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ABSTRACT

Blowin' in the Wind: Smog and Suicidal Ideation Among School-Age Children

This paper attempts to provide one of the first population-based causal estimates of the effect of air pollution on suicidal ideation—a key precursor to suicide attempt and completion—among school-age children. We use daily variations in the local wind direction as instruments to address endogeneity in pollution exposure. Matching a unique risk behavior survey of 55,000 students from 273 schools with comprehensive data on air pollutants and weather conditions according to the exact date and location of schooling, our findings indicate that a 1% decline in daily PM2.5 is associated with a 0.36% reduction in the probability of suicidal ideation. Moreover, the dose-response relationship reveals that the marginal effects increase significantly and non-linearly with elevated concentration of PM2.5. The effect is particularly pronounced among younger, male, students from low-educated families, and students with lower grades.

JEL Classification: I31, Q51, Q53

Keywords: suicidal ideation, air pollution, school-age children, risky behaviors, China

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1. Introduction

An extensive body of economic literature has documented the adverse effects of air pollution on various health outcomes (Ebenstein et al., 2017; Greenstone and Hanna, 2014; Schlenker and Walker, 2016). Moreover, a growing body of evidence suggests that air pollution exerts significant influences on brain functioning and behavior. These include impacts on cognitive performance (Zhang et al., 2018), emotional well-being and depressive symptoms (Levinson, 2012; Zhang et al., 2017), and productivity (Chang et al., 2016, 2019). The effects further extend not only to misbehaviors and criminal activities (Burkhardt et al., 2019; Heissel et al., 2020; Herrnstadt et al., 2021; Reyes, 2007), but also to risk aversion and impatience (Chew et al., 2021), indicating far-reaching consequences on human decision-making processes (Chen, 2019). Importantly, the impact of air pollution on the brain may begin at early stages of life (Currie et al., 2014).

There are two primary pathways through which air pollution, particularly fine particulate matter (PM2.5), known for its extended airborne presence and ability to carry toxins into the brain through minuscule passageways, can impact the brain and behavior, even in the short term (Maher et al., 2016; Pope and Dockery, 2006). First, air pollution may *psychologically* induce feelings of irritation, frustration, and uneasiness, potentially leading to increased aggression, impulsivity, and depressive mood. Exposure to heightened levels of air pollutants has been linked to physical symptoms such as headaches and a sensation of pressure in the head, which can contribute to emotional distress through psychological mechanisms (Heissel et al., 2020; Nattero and Enrico, 1996). Second, air pollution can also exert direct *physiological* effects on the brain. When PM2.5 enters the central nervous system, it can trigger neuroinflammation, increasing circulating proinflammatory cytokines, which are associated with depressive symptoms (Ganança et al., 2016; Kioumourtzoglou et al., 2017; Zundel et al., 2022). Growing evidence suggests that elevated cytokine levels are observed in individuals with suicidal ideation, suicide attempts, or completed suicide

(Janelidze et al., 2011; Tonelli et al., 2008).

Both physiological and psychological pathways may have a more pronounced impact on children, considering that they are among the most vulnerable groups to pollution due to their rapidly developing bodies and brains, higher metabolic rates, and larger volume of inhaled air (World Health Organization, 2005). Children may be particularly susceptible to the stress-inducing effects of air pollution due to physiological vulnerabilities, such as elevated heart rates and increased cortisol levels. These factors could harm their mental health and contribute to suicidal ideation. Mounting evidence demonstrates that air pollution influences school-related outcomes, including increased school absences (Chen, Guo, and Huang 2018; Currie, Neidell, and Schmieder 2009; Liu and Salvo 2018) and poor test performance (Ebenstein et al., 2016; Graff Zivin et al., 2020; Mohai et al., 2011). Despite these findings, no study has established a causal link between air pollution and more extreme outcomes at school, including suicidal behavior.

As such, this paper may offer the first causal effect estimate of air pollution on suicidal ideation among school-age children, matching a unique youth risk behavior survey of 55,000 students from 273 schools with comprehensive data on air pollutants and weather conditions according to exact date and school location. We instrument air pollution utilizing daily variations in the local wind directions, a widely-used instrumental variable (IV) in recent studies (Barwick et al., 2021; Bayer et al., 2009; Deryugina et al., 2019; Williams and Phaneuf, 2019), to address omitted variable bias and measurement errors. Our findings suggest that PM2.5 is associated with an elevated incidence of suicidal ideation, particularly pronounced among younger, male, students from low-educated families, and students with lower grades. A 1% decline in daily PM2.5 is associated with a 0.36% reduction in the probability of suicidal ideation. The dose-response relationship reveals that the marginal effects increase significantly and non-linearly with elevated concentration of PM2.5. Exposure to severely polluted days with PM2.5 levels above 250 $\mu g/m^3$, compared to days with excellent air quality (<35 $\mu g/m^3$), is associated with an increase in the rate of suicidal ideation by 0.110 percentage points. Furthermore, contemporaneous air pollution has a disproportionally larger effect on suicidal ideation than lagged or cumulated air pollution, suggesting that the effect is most likely noncumulative.

This study contributes to the literature on several fronts. First, we provide novel evidence that supports the causal relationship between air pollution and suicide rates.[1] Persico and Marcotte (2022) study the impact of air pollution on suicide deaths and suicide-related hospitalizations in the United States. Okuyama et al. (2022) find that the simultaneous occurrence of economic recessions and air pollution can trigger suicides among both adults and children. Our research is also closely related to Zhang et al. (2024), who investigate the effect of air pollution on suicide death rates in China. Our study differs from Zhang et al. (2024) in two key aspects. First, while Zhang et al. (2024) focus on suicide deaths among adults, we examine school-age children, a population that may be more vulnerable to environmental stressors. Second, rather than analyzing completed suicides, we investigate an early-stage suicidal measure—suicidal ideation—capturing upstream signals of suicide risk. Given that suicide is a multi-stage process, ranging from ideation and planning to attempts and, ultimately, suicide deaths, identifying risk factors at an earlier stage is crucial for effective intervention and prevention.

Second, examining the impact of air pollution on suicidal behavior is particularly crucial for school-age children, given their heightened vulnerability to mental health challenges. Solmi et al. (2022) discover that 62.5% of individuals experience the onset of mental disorders before the age of 25, underscoring the importance of early-life prevention and intervention. In China, the severity of suicidal behavior among young individuals is alarming—statistics indicate that among students aged 12–23, 19.6% have seriously considered attempting suicide, 6.0% have planned an attempt, and 2.4% have made one or more suicide attempts (Ji, 2007). In the United States, these figures are even higher, with 17.0% of students in this age group having seriously considered suicide, 13.6% having made plans, and 8.0% having attempted suicide at least once in

[1] Much of the literature on suicide has focused on policies or practices aimed at reducing suicide rates by controlling access to tobacco use (Harel-Fisch et al., 2012), addressing drug abuse (Borgschulte et al., 2018; Gunnell et al., 2005), mitigating gun violence (Duggan et al., 2011; Smith et al., 2020), and improving social and economic conditions (Chang et al., 2017; Peng et al., 2019; Ruhm, 2015).

2013 (Kann et al., 2014). Data from the Centers for Disease Control and Prevention (2024) show a concerning upward trend by 2023: the percentage of U.S. high school students who seriously considered attempting suicide increased to 20%, while those who made a suicide plan or attempted suicide rose to 16% and 9%, respectively. Moreover, suicide ranks as the third leading cause of death among individuals aged 15-24 in the United States.[2] To the best of our knowledge, few studies have focused on the relationship between air pollution and suicidal behaviors for this critical population group.

Third, while a growing body of epidemiological literature consistently indicates a positive correlation between exposure to air pollution and suicidal behaviors,[3] the extent to which this relationship is causal remains less explored. Two main sources of biases due to the endogeneity problem must be addressed. The first source is omitted variables. Pollution exposure might correlate with unobserved individual-level factors that also influence the risk of suicide. The second source—i.e., measurement errors with regard to air pollutants—may be attributable to aggregation of pollution data from sporadic monitoring stations or data manipulation (Ghanem and Zhang, 2014). This paper provides one of the first estimates on the causal effect of air pollution on suicidal ideation, following an identification strategy that explores plausibly exogenous spatial and temporal variations in air pollution from changes in wind directions (Barwick et al., 2021; Bayer et al., 2009; Deryugina et al., 2019), straw burning (Lai et al., 2021), and winter heating (Ebenstein et al., 2017).

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2 Data source: https://wisqars.cdc.gov/lcd.

3 See Davoudi et al. (2021) for a comprehensive literature review. Most studies focus on the association between air pollution and suicide mortality. For example, Kim et al. (2010) reveal a positive relationship between transient PM and suicide risk based on 4,341 suicide cases in seven cities in the Republic of Korea during 2004. Yang et al. (2011) investigate the positive association between various air pollutants and monthly suicide counts in the city of Taipei between 1991 and 2008. Bakian et al. (2015) find that short-term exposure to NO_2, SO_2, and PM is positively associated with completed suicide (n=1,546) in Salt Lake County, Utah, from 2000 to 2010. Ng et al. (2016) examine the positive relationship between short-term exposure to NO_2, SO_2, and PM and suicide mortality (n=29,939) in Tokyo from 2001 to 2011. Min, Kim, and Min (2018) show that long-term exposure to NO_2, SO_2, and PM10 is associated with a greater risk of death by suicide in South Korea from 2002-2013. In a paper most related to our research, Fan et al. (2019) estimate the association between 3-year annual average concentration of PM2.5 exposure and suicide attempts using the School-based Chinese Adolescents Health Survey during 2014–2015 in Guangdong, China. They find that PM2.5 exposure is positively associated with suicide attempts, especially among adolescents with sleep disturbance.

In addition to raising the rate of suicidal ideation, our results consistently demonstrate that air pollution may contribute to mental health issues among school-age children, including symptoms of sleeplessness and feelings of depression. Furthermore, exposure to elevated levels of PM2.5 appears to promote a range of undesirable behaviors, such as self-injury and internet addiction. This suggestive evidence lends support to potential shifts in the prevalence of risky behaviors in general and aligns with research suggesting that air pollution undermines risk aversion and patience (Chew et al., 2021), while also intensifying aggression and contributing to violent crimes (Burkhardt et al., 2019; Herrnstadt et al., 2021; Reyes, 2007).

Finally, we obtain the data from the youth risk behavior survey conducted in a large Chinese province experiencing rapid economic growth. The elevated pollution level in our study context, compared to that in developed countries, provides a dose-response function for the student population at higher pollution concentration. This allows us to identify potential nonlinear effect and sheds light on other developing countries. The dose-response relationship, the temporal mechanisms through which air pollution may heighten suicidal ideation, and the heterogeneous effects imposed by PM2.5 and its co-pollutants collectively strengthen our confidence that the effects we have identified are most likely causal.

The remainder of the paper is organized as follows. Section 2 describes our datasets and key measures. Section 3 discusses the empirical specification and the identification strategy. Section 4 presents the baseline results, robustness checks, and heterogeneous effects, while Section 5 concludes the paper.

2. Data

2.1. Suicidal ideation

Suicidal ideation data are obtained from the Jiangsu Youth Risk Behavior Survey (JYRBS), a provincially representative sample of students aged between 9 and 25 in Jiangsu Province. The JYRBS was carried out by the Jiangsu Provincial Center for Disease Control and Prevention (Jiangsu CDC) during October to December 2013, utilizing anonymous but mandatorily administered questionnaires.[4] A total of 273 middle schools, high schools, and colleges across Jiangsu Province were randomly selected. Within each school, respondents were surveyed randomly over several consecutive days, with an average of approximately 200 participants per school.[5] This approach ensures variability while allowing for the control of school fixed effects.[6]

In our analysis, suicidal ideation is defined as thoughts of suicide that range in severity from a vague desire to die to active suicidal ideation involving a specific plan and intent. We construct a binary indicator for suicidal ideation based on responses to the question: "Have you ever seriously considered attempting suicide?" with response options "YES" or "NO." Figure A2 presents the mean level of suicidal ideation at the city level in Jiangsu.

2.2. Pollution and weather measures

Air pollution measures are derived from the daily air quality report published by the Ministry of Ecology and Environment (MEE) of China. The report covers 68 monitoring stations in Jiangsu Province, along with longitude and latitude information for each station. Six pollutant measures are used in our analysis: particulate matter with a diameter smaller than 2.5 μm (PM2.5), particulate matter with a diameter smaller than 10 μm (PM10), carbon monoxide (CO), nitrogen dioxide (NO_2), ozone, and sulfur dioxide (SO_2). Figure A3 shows the daily mean PM2.5 and PM10 in Jiangsu. For most days in 2013, the concentrations of these two air pollutants were higher than the levels in WHO air quality guidelines.

Given the potential confounding effects of temperature—both due to its correlation with air pollution and its documented influence on neuroinflammation and serotonin

[4] Figure A1 displays the distribution of survey dates.

[5] All selected individuals were required to participate in the survey. However, if a student was absent from school during the survey period, they may be missing from our sample. Given that students most affected by air pollution are more likely to be absent, this could lead to an underestimation of the true effects.

[6] We found no significant relationship between survey dates and precipitation or an indicator of a set of bad weather conditions (fog, rain/drizzle, snow/ice pellets, hail, thunder, or tornadoes/funnel clouds). This lack of association indicates that the surveys were not predominantly conducted on rainy days or during other extreme weather conditions, which would have prevented students from outdoor activities and, thus, potentially introduced bias into the estimates.

neurotransmission, which may, in turn, affect suicidal ideation, we include weather controls in our analysis to better isolate the impact of air pollution from other meteorological factors. The weather data are provided by the China National Meteorological Data Service Center (CMDC), part of the National Meteorological Information Center of China. The dataset reports consecutive daily records of a wide range of weather conditions—such as temperature, precipitation, wind speed, and sunshine duration—from 13 monitoring stations in Jiangsu.

Figure 1 displays the spatial distribution of schools and air quality monitoring stations in the JYRBS. To merge the survey data with the air pollution and weather readings, we calculate the weighted average values of all the monitoring stations within 40 km to the location of each school, where the weights are equal to the inverse of the distance between each station and school location. All 272 schools in the survey are located within this radius to the monitoring stations. Owing to 223 missing values for the survey date, the final dataset for analysis comprises 55,138 observations.

3. Empirical strategy

Our baseline econometric specification is as follows:

$$Suicide_{ijct} = \alpha P_{jct} + X'_{ijct} r + W'_{ct} \phi + \delta_j + \eta_t + \varepsilon_{ijct} \quad (1)$$

The dependent variable $Suicide_{ijct}$ is the suicidal ideation of respondent i in school j of city c at date t. The key variable P_{jct} is the air quality measure in school j of city c at date t. We include a set of demographic controls X_{ijct}, including gender, age and its squared term, and the log form of household per capita income. To mitigate the concern that weather being correlated with both suicidal ideation and air quality, we also control for a vector of rich weather conditions W_{ct} at the city level, involving temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1°C-wide bins in between)[7]; precipitation; wind speed; and sunshine duration on the day of schooling.[8] δ_j

[7] Figure A4 shows the distribution of temperatures in the sample. Higher temperatures may increase suicide rates and ER visits for mental illness (Burke et al., 2018; Mullins and White, 2019).

[8] Studies have shown that sunshine affects individual moods, behaviors, and even mental health over a long period of time (Kämpfer and Mutz, 2013; Keller et al., 2005).

represents school and grade fixed effects, while η_t indicates month and day-of-week fixed effects.[9] ε_{ijct} is the error term. Standard errors are clustered at the school level. Table 1 describes key variables and their summary statistics.

OLS estimates of equation (1) may be biased due to two primary sources of endogeneity. The first source is omitted variable bias. Although the survey aimed to randomly assign survey dates across schools and grade levels, unobserved individual heterogeneity may still be correlated with both suicidal ideation and pollution exposure, thereby introducing endogeneity concerns. For example, students in poor health who are more sensitive to air pollution are more likely to be absent during the survey period, leading to their exclusion from the sample and potentially causing an underestimation of the true effects. Among students who are present in school, higher pollution levels may also promote those with suicidal ideation to more readily report their feelings in the survey. The second source is measurement error, as air pollution levels are calculated as averages from monitoring stations, which may introduce attenuation bias. To mitigate both omitted variable bias and measurement error, we employ an IV strategy, using daily wind direction in each city as an instrument for pollution.

Figure 2 visualizes the estimates of daily mean PM2.5 concentrations on a set of indicators for the daily wind directions, each falling into a particular 22.5-degree angle bin at the city level in Jiangsu Province. The regression includes controls for city, month, and day-of-week fixed effects. The reference wind direction bin is 337.5 degrees, where 315 degrees corresponds to a northwest wind direction. As illustrated by Figure 2, PM2.5 levels are significantly higher when the wind is blowing from between the south and the southwest. Therefore, the change in local wind direction is a strong predictor of changes in local air pollution levels.

We illustrate this relationship between local wind direction and air pollution levels

[9] Due to the nature of the cross-sectional data, we are unable to control for individual fixed effects. The results remain robust if we aggregate the data to the school-day level and control for school fixed effects. See details in the robustness check section.

using two natural experiments, straw burning[10] and winter heating.[11] As shown in Figure 2, Jiangsu borders five provinces in China: Shandong, Henan, Anhui, Shanghai and Zhejiang. The JYRBS was carried out during October to December in 2013 (Figure A4), which were seasons for straw burning with winter heating in succession. Figure A5 presents the number of straw-burning points on each day by province, while Figure A6a displays the locations of straw-burning points during this period.[12] Figure A6b further shows the distribution of winter heating zones.

Similarly, as displayed by Figure A6, changes in the main source of air pollution from straw burning to winter heating may lead to changes in the effect of wind direction on pollution levels. Before the winter heating season, pollution exposure is more driven by wind from the southwest, where Anhui and Henan are located, and therefore presumably more by straw burning (Figure A6a). When winter approaches, the polluted air becomes multi-directional. Pollution exposure is more driven by southwest and southeast wind, and therefore presumably more by the nearby industrial zones in southern Anhui and scattered non-collective winter heating in rural regions than by collective winter heating in the north (Figure A6b). Therefore, we generate a set of interaction terms to allow the wind instruments to vary before and during the winter heating season.

Since the effect of wind direction on PM2.5 levels may also vary by city, as illustrated in Figure A7, we also allow the wind instruments on our first stage estimation vary by city. Following a similar strategy in Deryugina et al. (2019), the specification for our first stage is:

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[10] In many developing countries like China, straw burning is a popular choice among farmers for rapidly eliminating agriculture crop residues mainly from rice, wheat and corn straws. China burns 112 million tons of crop straws per year (Lai et al., 2021). The proportion of straws disposed by burning is about four times the world average (Cai et al., 2011). Straw burning generates substantial gas emissions and contributes to severe seasonal air pollution (Zhang et al., 2016).

[11] China established the winter heating system during the 1950s to provide free winter heating for homes and offices in urban areas in North China, which is defined by the Qin-Huai line as the cutoff. The combustion of coal for winter heating results in release of air pollutants, especially the particulate matter, which is extremely harmful to human health (Ebenstein et al. 2017).

[12] Straw-burning points are locations where farmers burn crop residues, and they are monitored by remote sensing satellites. The MEE reports the locations with longitude and latitude information of each straw-burning point at the daily level.

$$P_{jct} = \sum_{c=1}^{13}\sum_{b=0}^{2}\sum_{k=0}^{1}\beta_{bk}^{c} 1[C_j = c] \times winddir_{ct}^{90b} \times WH_k + X'_{ijct} r + W'_{ct}\phi + \delta_j + \eta_t + \varepsilon_{ijct} \quad (2)$$

The excluded instruments are the variables $1[C_j = c] \times winddir_{ct}^{90b} \times WH_k$. We divide wind directions into four 90-degree intervals: [90*b*, 90*b*+90), where *b* = 0, 1, 2, 3. The omitted category corresponds to the interval [270, 360). Each variable in the set $winddir_{ct}^{90b}$ is equal to 1, if the daily wind direction in city *c* falls in the interval [90b,90b+90), and 0 otherwise. The variable $1[C_j=c]$ is an indicator for school *j* in city *c*. WH_0 is a dummy variable indicating days before winter heating season (November 10, 2013), while WH_1 represents days during winter heating season.[13] The coefficient on the interaction among these three variables, β_{bk}^{c}, is thus allowed to vary across 13 cities, 3 wind directions, and the initiation of the winter heating season.[14] Standard errors are clustered at the school level. Other control variables are defined as in equation (1).

The validation of using wind directions as IVs faces two primary challenges. First, wind direction could be correlated with seasonal variations, which, in turn, could influence suicidal thoughts (e.g., dark, bad weather in winter). To address this concern, we plot the daily frequency of the four wind directions in Jiangsu during the sample period in Figure A8. Overall, the daily wind direction is randomly distributed. Additionally, controlling for month fixed effects in the regressions may help partially absorb this correlation.

Second, individuals might choose their residence based on known wind patterns, introducing potential confounders from residential sorting. To mitigate this issue, we use daily wind direction, rather than prevailing wind direction, as instruments for daily pollution exposure. Figure A9 illustrates the frequency of southwest wind direction for each city from October to December over three consecutive years (2012-2014). The lack of consistent patterns in wind direction across the same period in different years

[13] As a robustness check, we use $1[C_j = c] \times \mathrm{winddir}_{ct}^{90b}$ as the excluded instruments. The results are quite robust and available upon request.
[14] Therefore, we use 78 (=13×3×2) IVs in total.

suggests that people are unlikely to sort into areas based on specific wind distributions.

Wind may affect pollution measured by a particular monitoring station via redistributing locally produced pollution (e.g., from traffic or local power plants) or transporting pollution produced elsewhere. Our empirical specification exploits only the wind-induced variations in pollution exposure that affects the whole city in a similar manner. This variation, which is more likely to arise from long-range transport of pollutants, reduces the potential for omitted variable bias and measurement error of residents' pollution exposure due to within-city transport. Overall, after flexibly controlling for a large number of fixed effects and covariates, our identification assumption is that changes in a city's wind direction are unrelated to changes in suicidal behaviors except through air pollution.

4. Results

4.1. Baseline results

Table 2 reports the transitory effect of PM2.5 on suicidal ideation.[15] Column (1) begins with OLS estimates, showing a significant coefficient for PM2.5 at the 1% level. A 10 $\mu g/m^3$ decrease in PM2.5 exposure is associated with a 0.109 percentage point reduction in the probability of suicidal ideation (equivalent to 1.20% of the mean incidence). This effect remains largely unchanged when demographic controls are added in column (2). Columns (3) and (4) provide the corresponding 2SLS estimates, using wind direction as an instrument for PM2.5. The first-stage results are shown in Table A1. The 2SLS estimate is also significant at the 1% level and is approximately three times larger than the OLS estimate. Specifically, the 2SLS estimate in column (4) indicates that a 10 $\mu g/m^3$ decrease in PM2.5 exposure leads to a 0.364 percentage point reduction in suicidal ideation probability (or 4.0% of the mean incidence). To make the magnitude of the coefficient more intuitive, we convert the point estimate to elasticity, which suggests that a 1% decrease in daily PM2.5 is associated with a 0.36% reduction

[15] Given that PM2.5 is the dominant pollutant for most of our sample, as shown in Figure A10, we primarily focus on PM2.5 in the baseline results and assess the impact of other pollutants as part of the robustness checks.

in the probability of suicidal ideation.

We compare our estimates of suicidal ideation with studies investigating the impact of air pollution exposure on suicides. Persico and Marcotte (2022) found that a 1% decrease in daily PM2.5 is associated with a 0.047% reduction in daily suicide death rates in the United States. Similarly, Zhang et al. (2024) reported that a 1% increase in PM2.5 levels raises daily suicide death rates by 0.056% in China. Notably, our paper focuses exclusively on potentially more vulnerable school-age children, while suicide data in these existing studies encompass all age groups.

As illustrated in Table 2, wind direction is a strong predictor of air pollution levels, which is confirmed by the large Kleibergen-Paap (KP) F-statistics in the table. A large difference between the OLS and 2SLS estimates on the effects of air pollution on health-related outcomes is common in the literature (Deryugina et al., 2019; Knittel et al., 2016; Moretti and Neidell, 2011). There are two possible reasons for this downward bias. First, some individual-level omitted variables, such as avoidance behaviors, are positively correlated with air pollution. As these behaviors likely reduce suicidal ideation, the omitted-variable bias is negative. Second, measurement error in PM2.5 due to the aggregation of pollution data from sporadic monitoring stations could lead to attenuation bias.

Figure 3 estimates a dose-response function to capture the potentially non-linear relationship between air pollution and suicidal ideation. According to the air quality standard published by the MEE, we classify the PM2.5 concentrations into six categories: "<35 μg/m^3 (excellent)"; "35-75 μg/m^3 (good)"; "75-115 μg/m^3 (lightly polluted)"; "115-150 μg/m^3 (moderated polluted)"; "150-250 μg/m^3 (heavily polluted)"; and ">250 μg/m^3 (severely polluted)".[16] We assign each category a dummy variable, and designate "<35 μg/m^3 (excellent)" as the reference group. We instrument for the five dummy variables using wind directions defined in equation (2). Figure 3 plots the estimated coefficients with 95% confidence intervals for the dummy variables of each PM2.5 category. As revealed by the figure, the marginal effects increase significantly

[16] For detailed information, please refer to https://en.wikipedia.org/wiki/Air_quality_index.

and non-linearly with elevated concentration of PM2.5. Exposure to severely polluted days with PM2.5 levels above 250 μg/m³, compared to days with excellent air quality (<35 μg/m³), is associated with an increase in the rate of suicidal ideation by 0.110 percentage points.

Table 3 reports the results for the long-term effects of PM2.5 on suicidal ideation, using the mean concentrations of PM2.5 over the past 7 days, 14 days, and 30 days. We instrument for PM2.5 using the number of days falling in each 90-degree wind direction interval during the respective PM2.5 exposure window. As displayed in Panel A of Table 3, except for the effect of 30-day PM2.5 exposure, which is significant at the 10% level (column 3), the coefficients for mean PM2.5 over a long period are statistically insignificant. In Panel B of Table 3, we simultaneously control for contemporaneous and cumulative PM2.5. It is evident that people tend to understate the impact of prior PM2.5 exposure on suicidal ideation, making contemporaneous exposure more influential. Furthermore, we calculate the deviation of PM2.5 on the interview date from its cumulative average over different time windows, finding that people are more sensitive to large, current-day deviations from longer-term averages.

The stronger contemporary, non-cumulative effect identified in our paper is consistent with findings in the existing literature. For instance, Zhang et al. (2024) show that the impact of PM2.5 on suicide rates occurs without temporal delay. Similarly, Herrnstadt et al. (2021) find that air pollution triggers short-term impulsive violent behavior, but not longer-term, premeditated property crimes. These findings are consistent with neurobiological evidence suggesting that PM2.5 exposure impairs emotional regulation and increases impulsive–aggressive behavior (Liu et al., 2023).

We further test a hypothesis that may explain the stronger contemporaneous effect using two methods, as shown in Table A2. First, we divide the sample into two subsamples based on the median level of city average PM2.5 in 2013. As shown in columns (1) and (2) of Table A2, students from less polluted areas are more affected than those from more polluted areas, indicating that people may adapt to poor air quality over time. Second, we measure relative PM2.5 exposure by calculating deviations from historical levels—specifically, the (standard) deviation from the annual mean PM2.5.[17] As reported in columns (3) and (4) of Table A2, both relative measures are significant, indicating that individuals are particularly sensitive to deviations from historical air pollution levels on the interview date. Taken together, these findings suggest that people adapt better to long-term air pollution exposure but remain highly sensitive to transitory deviations from historical averages. Thus, the non-cumulative effects tend to be more pronounced.

4.2. Robustness checks

We perform a range of regressions to check the robustness of our baseline results. First, the concentrations of various air pollutants are highly correlated, and thus the estimated effect of PM2.5 may be driven by the presence of other co-pollutants.[18] To explore whether PM2.5 dominates the effect on suicidal ideation, we jointly estimate the effects of different pollutants in column (1) of Table 4.[19] As shown in the table, PM2.5 is significant at the 5% level, while the other pollutants are statistically insignificant. Furthermore, in columns (2) through (6) of Table 4, we keep PM2.5 in the regressions and add co-pollutants, including PM10, CO, ozone, SO_2, and NO_2, as control variables, respectively. Consistent with the result in column (1), the statistical significance of PM2.5 remains, while the additional pollutant is statistically insignificant.[20] Therefore, PM2.5 is the major air pollutant associated with suicidal ideation that we focus on hereafter.

In Table 5, we present a set of alternative specifications to test the robustness of our findings. First, columns (1) and (2) report the results of placebo tests, examining whether "PM2.5 next day" and "PM2.5 on the same day in the subsequent year" influence suicidal ideation. As expected, both variables are statistically insignificant,

[17] The deviation from the annual mean represents the difference between the PM2.5 level on the interview date and the average annual PM2.5 level in 2013. The standard deviation from the annual mean indicates this difference measured in terms of the standard deviation of the annual PM2.5 levels in 2013.
[18] Table A3 presents the correlations between air pollutants.
[19] Due to missing values—3,022 for PM10, 1,083 for ozone, and 1,094 for SO_2—the sample sizes are slightly smaller for the estimates involving PM10, ozone, or SO_2 exposure.
[20] In Table 4, both PM2.5 and other co-pollutants are instrumented using wind directions defined in equation (2).

reinforcing the validity of our identification strategy.[21] Second, given the cross-sectional nature of our data, we cannot control for individual fixed effects. To address this limitation, column (3) aggregates the data to the school-day level and incorporates controls for environmental conditions, school fixed effects, as well as month and day-of-week fixed effects. The results confirm that our estimates remain robust under this specification. Furthermore, as shown in column (4), our estimates remain largely unchanged in both magnitude and significance when school-by-grade fixed effects are included. Finally, column (5) reports the IV estimate using a probit model, which also yields consistent and robust results.[22]

4.3. Heterogeneous effects

This section explores the heterogeneous effects of air pollution on suicidal ideation across different student subgroups. First, we consider gender differences in Panel A of Table 6. Notably, boys exhibit a stronger response to air pollution compared to girls. This finding aligns with existing literature on the impact of air pollution on subjective well-being. For instance, Zhang et al. (2017) show that males' hedonic happiness is more negatively affected by air pollution than that of females.

Second, we divide the sample by respondents' grade level.[23] As shown in Panel B of Table 6, middle school students are more sensitive to air pollution than students in higher grades. This heightened sensitivity may be attributed to their younger age, which could make them more vulnerable to the adverse effects of pollution. This finding is consistent with Li et al. (2021), who also report that air pollution has more pronounced negative effects on adolescents across age groups.

Furthermore, a mother's educational attainment may influence the impact of air pollution exposure on children's mental well-being. For instance, less educated mothers

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[21] We instrument for "PM2.5 next day" using wind directions next day and instrument for "PM2.5 the same day in the subsequent year" using wind directions the same day in the subsequent year.

[22] The parameter estimates in fixed-effect probit models, which assume that heterogeneity is correlated with explanatory variables, are not consistent, even when using dummy variables. Additionally, the coefficients from linear probability models are straightforward to interpret as marginal effects. Therefore, we have chosen linear probability models as our primary method.

[23] The grade level is shown in Figure A11. We classify 7th, 8th, and 9th grade as middle school; 10th, 11th, and 12th grade as high school; and freshmen, sophomores, juniors, and seniors as college level.

may have limited knowledge on how to protect their children from air pollution. As shown in Panel C of Table 6, children of less educated mothers are indeed more sensitive to air pollution. This finding is consistent with Bharadwaj et al. (2017), who report that the effects of CO exposure are significantly larger for children of mothers without a high school diploma.

In addition, we divide the sample into two subsamples based on the median level of average PM2.5 in 2013. As shown in Panel D of Table 6, students from less polluted areas are more affected than those from more polluted areas, indicating that people tend to adapt to poor air quality over time.

Finally, students with worse school performance may be more susceptible to air pollution. Their school performance is categorized in Figure A12. We combine two lower levels of academic performance into a low category, and two higher levels into a high category. As presented in Panel E of Table 6, the underachievers are indeed more affected by PM2.5, presumably because they may spend more time outside.

4.4. Mechanism

The survey also collects data on whether students have experienced symptoms of sleeplessness and depression or engaged in behaviors such as self-injury and internet addiction over the past 30 days. We examine the impact of air pollution exposure during this period on these depressive symptoms and undesirable behaviors among students, proposing several potential mechanisms. As shown in Table 7, our findings indicate that PM2.5 levels contribute to students reporting symptoms of sleeplessness and feelings of depression. Additionally, exposure to air pollution appears to induce undesirable behaviors such as self-injury and internet addiction. Our estimates suggest that a 1% increase in mean PM2.5 levels over the past month is associated with an increase in the probability of reporting symptoms of sleeplessness, feelings of depression, self-injury, and internet addiction by 0.75%, 0.61%, 2.03%, and 1.21%, respectively. While suicide-related behaviors represent extreme cases, the mental health issues and other risky behaviors we identify lend support to potential shifts in risk preference that may lead to suicidal ideation.

In addition, we investigate the heterogeneous effects of air pollution on these mechanisms, with the results presented in Tables A4–A7. Consistent with our heterogeneity analysis, the findings suggest that the impact of air pollution on the identified mechanisms is generally stronger and more pronounced among younger students, males, students from low-educated families, and those with lower academic performance, further reinforcing our interpretation.

5. Conclusion

This paper provides some of the first causal evidence that air pollution may raise the rate of suicidal ideation among school-age children. We match a unique youth risk behavior survey of 55,000 students from 273 schools conducted by China's CDC with comprehensive data on air pollutants and weather conditions, according to exact date and school location. To mitigate omitted variable bias and address measurement errors, we employ daily variations in local wind directions as instruments for air pollution. Our IV estimates indicate that a 10 μg/m^3 increase in daily PM2.5 would lead to a 0.364 percentage point rise in the probability of suicidal ideation, which accounts for a 4.0 percent of mean occurrence of suicidal ideation. Our heterogeneity analysis reveals that younger, male, students from low-educated families, and students with lower grades tend to have a higher risk of suicidal ideation.

Our results offer new insights into the additional social costs of air pollution. Assuming a proportional increase in both suicidal ideation and suicide mortality and, considering the 9.1% incidence rate of suicidal ideation in our sample and the reported 0.85-2.52 suicide mortality per 100,000 population among Chinese adolescents (10-24 years old) in 2016 (R. Chen et al., 2018), our back-of-the-envelope calculations suggest that a 0.364 percentage point (or 4 percent) rise in the probability of suicidal ideation may correspond to an estimated increase in suicide mortality by 0.034-0.101 per 100,000 population. If we adopt the value of a statistical life (VSL) as 7.46 million CNY for an average Chinese individual (Fan et al., 2020), the monetary value of prevented deaths resulting from a 10 μg/m^3 reduction in PM2.5 would translate to approximately 0.25-0.75 million CNY per 100,000 population. Considering a population of 302 million people aged 10-24 in China,[24] the total monetary value of averted deaths among adolescents due to a 10 μg/m^3 reduction in PM2.5 would be estimated at around 0.76-2.27 billion CNY.

As mounting evidence suggests, efforts to make a lasting reduction in suicide and related behaviors should extend their focus to address environmental issues, including the implementation of more rigorous regulations on air pollution. In tandem with the ongoing efforts of the U.S. Environmental Protection Agency to gather more scientific evidence on the understated social costs of air pollution, facilitating necessary adjustments to the current air quality guidelines, it becomes imperative to broaden the assessment of well-being to uncover the real social costs associated with air pollution.

[24] The data are obtained from the 2010 Population Census of China.

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Statements and Declarations
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The IZA Discussion Paper Series serves as a preprint server to deposit latest research for early feedback.

References

Bakian, A. V., Huber, R.S., Coon, H., Gray, D., Wilson, P., McMahon, W.M., Renshaw, P.F., 2015. Acute air pollution exposure and risk of suicide completion. Am. J. Epidemiol. 181, 295–303. https://doi.org/10.1093/aje/kwu341

Barwick, P.J., Li, S., Rao, D., Bin, Z.N., 2021. The Healthcare Cost of Air Pollution: Evidence from the World's Largest Payment Network. NBER Work. Pap.

Bayer, P., Keohane, N., Timmins, C., 2009. Migration and hedonic valuation: The case of air quality. J. Environ. Econ. Manage. 58, 1–14. https://doi.org/10.1016/j.jeem.2008.08.004

Bharadwaj, P., Gibson, M., Zivin, J.G., Neilson, C., 2017. Gray matters: Fetal pollution exposure and human capital formation. J. Assoc. Environ. Resour. Econ. 4, 505–542. https://doi.org/10.1086/691591

Borgschulte, M., Corredor-Waldron, A., Marshall, G., 2018. A path out: Prescription drug abuse, treatment, and suicide. J. Econ. Behav. Organ. 149, 169–184. https://doi.org/10.1016/j.jebo.2018.03.006

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S., Hsiang, S., 2018. Higher temperatures increase suicide rates in the United States and Mexico. Nat. Clim. Chang. 8, 723–729. https://doi.org/10.1038/s41558-018-0222-x

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J.D., O'Dell, K., Ford, B., Fischer, E. V., Pierce, J.R., 2019. The effect of pollution on crime: Evidence from data on particulate matter and ozone. J. Environ. Econ. Manage. 98, 102267. https://doi.org/10.1016/j.jeem.2019.102267

Cai, Y., Qiu, H., Xu, Z., 2011. Evaluation on Potentials of Energy Utilization of Crop Residual Resources in Different Regions of China. J. Nat. Resour. 26, 1637–1646.

Centers for Disease Control and Prevention, 2024. Youth Risk Behavior Survey Data Summary & Trends Report: 2013–2023, U.S. Department of Health and Human Services.

Chang, Q., Chan, C.H., Yip, P.S.F., 2017. A meta-analytic review on social relationships and suicidal ideation among older adults. Soc. Sci. Med. 191, 65–76. https://doi.org/10.1016/j.socscimed.2017.09.003

Chang, T., Zivin, J.G., Gross, T., Neidell, M., 2016. Particulate pollution and the productivity of pear packers. Am. Econ. J. Econ. Policy 8, 141–169. https://doi.org/10.1257/pol.20150085

Chang, T.Y., Zivin, J.G., Gross, T., Neidell, M., 2019. The effect of pollution on worker productivity: Evidence from call center workers in China. Am. Econ. J. Appl. Econ. 11, 151–172. https://doi.org/10.1257/app.20160436

Chen, R., An, J., Ou, J., 2018. Suicidal behaviour among children and adolescents in China. Lancet Child Adolesc. Heal. 2, 551–553. https://doi.org/10.1016/S2352-4642(18)30170-6

Chen, S., Guo, C., Huang, X., 2018. Air Pollution, Student Health, and School Absences: Evidence from China. J. Environ. Econ. Manage. 92, 465–497. https://doi.org/10.1016/j.jeem.2018.10.002

Chen, X., 2019. Smog, cognition and real-world decision-making. Int. J. Heal. Policy

Manag. 8, 76–80. https://doi.org/10.15171/ijhpm.2018.105
Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc. Natl. Acad. Sci. U. S. A. 110, 12936–12941. https://doi.org/10.1073/pnas.1300018110
Chew, S.H., Huang, W., Li, X., 2021. Does haze cloud decision making? A natural laboratory experiment. J. Econ. Behav. Organ. 182, 132–161. https://doi.org/10.1016/j.jebo.2020.12.007
Currie, J., Neidell, M., Schmieder, J.F., 2009. Air pollution and infant health: Lessons from New Jersey. J. Health Econ. 28, 688–703. https://doi.org/10.1016/j.jhealeco.2009.02.001
Currie, J., Zivin, J.G., Mullins, J., Neidell, M., 2014. What do we know about short- and long-term effects of early-life exposure to pollution? Annu. Rev. Resour. Econ. 6, 217–247. https://doi.org/10.1146/annurev-resource-100913-012610
Davoudi, M., Barjasteh-Askari, F., Amini, H., Lester, D., Mahvi, A.H., Ghavami, V., Rezvani Ghalhari, M., 2021. Association of suicide with short-term exposure to air pollution at different lag times: A systematic review and meta-analysis. Sci. Total Environ. 771. https://doi.org/10.1016/j.scitotenv.2020.144882
Deryugina, T., Heutel, G., Miller, N.H., Molitor, D., Reif, J., 2019. The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. Am. Econ. Rev. 109, 4178–4219. https://doi.org/10.1257/aer.20180279
Duggan, M., Hjalmarsson, R., Jacob, B.A., 2011. The short-term and localized effect of gun shows: Evidence from California and Texas. Rev. Econ. Stat. 93, 786–799. https://doi.org/10.1162/REST_a_00120
Ebenstein, A., Fan, M., Greenstone, M., He, G., Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. Proc. Natl. Acad. Sci. U. S. A. 114, 10384–10389. https://doi.org/10.1073/pnas.1616784114
Ebenstein, A., Lavy, V., Roth, S., 2016. The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. Am. Econ. J. Appl. Econ. 8, 36–65. https://doi.org/10.1257/app.20150213
Fan, B., Wang, T., Wang, W., Zhang, S., Gong, M., Li, W., Lu, C., Guo, L., 2019. Long-term exposure to ambient fine particulate pollution, sleep disturbance and their interaction effects on suicide attempts among Chinese adolescents. J. Affect. Disord. 258, 89–95. https://doi.org/10.1016/j.jad.2019.08.004
Fan, M., He, G., Zhou, M., 2020. The winter choke: Coal-Fired heating, air pollution, and mortality in China. J. Health Econ. 71. https://doi.org/10.1016/j.jhealeco.2020.102316
Ganança, L., Oquendo, M.A., Tyrka, A.R., Cisneros-Trujillo, S., Mann, J.J., Sublette, M.E., 2016. The role of cytokines in the pathophysiology of suicidal behavior. Psychoneuroendocrinology 63, 296–310. https://doi.org/10.1016/j.psyneuen.2015.10.008
Ghanem, D., Zhang, J., 2014. "Effortless Perfection:" Do Chinese cities manipulate air pollution data? J. Environ. Econ. Manage. 68, 203–225.

https://doi.org/10.1016/j.jeem.2014.05.003
Graff Zivin, J., Liu, T., Song, Y., Tang, Q., Zhang, P., 2020. The unintended impacts of agricultural fires: Human capital in China. J. Dev. Econ. 147. https://doi.org/10.1016/j.jdeveco.2020.102560
Greenstone, M., Hanna, R., 2014. Environmental regulations, air and water pollution, and infant mortality in India. Am. Econ. Rev. 104, 3038–3072. https://doi.org/10.1257/aer.104.10.3038
Gunnell, D., Saperia, J., Ashby, D., 2005. Selective serotonin reuptake inhibitors (SSRIs) and suicide in adults: Meta-analysis of drug company data from placebo controlled, randomised controlled trials submitted to the MHRA's safety review. BMJ 330, 385–388. https://doi.org/10.1136/bmj.330.7488.385
Harel-Fisch, Y., Abdeen, Z., Walsh, S.D., Radwan, Q., Fogel-Grinvald, H., 2012. Multiple risk behaviors and suicidal ideation and behavior among Israeli and Palestinian adolescents. Soc. Sci. Med. 75, 98–108. https://doi.org/10.1016/j.socscimed.2012.03.005
Heissel, J.A., Persico, C., Simon, D., 2020. Does Pollution Drive Achievement? The Effect of Traffic Pollution on Academic Performance. J. Hum. Resour. 1218-9903R2. https://doi.org/10.3368/jhr.57.3.1218-9903r2
Herrnstadt, E., Heyes, A., Muehlegger, E., Saberian, S., 2021. Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago. Am. Econ. J. Appl. Econ. 13, 70–100. https://doi.org/10.1257/app.20190091
Janelidze, S., Mattei, D., Westrin, Å., Träskman-Bendz, L., Brundin, L., 2011. Cytokine levels in the blood may distinguish suicide attempters from depressed patients. Brain. Behav. Immun. 25, 335–339. https://doi.org/10.1016/j.bbi.2010.10.010
Ji, C., 2007. China Youth Risk Behavior Survey Report 2005 (in Chinese). Peking University Medical Press.
Kämpfer, S., Mutz, M., 2013. On the Sunny Side of Life: Sunshine Effects on Life Satisfaction. Soc. Indic. Res. 110, 579–595. https://doi.org/10.1007/s11205-011-9945-z
Kann, L., Kinchen, S., Shanklin, S.L., Flint, K.H., Hawkins, J., Harris, W.A., Lowry, R., Olsen, E.O., McManus, T., Chyen, D., Whittle, L., Taylor, E., Demissie, Z., Brener, N., Thornton, J., Moore, J., Zaza, S., 2014. Youth risk behavior surveillance - United States, 2013. Centers Dis. Control Prev. MMWR 63, 1–168.
Keller, M.C., Fredrickson, B.L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., Conway, A., Wager, T., 2005. A warm heart and a clear head: The contingent effects of weather on mood and cognition. Psychol. Sci. 16, 724–731. https://doi.org/10.1111/j.1467-9280.2005.01602.x
Kim, C., Jung, S.H., Kang, D.R., Kim, H.C., Moon, K.T., Hur, N.W., Shin, D.C., Suh, I., 2010. Ambient particulate matter as a risk factor for suicide. Am. J. Psychiatry 167, 1100–1107. https://doi.org/10.1176/appi.ajp.2010.09050706
Kioumourtzoglou, M.A., Power, M.C., Hart, J.E., Okereke, O.I., Coull, B.A., Laden, F., Weisskopf, M.G., 2017. The association between air pollution and onset of depression among middle-aged and older women. Am. J. Epidemiol. 185, 801–809. https://doi.org/10.1093/aje/kww163

Knittel, C.R., Miller, D.L., Sanders, N.J., 2016. Caution, drivers! children present: Traffic, pollution, and infant health. Rev. Econ. Stat. 98, 350–366. https://doi.org/10.1162/REST_a_00548

Lai, W., Li, S., Li, Y., Tian, X., 2021. Air Pollution and Cognitive Functions: Evidence from Straw Burning in China. Am. J. Agric. Econ. https://doi.org/10.1111/ajae.12225

Levinson, A., 2012. Valuing public goods using happiness data: The case of air quality. J. Public Econ. 96, 869–880. https://doi.org/10.1016/j.jpubeco.2012.06.007

Li, M., Ferreira, S., Smith, T.A., Zhang, X., 2021. Air pollution and noncognitive traits among Chinese adolescents. Heal. Econ. (United Kingdom) 30, 478–488. https://doi.org/10.1002/hec.4193

Liu, H., Salvo, A., 2018. Severe air pollution and child absences when schools and parents respond. J. Environ. Econ. Manage. 92, 300–330. https://doi.org/10.1016/j.jeem.2018.10.003

Liu, X.Q., Huang, J., Song, C., Zhang, T.L., Liu, Y.P., Yu, L., 2023. Neurodevelopmental toxicity induced by PM2.5 Exposure and its possible role in Neurodegenerative and mental disorders. Hum. Exp. Toxicol. 42. https://doi.org/10.1177/09603271231191436

Maher, B.A., Ahmed, I.A.M., Karloukovski, V., MacLaren, D.A., Foulds, P.G., Allsop, D., Mann, D.M.A., Torres-Jardón, R., Calderon-Garciduenas, L., 2016. Magnetite pollution nanoparticles in the human brain. Proc. Natl. Acad. Sci. U. S. A. 113, 10797–10801. https://doi.org/10.1073/pnas.1605941113

Min, J. young, Kim, H.J., Min, K. bok, 2018. Long-term exposure to air pollution and the risk of suicide death: A population-based cohort study. Sci. Total Environ. 628–629, 573–579. https://doi.org/10.1016/j.scitotenv.2018.02.011

Mohai, P., Kweon, B.S., Lee, S., Ard, K., 2011. Air pollution around schools is linked to poorer student health and academic performance. Health Aff. 30, 852–862. https://doi.org/10.1377/hlthaff.2011.0077

Moretti, E., Neidell, M., 2011. Pollution, health, and avoidance behavior: Evidence from the ports of Los Angeles. J. Hum. Resour. 46, 154–175. https://doi.org/10.3368/jhr.46.1.154

Mullins, J.T., White, C., 2019. Temperature and mental health: Evidence from the spectrum of mental health outcomes. J. Health Econ. 68. https://doi.org/10.1016/j.jhealeco.2019.102240

Nattero, G., Enrico, A., 1996. Outdoor pollution and headache. Headache 36, 243–245. https://doi.org/10.1046/j.1526-4610.1996.3604243.x

Ng, C.F.S., Stickley, A., Konishi, S., Watanabe, C., 2016. Ambient air pollution and suicide in Tokyo, 2001-2011. J. Affect. Disord. 201, 194–202. https://doi.org/10.1016/j.jad.2016.05.006

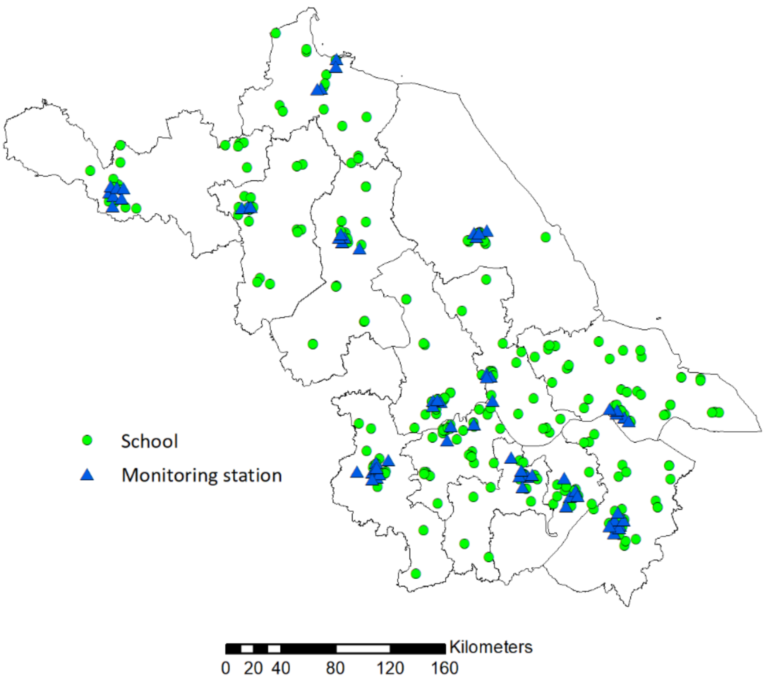
Okuyama, A., Yoo, S., Managi, S., 2022. Children mirror adults for the worse: evidence of suicide rates due to air pollution and unemployment. BMC Public Health 22. https://doi.org/10.1186/s12889-022-14013-y

Peng, S., Yang, X.Y., Rockett, I.R.H., 2019. A typology of social capital and its mixed blessing for suicidal ideation: A multilevel study of college students. Soc. Sci. Med.

243. https://doi.org/10.1016/j.socscimed.2019.112640
Persico, C., Marcotte, D.E., 2022. Air Quality and Suicide. NBER Work. Pap. No. 30626.
Pope, C.A., Dockery, D.W., 2006. Health effects of fine particulate air pollution: Lines that connect. J. Air Waste Manag. Assoc. 56, 709–742. https://doi.org/10.1080/10473289.2006.10464485
Reyes, J.W., 2007. Environmental policy as social policy? the impact of childhood lead exposure on crime. B.E. J. Econ. Anal. Policy 7. https://doi.org/10.2202/1935-1682.1796
Ruhm, C.J., 2015. Recessions, healthy no more? J. Health Econ. 42, 17–28.
Schlenker, W., Walker, W.R., 2016. Airports, air pollution, and contemporaneous health. Rev. Econ. Stud. 83, 768–809. https://doi.org/10.1093/restud/rdv043
Smith, M.E., Sharpe, T.L., Richardson, J., Pahwa, R., Smith, D., DeVylder, J., 2020. The impact of exposure to gun violence fatality on mental health outcomes in four urban U.S. settings. Soc. Sci. Med. 246. https://doi.org/10.1016/j.socscimed.2019.112587
Solmi, M., Radua, J., Olivola, M., Croce, E., Soardo, L., Salazar de Pablo, G., Il Shin, J., Kirkbride, J.B., Jones, P., Kim, J.H., Kim, J.Y., Carvalho, A.F., Seeman, M. V., Correll, C.U., Fusar-Poli, P., 2022. Age at onset of mental disorders worldwide: large-scale meta-analysis of 192 epidemiological studies. Mol. Psychiatry 27, 281–295. https://doi.org/10.1038/s41380-021-01161-7
Tonelli, L.H., Stiller, J., Rujescu, D., Giegling, I., Schneider, B., Maurer, K., Schnabel, A., Möller, H.J., Chen, H.H., Postolache, T.T., 2008. Elevated cytokine expression in the orbitofrontal cortex of victims of suicide. Acta Psychiatr. Scand. 117, 198–206. https://doi.org/10.1111/j.1600-0447.2007.01128.x
Williams, A.M., Phaneuf, D.J., 2019. The Morbidity Costs of Air Pollution: Evidence from Spending on Chronic Respiratory Conditions. Environ. Resour. Econ. 74, 571–603. https://doi.org/10.1007/s10640-019-00336-9
World Health Organization, 2005. Effects of air pollution on children's health and development: A review of the evidence.
Yang, A.C., Tsai, S.J., Huang, N.E., 2011. Decomposing the association of completed suicide with air pollution, weather, and unemployment data at different time scales. J. Affect. Disord. 129, 275–281. https://doi.org/10.1016/j.jad.2010.08.010
Zhang, L., Liu, Y., Hao, L., 2016. Contributions of open crop straw burning emissions to PM2.5 concentrations in China. Environ. Res. Lett. 11. https://doi.org/10.1088/1748-9326/11/1/014014
Zhang, P., Carleton, T., Lin, L., Zhou, M., 2024. Estimating the role of air quality improvements in the decline of suicide rates in China. Nat. Sustain.
Zhang, Xin, Chen, X., Zhang, Xiaobo, 2018. The impact of exposure to air pollution on cognitive performance. Proc. Natl. Acad. Sci. U. S. A. 115, 9193–9197. https://doi.org/10.1073/pnas.1809474115
Zhang, Xin, Zhang, Xiaobo, Chen, X., 2017. Happiness in the air: How does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manage. 85, 81–94. https://doi.org/10.1016/j.jeem.2017.04.001

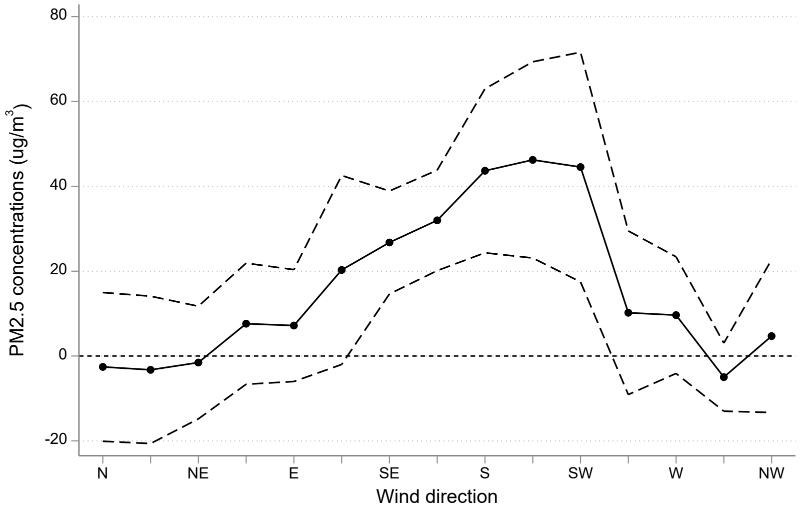
Zundel, C.G., Ryan, P., Brokamp, C., Heeter, A., Huang, Y., Strawn, J.R., Marusak, H.A., 2022. Air pollution, depressive and anxiety disorders, and brain effects: A systematic review. Neurotoxicology 93, 272–300. https://doi.org/10.1016/j.neuro.2022.10.011

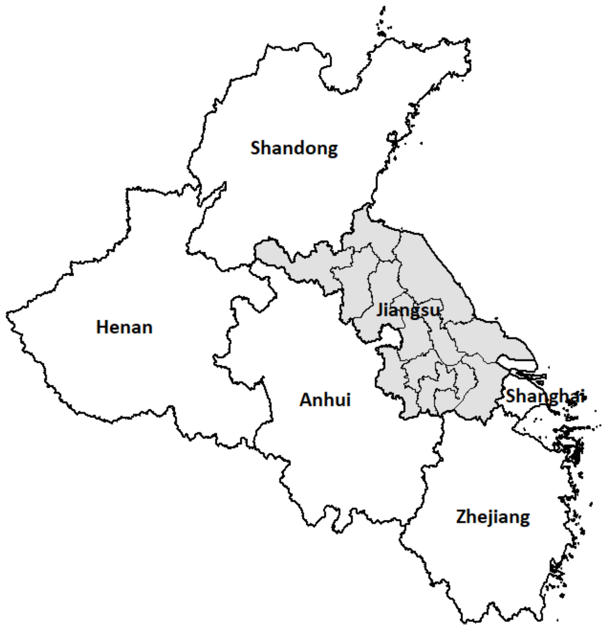
Figure 1 Schools and air quality monitoring stations in Jiangsu Province, China



Note: The figure displays the spatial distribution of schools and air quality monitoring stations in the sample.

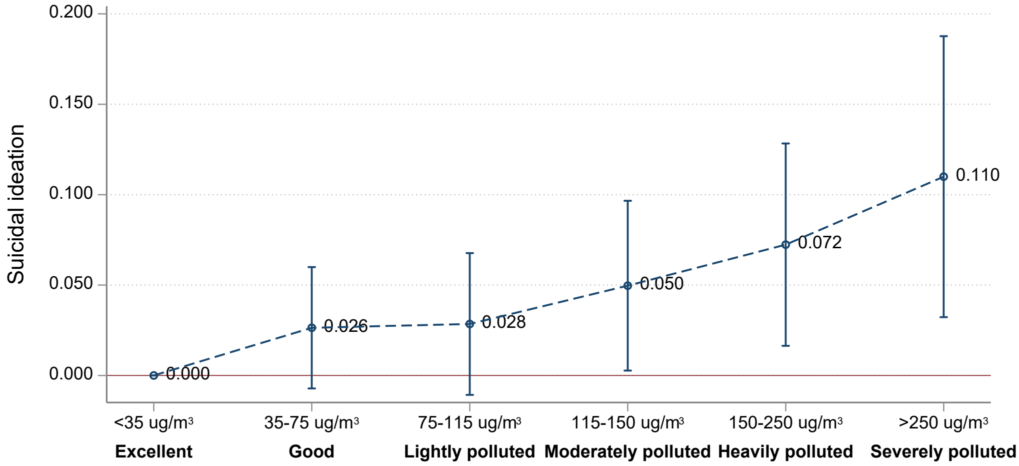
Figure 2 Relationship between daily wind direction and PM 2.5 concentrations in Jiangsu Province (October 1, 2013 - December 31, 2013)





Note: The figure on the left visualizes the estimates of daily mean PM2.5 concentrations on a set of indicators for the daily wind directions, each falling into a particular 22.5-degree angle bin at the city level in Jiangsu Province. The regression includes controls for city, month, and day-of-week fixed effects. The reference wind direction bin is 337.5 degrees, where 315 degrees corresponds to a northwest wind direction. The dashed lines represent 95 percent confidence intervals based on robust standard errors clustered at the city level. The figure on the right shows the location of Jiangsu Province, which borders five other provinces in China: Shandong, Henan, Anhui, Shanghai and Zhejiang.

Figure 3 Non-linear relationship between PM2.5 exposure and suicidal ideation



Note: The figure plots the estimated coefficients with 95% confidence intervals for the dummy variables of each PM2.5 category. According to the air quality standard published by the MEE, we classify the PM2.5 concentrations into six categories: "<35 μg/m^3 (excellent)"; "35-75 μg/m^3 (good)"; "75-115 μg/m^3 (lightly polluted)"; "115-150 μg/m^3 (moderated polluted)"; "150-250 μg/m^3 (heavily polluted)"; and ">250 μg/m^3 (severely polluted)". We assign each category a dummy variable, and designate "<35 μg/m^3 (excellent)" as the reference group. We instrument for the five dummy variables using wind directions. The regression includes school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. Robust standard errors are clustered at the school level.

Table 1 Summary statistics of key variables

Variable	Mean	Std. Dev.
Suicidal ideation	0.091	0.288
PM2.5 ($\mu g/m^3$)	91.042	59.479
Male	0.481	0.500
Age (÷10)	1.594	0.243
Household per capita income (log)	7.707	0.819
temperature bins		
<5 °C	0.048	0.214
5-6 °C	0.026	0.158
6-7 °C	0.016	0.126
7-8 °C	0.065	0.246
8-9 °C	0.044	0.206
9-10 °C	0.023	0.149
10-11 °C	0.024	0.152
11-12 °C	0.101	0.301
12-13 °C	0.094	0.291
13-14 °C	0.114	0.317
14-15 °C	0.123	0.329
15-16 °C	0.062	0.241
16-17 °C	0.111	0.314
17-18 °C	0.071	0.256
18-19 °C	0.035	0.183
>19 °C	0.045	0.207
total precipitation (mm)	0.407	2.018
mean wind speed (m/s)	1.996	0.965
sunshine duration (hour)	5.661	3.426

Source: Jiangsu Youth Risk Behavior Survey 2013.

Table 2 Effects of air pollution on suicidal ideation

Suicidal ideation	OLS estimates		2SLS estimates	
	(1)	(2)	(3)	(4)
PM2.5 (÷1000)	0.109**	0.110***	0.363***	0.364***
	(0.042)	(0.042)	(0.136)	(0.136)
Male		0.005		0.005
		(0.003)		(0.003)
Age (÷10)		-0.008		-0.025
		(0.097)		(0.098)
Age (÷10) square		-0.003		0.002
		(0.027)		(0.027)
Household per capita income (log)		-0.013***		-0.013***
		(0.002)		(0.002)
Weather controls	Yes	Yes	Yes	Yes
School and grade fixed effects	Yes	Yes	Yes	Yes
Month, day-of-week fixed effects	Yes	Yes	Yes	Yes
KP first-stage F-statistic			83.99	82.56
Hansen J statistic P-value			0.209	0.213
Observations	55,138	55,138	55,138	55,138
Mean of PM2.5 ($\mu g/m^3$)	91.042	91.042	91.042	91.042
Mean of suicidal ideation	0.091	0.091	0.091	0.091
Elasticity at the mean	0.11	0.11	0.36	0.36

Note: The coefficients on PM2.5 are scaled by 1000 to make them more readable. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. In columns (3) and (4), PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

Table 3 Cumulative effects of air pollution on suicidal ideation (2SLS estimates)

Dependent variable	A. Cumulative PM2.5			B. Transitory and cumulative PM2.5			C. PM2.5 deviation		
Suicidal ideation	7-day	14-day	30-day	7-day	14-day	30-day	7-day	14-day	30-day
	(1)	(2)	(3)	(4)	(5)	(6)			
PM2.5				0.243**	0.194**	0.174**			
				(0.102)	(0.093)	(0.083)			
Cumulative PM2.5	0.210	0.065	0.919*	0.144	-0.016	0.461			
	(0.273)	(0.393)	(0.532)	(0.229)	(0.328)	(0.494)			
PM2.5 deviation							0.229**	0.196**	0.194**
							(0.094)	(0.091)	(0.083)
KP first-stage F-statistic	39.79	39.12	66.18	164.4	196.1	319.5	202.6	195.9	330.9
Hansen J statistic P-value	0.165	0.315	0.211	0.149	0.467	0.292	0.175	0.485	0.333
Observations	55,138	55,138	55,138	55,138	55,138	55,138	55,138	55,138	55,138

Note: The PM2.5 deviation is defined as the difference between the PM2.5 levels on the interview date and the cumulative PM2.5 levels during the corresponding time window. **The coefficients are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. We instrument for PM2.5 using the number of days falling in each 90-degree wind direction interval during the corresponding PM2.5 exposure window. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

Table 4 Robustness checks: addressing correlations between air pollutants (2SLS estimates)

Dependent variable	Pollutant					
Suicidal ideation	All	PM2.5&PM10	PM2.5&CO	PM2.5&NO_2	PM2.5&O_3	PM2.5&SO_2
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5	0.470**	0.471**	0.327**	0.344**	0.349***	0.285**
	(0.236)	(0.240)	(0.138)	(0.138)	(0.133)	(0.142)
PM10	-0.266	-0.173				
	(0.188)	(0.170)				
CO	12.669		13.524×10^{-3}			
	(14.429)		(11.380×10^{-3})			
NO_2	0.256			0.249		
	(0.407)			(0.383)		
O_3	0.482				0.107	
	(0.436)				(0.375)	
SO_2	0.460					0.475
	(0.501)					(0.412)
KP first-stage F-statistic	16.71	42.15	62.12	83.20	24.63	53.67
Hansen J statistic P-value	0.340	0.438	0.163	0.174	0.229	0.208
Observations	51,444	52,116	55,138	55,138	54,055	54,044

Note: **The coefficients are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. All the air pollutants are instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

Table 5 Robustness checks: other air pollution exposure and modeling specifications

Dependent variable Suicidal ideation	Placebo test		Aggregate data at the school-day level	Add school-grade fixed effects	Probit
	PM2.5 next day	PM2.5 the same day in the subsequent year			
	(1)	(2)	(3)	(4)	(5)
PM2.5			0.689*	0.452**	2.440**
			(0.407)	(0.176)	(1.114)
PM2.5 next day	-0.020				
	(0.048)				
PM2.5 the same day in the subsequent year		0.058			
		(0.158)			
Demographic controls	Yes	Yes	No	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes	No	Yes
Grade fixed effects	Yes	Yes	No	No	Yes
School-grade fixed effects	No	No	No	Yes	No
Month, day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes
KP first-stage F-statistic	27.27	22.20	33.10	129.3	--
Hansen J statistic P-value	0.331	0.123	0.315	0.287	--
Observations	55,138	55,138	1,188	55,138	54,895

Note: **The coefficients on PM2.5 are scaled by 1000 to make them more readable.** Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. All the PM2.5 variables are instrumented using wind directions. Columns (1) through (4) are estimated using 2SLS method, and column (5) is estimated using ivprobit method. Marginal effect at mean is reported in column (5). Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

Table 6 Heterogeneous effects of PM2.5 on suicidal ideation (2SLS estimates)

Dependent variable	A. Gender		B. Grade	
Suicidal ideation	male	female	middle school	high school or college
	(1)	(2)	(3)	(4)
Dependent variable mean	*0.096*	*0.087*	*0.097*	*0.088*
SD	*(0.295)*	*(0.282)*	*(0.296)*	*(0.284)*
PM2.5	0.534**	0.118	0.667**	0.192
	(0.226)	(0.144)	(0.300)	(0.124)
KP first-stage F-statistic	92.98	76.52	98.32	52.48
Hansen J statistic P-value	0.362	0.499	0.697	0.330
Observations	26,536	28,602	19,034	36,104

Dependent variable	C. Mother's education		D. Performance		
Suicidal ideation	middle school or below	high school or above	low	median	high
	(5)	(6)	(7)	(8)	(9)
Dependent variable mean	*0.085*	*0.097*	*0.148*	*0.076*	*0.076*
SD	*(0.279)*	*(0.295)*	*(0.355)*	*(0.265)*	*(0.265)*
PM2.5	0.358**	0.106	1.201***	0.170	-0.002
	(0.164)	(0.205)	(0.409)	(0.173)	(0.170)
KP first-stage F-statistic	30.24	52.39	37.34	48.87	50.61
Hansen J statistic P-value	0.203	0.387	0.701	0.934	0.231
Observations	32,475	20,112	10,225	20,392	21,708

Note: **The coefficients on PM2.5 are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level. The school performance is categorized into five groups: low, lower middle, middle, higher middle, and high. We combine the low and lower middle as the low level and the higher middle and high as the high level.

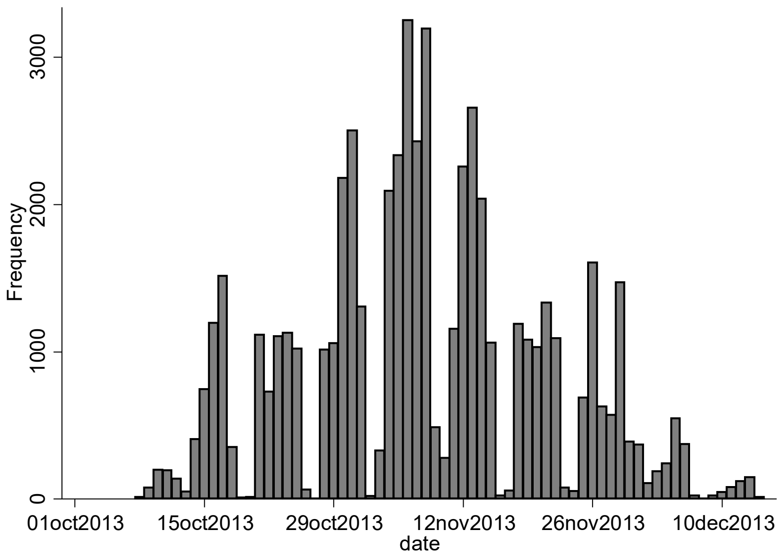
Table 7 Effects of PM2.5 on feelings of depression and undesirable behaviors (2SLS estimates)

Dependent variable	Sleeplessness	Depression	Self-injury	Internet addiction
	(1)	(2)	(3)	
Dependent variable mean	*0.402*	*0.130*	*0.016*	*0.045*
SD	*(0.490)*	*(0.337)*	*(0.127)*	*(0.206)*
PM2.5 over the past 30 days	4.268***	1.116**	0.458**	0.768*
	(1.335)	(0.556)	(0.232)	(0.392)
KP first-stage F-statistic	66.18	66.18	66.18	66.18
Hansen J statistic P-value	0.740	0.132	0.871	0.152
Observations	55,138	55,138	55,138	55,138

Note: **The coefficients are scaled by 1000 to make them more readable.** The dependent variables include dummy variables for reporting symptoms of sleeplessness, feelings of depression, self-injury and internet addiction within the past 30 days. All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. The average PM2.5 level is instrumented using the number of days within each 90-degree wind direction interval during the past 30 days. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

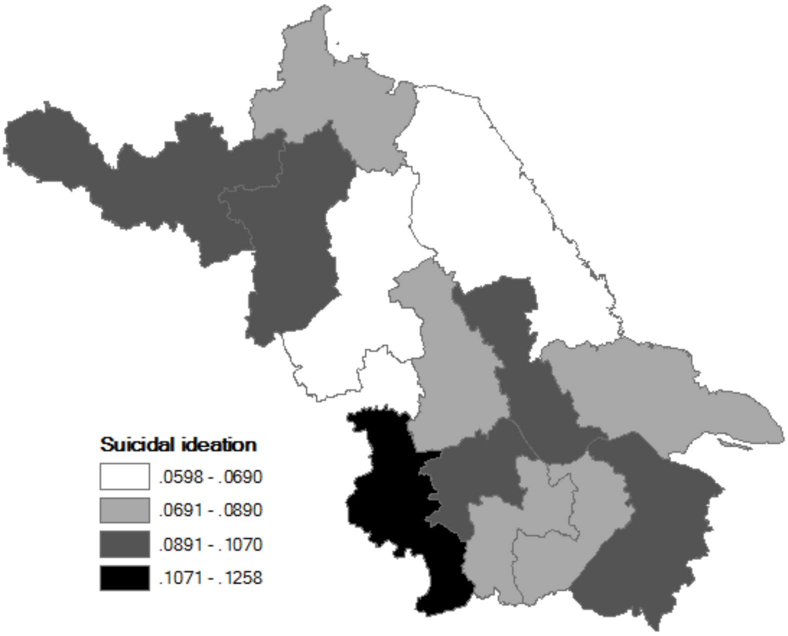
Appendix A: Supplementary Figures and Tables

Figure A1 Distribution of survey dates



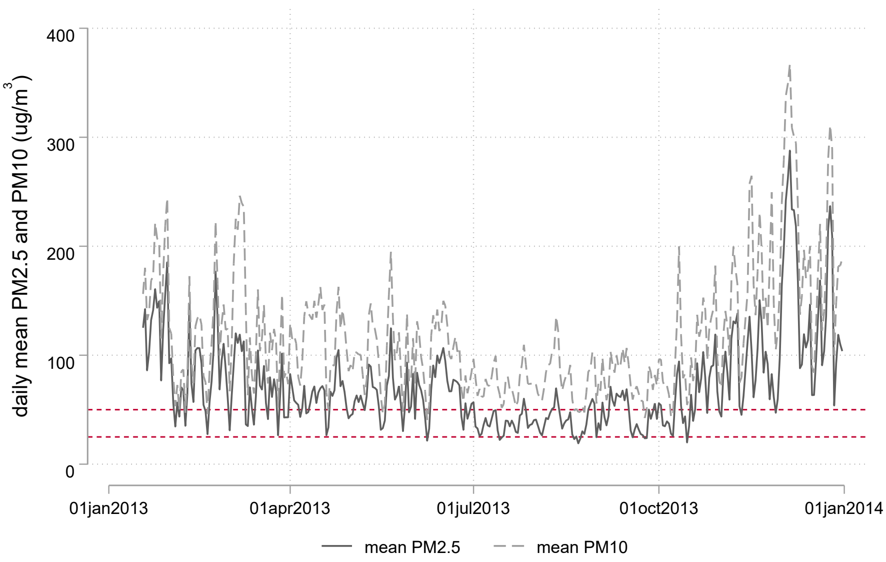
Note: The figure plots the distribution of survey dates.

Figure A2 Mean suicidal ideation at the city level



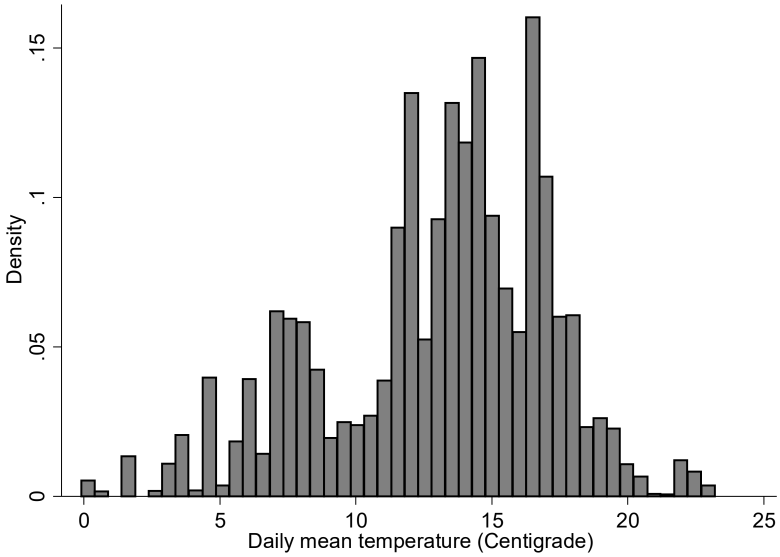
Note: The figure displays the mean level of suicidal ideation at the city level in Jiangsu Province.

Figure A3 Daily mean PM2.5 and PM10 (μg/m³) in Jiangsu Province, 2013



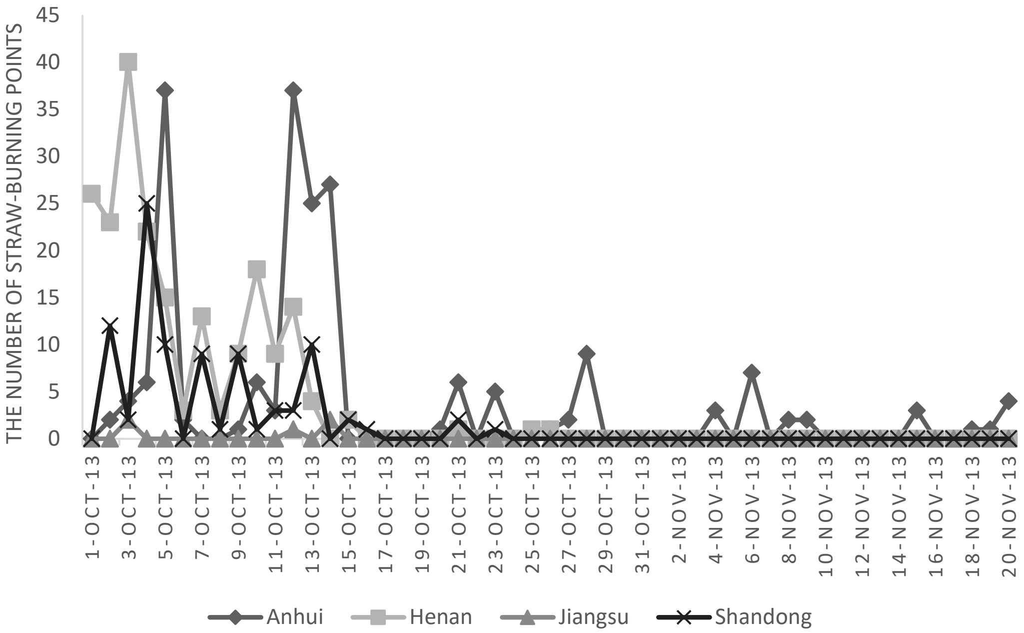
Note: The figure shows the daily mean PM2.5 and PM10 (μg/m³) in Jiangsu Province in 2013. The WHO standards for the 24-hour mean concentrations of PM2.5 and PM10 are 25 μg/m³ and 50 μg/m³, respectively.

Figure A4 Distribution of daily mean temperature in the survey



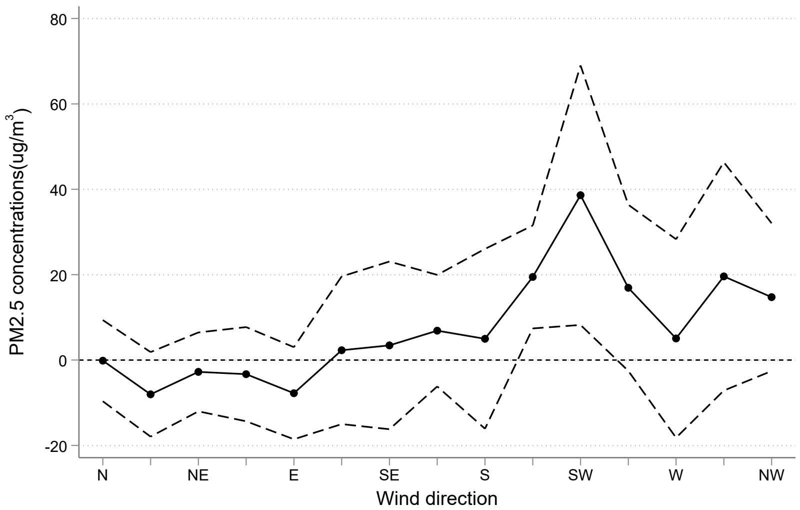
Note: The figure plots the distribution of daily mean temperature in the survey.

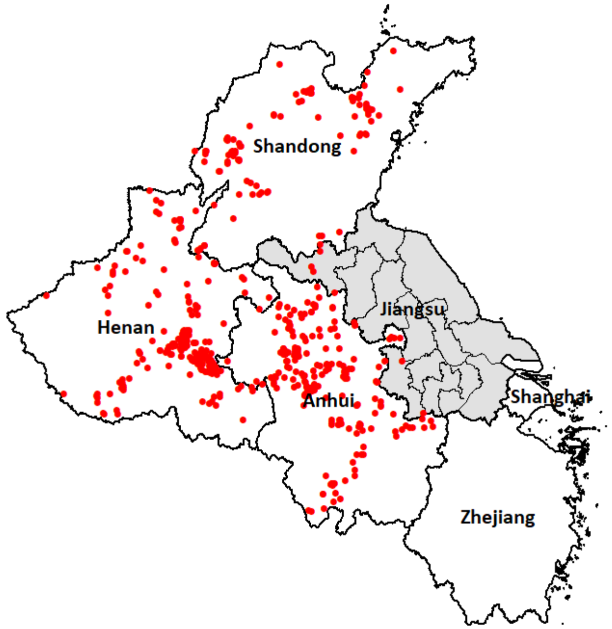
Figure A5 Number of straw-burning points by province



Source: The Ministry of Ecology and Environment of the People's Republic of China.
Note: The figure presents the number of straw-burning points on each day by province.

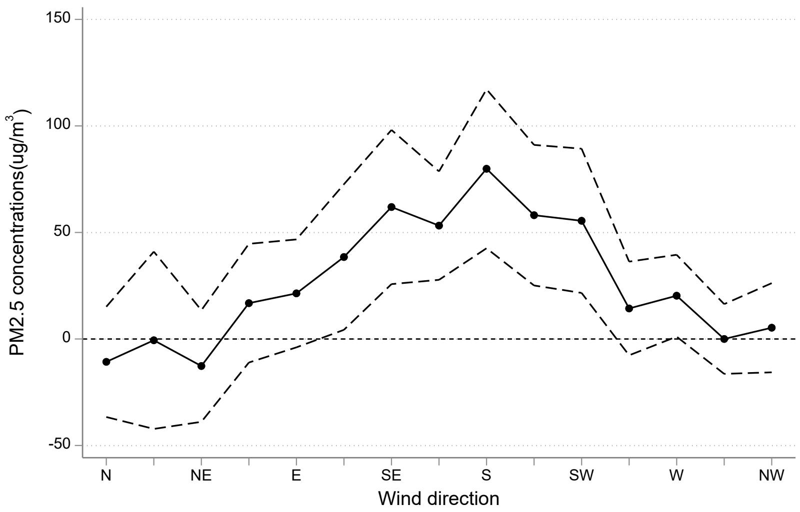
Figure A6a Relationship between daily wind direction and PM 2.5 concentrations in Jiangsu Province (October 1, 2013 - November 10, 2013)

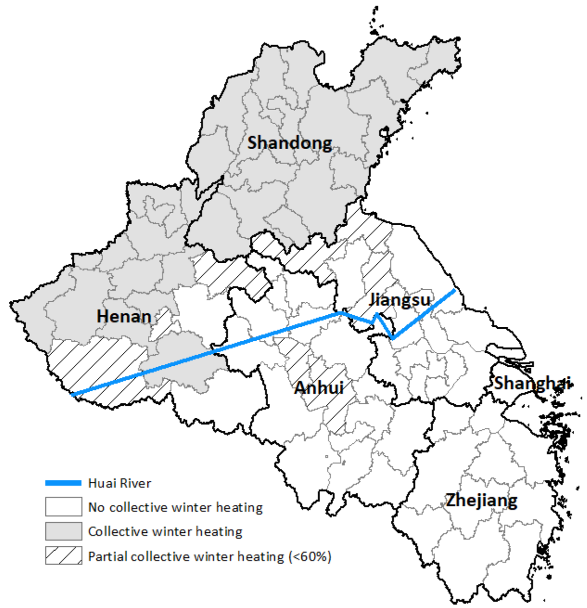




Source: The locations of straw-burning points are obtained from the Ministry of Ecology and Environment of the People's Republic of China.
Note: The figure on the left visualizes the estimates of daily mean PM2.5 concentrations on a set of indicators for the daily wind directions, each falling into a particular 22.5-degree angle bin, at the city level in Jiangsu Province before winter heating. The regression includes controls for city, month and day-of-week fixed effects. The reference wind direction bin is 337.5 degrees, where 315 degrees corresponds to a northwest wind direction. The dashed lines represent 95 percent confidence intervals based on robust standard errors clustered at the city level. The figure on the right displays the locations of straw-burning points during this period.

Figure A6b Relationship between daily wind direction and PM 2.5 concentrations in Jiangsu Province (November 10, 2013 – December 31, 2013)





Source: The winter heating zones are obtained from https://www.thepaper.cn/newsDetail_forward_4948429.
Note: The figure on the left visualizes the estimates of daily mean PM2.5 concentrations on a set of indicators for the daily wind directions, each falling into a particular 22.5-degree angle bin, at the city level in Jiangsu Province during winter heating (November 10, 2013 – December 31, 2013). The regression includes controls for city, month and day-of-week fixed effects. The reference wind direction bin is 337.5 degrees, where 315 degrees corresponds to a northwest wind direction. The dashed lines represent 95 percent confidence intervals based on robust standard errors clustered at the city level. The figure on the right shows the distribution of winter heating zones.

Figure A7 Mean concentrations of PM2.5 by wind direction and city

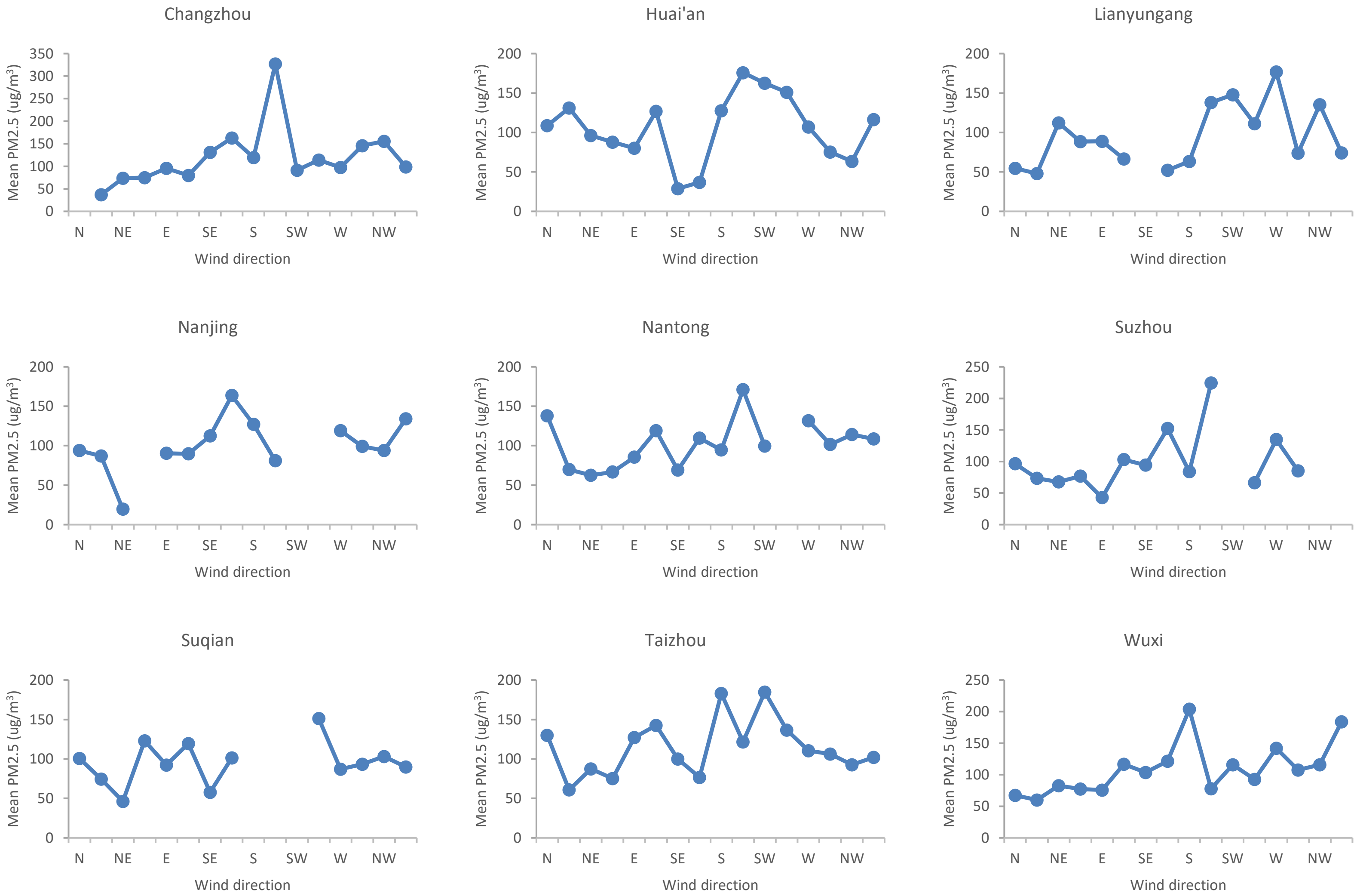
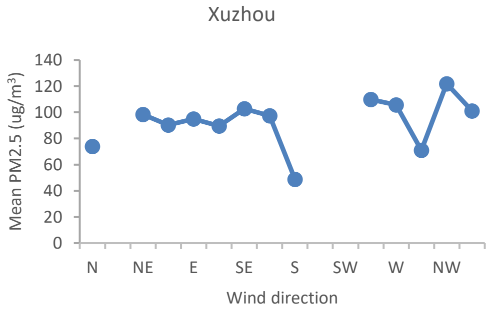
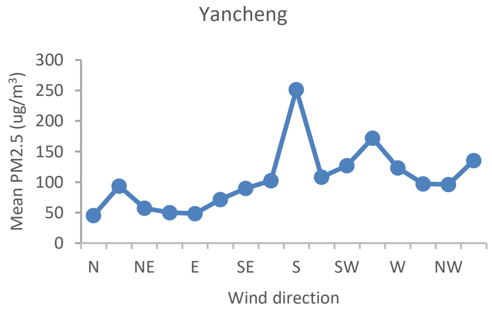
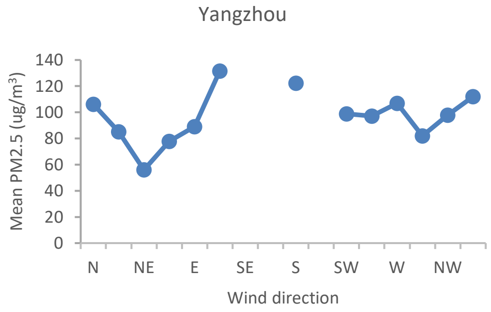
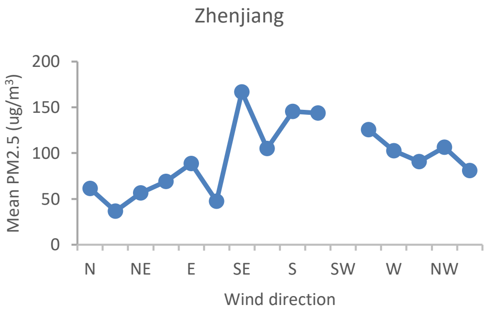


Figure A7 (continued) Mean concentrations of PM2.5 by wind direction and city



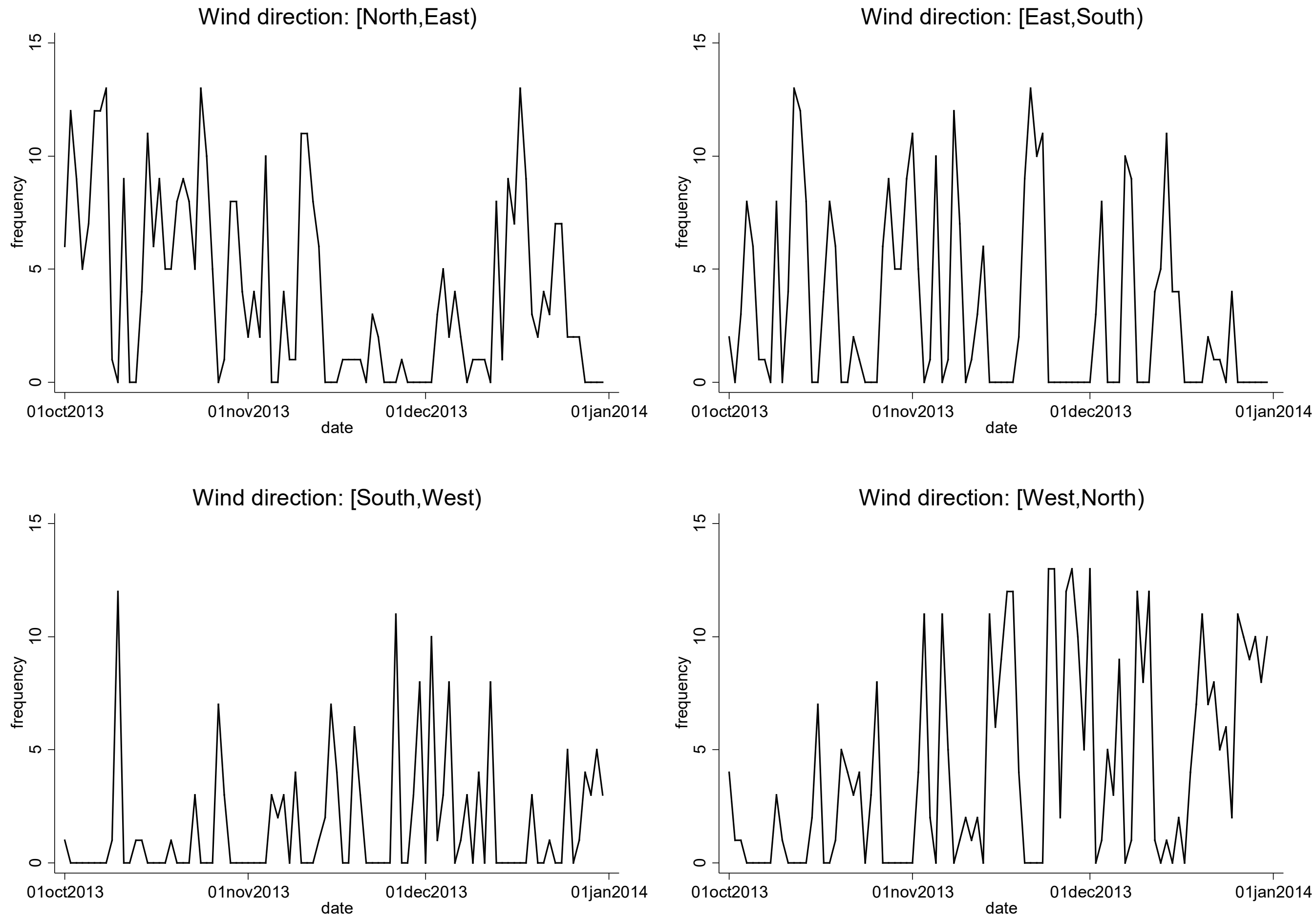






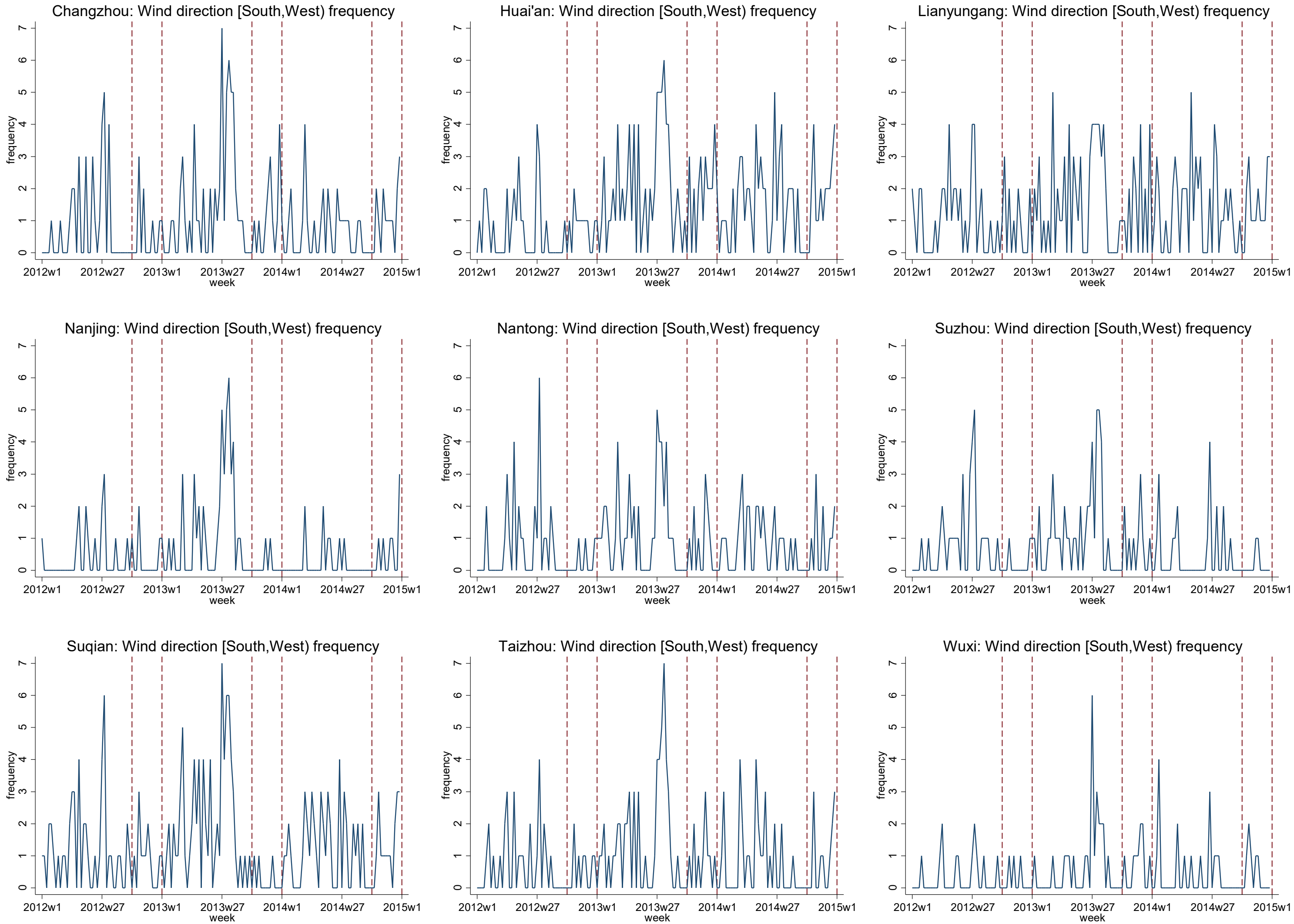
Note: The figures indicate the daily mean PM2.5 concentrations by wind direction for each city in Jiangsu Province. The missing connecting lines indicate that there are no corresponding wind directions in the city during the sample period.

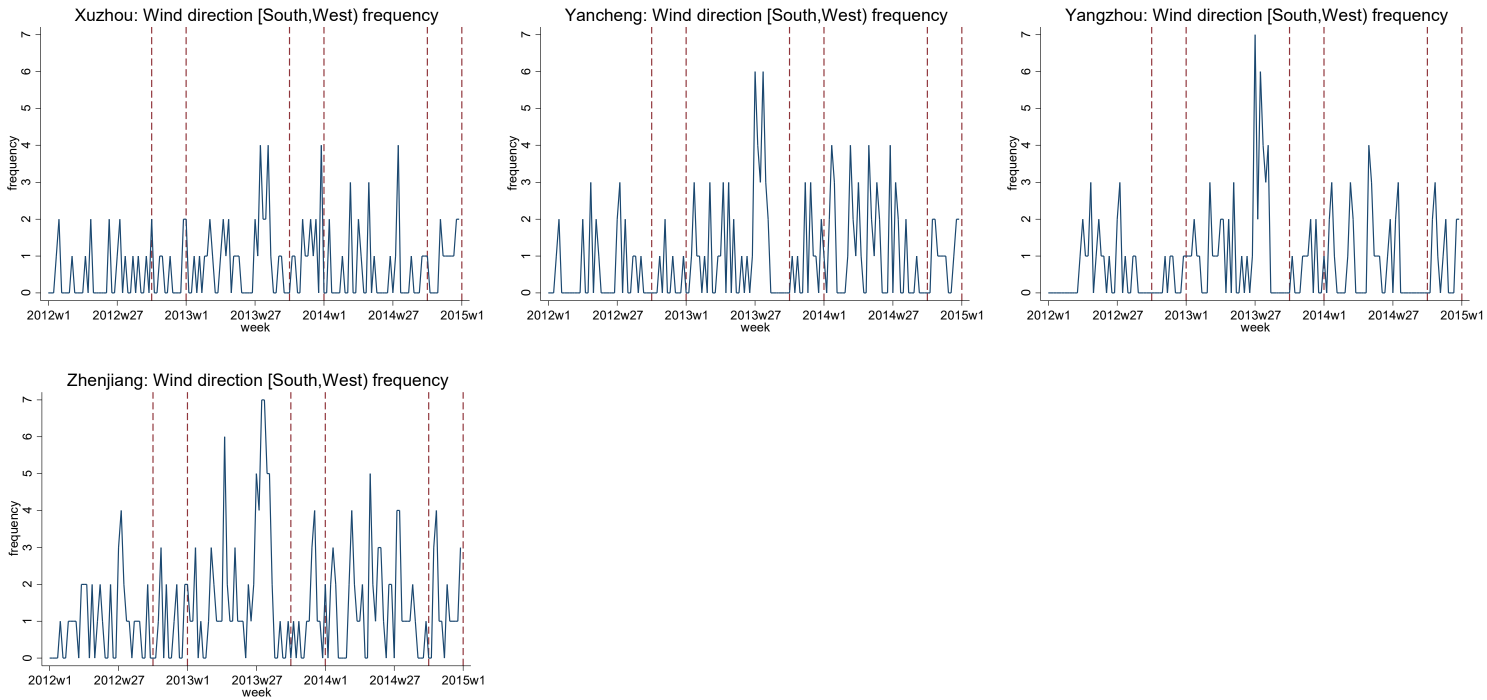
Figure A8 Frequency of wind directions in Jiangsu Province



Note: The figure shows the daily frequency of the four wind directions in Jiangsu during the sample period.

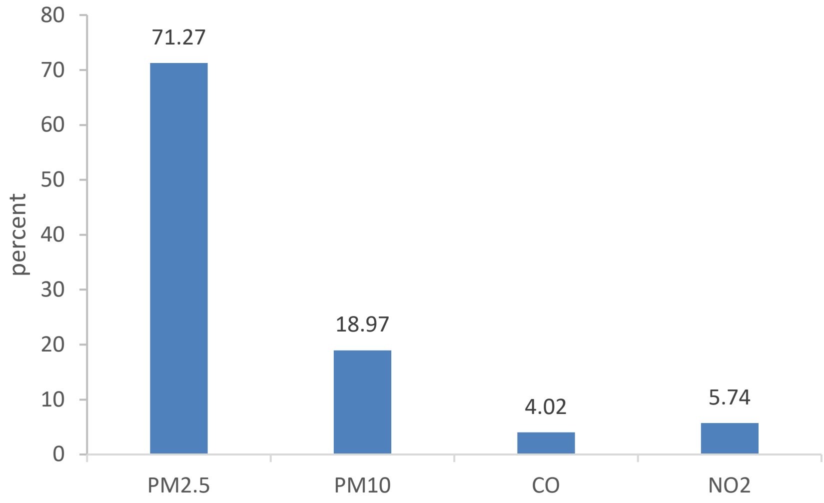
Figure A9 Weekly frequency of wind direction [South, West) for each city in Jiangsu Province





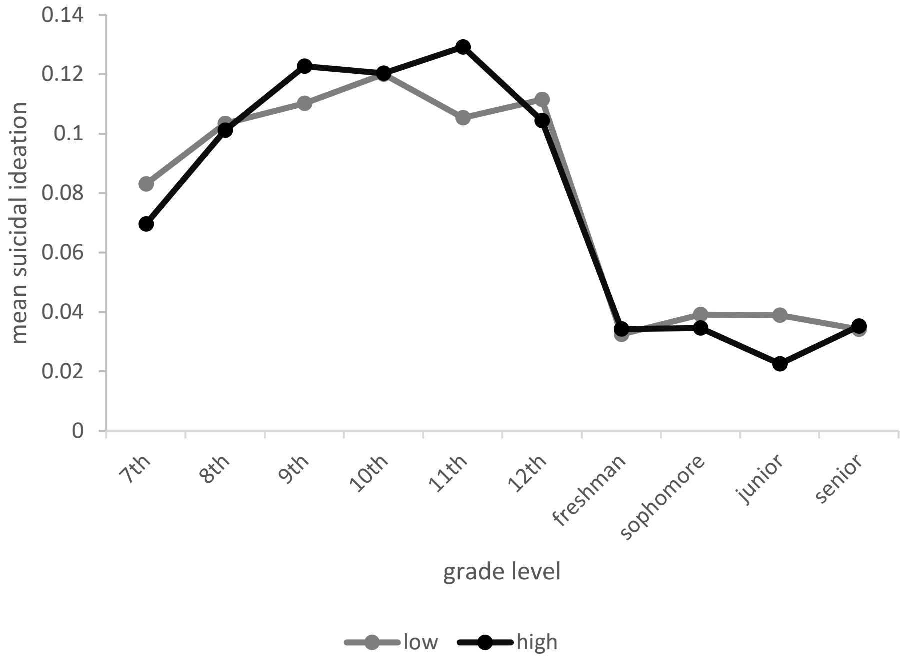
Note: The figure illustrates the frequency of southwest wind direction for each city from October to December over three consecutive years (2012-2014). The vertical lines indicate October to December in 2012, 2013 and 2014, respectively. Our sample period is October to December in 2013.

Figure A10 Distribution of dominant pollutant in the sample



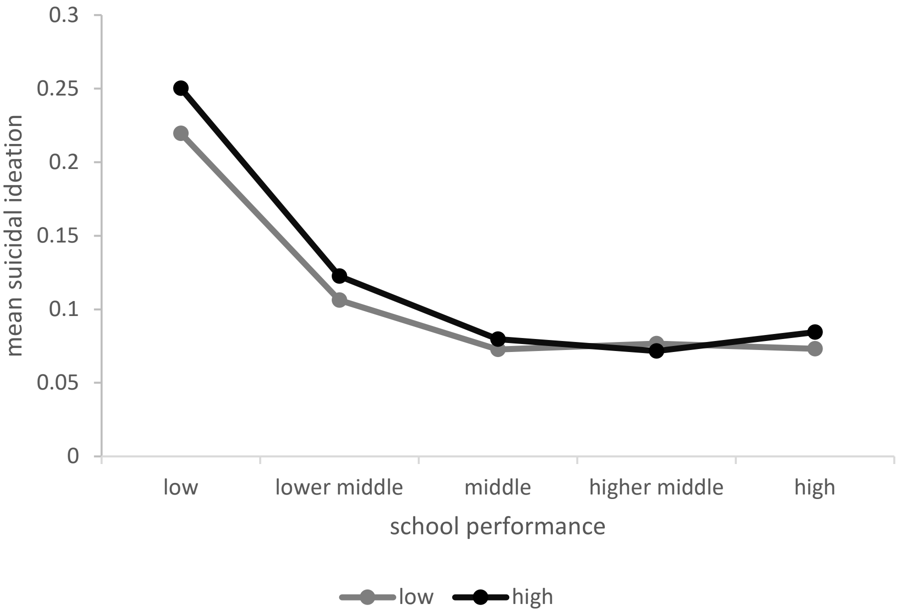
Note: The figure shows the distribution of dominant pollutant in the sample. PM2.5 = particulate matter with a diameter smaller than 2.5 micrometers. PM10 = particulate matter with a diameter smaller than 10 micrometers. CO = carbon monoxide. NO_2 = nitrogen dioxide.

Figure A11 Mean suicidal ideation by grade and level of pollution



Note: The pollution level is divided by the median of PM2.5 concentrations.

Figure A12 Mean suicidal ideation by school performance and level of pollution



Note: The pollution level is divided by the median of PM2.5 concentrations.

Table A1 First-stage effects of daily wind directions on PM2.5

IVs	PM2.5 (÷1000)	IVs	PM2.5 (÷1000)
city1#[0,90)#WH_0	-0.026**	city1#[180,270)#WH_0	-0.039**
	(0.011)		(0.016)
city2#[0,90)#WH_0	-0.090***	city2#[180,270)#WH_0	-0.114***
	(0.023)		(0.034)
city3#[0,90)#WH_0	-0.010	city3#[180,270)#WH_0	-0.022
	(0.020)		(0.019)
city4#[0,90)#WH_0	0.026*	city4#[180,270)#WH_0	
	(0.015)		
city5#[0,90)#WH_0	-0.041*	city5#[180,270)#WH_0	-0.064
	(0.024)		(0.067)
city6#[0,90)#WH_0	-0.008	city6#[180,270)#WH_0	-0.006
	(0.018)		(0.021)
city7#[0,90)#WH_0	0.029*	city7#[180,270)#WH_0	-0.039***
	(0.015)		(0.015)
city8#[0,90)#WH_0	-0.031**	city8#[180,270)#WH_0	-0.160*
	(0.016)		(0.082)
city9#[0,90)#WH_0	-0.012	city9#[180,270)#WH_0	-0.086*
	(0.017)		(0.051)
city10#[0,90)#WH_0	-0.020	city10#[180,270)#WH_0	-0.029
	(0.015)		(0.024)
city11#[0,90)#WH_0		city11#[180,270)#WH_0	
city12#[0,90)#WH_0	0.006	city12#[180,270)#WH_0	-0.074***
	(0.016)		(0.022)
city13#[0,90)#WH_0	0.020	city13#[180,270)#WH_0	
	(0.018)		
city1#[90,180)#WH_0	-0.063	city1#[0,90)#WH_1	0.033***
	(0.044)		(0.011)
city2#[90,180)#WH_0	-0.121***	city2#[0,90)#WH_1	-0.094***
	(0.033)		(0.026)
city3#[90,180)#WH_0	-0.087***	city3#[0,90)#WH_1	-0.017
	(0.018)		(0.012)
city4#[90,180)#WH_0	-0.009	city4#[0,90)#WH_1	0.039
	(0.011)		(0.046)
city5#[90,180)#WH_0	-0.012	city5#[0,90)#WH_1	-0.016
	(0.019)		(0.011)
city6#[90,180)#WH_0	-0.034*	city6#[0,90)#WH_1	-0.008
	(0.019)		(0.018)
city7#[90,180)#WH_0	-0.012	city7#[0,90)#WH_1	-0.046***
	(0.013)		(0.014)
city8#[90,180)#WH_0	-0.068***	city8#[0,90)#WH_1	-0.044***
	(0.019)		(0.009)
city9#[90,180)#WH_0	-0.019	city9#[0,90)#WH_1	-0.018
	(0.019)		(0.015)
city10#[90,180)#WH_0	-0.015	city10#[0,90)#WH_1	-0.066***
	(0.010)		(0.013)
city11#[90,180)#WH_0		city11#[0,90)#WH_1	-0.074*
			(0.041)
city12#[90,180)#WH_0	-0.048*	city12#[0,90)#WH_1	-0.011
	(0.027)		(0.011)
city13#[90,180)#WH_0	-0.020	city13#[0,90)#WH_1	-0.045***
	(0.014)		(0.014)

(*continued*)

IVs	PM2.5 (÷1000)
city1#[90,180)# WH_1	
city2#[90,180)# WH_1	-0.059**
	(0.025)
city3#[90,180)# WH_1	-0.003
	(0.017)
city4#[90,180)# WH_1	0.014
	(0.011)
city5#[90,180)# WH_1	0.021*
	(0.013)
city6#[90,180)# WH_1	0.053***
	(0.013)
city7#[90,180)# WH_1	0.004
	(0.011)
city8#[90,180)# WH_1	0.012
	(0.018)
city9#[90,180)# WH_1	
city10#[90,180)# WH_1	-0.063***
	(0.021)
city11#[90,180)# WH_1	-0.073**
	(0.037)
city12#[90,180)# WH_1	-0.008
	(0.017)
city13#[90,180)# WH_1	0.003
	(0.012)
city1#[180,270)# WH_1	
city2#[180,270)# WH_1	-0.024
	(0.027)
city3#[180,270)# WH_1	0.045*
	(0.024)
city4#[180,270)# WH_1	0.045***
	(0.016)
city5#[180,270)# WH_1	-0.010
	(0.016)
city6#[180,270)# WH_1	0.047***
	(0.017)
city7#[180,270)# WH_1	
city8#[180,270)# WH_1	0.037*
	(0.020)
city9#[180,270)# WH_1	0.029
	(0.021)
city10#[180,270)# WH_1	0.013
	(0.014)
city11#[180,270)# WH_1	-0.009
	(0.027)
city12#[180,270)# WH_1	-0.010
	(0.026)
city13#[180,270)# WH_1	-0.006
	(0.019)

IVs	PM2.5 (÷1000)
School and grade FE	Yes
Month, day-of-week FE	Yes
Demographic controls	Yes
Weather controls	Yes
Observations	55,138
R-squared	0.782

Note: city1=Changzhou city2=Huai'an
city3=Lianyungang city4=Nanjing
city5=Nantong city6=Suzhou
city7=Suqian city8=Taizhou
city9=Wuxi city10=Xuzhou
city11=Yancheng city12=Yangzhou
city13=Zhenjiang
WH_0: before WH
WH_1: during WH

Table A2 Adaptation to air pollution (2SLS estimates)

Dependent variable	Historical level of air pollution		Deviation from historical level	
Suicidal ideation	less polluted	polluted	deviation from the annual mean	standard deviation from the annual mean
	(1)	(2)	(3)	(4)
PM2.5	0.485***	0.135		
	(0.184)	(0.140)		
Deviation from the annual mean			0.364***	
			(0.136)	
Standard deviation from the annual mean				0.020***
				(0.007)
KP first-stage F-statistic	103.6	27.20	82.56	78.73
Hansen J statistic P-value	0.255	0.345	0.213	0.231
Observations	27,682	27,456	55,138	55,138

Note: The deviation from the annual mean represents the difference between the PM2.5 level on the interview date and the average annual PM2.5 level in 2013. The standard deviation from the annual mean indicates this difference measured in terms of the standard deviation of the annual PM2.5 levels in 2013. **The coefficients on PM2.5 and deviation from the annual mean are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. All the PM2.5 exposures are instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level.

Table A3 Correlations between pollutants

	PM2.5	PM10	CO	NO_2	O_3	SO_2
PM2.5	1.000					
PM10	0.825	1.000				
CO	0.537	0.512	1.000			
NO_2	0.560	0.576	0.404	1.000		
O_3	-0.071	-0.061	-0.103	-0.107	1.000	
SO_2	0.500	0.548	0.472	0.561	-0.074	1.000

Note: CO = carbon monoxide. NO_2 = nitrogen dioxide. O_3 = ozone. PM2.5 = particulate matter with a diameter smaller than 2.5 micrometers. SO_2 = sulfur dioxide.

Table A4 Heterogeneous effects of PM2.5 on sleeplessness (2SLS estimates)

Dependent variable	A. Gender		B. Grade	
Suicidal ideation	male	female	middle school	high school or college
	(1)	(2)	(3)	(4)
PM2.5	4.231***	3.957***	4.157**	1.495
	(1.527)	(1.455)	(1.622)	(1.591)
KP first-stage F-statistic	74.93	85.92	429.3	819.5
Hansen J statistic P-value	0.826	0.409	0.649	0.571
Observations	26,536	28,602	19,034	36,104

Dependent variable	C. Mother's education		D. Performance		
Suicidal ideation	middle school or below	high school or above	low	median	high
	(5)	(6)	(7)	(8)	(9)
PM2.5	4.429**	3.649**	5.464***	5.344***	2.895*
	(1.800)	(1.425)	(1.701)	(2.046)	(1.739)
KP first-stage F-statistic	55.26	73.93	87.86	57.67	53.39
Hansen J statistic P-value	0.395	0.441	0.360	0.142	0.473
Observations	32,475	20,112	10,225	20,392	21,708

Note: **The coefficients on PM2.5 are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level. The school performance is categorized into five groups: low, lower middle, middle, higher middle, and high. We combine the low and lower middle as the low level and the higher middle and high as the high level.

Table A5 Heterogeneous effects of PM2.5 on depression (2SLS estimates)

Dependent variable	A. Gender		B. Grade	
Suicidal ideation	male	female	middle school	high school or college
	(1)	(2)	(3)	(4)
PM2.5	1.498**	0.529	1.581*	0.710
	(0.633)	(0.858)	(0.893)	(0.598)
KP first-stage F-statistic	85.92	74.93	819.5	429.3
Hansen J statistic P-value	0.627	0.124	0.274	0.319
Observations	26,536	28,602	19,034	36,104

Dependent variable	C. Mother's education		D. Performance		
Suicidal ideation	middle school or below	high school or above	low	median	high
	(5)	(6)	(7)	(8)	(9)
PM2.5	1.522**	0.195	3.109**	0.686	0.714
	(0.766)	(0.903)	(1.343)	(0.646)	(0.844)
KP first-stage F-statistic	73.93	55.26	57.67	87.86	53.39
Hansen J statistic P-value	0.234	0.518	0.458	0.590	0.302
Observations	32,475	20,112	10,225	20,392	21,708

Note: **The coefficients on PM2.5 are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level. The school performance is categorized into five groups: low, lower middle, middle, higher middle, and high. We combine the low and lower middle as the low level and the higher middle and high as the high level.

Table A6 Heterogeneous effects of PM2.5 on self-injury (2SLS estimates)

Dependent variable	A. Gender		B. Grade	
Suicidal ideation	male	female	middle school	high school or college
	(1)	(2)	(3)	(4)
PM2.5	0.450**	0.595	1.205**	0.111
	(0.223)	(0.418)	(0.553)	(0.180)
KP first-stage F-statistic	85.92	74.93	819.5	429.3
Hansen J statistic P-value	0.836	0.803	0.385	0.488
Observations	26,536	28,602	19,034	36,104

Dependent variable	C. Mother's education		D. Performance		
Suicidal ideation	middle school or below	high school or above	low	median	high
	(5)	(6)	(7)	(8)	(9)
PM2.5	0.755**	-0.060	0.603	0.289	0.545*
	(0.330)	(0.296)	(0.774)	(0.282)	(0.316)
KP first-stage F-statistic	73.93	55.26	57.67	87.86	53.39
Hansen J statistic P-value	0.575	0.948	0.256	0.644	0.515
Observations	32,475	20,112	10,225	20,392	21,708

Note: **The coefficients on PM2.5 are scaled by 1000 to make them more readable.** All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level. The school performance is categorized into five groups: low, lower middle, middle, higher middle, and high. We combine the low and lower middle as the low level and the higher middle and high as the high level.

Table A7 Heterogeneous effects of PM2.5 on internet addiction (2SLS estimates)

Dependent variable	A. Gender		B. Grade		
Suicidal ideation	male	female	middle school	high school or college	
	(1)	(2)	(3)	(4)	
PM2.5	0.723	0.667*	0.679	0.746	
	(0.661)	(0.367)	(0.736)	(0.455)	
KP first-stage F-statistic	74.93	85.92	819.5	429.3	
Hansen J statistic P-value	0.110	0.311	0.472	0.428	
Observations	26,536	28,602	19,034	36,104	
Dependent variable	C. Mother's education		D. Performance		
Suicidal ideation	middle school or below	high school or above	low	median	high
	(5)	(6)	(7)	(8)	(9)
PM2.5	0.528	0.939	1.884	0.245	0.774
	(0.474)	(0.571)	(1.153)	(0.467)	(0.510)
KP first-stage F-statistic	73.93	55.26	57.67	87.86	53.39
Hansen J statistic P-value	0.0486	0.614	0.203	0.353	0.389
Observations	32,475	20,112	10,225	20,392	21,708

Note: The coefficients on PM2.5 are scaled by 1000 to make them more readable. All the regressions include school fixed effects, grade fixed effects, and month, day-of-week fixed effects. Demographic controls include gender, age and its square term, and log form of household per capita income. The weather controls include temperature bins (lower than 5 °C bin, higher than 19 °C bin, and fourteen 1 °C-wide bins in between), total precipitation, mean wind speed, and sunshine duration. PM2.5 is instrumented using wind directions. Robust standard errors, clustered at the school level, are presented in parentheses. *10% significance level. **5% significance level. ***1% significance level. The school performance is categorized into five groups: low, lower middle, middle, higher middle, and high. We combine the low and lower middle as the low level and the higher middle and high as the high level.