Severe Air Pollution and Child Absences When Schools and Parents Respond

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Abstract

We examine how absences respond to particle pollution in a multi-year individual panel comprising 6,500 children enrolled at international schools situated in a major economic hub in north China. These schools (and their parents) have been willing and able to respond to the dire state of air quality, by implementing defensive procedures (thresholds for outdoor play) and capital (air-tight windows and central air-conditioned filtration systems). Even in this setting, we find substantial heterogeneity in the response to ambient PM2.5. Pollution sensitivity is stronger among US/Canadian/European than Chinese, children who miss school the most, and a minority of children who depart within one year of arrival, but overall is modest compared to estimates for the US. This suggests that to some extent the school response can substitute, through defensive behavior, for the absence response. We offer a benchmark for school administrators in polluted middle-income countries, yet caution that more research is needed on the long-term implications of PM2.5 exposure.

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

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1 Introduction

Consider a family of skilled workers with young children, living in a rich country and facing the opportunity to transfer to the developing world, whether Americans pursuing career advancement or Chinese returning to their home country. Aware of the routinely severe air pollution in typical host cities (Van Mead, 2017), from Beijing to Calcutta to Dhaka, one consideration is likely to be: To what extent will air pollution act as an impediment to my child attending school, due both to sickness from exposure and to actions taken to reduce exposure? To our knowledge, there is no systematic evidence on this question.

Schools in polluted cities that admit international students have naturally responded to the dire state of air quality. Catering to educated parents on high incomes, they have invested in defensive capital and implemented avoidance procedures. One can view these so-called international schools as lying at the forefront of averting behavior. For example, TimeOut (2015) surveyed nine international schools in Beijing on controls that were in place. This "Q&A on air quality" describes measures such as central air-conditioned filtration systems, individual room air monitors to ensure windows stay shut, and thresholds for outdoor play. Should such behavior be effective in keeping children in school, the wider community of policymakers, school administrators and parents elsewhere may consider adopting similar averting practices and capital. Across the developing world, schools commonly lack even basic infra-structure and procedures, such as windows that can be shut, air conditioning systems that can be turned on, and play that can move indoors when particle levels rise. To our knowledge, how student attendance at these leading schools responds to ambient air pollution has not been assessed.[1]

To provide such a benchmark, we examine how absences respond to particle pollution in a sample of 6,500 children of all ages enrolled at three international schools in a major urban center in north China. The three schools have adopted measures as described in the TimeOut survey, including air conditioning and air purifiers throughout campus and strict

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

procedures on outdoor play. We gained access to individual-level attendance records over multiple years, jointly covering 2008 to 2014, allowing us to control for potential confounds and sources of variability, including seasonality, weather and unobserved heterogeneity.

Over the period, daily PM2.5 (particulate matter of diameter up to 2.5 micrometers) concentrations measured at the US embassy at most 20 km from each school averaged 98 μg/m^3. This mean level is eight times the primary one-year average National Ambient Air Quality Standard (NAAQS) of 12 μg/m^3 set by the US Environmental Protection Agency. That the US State Department monitors PM2.5 in several cities in the developing world underscores the relative threat particles pose (other pollutants are not monitored), the defensive behavior that can be elicited, and the potential friction to international workers (US citizens in this case).[2] We observe child nationalities, both foreign and Chinese, and the time since first enrolling at the school, which for most children may reasonably proxy for their time of residence in China. We can look for heterogeneous short-run PM2.5 effects on absences across nationality, age, duration and stage of enrollment (some children may have short residence), calendar year (should defensive behavior have evolved), and among children who vary widely in their overall levels of absenteeism (across all causes).

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 absences that may drive or correlate with PM2.5 levels. Our 2SLS estimates are based on the exclusion restriction that atmospheric ventilation conditions, which fluctuate from day to day, induce absences only indirectly, by shifting PM2.5, and this exogenous PM2.5 component then drives absences. Previous research has adopted designs using the degree of atmospheric stagnation to infer the causal impact of air pollution on economic outcomes, both in China and elsewhere (Ransom and Pope, 2013; Hanna and Oliva, 2015; He et al., 2018b). We provide visual in-sample evidence of how atmospheric ventilation drives the build-up and removal of particles, such as

[2] In its mission to protect US citizens, the US State Department measures and reports PM2.5, in real time, in cities across Bangladesh, China, Colombia, India, Indonesia, Vietnam, and others. The media has covered the cost to international families of adapting to China's air (Thomas, 2014; Wong, 2015). The flow of international talent and the investments they enable are key inputs to the modern global economy (OECD, 2008; Freeman, 2010; UNCTAD, 2013).

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 key economic hub in Asia respond to short-run fluctuation in PM2.5. Severe PM2.5 on the day before—defined here as a 24-hour mean above 200 $\mu g/m^3$—raises the probability of an absence by 0.9 percentage point, or +14% relative to an absence rate of 6.2% in the sample.[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). It is thus conceivable that the routinely high PM2.5 already contributes to some absenteeism beyond the variation we pick up.[4] Yet an overall absence rate of 6%, and 5% for children aged 10, are comparable to the 4 to 5% reported for elementary and middle school children in Utah Valley and Texas (Ransom and Pope, 1992; Currie et al., 2009), and lower than the 10% reported for Salt Lake City, where PM2.5 averages 10 $\mu g/m^3$ (Hales et al., 2016). Lower absenteeism among nationals of Japan, Korea and Singapore, and higher absenteeism among teenagers, points to the importance of behavior, even behavior-moderated health (a parent's judgement call on whether a child is "well enough" to attend school). To emphasize, pollution-induced absence behavior includes both remedial and avoidance responses. For example, parents may keep a child at home to recover from sickness, or a teenager may not feel like leaving home on a smoggy day. Beyond absences and the disruption to human capital formation, the data provide insight on how air quality impacts these families' lives.

We specify models with richer lag structures that allow more prolonged PM2.5 exposure to explain absences, beyond simply PM2.5 on the day before or early morning of the school day. In particular, biological effects may not be manifested in the form of an absence immediately.[5] Distributed lag models with up to 14 days of delay yield estimated cumulative PM2.5 effects that tend to grow with the number of lags. In a model with cubic functions of daily PM2.5 in each of the 14 days preceding a school day, a large

[3]Here we report 2SLS estimates, which exceed their OLS counterparts. Consider a world in which labor co-produces pollution. Then, positive shocks to parental labor demand may reduce absences (through less home care supplied) and raise pollution.

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

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

and infrequent shift in the pollution dose from 100 to 200 μg/m^3 sustained over an entire fortnight raises the probability of an absence by 1.8 percentage point, or +29% relative to the sample mean absence of 6.2% (a risk ratio of 1.29).

We find that the sensitivity to PM2.5 varies considerably across students. PM2.5 impacts absences less for Chinese relative to US, Canadian and European children.[6] The response of absences to PM2.5 is stronger among children who exhibit higher absenteeism overall, particularly those in the top quintile of the distribution of individual absence rates over the 6,500 children. Children who depart within one year of arrival exhibit a steeper pollution-absence relationship; pollution may be one factor why their enrollment did not exceed one year. The majority of children who arrive remain enrolled beyond two years. The pollution-absence relationship for this majority of children is stable over their enrollment period. This is consistent with their health not deteriorating over the observed time frame.

On a positive note, combining the empirical PM2.5 variation in this city with our estimated responses reveals that severe PM2.5 explains only a fraction of one percentage point of the overall 6 percent absence rate. Only for the most sensitive subgroups does severe PM2.5 explain around one percentage point. In our setting, the share of absences explained by shifts in ambient air quality is not large relative to estimates from aggregate data for the US. Ransom and Pope (2013) find that PM10 in Utah Valley "caused 2.25 percent of students to be absent on the average day... roughly *half* of the total rate of absenteeism" (p.14, emphasis added).[7] Currie et al. (2009) estimate a 0.8 percentage point reduction in absences for El Paso in 2000/01, a year with lower CO levels compared to 1986, when CO exceeded the NAAQS on 16 days. Hales et al. (2016) study Utah absences over a later period than in their seminal work, finding that "a 100 μg/m^3 increase in 7-day moving average PM10 is associated with a 10% to 15% increase in absences" (p.11)—a response that is still higher but closer to what we find. Currie et al. (2009) helpfully review

[6] Family experience and culture may play a role in avoidance behavior (as in fertility and work outcomes, e.g., Fernandez and Fogli (2006)), an aspect that has not been studied. Our multinational sample concurrently enjoys similar income and schooling. Moreover, unless outdoor exposure during non-school hours varies materially, children experience a similar environment overall.

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

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.[8]

Our paper makes several contributions over the extant literature linking school attendance to air pollution. We offer a window into the daily functioning of a multinational group of children being subjected to a developing nation's urban air, often for the first time. The setting provides insight on whether defensive procedures and capital that are in place in these children's lives can keep them in school, offering a benchmark for policymakers who oversee schools in the polluted developing world. The absenteeism data are at the individual level, and we document substantial heterogeneity in the response to ambient air pollution, even for a population with similar income and education. If environmental shocks induce, through health and behavior, unequal outcomes in our sample, their contribution to social inequality in the wider Chinese and global populations is likely to be larger still.[9] Our study examines a child by day panel for a sizable population over multiple years, considers a PM2.5 range that is most relevant to developing countries, and allows a plausible lag structure. Like Ransom and Pope (2013), our approach adopts credible exclusion restrictions based on daily atmospheric ventilation conditions that critically determine local air quality and yet do not respond to anthropogenic activity.

Our analysis infers the causal effect of ambient PM2.5 on absences for the population of children enrolled at international schools arguably at the frontier of defensive expenditure. While we cannot rule out that particularly vulnerable children with pre-existing respiratory conditions may not have left their country of origin in the first place, we argue that adaptive responses including coping mechanisms are a key part of story here. This is mainly a story of an absence response to ambient pollution that is moderated by defensive behavior, by the schools and the parents they cater to, not a story where an analyst

[8]Table 1 in Currie et al. (2009) summarizes the design 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. Zhang et al. (2018) report +37% absence per +10 $\mu g/m^3$ of PM2.5, and an absence rate of 0.26 per 100 child-days, using self-reported absences over 6 weeks by 615 children aged 8-13 at one school in Jinan, China.

[9]School attendance is an input to human capital formation and its social benefits (Grossman and Kaestner, 1997; Gottfried, 2014).

observes only a self-selected elite.[10] About one-quarter of the children who leave within one year from enrollment exhibit a pollution-absence response that is double that of the majority who remain enrolled in the third year, yet even for the former subpopulation we find that pollution explains a small proportion of absences. We learn that despite the excess pollution the absentee response is not excessive relative to what the literature finds for the US. This suggests that the schools (and parents) we study have responded to the poor air quality such that student attendance does not respond as much as it otherwise might. Understanding the effect of pollution on the wider Chinese population, given existing behavior, is an interesting and open research question. We also caution that our findings do not speak to the effect of long-run exposure to pollution, for example, via lung function development. Moving life indoors and staying inside air-conditioned spaces at school and home may partly be protective of one's health, even if temporary residence in China comes at the expense of long-term health, a topic that remains open for research.

Related health literature. A literature, mostly in epidemiology, examines the relationship between acute exposure to air pollution and public health outcomes, observed from vital records or encounters with health suppliers. When it comes to more subtle manifestations of morbidity that do not lead to health encounters, the evidence is more sparse.[11] Economists have recently examined the causal effect of short-run pollution exposure on medication purchases (Deschenes et al., 2017), hours worked (Hanna and Oliva, 2015; Aragon et al., 2018) and productivity while at work (Graff Zivin and Neidell, 2012; Chang et al., 2016b,a; He et al., 2018b). Unlike us, studies have typically had to rely on aggregate data, rather than individual-level panels, or examined rich-world settings, where particle concentrations in ambient air are much lower than in developing countries.[12]

[10] We are not examining rare "superhuman" individuals, but children of international families numbering in the tens of thousands that have ventured to this regional powerhouse. Even TimeOut magazine runs a local edition targeted at international families.

[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).

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

2 Institutional background and data

Origin of student attendance records. In 2013, we contacted the principals of 16 international schools located in a Chinese city that is routinely exposed to severe PM2.5 pollution. These schools cater largely to the international community and, to a lesser extent, to Chinese families that have some international connection, such as families that have lived outside China. We explained that we were interested in studying the effect of air pollution on student absences at several schools and that, in view of the topic's sensitivity, the addressee's school would be anonymized were it ultimately included in our sample. Among the 16 schools that we contacted, principals at seven schools agreed to meet with us. Ultimately, longitudinal child-level attendance records were shared by three of these schools.[13]

Variation in absence rates and absence inequality. Key aspects of the data are its longitudinal structure and high frequency. We follow the same child day by day often over multiple years, and can thus 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 school caters to children of all ages, from 3 to 19 years.

In terms of child nationality, rich countries grouped by continent—US/Canada, Europe, Japan/Korea/Singapore—each account for at least one-third of enrollment for at least one school, e.g., at one school, US/Canada accounts for one-third of enrollment and Europe accounts for another one-third of students. Chinese nationals account for 7% to 20% of the student body at each school. For each school sample, the 10th percentile of the distribution of enrollment duration among departing students is below one year; the 90th percentile is above four years (see Figure A.1(b)). The data allows us to examine children of different enrollment duration as well as over their period of enrollment. There are 6,545 children in the combined sample (henceforth, sample).

[13]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.

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 child by school day (henceforth, child-day) observations. The sample consists of 2.5 million child-day pairs. Compared to the absence rate for nationals of Japan/Korea/Singapore, at 4.7% of child-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.

Figure 1 summarizes how absence rates vary over time and across children. For every day in the sample, when at least one school is in session, we compute the proportion of enrolled children 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%. We examine the extent to which the day-to-day variation in absenteeism is driven by variation in concurrent and recent exposure to ambient PM2.5, once we account for other time-varying determinants.

Despite the plausibly similar and high levels of parental income and education, there is substantial individual heterogeneity in absence behavior, or absence inequality. For every child, we divide the child's overall number of days absent by the number of school days in the sample during which she was enrolled. To illustrate, say that a child is enrolled over 10 school days, Monday to Friday of week 1 and Monday to Friday of week 2, and is absent on Friday of week 1 and Monday of week 2. Her individual absence rate is 2/10. Her enrollment is characterized by one spell of consecutive absence days, lasting two school days.[14] Panel (b) shows a right-skewed distribution of the individual absence rate over the 6,545 children. The median child is absent on 5.1% of days. Some children exhibit a significantly higher absence rate than others. Fixing enrollment, the top 10% of absentees account for 35% of aggregate absences, with a mean absence rate of 23%.

For each child, we divide the number of school days while enrolled by her number of absence spells. Figure 1(c) shows much cross-sectional variation in this school days/absence spell statistic. Figure A.1(a) reports the distribution across children of school days while enrolled; one academic year consists of just under 200 school days. In-sample enrolled days are low for some children who enrolled at the school near the end of the sample period in 2014. Figure A.2 shows that children with short duration in the sample, in panel (a), or short duration at the school, in panel (b), are associated with higher absence rates. Costly adaptation to pollution may shorten enrollment duration. Alternatively, some families planning shorter stays may tolerate higher absenteeism for their children.

Figure 2 considers several time-varying drivers of absences, factors that we control for in our empirical model. There are non-monotonic relationships between absenteeism and age, in panel (a), and day of the week, in panel (b). The absence rate is lower at age 8-10 years compared to younger and older children. Higher absenteeism among teenagers than among children aged 8-10 is suggestive of behavior beyond health channels, whether induced by environmental factors or not. The absence rate is higher on Mondays and Fridays compared to midweek. A weekend effect may partly be driven by activities that compete with school, such as trips. Panel (c) shows the effect of (pre-determined) vacations and breaks on surrounding school days. Absence rates tend to increase in the five days leading up to a vacation/break, and decrease in the five days following a vacation/break, likely due in part to families taking off early for a trip, or returning late.[15]

Panel (d) reports on seasonal variation, with lower absence rates around August, as the

[14] The sample contains 165,698 child-day absences and 97,164 absence spells. 70% of absence spells last one day, 15% last two (school) days, and 6% last three days.

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

academic year starts, and in May, usually its last full month, compared to more absences in December through February. We observe more absences on colder winter days.[16] Since newly enrolled children 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 child's first year of enrollment versus subsequent years. We find little variation along this margin—if anything, absences appear slightly lower during a child'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. This outdoor air monitoring site is located no more than 20 km from the three schools. The schools informed us that most students live within 10 km of the school, likely due in part to the state of road congestion in major Chinese cities (Viard and Fu, 2015; Gu et al., 2017).

Alternative PM2.5 measurements at Chinese Ministry of Environmental Protection (CMEP) sites across the city, available only from 2013, show tight spatial correlation not only across CMEP sites but also with US embassy records in the overlapping period. Specifically, in 2013 and 2014 the correlation coefficient between (24-hour) PM2.5 at the US embassy and the average for CMEP sites is 0.97.[17] This correlation speaks to the importance of regional atmospheric ventilation shocks, discussed below, that govern the dispersion of pollutants and are plausibly exogenous to unobserved determinants of absences. As attested by local and foreign media coverage, fluctuation in PM2.5 severity is a citywide—not a neighborhood—phenomenon.

For the same-day air quality as a potential shifter of absences, we take the PM2.5 reading at 6 am, prior to leaving home for school. To allow for more prolonged pollution exposure, over up to the 14 preceding calendar days, to explain absences, 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,

[16] 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.

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

as children may have been out of town and we are unable to assign lagged exposure.

Figure 3(a) shows wide variation in daily PM2.5 over the 2008 to 2014 period. There is substantial density beyond 100 μg/m^3, and even beyond 200 μg/m^3. In panel (b), variation up to 400 μg/m^3 remains even after regressing daily PM2.5 on month-of-year fixed effects and day-of-week fixed effects. Pollution is not exclusively a winter phenomenon: PM2.5 averages 88 μg/m^3 between April and September. Panel (c) reports the distribution of the absolute change in daily PM2.5 from one day to the next, where the median shift is a high 37 μg/m^3 (the 75th percentile is 68 μg/m^3). Table 1 shows that much variation also remains even as we aggregate PM2.5 over consecutive days, e.g., the 7-day and the 14-day averages have ranges of 25-346 and 34-270 μg/m^3, respectively.

We obtained weather conditions at ground level, compiled by NASA for the sampled city and period, namely, 3-hour readings for ambient temperature, relative humidity and precipitation. We control for these variables in the student absence equation, as such weather conditions may shift absences directly (Section 3). Compared to the magnitude of PM2.5 shocks from one day to the next, Figure A.3 suggests that weather is more persistent, with median shifts in daily mean temperature and relative humidity from one day to the next of 1.2 °C and 7.7%, respectively.[18]

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. Our 2SLS estimates allow for measurement error in students' pollution exposure, as well as time-varying omitted correlates or determinants of absences. In such specifications, we instrument for measured PM2.5 using PM2.5 variation induced by atmospheric ventilation shocks, as proxied by temperature-altitude gradients and wind conditions.

Figure 3's three last panels report on the strength of the atmospheric ventilation instruments. The plots show (all variables are daily means) PM2.5 against: (d) the temperature difference from ground level to a pressure point of 1000 mb, (e) the temperature difference

[18] 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.

from 1000 to 925 mb, and (f) ground-level wind speed. We partial out confounding systematic seasonal and weekly variation from each series. Positive and steeper temperature gradients with altitude (e.g., a layer of hot air stationed overhead that traps pollutants close to the ground, where they are emitted), as well as lower wind speeds (e.g., still air), are strongly associated with a deterioration in air quality, as indicated by higher fine particle levels. The 2SLS identifying assumption is that day-to-day shifts in ventilation, both vertical (thermal inversions set in and lift) and horizontal (wind changes in intensity and direction), do not affect absences directly or correlate with unobserved absence shifters.

3 Empirical model

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

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

and binary variable A_{it} (denoting absence) is 1 if and only if $y_{it}^{*} > 0$. Row vector Z_t of pollution variables includes concurrent exposure (e.g., PM2.5 at 6 am of school day t) and, more generally, lagged-day exposure, Z_{tp}, where $p = 0, 1, ..., P$ indexes the lag in calendar days relative to t, starting with $p = 0$, the period concurrent to school day t, and $P \geq 0$. For example, a model with $P = 1$ restricts only prior-day (and same-day) pollution to influence absences. Z_{tp} can be a non-parametric or parametric function of exposure, e.g., a dummy for PM2.5 above a threshold, or a cubic function of PM2.5.[19]

Vector W_t consists of concurrent weather covariates, namely, ground-level temperature, relative humidity and rain.[20] W_t can affect both direct and opportunity costs of attending school. For instance, cold and rain may raise the effort required to get out of bed and commute to school, including through any health channels. At the same time, bad weather

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

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

can reduce the value of outdoor activities that may compete with school.

Following Section 2, X_{it} captures time-varying child-level determinants or correlates of absences, such as granular age bins and functions of time since first enrolling at the school, e.g., indicators for the child's first two semesters of enrollment. Child fixed effect α_i captures the unobserved characteristics that affect an individual's utility from not attending school. To account for systematic annual and weekly cycles and other time-varying drivers of absences, vector α_t includes year-month (month-of-sample) fixed effects and day-of-week fixed effects. The latter includes an indicator for public holidays when the child'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.[21]

We then estimate a linear probability model (LPM) of student absences:

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

Distributed lag structure for PM2.5 exposure. Following Zanobetti et al. (2002, 2003), we estimate models with distributed lag structures increasing from $P = 1$ to $P = 14$ days prior to the observed absence decision, to capture the cumulative impact from more prolonged exposure to PM2.5. For example, in a model in which P PM2.5 covariates enter linearly, we estimate $1 + P$ parameters β_p in (2), and report the cumulative shift in the probability of absence from a given PM2.5 increase sustained in each of $1 + P$ concurrent and lagged days of exposure, $\sum_{p=0}^{P} \beta_p$. This model is the unconstrained distributed lag, UDL(P). Although serial correlation in Z can make estimation of each 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 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. Besides UDL models, we estimate PDL($P, 2$) models constraining the β_p to follow a quadratic, and find a similar cumulative impact $\sum_{p=0}^{P} \beta_p$.

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

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). To compare with studies of daily aggregate elementary school absences, Ransom and Pope (2013) specify 7-day lagged averages for PM10 (and CO) as the measure of exposure, whereas Gilliland et al. (2001) allow acute pollution effects to be distributed over up to 30 days.

Endogenous PM2.5 exposure. Besides OLS, we estimate models by 2SLS to alleviate concern that PM2.5 exposure is measured with error,[22] leading to attenuation bias, or endogenous. For instance, a positive shock to parental labor demand could lower school absences and, through economic activity, raise emissions, leading to downward bias. Shocks to economic activity may shift both parents' opportunity cost of home care and emissions. Similarly, shifts in the value of leisure activities that compete with school may raise absences while lowering pollution. Alternatively, shocks to road congestion may raise vehicle emissions and absences.

The exclusion restriction is that atmospheric ventilation, V, only affects absences through its effect on pollution. Specifically, V includes the 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.[23] Such variables are key drivers of PM2.5 and are unlikely to correlate with unobserved absence shocks, ϵ_{it}. As shown, PM2.5 is higher the less negative is the temperature-altitude gradient, since warmer air overhead traps PM2.5 that is emitted or formed near the ground, and similarly when the air is still and horizontal ventilation is poor. We use ventilation V to form an instrument, $\hat{Z}$, for measured 24-hour PM2.5, Z,

[22] For example, in the 2013/14 CMEP records at over one dozen PM2.5 sites across the city, the cross-site standard deviation of 24-hour means averages about 10 $\mu g/m^3$.

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

by fitting:

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

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

To be clear, (3) is not the first-stage equation. This ventilation-pollution model produces fitted values $\hat{Z}$ that, together with covariates in the absences model (2) such as weather (W_t), child age (X_{it}) and fixed effects, comprise our first stage.[24] With regard to the exogeneity of wind speed (a component of V) and thus of $\hat{Z}$, the routinely mild wind in our setting,[25] while clearing the atmosphere, is unlikely to impact behavior. In a robustness test, we add wind speed to other ambient weather conditions (temperature, humidity and rain) that are allowed to affect absences directly.

4 Pollution and child absences

We first examine the relationship between absences on a given school day and PM2.5 levels on the day before, and subsequently enrich the model's lag structure to allow more prolonged PM2.5 exposure to explain absences. We investigate heterogeneity in the absence response to pollution, for example, according to child nationality. We obtain our preferred estimation sample from the original child-day observations as follows. For each school by age group pair (three schools each with preschool, primary, middle and high school divisions, totaling 12 pairs), we compute the fraction of enrolled children who are absent on each school day. Child-day observations pertaining to a school day in which the child'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.[26]

[24] Isen et al. (2017) instrument for pollution using fitted pollution, imputed from a policy rather than atmospheric intervention. Alternatively, V can instrument for Z directly (Angrist and Krueger, 2001).

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

[26] Figure 1(a) shows low density already at an absence rate of 20%. Table 6 shows that estimates are robust to: not dropping observations on these very high absence days, or instead to only dropping observations pertaining to days in which the absence rate exceeds 50%.

All but one column of Table 2 report estimates of linear probability model (2) of absences and, as alternative measures of immediate exposure to PM2.5, consider: an indicator that daily mean PM2.5 on the day before the observed absence exceeded 200 μg/m^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 (zero, one, two or three); a linear spline function of daily mean PM2.5 on the day before the absence; or a cubic function of daily mean PM2.5 on the day before the absence. In column 1, severe PM2.5 on the day before, defined here as a mean above 200 μg/m^3, raises the probability of an absence by a precisely estimated 0.25 percentage point. Relative to a sample mean of 6.19 percent, this is a 4.0% increase. We include an indicator for a same-day PM2.5 reading (at 6 am shortly before classes start) below 50 μg/m^3, obtaining a marginally significant estimate of 0.07 percentage point. In our urban China setting where skies are routinely *not* "blue," PM2.5 levels below 50 μg/m^3 may induce some students to skip school.[27] An alternative probit model, in column 2, yields similar marginal effects. Column 4 reports OLS estimates that each additional severe PM2.5 day in the preceding three days raises the absence probability by 0.08 percentage point. Thus, the incidence of severe PM2.5 in all three preceding days raises the absence probability by $0.08 \times 3 = 0.24$ percentage point.

In column 3, we instrument for the prior-day severe and same-day "blue sky" PM2.5 indicators using fitted ventilation-induced PM2.5, its square and its cube (both prior-day and same-day).[28] We obtain a 2SLS estimate of the effect of severe PM2.5 that is about three times the OLS estimate. This is likely due to a combination of attenuation bias (e.g., error in measuring the child's actual exposure) and omitted variable bias (e.g., lower pollution associated with shocks to the value of activities that compete with school). The occurrence of severe PM2.5 yesterday raises the probability of an absence by 0.88 percentage point, i.e., a 14% increase relative to a sample mean of 6.19 percent. Again, the exclusion restriction is that absences respond to atmospheric thermal gradients and

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

[28] This is conventional 2SLS (Angrist and Pischke, 2009), with the first-stage linear regressions of each PM2.5 dummy on (prior-day and same-day) fitted PM2.5, its square and its cube (and exogenous covariates). All estimates on the severe PM2.5 dummy are robust to dropping the blue-sky PM2.5 control.

surface wind only indirectly, through these variables' effect on particle levels.

Column 5 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. The likelihood of an absence falls by 0.15 percentage point as prior-day PM2.5 increases over the 3 to 50 μg/m^3 range, only to grow as PM2.5 increases beyond 100 μg/m^3. A shift from 200 to 400 μg/m^3 raises the absence probability by 0.40 percentage point.

The non-monotonicity in the pollution-absence relationship in our setting can be seen directly in the data, in Figure 4. Panels (a) and (b) report the absence rate over prior-day PM2.5 bins of width fixed at 20 or 30 μg/m^3, e.g., in (a), 0-20, 20-40, etc (with varying density). Absence rates fall over the first three or four bins and then rise. To highlight the relationship at lower PM2.5, panel (c) shows the absence rate against percentiles of the PM2.5 distribution, with absence rates decreasing up to the 40th percentile, or 64 μg/m^3, and increasing beyond this level (panel (d)). Panels (e) and (f) show the same absence pattern against percentile of the distribution of PM2.5 residuals, after partialling out co-variation with other absence shifters in the model, in particular, season and weather.

The parametric specification in columns 6 and 7 of Table 2, in which we include linear, quadratic and cubic terms in prior-day PM2.5, similarly yields a non-monotonic pollution-absence relationship. According to the 2SLS estimates of column 7, shifts from 100 to 200 μg/m^3 and from 200 to 400 μg/m^3 raise the absence probability by 0.32 and 1.36 percentage point, respectively. Again, estimated marginal effects are lower under OLS.[29]

Heterogeneity. Table 3 implements the 2SLS estimator of the prior-day severe PM2.5 dummy (and same-day blue-sky control) on separate subsamples based on: (1) the time elapsed since first enrolling at the school; (2) academic year; (3) nationality group; (4) age group; and (5) quintile of the distribution of individual absence rates across the 6,545 children in the sample, i.e., over 80th percentile absentee, 60th to 80th percentile, etc.[30] As a less flexible alternative to this subsample analysis, Table 4 reports on 2SLS regressions

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

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

implemented on the full sample but now interacting the PM2.5 dummies with specific time or child characteristics. The time-child specific PM2.5 covariates are instrumented with corresponding interactions of fitted ventilation-induced PM2.5, its square and its cube. We also show OLS estimates.

Alternative estimates in Tables 3 and 4 suggest that Chinese nationals display lower absence responses to severe PM2.5 than US/Canadian nationals. In, columns 3 and 4 of Table 4, p-values for tests of equal responses for these two nationality groups are 0.002 (OLS) and 0.178 (2SLS, generally less precise). Both flexible and less-flexible implementations indicate that children who exhibit higher absenteeism overall are also more sensitive to PM2.5. The estimated coefficient on the severe PM2.5 dummy increases as we separately consider subsamples of children in higher absenteeism quintiles (Table 3, column 5). We find some evidence that the pollution-absence response was lower in the sample's later years compared to earlier years (column 2 of both Tables 3 and 4). This is consistent with parents over the years feeling increasingly reassured of their children attending school when PM2.5 is severe, given the defensive technology and procedures in place.

Moreover, Table 3 suggests that the absence sensitivity to severe PM2.5: (i) is similar in the first semesters of enrollment compared with subsequent semesters (column 1), and (ii) lower among 5-8 and 9-12 year-olds compared with younger and older children (column 4). An adverse impact of pollution on child health may not necessarily drive an absence (Zhang et al., 2018). If the cost of staying at home is higher for pre-teen children than for teenagers, through differential home care demands say, then it is conceivable that the pre-teen absence rate is less sensitive to PM2.5 even if their health is more susceptible to pollution than that of teenagers.

Figure 5 plots the heterogeneous absence response to PM2.5 by nationality group, age group and absenteeism quintile estimated in Table 3. It is possible that some of these results reflect differences in time outdoors, particularly on weekends when parents have more control. For example, US parents might allow more outdoor play than Chinese parents, or parents may be more able to keep 5 to 12 year-olds inside compared with teenagers. To control for this, we can focus on school days on Tuesday to Fridays, which are more distant from the weekend. Figure A.4 shows estimates when we drop Mondays from the estimation sample. The patterns are very similar to those documented above.

Stratifying by enrollment duration. The above analysis seeks to infer the causal effect of PM2.5 on absences for the population of children enrolled at these schools. There may be a subpopulation of children for whom enrollment duration responds to the degraded environment. Families with higher adaption costs might have shorter residence, or families planning to stay less time may tolerate higher absenteeism for their children. Table 5 describes how the PM2.5-absence relationship, as well as the absence level, varies by enrollment duration, across three columns: (1) 931 children who departed within one year from first enrolling at the school, (2) 957 children who departed between one and two years from arrival, and (3) 1,893 children enrolled beyond two years. We cannot assign an enrollment duration type (1) to (3) to children enrolled for less than two years when our sample period ends. We also report how the PM2.5-absence relationship varies by time since first enrolling, across three rows. We report 2SLS estimates for alternative PM2.5 specifications (non-parametric or parametric) and implementations (flexibly by type subsample or on the full sample, interacting PM2.5 with type).

We find that the PM2.5-absence relationship tends to be steeper, and the overall absence rate higher, for children with enrollment duration up to one year (all panels, row 1, column 1), or for children with enrollment duration 1-2 years in their second and final year (panel B, row 2, column 2). For some of these children, enrollment—as a proxy for residence in China—may have been short due to costly adaptation.[31]

Column 3 of the table, describing children with enrollment duration beyond two years, indicates that for a majority of children a 100 to 200 $\mu g/m^3$ PM2.5 shift is associated with an absence rate increase of about 0.5 percentage point, or 10% of the subsample mean (column 3, panels C and D). Moreover, this relationship is quite stable over their enrollment period—year 1, year 2, year 3 on. This is interesting as one might have expected a more gradual adaptation, with the elasticity to pollution diminishing over

[31] We thank a reviewer for pointing out that even for the short-stay children, higher absences need not be due to costly adjustment; it may simply reflect greater tolerance of absences by their parents, the most transitory workers.

time. Estimates remain stable and tend to be slightly larger if we restrict the estimation samples to non-Chinese (Table A.1).

Finally, we checked whether student turnover was roughly steady over the sample period, or whether departure (and arrival) rates changed markedly in the aftermath of two more polluted winters, in 2013 and 2014, compared to earlier winters. We do not observe clear evidence of the latter. Table A.2 reports that departure rates in the last quarter of the academic years following the more polluted 2013 and 2014 winters was not significantly higher. Similarly, the arrival rate in the 2013 and 2014 July-September quarters, when a new academic year started, did not deviate from its long-term trend. Specifically, departures and arrivals are similar in 2013 compared to 2012 (each about 600 per last or first quarter).

Robustness. Tables 6, A.3 and A.4 show many robustness tests. We vary the estimation sample, e.g., do not drop the very high absence days; drop children who arrived after 2012, in the aftermath of winter 2013; or drop the second and subsequent absence day within absence spell. We vary the set of controls, e.g., control for temperature with granular bins 3 °C wide; add week-of-year dummies for finer seasonal controls; or interact year-month fixed effects with school-division fixed effects. We vary the set of excluded instruments. Estimates are robust and precise across all variants. Dropping the second and subsequent absence day within absence spell lowers estimates (Table 6, column 7).

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

More prolonged pollution exposure. We now enrich the lag structure 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 absence probability for alternative: PM2.5 measures (non-parametric or parametric); distributed lag models (lagged exposure coefficients disciplined or not); identifying restrictions (all measured PM2.5 variation or only that induced by atmospheric ventilation); and estimation samples (full sample or specific subsamples). Estimated responses tend to be higher: under 2SLS than OLS, particularly for models with less lags; higher for US/Canadian than for Chinese children; and higher for children who generally miss school the most. Precision is lower under 2SLS than OLS, and for models with more lags.

Panels A, C and E of Table 7 characterize pollution at each lag by a dummy indicating 24-hour PM2.5 in excess of 200 μg/m^3 (all models include a concurrent blue-sky PM2.5 control). For $P = 13$, for example, a large shift in exposure over the preceding 13 days, from 0 to 13 days of severe PM2.5, raises the absence probability by: 0.9 percentage point in the full sample (panel A, right and Figure 6(b)); 1.9 percentage point among US/Canadian children (panel C, left); and 2.8 percentage points for children in the top quintile of the absenteeism distribution (panel C, right).[32]

To quantify the empirical importance of PM2.5 fluctuations around a severe threshold at explaining absences overall, we 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. As shown in the columns labeled "Absence counterfactual," in-sample severe PM2.5 variation explains considerably less than one percentage point—less than one-sixth—of absences in the overall child population. For $P = 13$ for example, truncating the right tail of the 24-hour PM2.5 distribution at 200 μg/m^3 would lower the overall absence rate by 0.1 percentage point (panel A, right), and by 0.2, 0.3 and 0.3 percentage point for sensitive groups

[32] 2SLS estimates based on a UDL(13). We instrument for PM2.5 at daily lag p using fitted ventilation-induced PM2.5, its square and its cube at daily lag p (up to $P = 13$ lags). Figure 6, panel (b) reports on models with other P lags, and panel (d) reports on a relatively smoother PDL$(P, 2)$.

US/Canadian, top quintile absenteeism and short duration children, respectively (panels C, left; C, right; E, left). An alternative definition of severe PM2.5 in panel D, using a threshold of 100 rather than 200 μg/m^3 at each daily lag, suggests that truncating PM2.5 at 100 μg/m^3 would reduce absences by 1.1 and 1.5 percentage point for US/Canadian and top quintile absenteeism, respectively.

Panel B of Table 7 specifies daily lags of 24-hour PM2.5, its square and its cube. A sizable shift in week-long exposure, from 100 to 200 μg/m^3 sustained over 7 days, raises the probability of an absence by 1.5 percentage point (panel B, right, $P = 7$).[33] 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 child 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 Discussion

We find that the severity of particle pollution drives school absences in a 1,234-school day panel of 6,545 children attending international schools in north China. These are schools that have been willing and able to respond defensively to the dire state of air quality. A 2SLS model with 14 lagged days of exposure indicates that the incidence of absences is 0.9 percentage point higher in the wake of daily PM2.5 exceeding 200 μg/m^3 *two weeks* in a row compared to a less polluted fortnight in which daily PM2.5 remains below 200 μg/m^3 throughout (95% CI = [0.3,1.5]). A cubic PM2.5 specification, similarly allowing for a delayed response and identified off exogenous shifts in atmospheric ventilation, indicates that raising the preceding fortnight's dose from a constant 100 μg/m^3 to a constant 200 μg/m^3—a sizable and sustained variation in dose—raises the absence probability by 1.9 percentage point (95% CI = [1.2,2.7]).

[33] 2SLS estimates based on a PDL(7,2). The caption to the table describes the smoothness constraints. Denoting PM2.5 at 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 $\sum_{p=1}^{7}(200-100)\beta_{1p} + (200^2-100^2)\beta_{2p} + (200^3-100^3)\beta_{3p}$.

Such illustrative responses of +0.9 and +1.9 percentage point, amounting to +14% and +31% over a sample mean absence rate of 6.2%, 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, particle pollution still explains only 0.1 to 0.4 absence among 6.2 overall absences per 100 school days. It is possible that the generally high levels of ambient PM2.5 in north China 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. This 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 is that the educated population examined here is able to adapt and cope. Life shifts 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. We hope that our study of pollution and absences, moderated by defensive behavior, serve as a benchmark for school administrators in polluted middle-income countries.

The lower absence response to PM2.5 that we estimate among Chinese nationals compared to 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 and child behavior. It is also consistent with lower PM2.5 exposure by Chinese children, for instance, if non-Chinese parents allow their children more time outdoors, at least for the late afternoon hours of the day when they are not in school.[34] That estimates are robust to dropping Mondays from the estimation sample suggests that differences in outdoor time during weekends are not driving the heterogeneous elasticities. Another possibility is that Chinese parents might be less tolerant of their children missing school, yet the similar absence *levels* for Chinese and non-Chinese in our sample seems at

[34] Children at school receive similar treatment regardless of their nationality. School starts at 8 am and ends at 3 pm or later, if the child attends extra-curricular activities or extra tuition, as is common.

odds with this interpretation. The pattern is 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. Except for a minority of children who depart within one year of first enrolling, 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. One might have expected the elasticity of pollution diminishing over time, through more gradual adaptation, or growing over time, if a health deterioration were detectable over the time frame.

Subsequent research can attempt to investigate the different mechanisms that give rise to the substantial heterogeneity documented here, including differences in outdoor play outside of school hours and the ability to cope with health shocks. We observe a markedly stronger absence response to PM2.5 among students who generally miss school the most. The heterogeneity in both the absence level and the response to pollution among a fairly similar socioeconomic group suggests that heterogeneity in a wider population, and the resulting inequality in economic outcomes, is likely to be at least as large.

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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 an enrolled child by school day pair (child-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 in north China, 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, 2SLS or Probit**

Dependent variable is 1 (100%) if the child is absent, & 0 otherwise. Marginal effects are thus reported in percentage points.	(1) Severe prior day **OLS**	(2) Severe prior day **Probit**	(3) Severe prior day **2SLS**	(4) Severe past 3 d **OLS**	(5) Spline function **OLS**	(6) Cubic prior day **OLS**	(7) Cubic prior day **2SLS**
Prior-day PM2.5 > 200 μg/m^3,	0.25***	0.31***	0.88***				
24-hour mean (yes=1)	(0.06)	(0.06)	(0.12)				
Same-day PM2.5 < 50 μg/m^3,	0.07*	0.06	0.31***	0.06			
at 6 am (yes=1)	(0.04)	(0.04)	(0.08)	(0.04)			
Past 3 days PM2.5 > 200 μg/m^3,				0.08**			
count of days				(0.03)			
Prior-day PM2.5 ($\times$100 μg/m^3)						-0.51***	-1.35***
						(0.13)	(0.34)
Prior-day PM2.5 squared						0.29***	0.78***
						(0.08)	(0.24)
Prior-day PM2.5 cubed						-0.04***	-0.09**
						(0.01)	(0.04)
Impact of prior-day PM2.5 shift:							
From 3 to 50 μg/m^3					-0.15*	-0.17***	-0.45***
					(0.09)	(0.04)	(0.11)
From 50 to 100 μg/m^3					-0.09	-0.07***	-0.17***
					(0.06)	(0.02)	(0.04)
From 100 to 200 μg/m^3					0.13*	0.10***	0.32***
					(0.07)	(0.04)	(0.09)
From 200 to 400 μg/m^3					0.40***	0.42***	1.36***
					(0.14)	(0.12)	(0.32)
Observations	2,302,148	2,302,148	2,293,808	2,257,025	2,354,948	2,354,948	2,349,223
No. of children	6,439	6,439	6,439	6,439	6,439	6,439	6,439
Regressors (other than child FE)	119	119	119	119	121	120	120
R-squared (within)	0.009		0.009	0.009	0.009	0.009	0.009
First-stage F-statistic			723,972				85,873
Mean value of dependent var. (%)	6.19	6.19	6.19	6.20	6.18	6.18	6.18

Notes: The table shows estimates for 4 OLS LPM regressions, 2 2SLS LPM regressions and 1 probit. The sample consists of all children enrolled at three international schools in north China, over a combined period from September 2008 to December 2014. An observation is an enrolled child by school day. The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise, so marginal effects of PM2.5 on the probability of an absence are reported in percentage points (for the probit we report marginal effects too). In the linear spline specification of column 5, we set three knots at 50, 100 and 200 μg/m^3 and, for brevity, omit the four estimated slopes, reporting only the impact of specific PM2.5 shifts. 2SLS estimates instrument for measured PM2.5 (both non-parametric and parametric specifications) using PM2.5 fitted by atmospheric ventilation conditions (note 23) and the square and cube of these ventilation-induced fitted values. Controls include weather, child age bins (width 1 year), bins for the first 2 semesters of enrollment, child fixed effects (FE), year-month FE, day-of-week FE, bins for days near vacations/breaks and near short holidays. Weather controls are flexible functions of temperature, relative humidity and rain observed on the previous day and at 6 am on the day (note 20). 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: A non-parametric PM2.5 specification with **heterogeneous effects**, estimated by **2SLS**, implemented 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	1.15*** (0.27)				
Mean value of DV (%)	6.35				
181 to 360 days from first enrolling	0.52 (0.35)				
Mean value of DV (%)	6.35				
Over 360 days from first enrolling	0.85*** (0.14)				
Mean value of DV (%)	6.11				
Academic year 2011/12 or before		1.35*** (0.17)			
Mean value of DV (%)		6.07			
Academic year 2012/13 onward		0.24 (0.17)			
Mean value of DV (%)		6.33			
Nationals of US/Canada			1.08*** (0.23)		
Mean value of DV (%)			5.96		
Nationals of Europe			1.03*** (0.23)		
Mean value of DV (%)			6.69		
Nationals of Japan/Korea/S'pore			0.93*** (0.23)		
Mean value of DV (%)			4.33		
Nationals of China			0.15 (0.39)		
Mean value of DV (%)			6.85		
Nationals of other countries			0.75** (0.32)		
Mean value of DV (%)			6.99		
Children aged up to 4 years				1.46** (0.74)	
Mean value of DV (%)				10.92	
Children aged 5 to 8 years				0.25 (0.23)	
Mean value of DV (%)				5.54	
Children aged 9 to 12 years				0.51*** (0.19)	
Mean value of DV (%)				4.52	
Children aged 13 to 16 years				1.52*** (0.22)	
Mean value of DV (%)				6.31	
Children aged 17 years and over				1.62*** (0.42)	
Mean value of DV (%)				10.09	
Children in absenteeism quintile 1					0.46*** (0.15)
Mean value of DV (%)					1.29
Children in absenteeism quintile 2					0.63*** (0.19)
Mean value of DV (%)					2.94
Children in absenteeism quintile 3					0.75*** (0.24)
Mean value of DV (%)					4.88
Children in absenteeism quintile 4					1.10*** (0.31)
Mean value of DV (%)					7.56
Children in absenteeism quintile 5					1.58*** (0.41)
Mean value of DV (%)					15.62

Notes: The table shows estimates for 20 2SLS LPM regressions, separately implemented on subsamples defined on: (1) the time elapsed since first enrolling at the school, (2) academic year, (3) nationality, (4) age, and (5) overall absenteeism quintile. An observation is a child by day. The dependent variable (DV) is 1 (100%) if the child is absent on the day, and 0 otherwise. Controls include a dummy for PM2.5 < 50 μg/m^3 at 6 am (same-day blue-sky control), weather, child age bins (width 1 year), bins for the first 2 semesters of enrollment (except in column 1), child FE, year-month FE, day-of-week FE, bins for days near vacations/breaks and 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: A non-parametric PM2.5 specification with **heterogeneous effects**, estimated by **OLS or 2SLS**, implemented on the **full sample**

Interaction with PM2.5	Academic year		Nationality		Absenteeism quintile	
Dependent variable is 1 (100%) if the child is absent, and 0 otherwise.	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Prior-day PM2.5>200 μg/m^3 (yes=1)	0.14*	1.13***	0.51***	1.50***	-0.24***	0.03
	(0.08)	(0.16)	(0.15)	(0.27)	(0.08)	(0.15)
... × academic year 2012/13 onward	0.22*	-0.60***				
	(0.12)	(0.19)				
... × national of US/Canada			-0.10	-0.40		
			(0.19)	(0.32)		
... × national of Europe			-0.28	-0.79**		
			(0.19)	(0.32)		
... × national of Japan/Korea/S'pore			-0.38*	-1.04***		
			(0.20)	(0.33)		
... × national of China			-0.78***	-0.90**		
			(0.24)	(0.41)		
... × child in absence rate quintile 2					0.20*	0.35**
					(0.11)	(0.17)
... × child in absence rate quintile 3					0.28**	0.63***
					(0.13)	(0.21)
... × child in absence rate quintile 4					0.78***	1.21***
					(0.16)	(0.27)
... × child in absence rate quintile 5					1.28***	2.25***
					(0.23)	(0.39)
Observations	2,302,148	2,293,808	2,278,775	2,270,545	2,302,148	2,293,808
Number of children	6,439	6,439	6,267	6,267	6,439	6,439
Mean value of dependent variable (%)	6.19	6.19	6.15	6.15	6.19	6.19

Notes: The table shows estimates for 3 OLS and 3 2SLS LPM regressions implemented on the full sample, interacting both PM2.5 dummies (prior-day severe and same-day blue-sky) with: a dummy for academic year 2012/13 and beyond, in columns 1 and 2; or the child's nationality group, in columns 3 and 4; or the student's overall absenteeism quintile, in columns 5 and 6. The reference category is: a school day in academic year 2011/12 or before, in columns 1 and 2; or a national of other countries, in columns 3 and 4; or the first absenteeism quintile, in columns 5 and 6. An observation is a child by day. The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise. Controls include weather, child age bins (width 1 year), bins for first 2 semesters of enrollment, child FE, year-month FE, day-of-week FE, bins for days near vacations/breaks and 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: Pollution-absence relationship by (resolved) **enrollment duration** at the school and **period of enrollment**: Alternative non-parametric/parametric PM2.5 specifications, estimated by **2SLS**, implemented flexibly by subsample/on the full sample

DV is 1 if child is absent	Enrollment duration at school (time-invariant child characteristic)		
Time since first enrolling (time-varying child characteristic)	**C1**: Up to 1 year	**C2**: Between 1 and 2 years	**C3**: More than 2 years
Panel A: Impact of prior-day PM2.5 > 200 $\mu g/m^3$ on absence probability, and implement separately on each of six time-varying child type subsamples (flexible estimation as in Table 3).			
R1: Year 1 of enrollment	2.16*** (0.57)	0.81 (0.53)	0.57* (0.33)
Observations	120,793	148,992	289,488
No. of children	931	957	1,893
Mean value of DV (%)	7.42	7.61	5.84
R2: Year 2 of enrollment		0.70 (0.53)	0.88*** (0.32)
Observations		131,160	354,298
No. of children		1,068	2,265
Mean value of DV (%)		8.54	5.98
R3: Years 3 on of enrollment			0.93*** (0.17)
Observations			1,007,835
No. of children			3,231
Mean value of DV (%)			5.89
Panel B: Impact of prior-day PM2.5 > 200 $\mu g/m^3$ on absence probability, and implement on the full sample interacting PM2.5 with six time-varying child types (full sample estimation as in Table 4).			
R1: Year 1 of enrollment	1.60*** (0.45)	0.70 (0.46)	0.90*** (0.28)
R2: Year 2 of enrollment		1.85*** (0.45)	0.74*** (0.26)
R3: Years 3 on of enrollment			0.80*** (0.16)
Panel C: Cubic prior-day PM2.5 specification, impact of 100 to 200 $\mu g/m^3$ shift on absence, and implement separately on each of six time-varying child type subsamples.			
R1: Year 1 of enrollment	1.40*** (0.44)	0.60 (0.38)	0.64** (0.29)
R2: Year 2 of enrollment		0.40 (0.42)	-0.05 (0.23)
R3: Years 3 on of enrollment			0.39*** (0.13)
Panel D: Cubic prior-day PM2.5 specification, impact of 100 to 200 $\mu g/m^3$ shift on absence, and implement on full sample interacting with six time-varying child types.			
R1: Year 1 of enrollment	1.26*** (0.44)	0.72** (0.36)	0.67** (0.31)
R2: Year 2 of enrollment		0.54 (0.40)	0.26 (0.23)
R3: Years 3 on of enrollment			0.24* (0.14)

Notes: Panels A and C each report estimates for 6 2SLS LPM regressions, separately implemented on six subsamples jointly defined on the child's enrollment duration ($\leq$ 1 y, 1 to 2 y, and > 2 y) and enrollment period (y 1, y 2, y 3 and beyond) at the school. Panels B and D each report estimates for 1 2SLS LPM regression implemented on the full sample, interacting PM2.5 covariates with child type. Children enrolled for no more than two years at the end of the sample period (6/2014 for schools 1 and 3, 12/2014 for school 2) are omitted from the estimation samples as we cannot assign an enrollment duration type. PM2.5 covariates are the prior-day severe and same-day blue-sky dummies in panels A and B, and prior-day PM2.5, its square and its cube in panels C and D. An observation is a child by day. The dependent variable (DV) is 1 (100%) if the child is absent on the day, and 0 otherwise. Controls follow Table 2 (weather, age, first 2 semesters, child, year-month, day-of-week, around vacations/breaks and short holidays) and additionally include enrollment periods (y 1, y 2, y 3 and beyond) in levels. Other notes to Table 2 apply.

Table 6: Robustness to sample, based on a non-parametric PM2.5 specification estimated by OLS or 2SLS

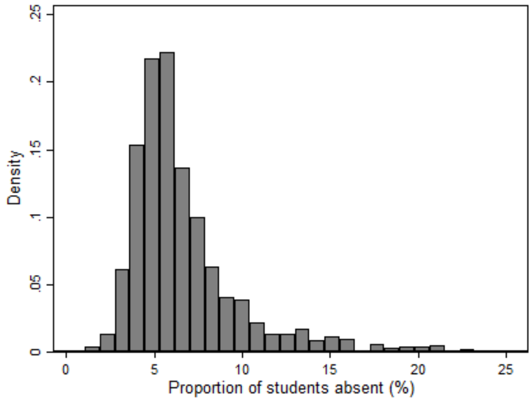
Robustness test	Baseline Table 2 Col. 1&3	(1) Full sample	(2) Drop zero absence days	(3) Drop > 50% absence days	(4) Drop arrivals after 2012	(5) Drop first month enroll	(6) Drop IB exam period	(7) All days of absence spell
Panel A: Estimation by **OLS**								
Prior-day PM2.5 > 200 μg/m^3,	0.25***	0.15**	0.22***	0.25***	0.24***	0.25***	0.25***	0.19***
24-hour mean (yes=1)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Observations	2,302,148	2,317,591	2,285,764	2,310,517	2,090,403	2,210,632	2,266,356	2,245,573
R-squared (within)	0.009	0.012	0.009	0.010	0.009	0.009	0.010	0.006
Mean value of dependent var. (%)	6.19	6.53	6.28	6.35	6.26	6.30	6.22	3.83
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 > 200 μg/m^3,	0.88***	0.77***	0.88***	0.92***	0.92***	0.88***	0.87***	0.49***
24-hour mean (yes=1)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.09)
Observations	2,293,808	2,309,251	2,277,424	2,302,177	2,082,063	2,202,392	2,258,016	2,237,554
R-squared (within)	0.009	0.012	0.009	0.010	0.009	0.009	0.010	0.006
First-stage F-statistic	723,972	798,389	671,624	784,586	741,517	736,581	629,235	454,591
Mean value of dependent var. (%)	6.19	6.53	6.28	6.35	6.26	6.30	6.22	3.83
Number of children	6,439	6,439	6,439	6,439	5,131	6,409	6,439	6,439
Number of regressors	119	119	119	119	119	119	119	119

Notes: The table shows estimates for 7 OLS (Panel A) and 7 2SLS (Panel B) LPM regressions. The point of departure are the OLS and 2SLS non-parametric PM2.5 specifications of Table 2, columns 1 and 3, reproduced in the leftmost column. An observation is a child by 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 children who arrived at the school after 2012. Column 5 drops observations pertaining to a child's 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 drops the second and subsequent adjacent absence days within each observed absence spell. The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise—except in column 7, where the dependent variable is 1 if the student initiates an absence spell on the day, and 0 otherwise. Controls include a same-day blue-sky dummy, weather, child age bins (width 1 year), bins for the first 2 semesters of enrollment, child FE, year-month FE, day-of-week FE, bins for days near vacations/breaks and short holidays. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

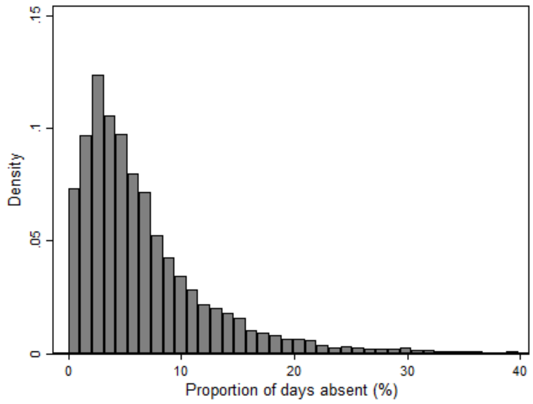
Table 7: Student absences and more prolonged pollution exposure: Non-parametric and parametric PM2.5 specifications, with P daily lags, estimated by OLS or 2SLS

Panel A: 24-h PM2.5 > 200 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)									
Lags in	OLS				2SLS				
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	2,302,148	0.25***	(0.06)	-0.03 pct pt	2,293,808	0.88***	(0.12)	-0.11 pct pt
3	2,244,013	0.32***	(0.10)	-0.04 pct pt	2,235,673	0.98***	(0.15)	-0.11 pct pt
7	2,098,126	0.06	(0.17)	-0.01 pct pt	2,079,319	0.57**	(0.24)	-0.07 pct pt
13	1,919,616	0.70***	(0.25)	-0.08 pct pt	1,890,331	0.89***	(0.31)	-0.11 pct pt
Panel B: 24-h PM2.5, PM2.5 squared, PM2.5 cubed (each lag) & Constrained exposure coefficients, PDL(P, 2)								
Lags in	OLS				2SLS			
model, P	Observations	Cumulative effect 100→200 μg/m^3		Absence counterf.: Truncate 100 μg/m^3	Obser-observ.	Cumulative effect 100→200 μg/m^3		Absence counterf.: Truncate 100 μg/m^3
3	2,288,191	0.21***	(0.06)	-0.06 pct pt	2,282,466	0.60***	(0.18)	-0.17 pct pt
7	2,142,304	0.53***	(0.10)	-0.10 pct pt	2,126,112	1.47***	(0.26)	-0.25 pct pt
13	1,953,199	1.15***	(0.18)	-0.26 pct pt	1,926,529	1.94***	(0.38)	-0.38 pct pt
Panel C: 24-h PM2.5 > 200 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)								
Lags in	2SLS: US/Canada nationality subsample				2SLS: 5th absenteeism quintile subsample			
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	561,238	1.08***	(0.23)	-0.13 pct pt	387,101	1.58***	(0.41)	-0.19 pct pt
3	545,398	1.26***	(0.30)	-0.15 pct pt	378,139	2.26***	(0.53)	-0.27 pct pt
13	458,352	1.92***	(0.60)	-0.23 pct pt	320,371	2.76**	(1.10)	-0.34 pct pt
Panel D: 24-h PM2.5 > 100 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)								
Lags in	2SLS: US/Canada nationality subsample				2SLS: 5th absenteeism quintile subsample			
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	561,238	0.45***	(0.16)	-0.18 pct pt	387,101	0.61**	(0.28)	-0.25 pct pt
3	545,398	0.69***	(0.25)	-0.28 pct pt	378,139	1.04**	(0.43)	-0.43 pct pt
13	458,352	2.75***	(0.64)	-1.11 pct pt	320,371	3.68***	(1.16)	-1.51 pct pt
Panel E: 24-h PM2.5 > 200 μg/m^3 (Yes=1, each lag) & Unconstrained exposure coefficients, UDL(P)								
Lags in	2SLS: Depart within 1 year of arrival				2SLS: Years 3 on of enrollment			
model, P	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No	Observations	Cumulative effect No→Yes all lags		Absence counterf.: PM2.5 always No
1	120,793	2.16***	(0.57)	-0.27 pct pt	1,007,835	0.93***	(0.17)	-0.11 pct pt
3	117,898	1.96***	(0.72)	-0.24 pct pt	982,382	1.30***	(0.22)	-0.15 pct pt
13	99,372	2.23	(1.54)	-0.26 pct pt	836,586	0.77*	(0.44)	-0.10 pct pt

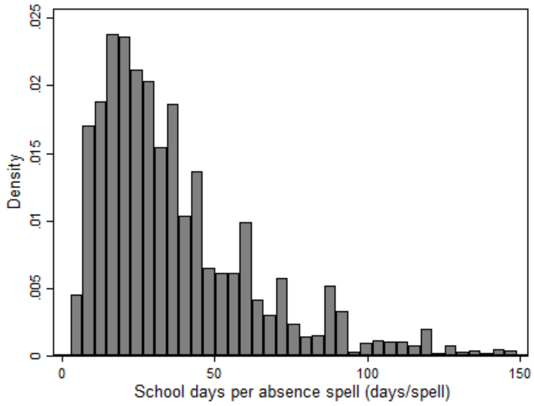
Notes: The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise. Distributed-lag LPM models, estimated by OLS (panels A and B, left) or 2SLS (otherwise), include P lags of the daily PM2.5 measure given by: (panels A, C and E) 1 if the respective 24-hour PM2.5 > 200 μg/m^3 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 24-hour PM2.5 level, its square and its cube. In panel B (cubic in PM2.5), 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 estimation sample to US/Canadian nationals, or to children in the top absenteeism quintile. Panel E restricts the sample to children who depart within one year of arrival, or to observations in Years 3 on of enrollment. An observation is a child by day. All notes, including a same-day blue-sky dummy, reported in Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.



(a) Absence rates, over school days

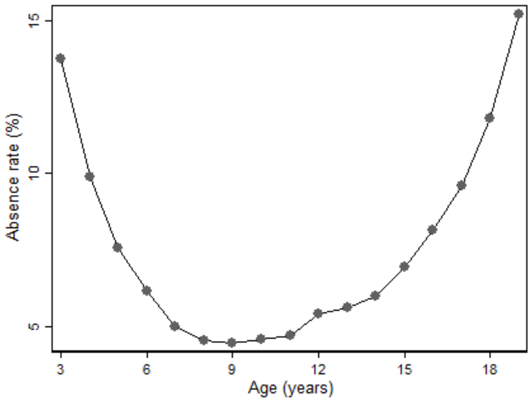


(b) Absence rates, across individual children

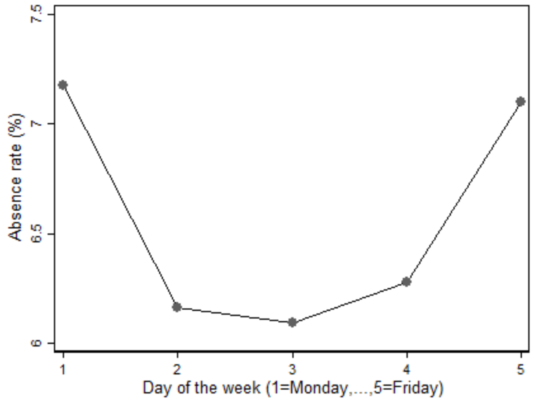


(c) School days per absence spell, across children

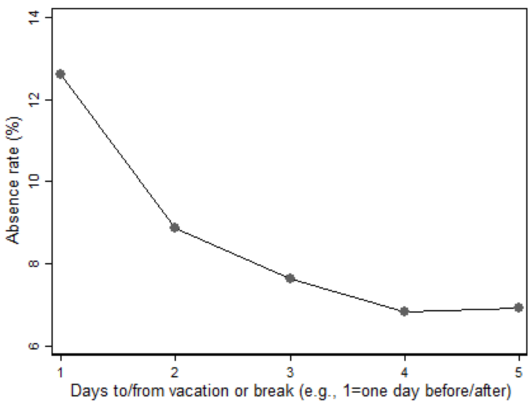
Figure 1: Distribution of absence rates: (a) over school days, and (b) across individual children in the sample (shown up to 40% for better visualization). Panel (c) reports the distribution across individuals of the ratio of a child's total school days to total absence spells (shown up to 150 days/absence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



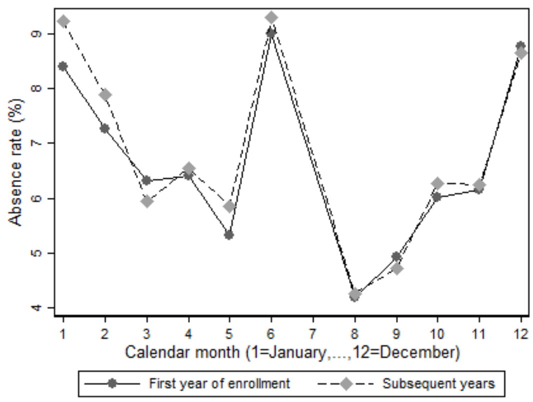
(a) By child age



(b) By day of the week

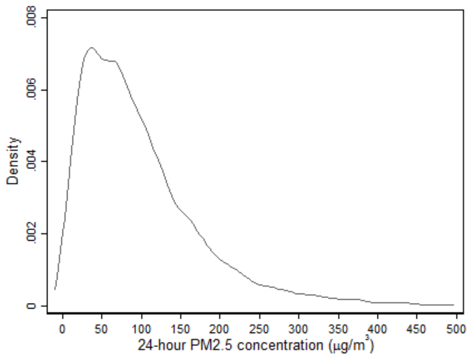


(c) By days to/from vacation or break

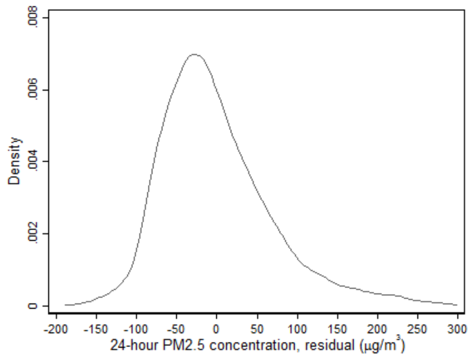


(d) By calendar month, by year of enrollment

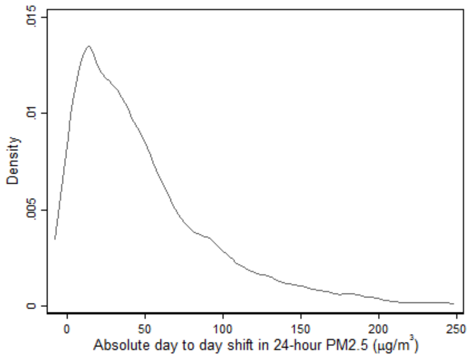
Figure 2: Absence rates over child-days in the sample: (a) by child age, (b) by day of the week, (c) by the number of days leading up to, or following, a vacation or break, and (d) by calendar month. In panel (d), we separately plot absence rates over the calendar months in a child's first year of enrollment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



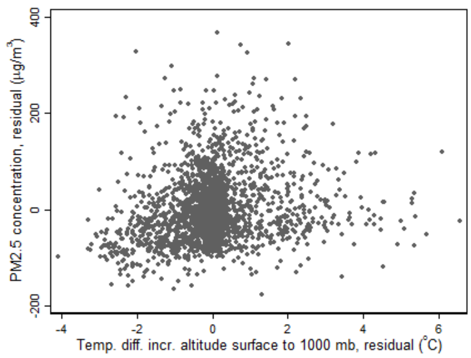
(a) PM2.5 distribution



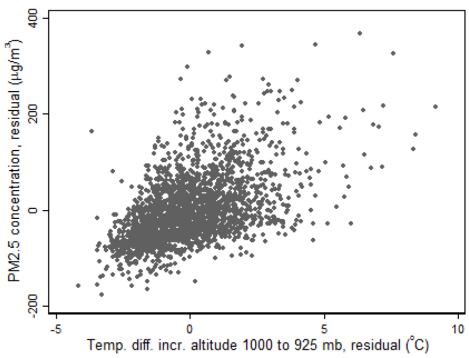
(b) PM2.5 distribution: Deaseasoned



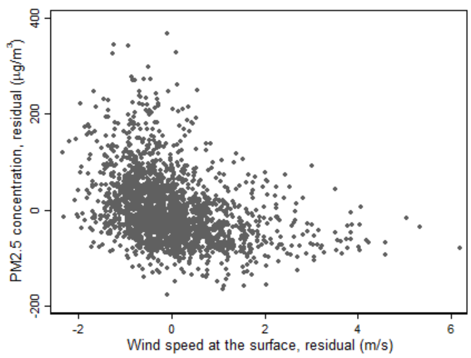
(c) Day to day shift (up or down) in PM2.5



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

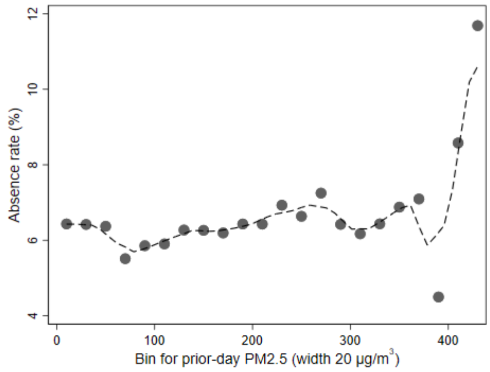


(e) PM2.5 & temp. inversion layer 2

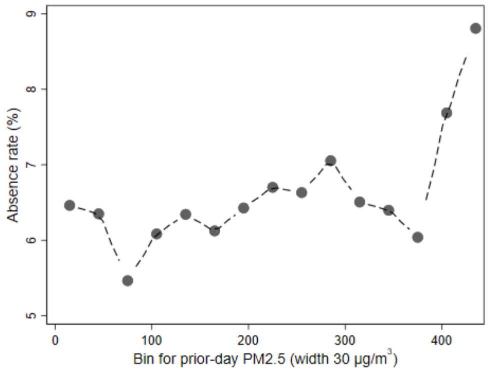


(f) PM2.5 & wind speed

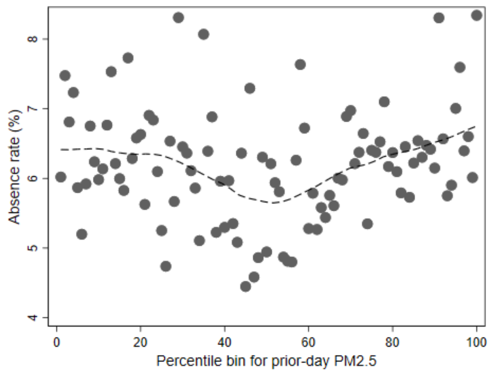
Figure 3: Variation in 24-hour mean PM2.5 concentration (μg/m^3) in the sample: (a) PM2.5 distribution (shown up to 500 μg/m^3 for better visualization); (b) residual PM2.5 distribution, once systematic temporal variation (year-month and day-of-week) is partialed out (shown up to 300 μg/m^3); (c) distribution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



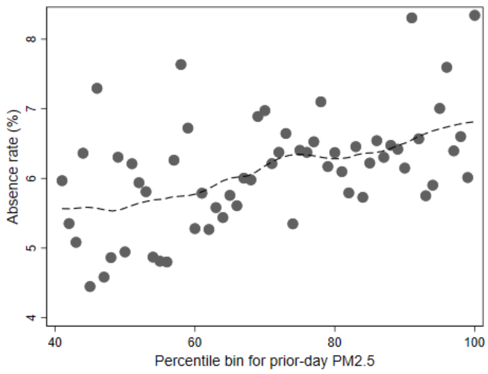
(a) PM bin 20 μg/m^3 wide



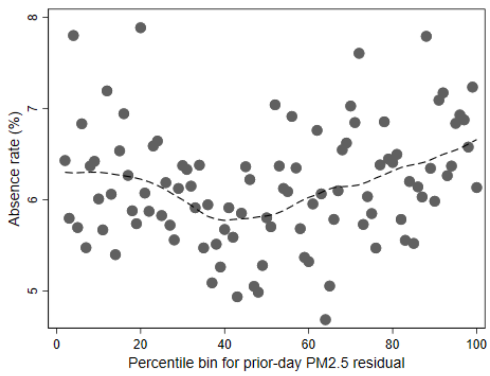
(b) PM bin 30 μg/m^3 wide



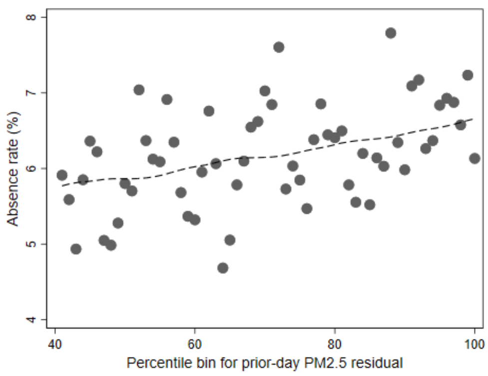
(c) PM centile: highlight low PM



(d) PM centile: 40th and above

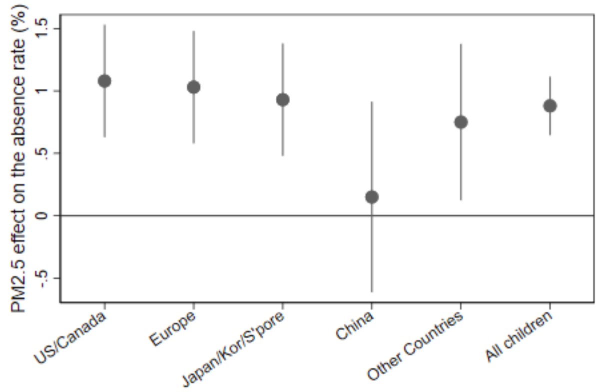


(e) PM residual centile: highlight low PM

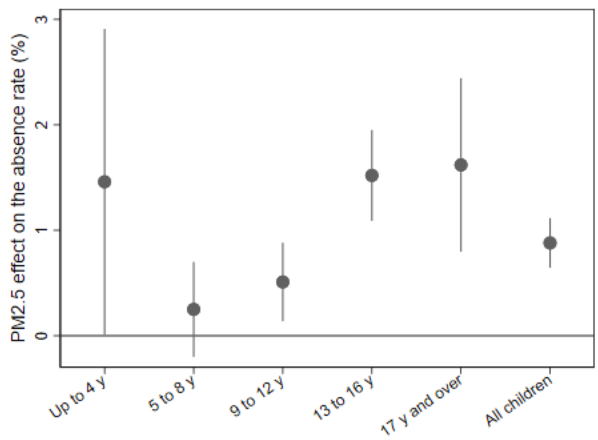


(f) PM residual centile: 40th and above

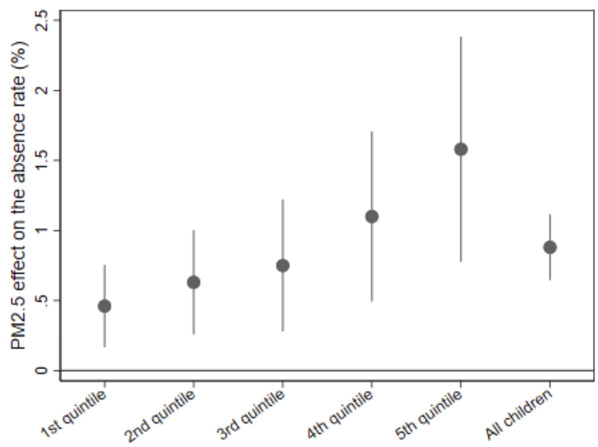
Figure 4: A non-linear pollution-absence relationship in the aggregated data. Panels (a) and (b) show absence rates against prior-day PM2.5 bins of, respectively, width 20 and 30 μg/m^3, labeled at the bin midpoint. Panels (c) and (d) show absence rates against prior-day PM2.5 percentiles. Panels (e) and (f) partial out co-variation with other absence shifters in the model prior to taking PM2.5 percentiles. We drop observations pertaining to a school day in which the child's school-division specific absence rate exceeds 30%.



(a) Heterogeneous effects over child's nationality

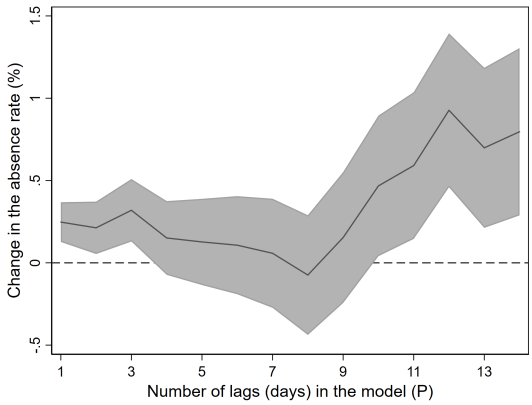


(b) Heterogeneous effects over child's age

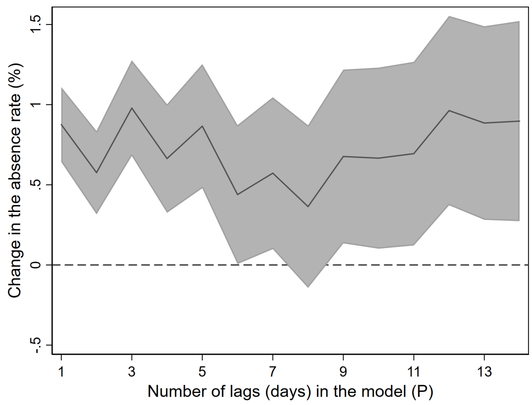


(c) Heterogeneous effects over child's absenteeism quintile

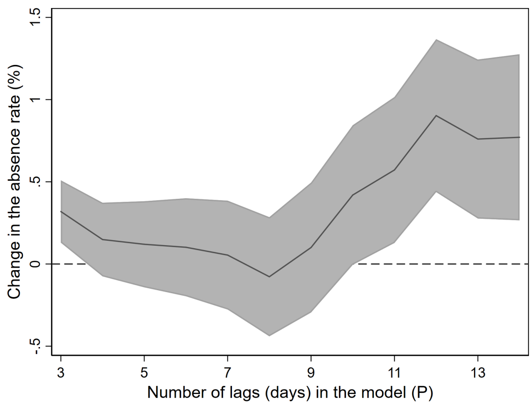
Figure 5: Heterogeneous sensitivity of absences to severe concurrent pollution, by child: (a) nationality, (b) age, and (c) absenteeism quintile. 95% confidence intervals on the effect of severe PM2.5 (defined as prior-day 24-hour mean > 200 μg/m^3) on the probability of an absence. All regressions include a same-day blue-sky control (a dummy for PM2.5 < 50 μg/m^3 at 6 am). Source: 2SLS estimates flexibly implemented separately by subsample, reported in columns 3 to 5 of Table 3; 2SLS estimate implemented on the full sample, reported in column 3 of Table 2.



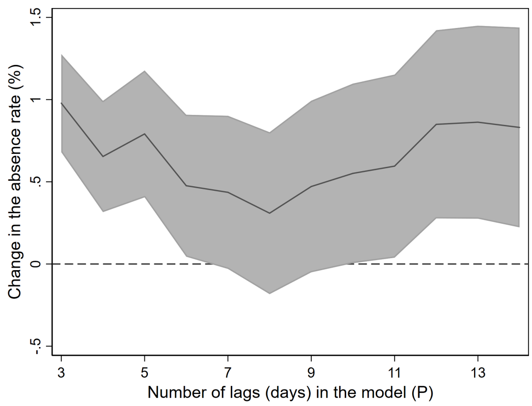
(a) Severe PM2.5, UDL(P), OLS



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



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



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

Figure 6: Cumulative impact of more prolonged PM2.5 exposure on the probability of an absence. The panels report estimates, for a severe PM2.5 dummy (24-hour mean > 200 μg/m^3) specification, of the cumulative effect on absences from P preceding days of severe PM2.5, relative to zero days of severe PM2.5. Panels (a) and (b) (resp., panels (c) and (d)) implement unconstrained UDL(P) (resp., quadratic PDL($P, 2$)) distributed lag models. Distributed lag models in panels (a) and (c) are estimated by OLS; those in panels (b) and (d) 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 notes reported in Table 2 apply.

A Appendix

Table A.1 reports the PM2.5-absence relationship, as well as the absence rate, by the child's enrollment duration at the school and by the time elapsed since first enrolling, among children of non-Chinese nationality. Table A.2 reports the evolution of student enrollment, departures and arrivals in the combined three-school sample, as well as the evolution of winter PM2.5, over the study period. Tables A.3 and A.4 report additional robustness tests, as explained in the text. The figures that follow further describe the data and are referenced in the text.

Table A.1: Pollution-absence relationship by (resolved) enrollment duration at the school and period of enrollment: Children of non-Chinese nationality only

DV is 1 if child is absent	Enrollment duration at school (time-invariant child characteristic)		
Time since first enrolling (time-varying child characteristic)	**C1**: Up to 1 year	**C2**: Between 1 and 2 years	**C3**: More than 2 years
Panel A: Impact of prior-day PM2.5 > 200 μg/m^3 on absence probability, and implement separately on each of six time-varying child type subsamples (flexible estimation as in Table 3).			
R1: Year 1 of enrollment	2.63*** (0.61)	0.67 (0.54)	0.73** (0.35)
Observations	104,592	135,170	263,290
No. of children	785	865	1,719
Mean value of DV (%)	7.32	7.33	5.75
R2: Year 2 of enrollment		0.55 (0.55)	1.05*** (0.34)
Observations		118,838	321,480
No. of children		948	2,056
Mean value of DV (%)		8.15	5.94
R3: Years 3 on of enrollment			1.02*** (0.18)
Observations			899,369
No. of children			2,908
Mean value of DV (%)			5.84
Panel B: Impact of prior-day PM2.5 > 200 μg/m^3 on absence probability, and implement on the full sample interacting PM2.5 with six time-varying child types (full sample estimation as in Table 4).			
R1: Year 1 of enrollment	2.01*** (0.48)	0.83* (0.47)	1.06*** (0.30)
R2: Year 2 of enrollment		1.59*** (0.45)	0.87*** (0.28)
R3: Years 3 on of enrollment			0.91*** (0.17)
Panel C: Cubic prior-day PM2.5 specification, impact of 100 to 200 μg/m^3 shift on absence, and implement separately on each of six time-varying child type subsamples.			
R1: Year 1 of enrollment	1.56*** (0.46)	0.58 (0.39)	0.66** (0.30)
R2: Year 2 of enrollment		0.65 (0.44)	0.21 (0.24)
R3: Years 3 on of enrollment			0.40*** (0.14)
Panel D: Cubic prior-day PM2.5 specification, impact of 100 to 200 μg/m^3 shift on absence, and implement on full sample interacting with six time-varying child types.			
R1: Year 1 of enrollment	1.41*** (0.47)	0.79** (0.37)	0.74** (0.32)
R2: Year 2 of enrollment		0.77* (0.42)	0.43* (0.24)
R3: Years 3 on of enrollment			0.26* (0.15)

Notes: This table replicates the analysis of Table 5 restricting estimation samples to children of non-Chinese nationality. Other notes to Table 5 apply, e.g., endogenous PM2.5 covariates are the prior-day severe and same-day blue-sky dummies in panels A and B, and prior-day PM2.5, its square and its cube in panels C and D.

Table A.2: Evolution of pollution and student enrollment, departures and arrivals

Calendar year	2009	2010	2011	2012	2013	2014
PM2.5 winter means						
January to March (μg/m^3)	79†	96	85	101	148	133
Feb 15 to Mar 31 (μg/m^3)	79†	104	114	98	131	152
Children enrolled in the last quarter before the summer	1,463‡	1,913	2,233	2,663	2,895	2,738
Children departing in the last quarter before the summer	258‡	327	355	597	633	621
Departure rate (%)	17.6‡	17.1	15.9	22.4	21.9	22.7
Children enrolled in the first quarter after the summer	1,587‡	2,223	2,522	2,656	2,883	984⋆
Children arriving in the first quarter after the summer	375‡	643	655	597	618	191⋆
Arrival rate (%)	23.6‡	28.9	26.0	22.5	21.4	19.4⋆

Notes: January to March are winter months during which particle levels are typically higher (though not exclusively high, e.g., PM2.5 averages 88 μg/m^3 between April and September). Departures typically peak at the end of the academic year, before the summer vacation, typically in June. Arrivals typically peak at the start of the academic year, after the summer vacation, typically in August. 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. †PM2.5 records are missing in 2009 until mid February. ‡2009 departures before the summer and arrivals after the summer are available for only one school. ⋆2014 arrivals after the summer are available for only one school.

Table A.3: Other robustness tests, based on a non-parametric PM2.5 specification estimated by OLS or 2SLS

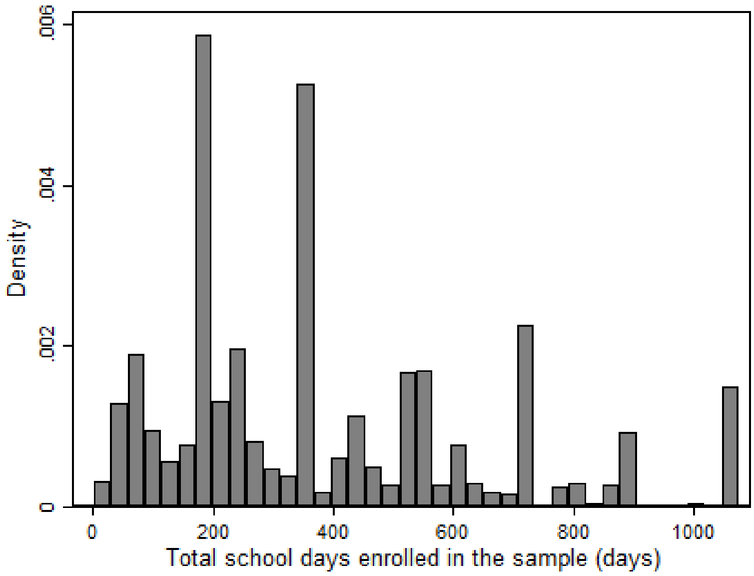
Robustness test		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Alternative controls W_t or α_t					Alternative instruments	
	Table 2 Col. 1&3	Temperature bins (3 °C)	Include week	Year-month × school-divis.	Trend × school-divis.	Include wind speed	$\hat{Z}$ w/o wind dir.	$\hat{Z}$ with 1-d lag for V
Panel A: Estimation by **OLS**								
Prior-day PM2.5 > 200 μg/m^3,	0.25***	0.25***	0.31***	0.26***	0.18***	0.25***		
24-hour mean (yes=1)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)		
Observations	2,302,148	2,302,148	2,302,148	2,302,148	2,302,148	2,299,533		
R-squared (within)	0.009	0.009	0.010	0.013	0.009	0.009		
Mean value of dependent var. (%)	6.19	6.19	6.19	6.19	6.19	6.19		
Panel B: Estimation by **2SLS**								
Prior-day PM2.5 > 200 μg/m^3,	0.88***	0.78***	0.76***	0.94***	0.64***	0.70***	0.86***	0.87***
24-hour mean (yes=1)	(0.12)	(0.12)	(0.14)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)
Observations	2,293,808	2,293,808	2,293,808	2,293,808	2,293,808	2,293,808	2,293,808	2,295,363
R-squared (within)	0.009	0.009	0.010	0.013	0.008	0.009	0.009	0.009
First-stage F-statistic	723,972	745,883	581,367	707,267	864,366	733,819	686,771	639,248
Mean value of dependent var. (%)	6.19	6.19	6.19	6.19	6.19	6.19	6.19	6.19
Number of regressors	119	131	163	567	91	120	119	119
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			

Notes: The table shows estimates for 5 OLS (Panel A) and 7 2SLS (Panel B) LPM regressions. The point of departure are the OLS and 2SLS non-parametric PM2.5 specifications of Table 2, columns 1 and 3, reproduced in the leftmost column. An observation is a child by day. The number of children is 6,439 in all regression samples. Controls include a same-day blue-sky dummy, weather, child age bins (width 1 year), bins for the first 2 semesters of enrollment, child FE, day-of-week FE, bins for days near vacations/breaks and short holidays. 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 20). Column 2 includes 51 week-of-year FE. Column 3 interacts year-month FE with school by division indicators. Column 4 replaces year-month FE with a quadratic trend interacted with school by division indicators, as well as 11 month-of-year FE. Column 5 includes prior-day 24-hour mean wind speed as an absence shifter (dropping wind speed from the exclusion restrictions). Column 6 drops wind direction when fitting ventilation-induced PM2.5, $\hat{Z}$. Column 7 includes 24-hour mean ventilation conditions on the day and one preceding day (not two) when fitting ventilation-induced PM2.5, $\hat{Z}$ (see note 23). The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

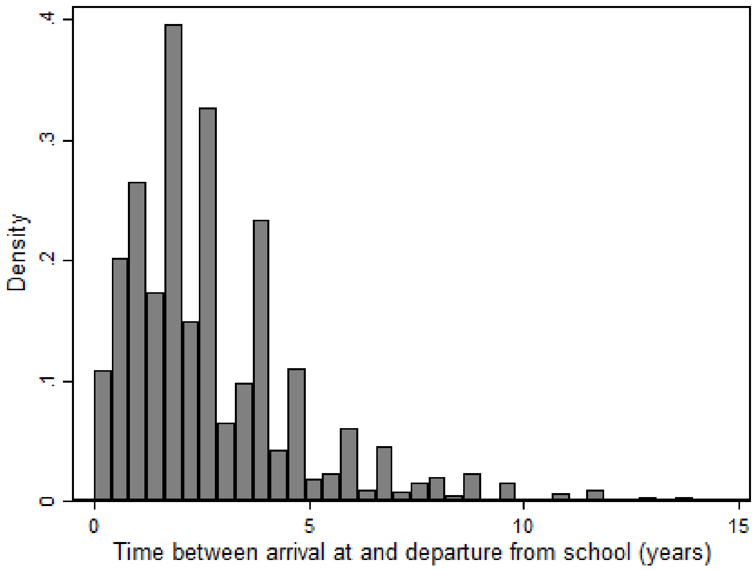
Table A.4: Other robustness tests, based on a parametric (cubic) PM2.5 specification estimated by OLS or 2SLS

Robustness test		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Alternative controls W_t or α_t					Alternative instruments	
	Table 2 Col. 6&7	Temperature bins (3 °C)	Include week	Year-month × school-divis.	Trend × school-divis.	Include wind speed	$\hat{Z}$ w/o wind dir.	$\hat{Z}$ with 1-d lag for V
Panel A: Estimation by **OLS**. For brevity, we only report the impact on the absence probability for specific prior-day PM2.5 shifts.								
From 100 to 200 μg/m^3	0.10***	0.11***	0.11***	0.11***	0.16***	0.10***		
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)		
From 200 to 400 μg/m^3	0.42***	0.46***	0.31**	0.46***	0.01	0.42***		
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)		
Observations	2,354,948	2,354,948	2,354,948	2,354,948	2,354,948	2,352,333		
R-squared (within)	0.009	0.009	0.010	0.013	0.008	0.009		
Mean value of dependent var. (%)	6.18	6.18	6.18	6.18	6.18	6.18		
Panel B: Estimation by **2SLS**. For brevity, we only report the impact on the absence probability for specific prior-day PM2.5 shifts.								
From 100 to 200 μg/m^3	0.32***	0.22**	0.51***	0.37***	0.29***	0.32***	0.22**	0.23**
	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)	(0.11)	(0.09)	(0.10)
From 200 to 400 μg/m^3	1.36***	1.48***	0.09	1.36***	0.68**	0.93***	1.69***	1.61***
	(0.32)	(0.33)	(0.34)	(0.32)	(0.33)	(0.35)	(0.32)	(0.34)
Observations	2,349,223	2,349,223	2,349,223	2,349,223	2,349,223	2,349,223	2,349,223	2,350,778
R-squared (within)	0.009	0.009	0.010	0.013	0.008	0.009	0.009	0.009
First-stage F-statistic	85,873	101,017	35,936	86,688	79,378	33,668	28,878	29,641
Mean value of dependent var. (%)	6.18	6.18	6.18	6.18	6.18	6.18	6.18	6.18
Number of regressors	120	132	164	568	92	121	120	120
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			

Notes: The table shows estimates for 5 OLS (Panel A) and 7 2SLS (Panel B) LPM regressions. The point of departure are the OLS and 2SLS parametric (cubic) PM2.5 specifications of Table 2, columns 6 and 7, reproduced in the leftmost column. An observation is a child by day. The number of children is 6,439 in all regression samples. Controls include weather, child age bins (width 1 year), bins for the first 2 semesters of enrollment, child FE, day-of-week FE, and bins for days near vacations/breaks and short holidays. 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 20). Column 2 includes 51 week-of-year FE. Column 3 interacts year-month FE with school by division indicators. Column 4 replaces year-month FE with a quadratic trend interacted with school by division indicators, as well as 11 month-of-year FE. Column 5 includes prior-day 24-hour mean wind speed as an absence shifter (dropping wind speed from the exclusion restrictions). Column 6 drops wind direction when fitting ventilation-induced PM2.5, $\hat{Z}$. Column 7 includes 24-hour mean ventilation conditions on the day and one preceding day (not two) when fitting ventilation-induced PM2.5, $\hat{Z}$ (see note 23). The dependent variable is 1 (100%) if the child is absent on the day, and 0 otherwise. Other notes to Table 2 apply. Standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

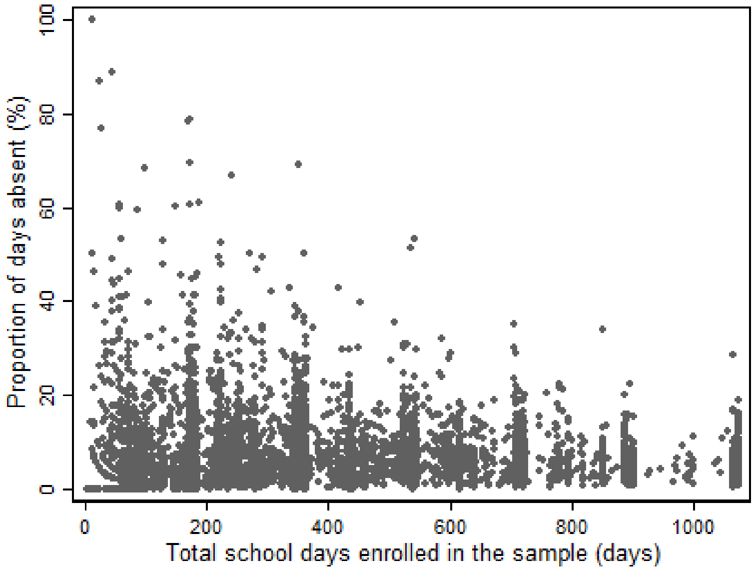


(a) Days enrolled in the sample, across students

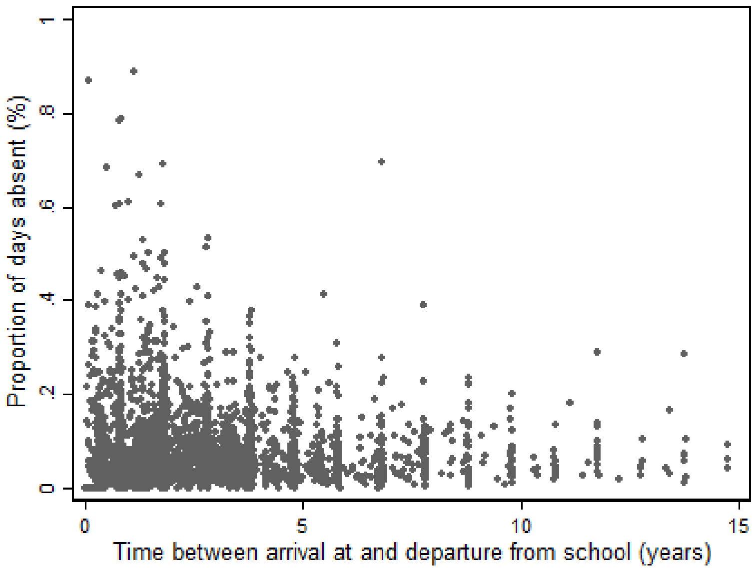


(b) Total duration at the school, across departed students

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

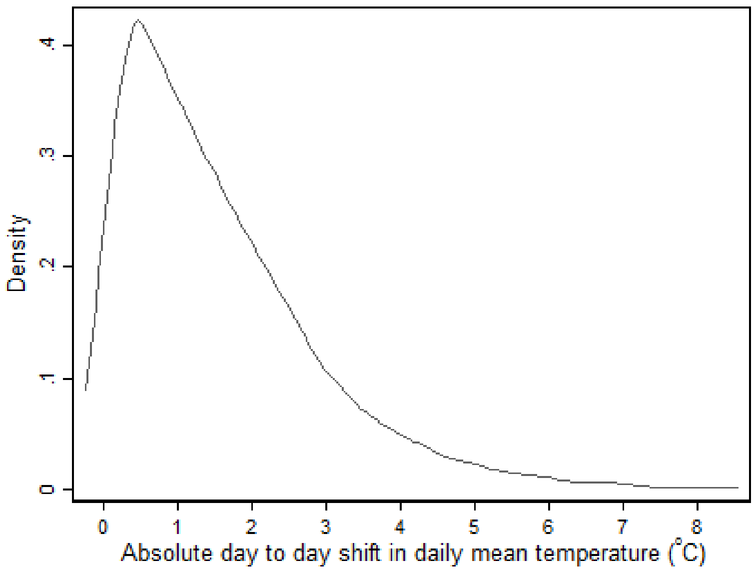


(a) Absence rate & days enrolled in the sample, across students

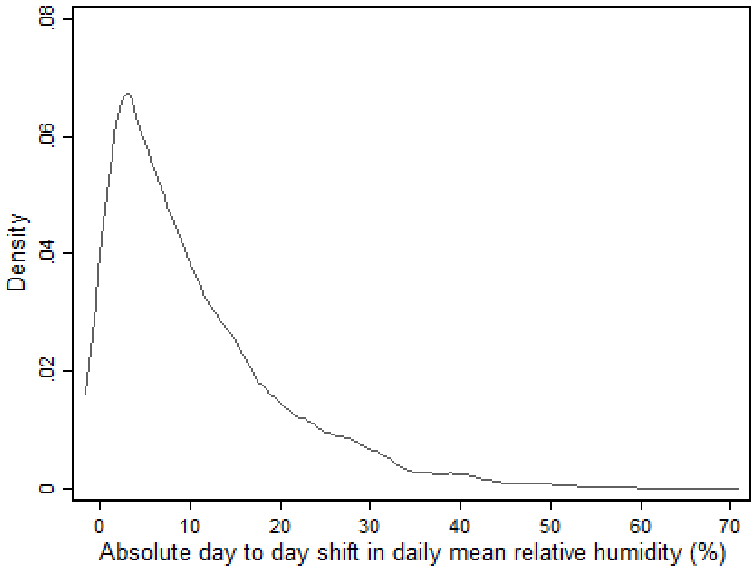


(b) Absence rate & duration at the school, across departed students

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

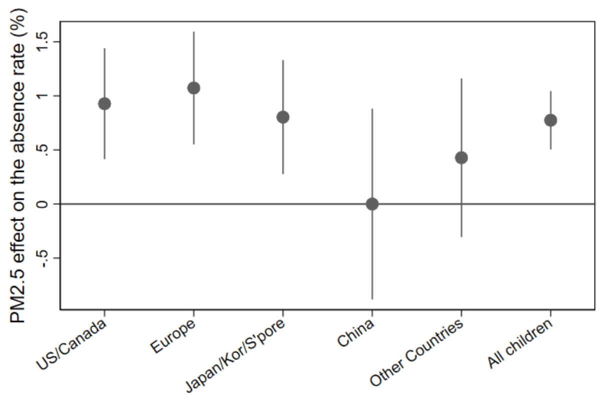


(a) Day to day shift (up or down) in ground temperature

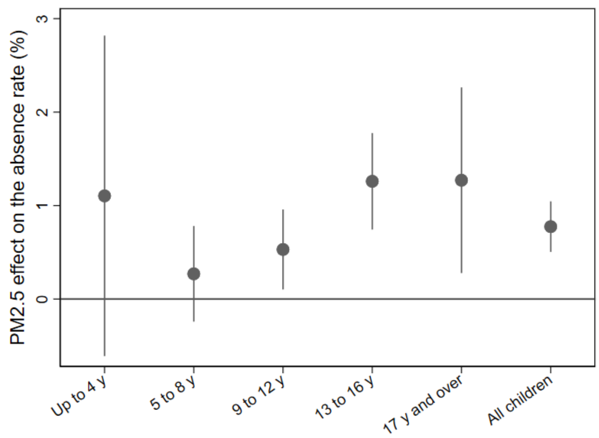


(b) Day to day shift (up or down) in ground humidity

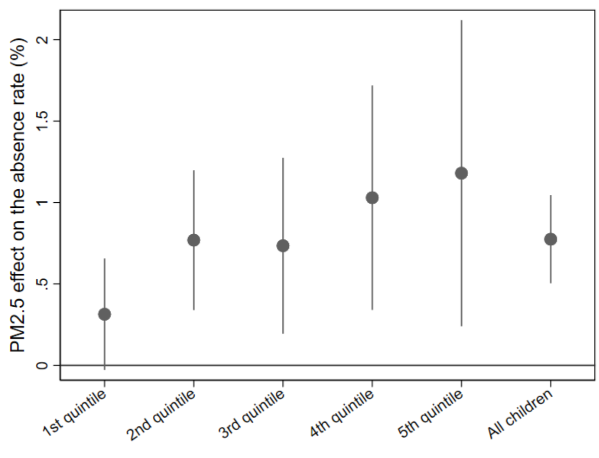
Figure A.3: Ground-level weather conditions persist from one day to the next. Distribution of the absolute shift in daily mean ambient: (a) temperature, and (b) relative humidity, from one day to the next. We partial out systematic temporal variation (year-month and day-of-week), though doing so makes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



(a) Heterogeneous effects over child's nationality



(b) Heterogeneous effects over child's age



(c) Heterogeneous effects over child's absenteeism quintile

Figure A.4: Heterogeneous sensitivity of absences to severe concurrent pollution, by child: (a) nationality, (b) age, and (c) absenteeism quintile, excluding Mondays. 95% confidence intervals on the effect of severe PM2.5 on the probability of an absence. Source: Specifications exactly as in Figure 5 (per columns 3 to 5 of Table 3 and column 3 of Table 2) except that Mondays are dropped from the estimation sample.