currie et al., 2009; Ransom and Pope, 2013). Studies have typically relied 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.[1]

We examine how student absences respond to particle pollution in a major urban center in north China that is routinely exposed to severe levels of PM2.5 (particulate matter of diameter up to 2.5 micrometers). Our subjects are about 6,500 high-income students, aged 3 to 19 years, enrolled at three international schools in the same city.[2] 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 (temperature, humidity and rain on the ground) and unobserved heterogeneity. We observe students' nationalities, both foreign and Chinese, and the time since first enrolling at the school which, for children of expatriate families, 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,

[1] Exceptions are studies examining worker or household-level panels in China and Peru (Chang et al., 2016a; He et al., 2017; Aragon et al., 2016). Given their developing country setting, these three studies focus on particulate matter. The economic impact of ozone, an oxidizing agent and very different pollutant formed under radiation and heat, has been studied in US settings (e.g. Graff Zivin and Neidell, 2012; Deschenes et al., 2017). 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).

[2] Annual tuition fees reach (and in middle/high school exceed) one quarter of a million Chinese Yuan, or about US$ 40,000. In terms of income, a correlate of health status, our population is quite homogeneous.

duration at the school, student age, calendar year (to the extent that awareness of PM2.5 and its health impact has shifted, say, since 2012/2013), and among students who vary widely in their overall levels of absenteeism (irrespective of reason).

Over our sample period, daily 24-hour PM2.5 concentrations averaged 98 μg/m^3, to be contrasted with the primary one-year average National Ambient Air Quality Standard (NAAQS) of 12 μg/m^3 set by the US Environmental Protection Agency.[3] Given concerns that pollution readings published by the Chinese authorities in the early years of the sample may have been manipulated (Andrews, 2008; Ghanem and Zhang, 2014), we are fortunate to rely on high-frequency ambient PM2.5 measurements since 2008 by the US State Department on the rooftop of a US embassy located at most 20 km from each school. The embassy is likely at a similar distance from students' homes and daily activities.

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 such as temperature-altitude gradients, which fluctuate from day to day, induce student absences only indirectly, by shifting PM2.5, and this exogenous PM2.5 component then drives absences. Previous research has adopted designs using atmospheric ventilation (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., 2017). We provide visual in-sample evidence of how atmospheric ventilation drives the dispersion 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 find that international school absences in this severely polluted Chinese city significantly respond to short-run fluctuations in PM2.5. The occurrence of severe PM2.5 on

[3]We emphasize that particulate matter likely accounts for the bulk of health damage from exposure to ambient air pollution in the developing world. 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. Even in rich nations, the health damage from PM2.5 is estimated to be an order of magnitude higher than that from ozone, e.g., 320,000 PM2.5 versus 19,000 ozone-related annual deaths in the US (Fann et al., 2012). The relative threat posed by PM2.5 is likely a reason why ozone or CO are not monitored at the US embassy.

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.[4] An overall absence rate of 6% tends to be higher than reported for elementary and middle school children in the US.[5] Besides students being mostly expatriates, taking trips abroad and often missing some school days shortly before or after vacations, it is conceivable that the high PM2.5 even at the left tail of the sample distribution already contributes to some absenteeism beyond the variation we pick up.[6] Our favored estimation sample drops any second and subsequent adjacent absence days within the same absence spell by a student, with the aim of examining the likely single decision by the student or her parent behind the absence spell. Absence spells triggered by pollution include both remedial responses and avoidance 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 the severe pollution. 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 levels 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.[7] In a model including 24-hour PM2.5 levels in each of the 14 days preceding a school day, shifting the pollution dose from 0 to 14 days of severe PM2.5—a huge variation in dose—raises the probability that

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

[5]Absence rates are a lower 4% to 5% in Ransom and Pope (1992) and Currie et al. (2009), but Hales et al. (2016) report a higher 10% in Salt Lake City, where PM2.5 averages 10 μg/m^3. In our sample, absenteeism is lowest among nationals of Japan, Korea and Singapore.

[6]The 5th percentile of the daily PM2.5 distribution over our sample period is 17 μg/m^3 (again, the US NAAQS is 12 μg/m^3). 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).

[7]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.

an absence spell is initiated by about 1.5 percentage point. In a model with cubic functions of daily PM2.5 in each of 14 days preceding a school day, a lower though still large shift from 100 to 200 μg/m^3 sustained over the fortnight raises the probability that an absence spell is initiated by 0.8 percentage point, or a 20% increase 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 nationals. The sensitivity of absences to PM2.5 is stronger among students who exhibit higher absenteeism overall, particularly in the top quintile (80th percentile and above) of the distribution of individual absence rates over the 6,500 students in the sample. Our data uniquely allow us to track a student as she ages or as her duration at the school increases. We find a U-shaped response to PM2.5 over age, though of marginal significance. The PM2.5 response does not vary with the time of residence in China, as proxied by the time since first enrolling at the school.

Our paper makes several contributions over the extant literature linking student absences to air pollution. It is the first to examine a student by day panel for a sizable population (thousands) over multiple years, and the first to examine a wide range of particle pollution that is most relevant to developing countries. Like Ransom and Pope (2013), our paper provides estimates using credible exclusion restrictions based on high-frequency atmospheric ventilation conditions that critically determine local air quality and yet do not respond to anthropogenic activity. It is the first study to offer a window into the health and avoidance responses of a group of young, high-income and mostly rich-country nationals being subjected to north China's urban air, often for the first time.[8]. We obtain positive absence responses to severe PM2.5. Responses are larger among US/Canadian than among Chinese nationals, larger among students who generally miss school the most, and larger when we do not restrict the (biological/behavioral) response to be immediate.

While the effects described above are considerable, when applied to in-sample exposure variation we obtain that severe PM2.5 explains only a fraction of one percentage point of the overall 4 percent absence incidence; only for the most sensitive subgroups does

[8]Stories of costly adaptation to China's air by foreign executives—whose children might be in our sample—abound, e.g., Wong (2015); Liu (2017)

severe PM2.5 explain one full percentage point.[9] The proportion of absences explained by the severe PM2.5 fluctuations in our setting is not large relative to what Currie et al. (2009) and Ransom and Pope (2013) find for CO in Texas (1996-2002) and PM10 in Utah Valley (1985-1991), respectively. Using aggregate school by period (six periods per academic year) data, 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 Air Quality Standard on 16 days. Ransom and Pope (2013) conclude that PM10, averaging 45 μg/m^3 in their sample (PM10 is usually double PM2.5 mass), "caused 2.25 percent of students to be absent on the average day...roughly half of the total rate of absenteeism" (p.14). Hales et al. (2016) study Utah absences over a later period than in their seminal work. Selecting absences at one specific school district as a quasi-control, they find 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.[10]

School attendance is a key input to the production of privately and socially beneficial human capital (Grossman and Kaestner, 1997; Gottfried, 2014). Beyond children's health,[11] our paper contributes to our understanding of (impediments to) human capital formation, and the coping strategies by affluent households, in heavily polluted cities in the developing world. On a more positive note, 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

[9] 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).

[10] 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.

[11] 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).

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.

2 Institutional background and data

Origin of student attendance records. In 2013, we contacted the principals of 16 international schools located in a large urban center in China that is routinely exposed to severe PM2.5 pollution. These schools cater largely to the expatriate 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 in China and that, in view of the topic's sensitivity, the addressee's school would be anonymized were it ultimately included in our sample. We decided to focus our data collection effort on such schools given our understanding that they might be more open to sharing their attendance records with us. Moreover, such data might inform on possible adaptation by newly enrolled students 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 over time and across students. 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.

[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.

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. At each school, the median enrollment duration among students who depart in-sample ranges between 1.8 and 2.8 years, with the 10th percentile below one year and the 90th percentile above four years (see Figure A.1, panel (b)). Due to the high turnover, as well as enrollment growth at one school in particular, 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 to June, 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. There are 2.5 million student-day pairs in the sample, with absences accounting for 6.6% of observations. 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 travel and health, 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, equivalently for our purpose, 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 out of town 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 individual students. 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%, 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 the extent to which this temporal variation is driven by variation in concurrent and recent exposure to ambient PM2.5 levels, once we account for other time-varying determinants. Another important control for absenteeism is unobserved individual heterogeneity. For every student in the sample, we divide the student's overall number of days absent by the number of school days in the sample during which the student 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. The plot illustrates why we control for individual heterogeneity.

For each student, 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. Panel (c) of Figure 1 shows wide variation across students in the school days per 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

[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.

that some students leave China earlier than anticipated due to difficulty adapting to the city's polluted environment. Figure A.1, panel (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 of school absences. 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 for students aged around 10 years compared to younger and older students. The absence rate is higher on Mondays and Fridays compared to the middle of the week. The proximity-to-weekend effect may in part be driven by activities that compete with school, such as short 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 or break, and decrease in the five days following a vacation or 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 higher absence rates in December through February. The winter months of December through February are colder and tend to exhibit higher particle levels than other months.[15] In addition, 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

[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, student absences 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. While 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.

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, the correlation coefficient between (24-hour) PM2.5 at the US embassy and the CMEP site average over days in 2013 and 2014 is a very high 0.97. As suggested by typical media coverage both local and foreign, fluctuation in PM2.5 severity is a citywide—not a neighborhood—phenomenon, not least due to regional atmospheric ventilation shocks, discussed below, that govern the dispersion of pollutants and are plausibly exogenous to unobserved determinants of absences.

For the same-day pollution level 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, panel (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. Much variation remains, in panel (b), even after regressing daily PM2.5 on month-of-year fixed effects and day-of-week fixed effects (Monday, ..., Sunday, and public holiday). 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 to 346 and 34 to 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, humidity and precipitation. We control for temperature, humidity and rain in our student absence equations, as such weather conditions on the ground 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.[16]

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 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.

The last three panels of Figure 3 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 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 higher fine particle levels. The 2SLS identifying assumption is that day-to-day fluctuations in vertical ventilation, as thermal inversions set in and lift, and horizontal ventilation, as wind changes in intensity (and direction), while

[16]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.

strong predictors of PM2.5, do not affect absences directly or correlate with unobserved determinants of absences.

3 Empirical model

A student i's absence decision on school day t can be described by a latent utility model, where the utility from not attending school is:

$$y^*_{it} = \alpha_0 + Z_t\beta + W_t\alpha_1 + X_{it}\alpha_2 + \alpha_i + \alpha_t + \epsilon_{it} \tag{1}$$

and an absence is observed if and only if $A_{it} = 1[y^*_{it} > 0]$, where A_{it} is a binary variable. Row vector Z_t of pollution exposure variables includes concurrent exposure (e.g., PM2.5 concentration 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. Further, 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.

Vector W_t consists of concurrent weather covariates, namely, ground-level temperature, humidity and rain.[17] W_t can affect both direct and opportunity costs of attending school. For instance, cold and rainy weather may raise the effort required to get out of bed and commute to school, including through any health channels. At the same time, cold and rain 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[18] 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

[17] We include linear and quadratic terms for: the 24-hour means of temperature, relative humidity and rain observed on the previous day $t-1$; the temperature, humidity and rain reading at 6 am on day t. We further include indicators for any rain on day $t-1$ and rain at 6 am on day t.

[18] For example, indicators for the student's first two semesters of enrollment. We find that students in the first semester of enrollment display lower absences than in subsequent semesters. We further interact these indicators with nationality and find that lower first-semester absences arise among non-Chinese.

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 (our label for three or more successive weekdays in which the school breaks).[19]

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. 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). While 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 $P > 2$), 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 a study of daily aggregate absences at

[19]These indicators can again be interacted with nationality group (our findings are robust to doing so). We further add indicators for each of the two school days that lead up to, or that follow, a short holiday (our label for one or two successive weekdays without school).

an elementary school in Utah, Ransom and Pope (2013) specify 7-day lagged averages for PM10 (and CO) as the measure of exposure. Gilliland et al. (2001) allow acute effects of pollution on 4th grade absences in California 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 or endogenous.[20] 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.[21] Such variables are key determinants of PM2.5 and are unlikely to correlate with unobserved absence shocks, ϵ_{it}. Recall from panels (d) to (f) of Figure 3 that PM2.5 is higher the larger (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; moreover, PM2.5 is higher when the air is still and horizontal ventilation is poor. We thus use ventilation conditions V to form an instrument for measured PM2.5 pollution Z:

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

To be clear, V does not include weather W_t, namely ambient temperature, humidity and rain, which we allow to directly affect absences. δ_t are time fixed effects (year-month, day-of-week), and ν_t is a disturbance. We fit $\hat{Z}$ using (3) implemented on daily observations t between August 2008 and December 2014, and employ these fitted values to instrument for measured PM2.5 in the linear probability model of student absences (2).[22]

[20]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.

[21]For continuous variables, we include squares. We include 24-hour mean ventilation conditions on the day and (in the baseline immediate exposure analysis) in each of the two preceding days. Table 6 tests for robustness. For comparison, 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.

[22]To obtain 2SLS estimates, we still generate first-stage predictions of PM2.5 from these fitted values and all other non-PM2.5 covariates in the second-stage absence equation. Isen et al. (2017) similarly instrument for pollution using fitted pollution, imputed from a policy rather than atmospheric intervention as we do. As an alternative to using fitted values from (3), we can instrument for pollution using V. In linear models

4 Severe air pollution and student absences

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 proportion 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 likely due to recording error. This drops only 0.7% or 17,547 out of 2,528,567 observations in the original sample.[23] As explained in Section 2, 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 (by the student or her parent) that drove the first absence day in the absence spell, for example, health or travel, including remedial or defensive responses to pollution.[24] We thus arrive at an estimation sample with 2,448,516 observations. We examine spell-adjusted absences, where an absence is the first school day of an absence spell.

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 μg/m^3 (recall panel (a) of Figure 3); (column 3) a count of the days in which daily mean PM2.5 exceeded 200 μg/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

such as ours, results should be similar (Angrist and Krueger, 2001), as indeed we find (Table 6).

[23] Panel (a) of Figure 1 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 dropping observations pertaining to days in which the absence rate exceeds 50% (rather than 30%).

[24] Table 5 shows that estimates are robust to keeping 62,504 observed second and subsequent absence days within absence spell in the estimation sample. Intuitively, estimated effects are even higher. Similarly, Gilliland et al. (2001) examine "incident" (first-day) absences as opposed to "prevalent" absences.

as a mean above 200 μg/m^3) raises the probability that an absence spell is initiated by a precisely estimated 0.20 percentage point, that is, a 5.2% increase (0.2/3.83) relative to a sample mean of 3.83 percent. In column 2, we instrument for the severe PM2.5 dummy using fitted ventilation-induced PM2.5 and its square (i.e., as driven by atmospheric ventilation conditions per note 21), obtaining 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 speed and direction (panels (d) to (f) of Figure 3) only indirectly, through these variables' effect on particle concentrations. A higher absence response estimated by 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, and then grows 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.[25]. A non-

[25] 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

monotonic absence response, by which absences initially fall as pollution rises from low levels and 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% (and 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 percentiles of the PM2.5 distribution (panel (a), Figure 3). 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, 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 regression 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).

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 consider 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

days with blue sky and seemingly clean air are treasured, and I usually go out and do exercise."

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 suggests that the estimated student absence response to PM2.5 is: (i) stronger if one allows for endogenous PM2.5 exposure, (ii) stronger if one allows for a more delayed response than the day (or a few hours) before the absence decision, and (iii) non-monotonic, at least over the initial range of PM2.5 variation in our urban China setting where particle pollution is typically severe, i.e., skies are routinely *not* blue.

Heterogeneous response to air pollution, 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 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, panel (b)), i.e., over 80th percentile absentee, 60th to 80th percentile, etc. 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, and we reject equal responses by both 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 students 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 student 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 student 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 and A.2), we re-estimated the Table 4, column 4 specification on a subsample restricted to students with over 200 school days, or about one academic year, of observation. This shrinks the number of students 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.

Finally, Tables 5 and 6 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 the sample 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, e.g., fitting PM2.5 using atmospheric ventilation conditions up to one day before PM2.5 is measured, but not two days before.

More prolonged exposure to air pollution. 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 student'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: 0.98 percentage point in the full sample (panel A, right and Figure 6b, row/horizontal axis marked $P = 7$); 1.02 percentage point among US/Canada nationals (panel C, left); and 2.57 percentage points among students in the top quintile of the absenteeism distribution (panel C, right).[26] 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, or one-quarter, of student absences in the overall population.[27]

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

[26] 2SLS estimates based on a UDL(7). Figure 6d reports on an alternative quadratic PDL(7,2).

[27] 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).

the probability that an absence spell is initiated by 0.98 percentage point (panel B, right and Figure 6f, row/horizontal axis marked $P = 7$).[28] 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 the model has been estimated).

5 Conclusion

We find that short-run fluctuations in the severity of particle pollution drive 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,[29] particle pollution still explains only 0.1 to 0.2 absence among 3.8 overall absences per 100 school

[28] 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_{tp}^2 and its cube Z_{tp}^3, the cumulative effect of the 100 to 200 μg/m^3 shift in week-long exposure is calculated as $\sum_{p=1}^{7}(200-100)\beta_{1p} + (200^2-100^2)\beta_{2p} + (200^3-100^3)\beta_{3p}$.

[29] For example, the median two-day difference in daily 24-hour PM2.5 is 51 μg/m^3 (note 16).

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 child 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 filters. 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 heterogeneous pattern of response 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 obtain 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 more severe health outcomes such as hospital admissions to be driven by chronically unhealthy individuals in the population.

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 more polluted, colder and drier 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 informed, high-income parents.

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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 21) 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 17). 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) 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 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

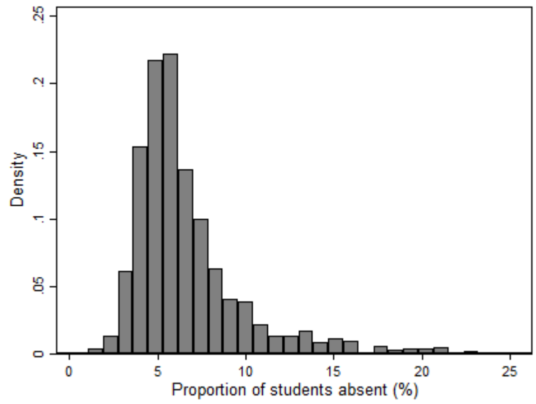
Robustness test		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Alternative controls W_t or α_t				Alternative instruments		
	Table 2 Col. 5 & 7	Temperature bins (3 °C)	Include week	Year-month × school-divis.	Trend × school-divis.	$\hat{Z}$ with 1-d lag for V	$\hat{Z}$ w/o wind dir.	V, not V-induced $\hat{Z}$
Panel A: Estimation by **OLS**								
Prior-day PM2.5 (×100 μg/m^3)	-0.24***	-0.24***	-0.21***	-0.24***	-0.16***			
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)			
Prior-day PM2.5 squared	0.08***	0.07***	0.06***	0.08***	0.04***			
	(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			
R-squared (within)	0.006	0.008	0.008	0.008	0.006			
Mean value of dependent var. (%)	3.83	3.83	3.83	3.83	3.83			
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 (×100 μg/m^3)	-0.55***	-0.47***	-0.53***	-0.53***	-0.63***	-0.59***	-0.59***	-0.47***
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.10)	(0.12)
Prior-day PM2.5 squared	0.18***	0.16***	0.15***	0.18***	0.18***	0.20***	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	2,293,228	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	119	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 17). 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 24-hour mean ventilation conditions on the day and one preceding day (not two) when fitting ventilation-induced PM2.5, $\hat{Z}$ (see note 21). Column 6 excludes 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%.

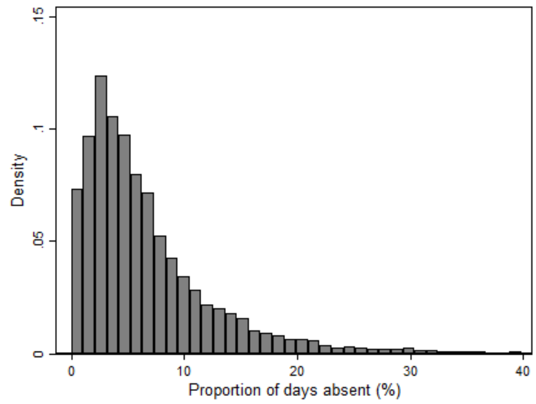
Table 7: Student absences and more prolonged pollution exposure: Non-parametric and parametric PM2.5 specifications, with P daily lags, estimated by OLS or 2SLS

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	Obser-vations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Obser-vations	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	Obser-vations	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	Obser-vations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Obser-vations	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	Obser-vations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Obser-vations	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

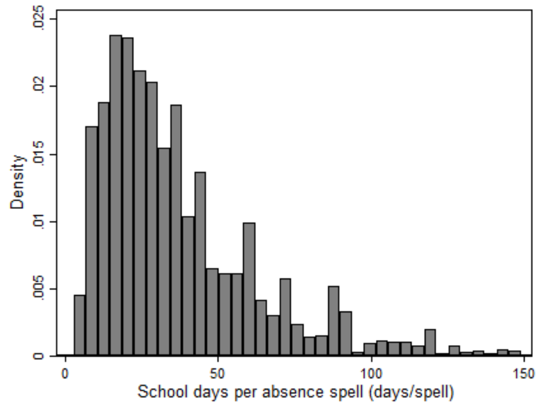
Notes: The dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Distributed lag models, estimated by OLS or 2SLS (as labeled), include P lags of the daily PM2.5 measure given by: (panels A and C) 1 if the respective 24-hour PM2.5 > 200 μg/m^3 and 0 otherwise; (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

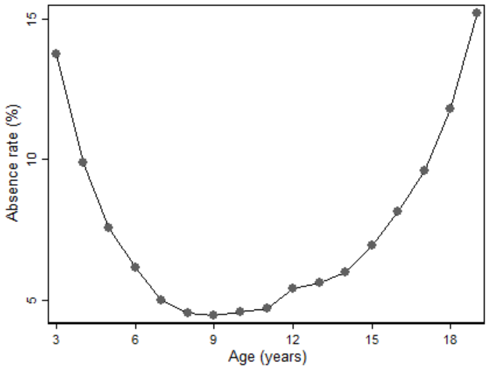


(b) Absence rates, across individual students

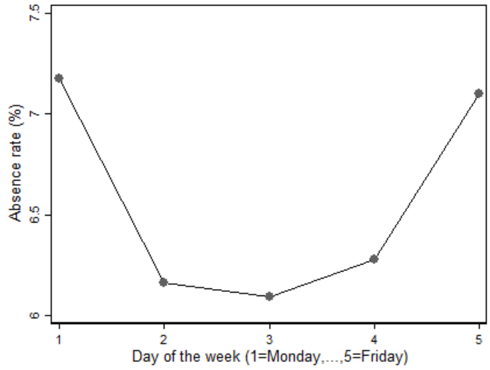


(c) School days per absence spell, across students

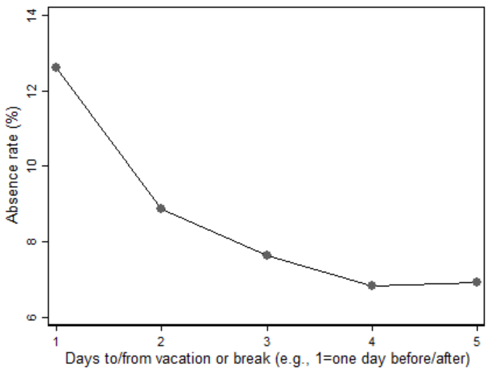
Figure 1: Distribution of absence rates: (a) over school days, and (b) across individual students in the sample (shown up to 40% for better visualization). Panel (c) reports the distribution across individuals of the ratio of a student's total school days to total absence spells (shown up to 150 days/absence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



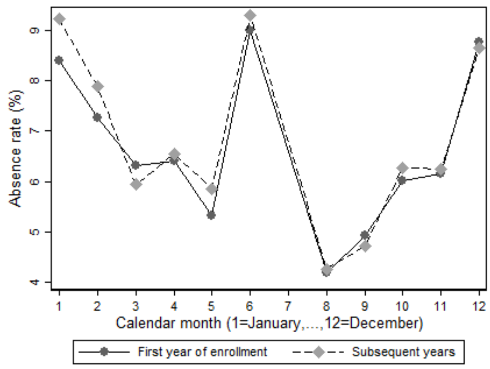
(a) By student age



(b) By day of the week

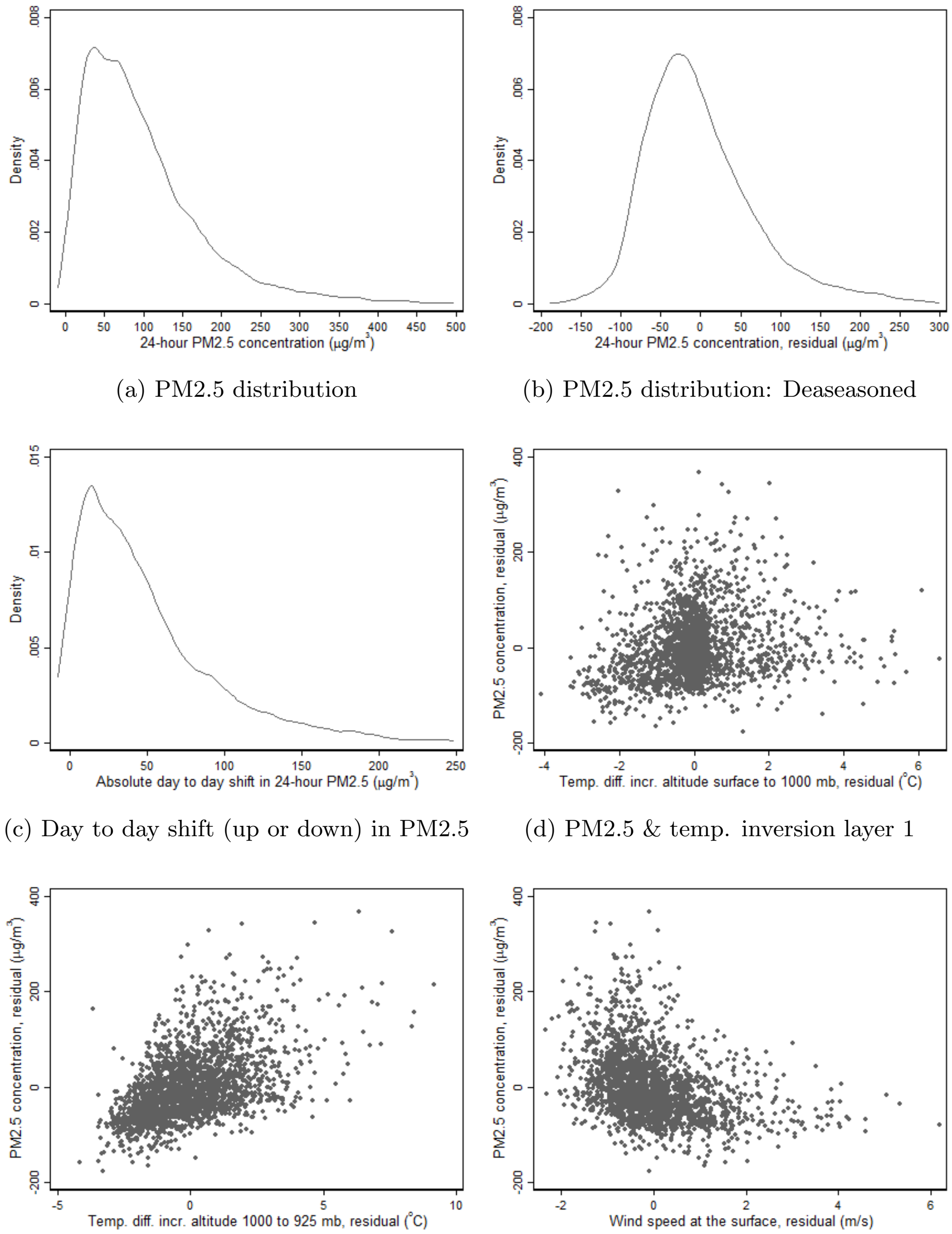


(c) By days to/from vacation or break



(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

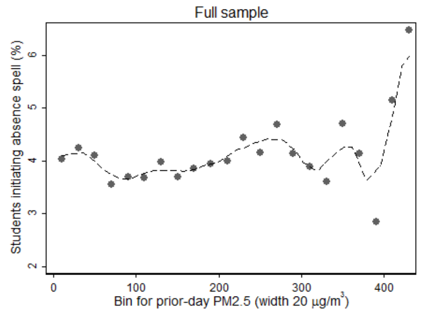
(c) Day to day shift (up or down) in PM2.5

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

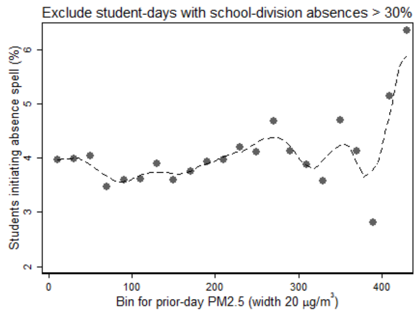
(e) PM2.5 & temp. inversion layer 2

(f) PM2.5 & wind speed

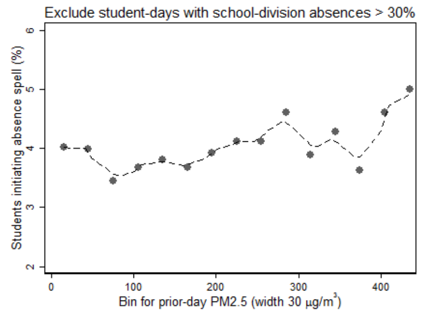
Figure 3: Variation in 24-hour mean PM2.5 concentration (μg/m^3) in the sample: (a) PM2.5 distribution (shown up to 500 μg/m^3 for better visualization); (b) residual PM2.5 distribution, once systematic temporal variation (year-month and day-of-week) is partialed out (shown up to 300 μg/m^3); (c) distribution 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.



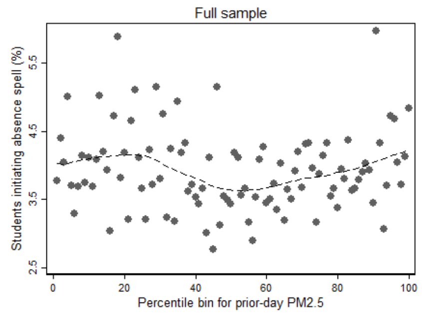
(a) PM bin 20 μg/m^3 wide, orig. sample



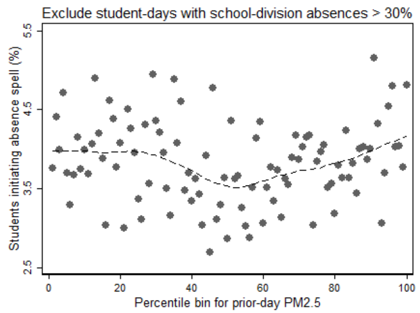
(b) PM bin, $\leq$30% absence days



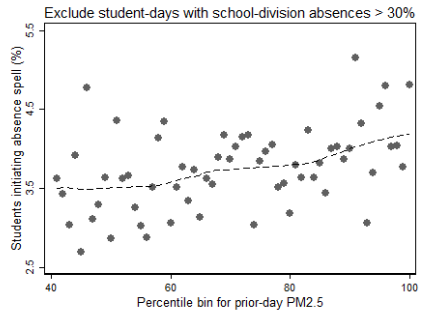
(c) PM bin 30 μg/m^3 wide



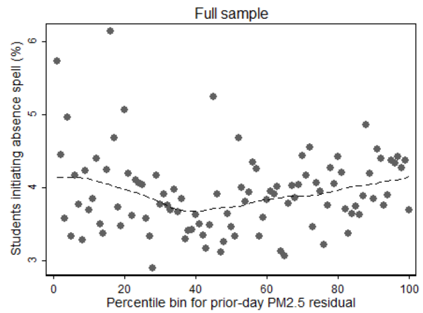
(d) Percentile PM, orig. sample



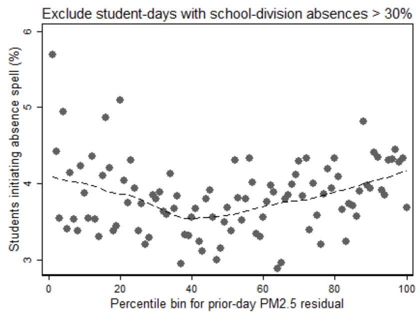
(e) Percentile PM, $\leq$30% absence days



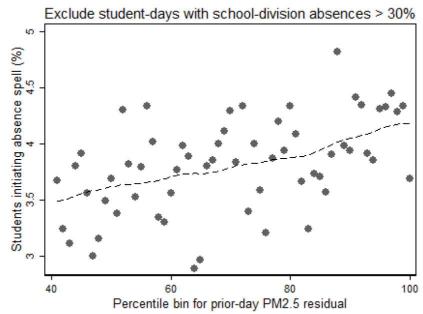
(f) Percentile PM, 40 to 99



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

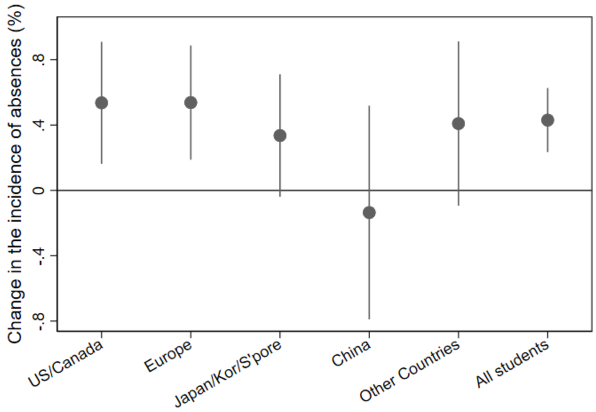


(h) P'tile PM res., $\leq$30% absence days

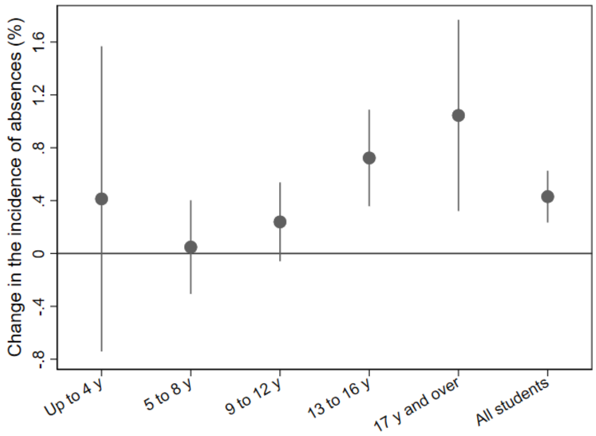


(i) P'tile PM resid., 40 to 99

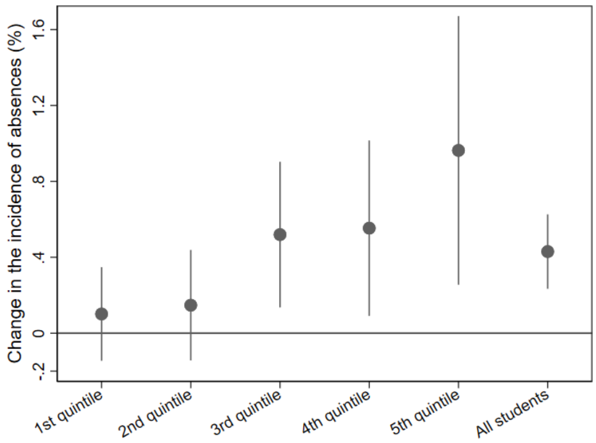
Figure 4: A non-linear pollution-absence relationship in the aggregated data. Panels (a) to (c) show, for the original sample or the estimation sample without high absence days, the proportion of students initiating an absence spell against prior-day PM2.5 bins of width 20 (or 30) μg/m^3, labeled at 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

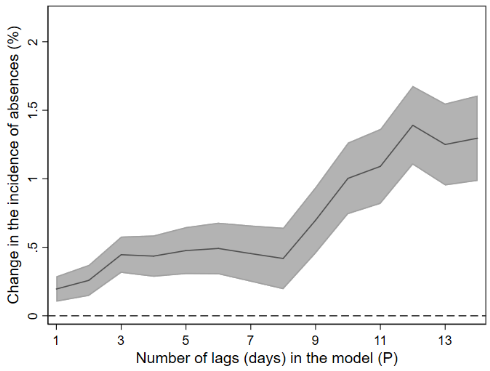


(b) Heterogeneous effects over age

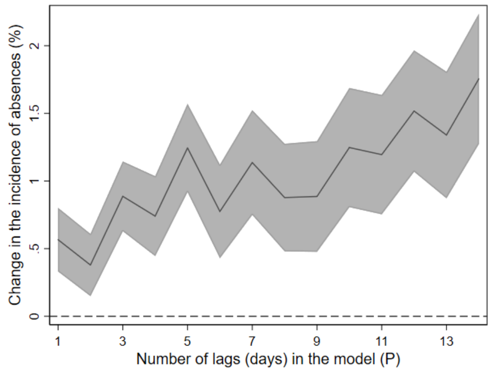


(c) Heterogeneous effects over absenteeism quintile

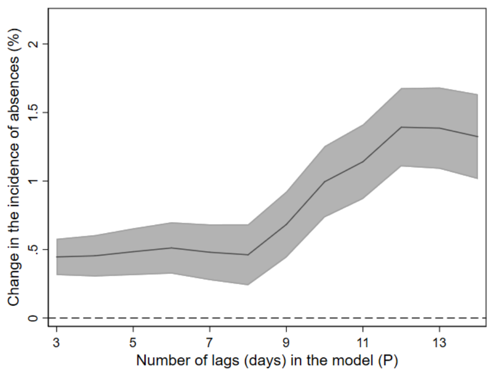
Figure 5: Heterogeneous sensitivity of absences to concurrent pollution: (a) by student nationality, (b) by student age, and (c) by student absenteeism quintile. 95% confidence intervals on the effect of severe PM2.5 (defined as prior-day 24-hour mean > 200 μg/m^3) on the probability that an absence 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.



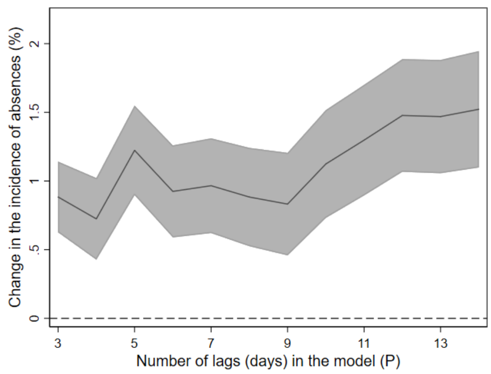
(a) Severe PM2.5, UDL(P), OLS



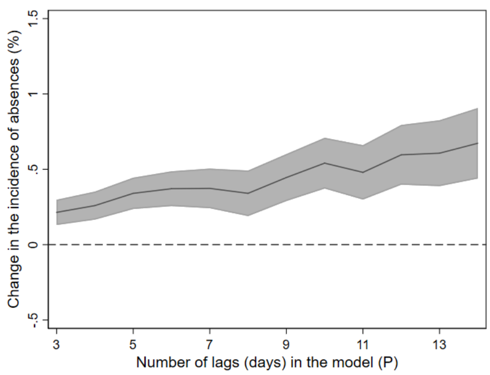
(b) Severe PM2.5, UDL(P), 2SLS



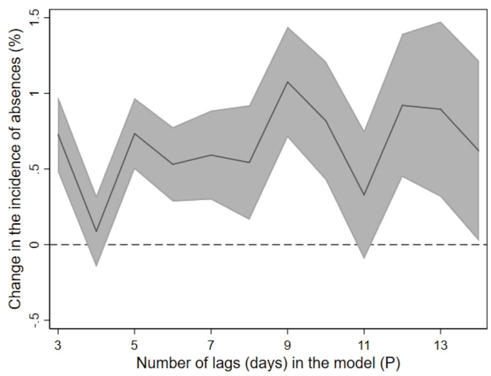
(c) Severe PM2.5, PDL($P, 2$), OLS



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



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

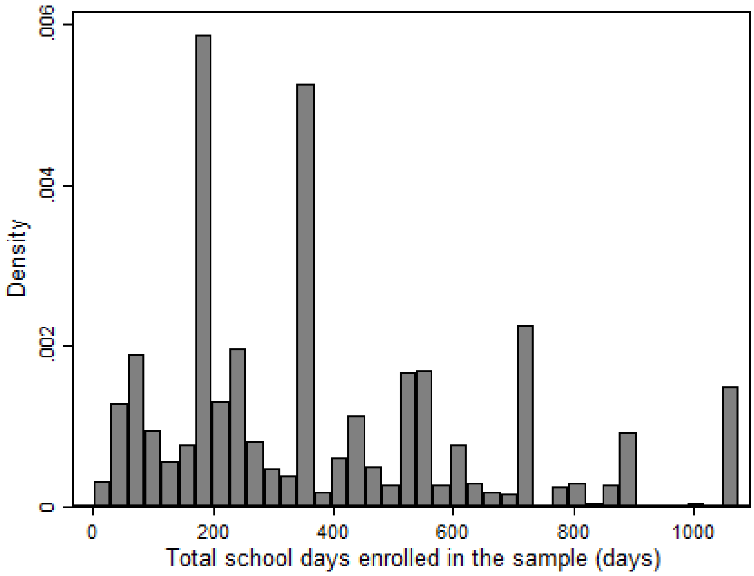


(f) Cubic PM2.5, PDL($P, 2$), 2SLS

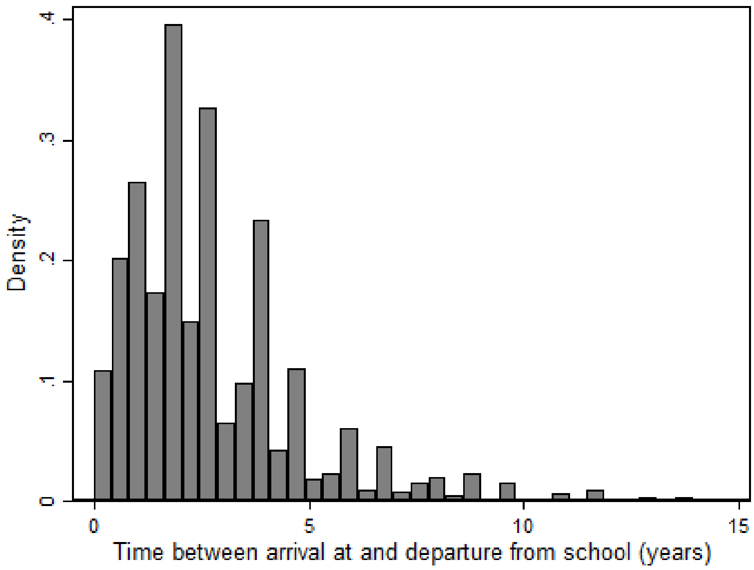
Figure 6: Cumulative impact of more prolonged PM2.5 exposure on the probability that an absence spell is initiated. Panels (a) to (d) show estimates, for a severe PM2.5 dummy (24-hour mean $> 200\ \mu g/m^3$) specification, of the cumulative effect on absences from P preceding days of severe PM2.5, relative 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 $\mu g/m^3$. 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

The figures that follow provide further description of the data, and are referenced in the text.

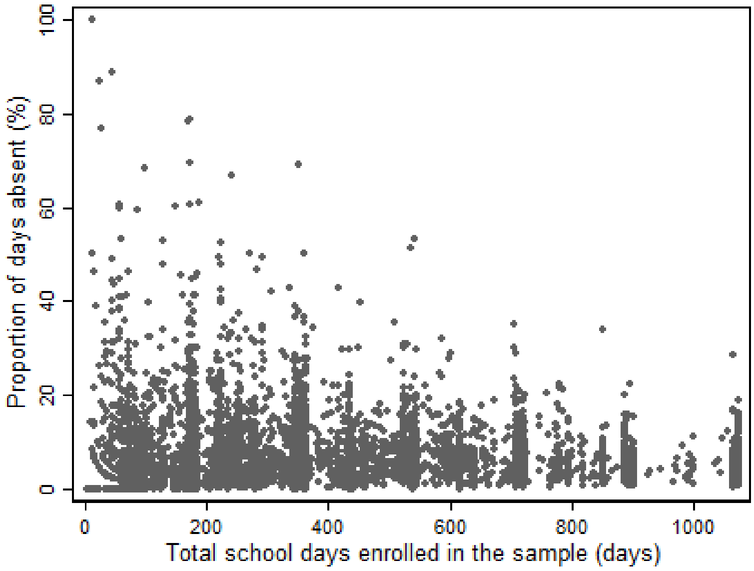


(a) Days enrolled in the sample, across students

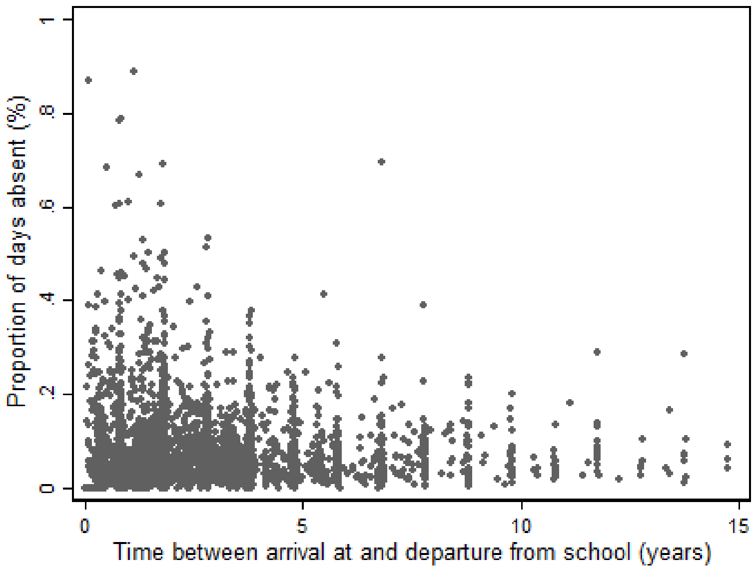


(b) Total duration at the school, across departed students

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.

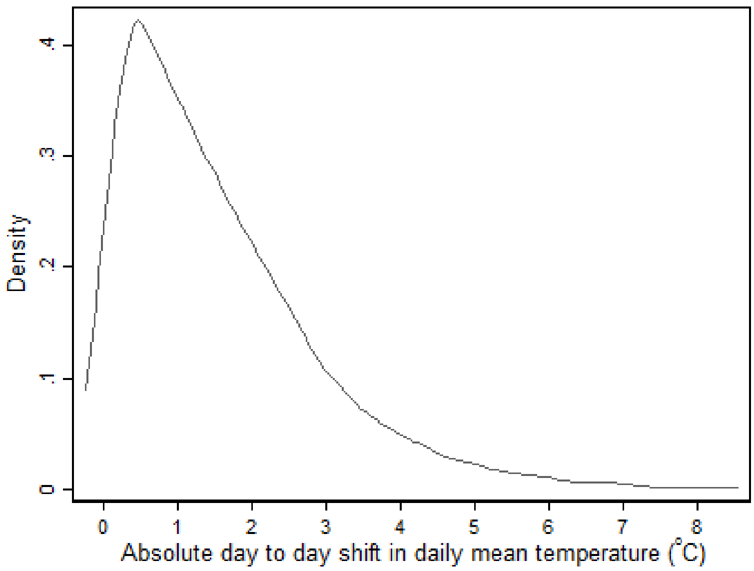


(a) Absence rate & days enrolled in the sample, across students

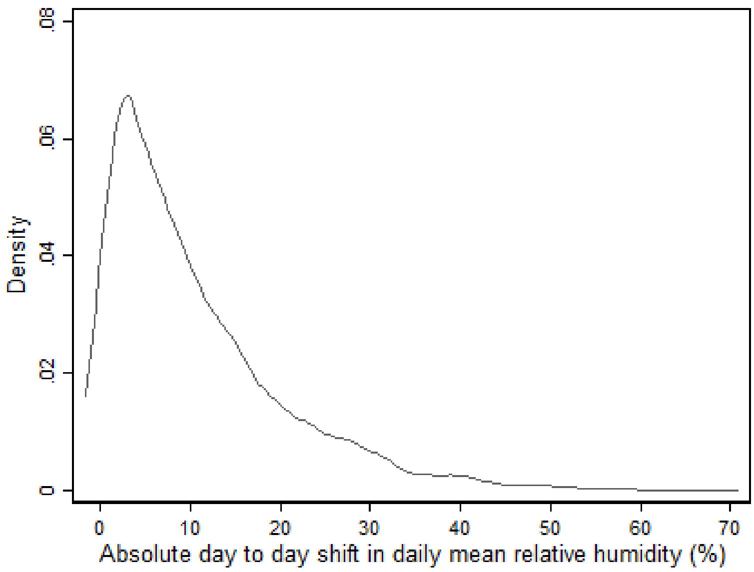


(b) Absence rate & duration at the school, across departed students

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.