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ABSTRACT

Smog in Our Brains: Gender Differences in the Impact of Exposure to Air Pollution on Cognitive Performance*

While there is a large body of literature on the negative health effects of air pollution, there is much less written about its effects on cognitive performance for the whole population. This paper studies the effects of contemporaneous and cumulative exposure to air pollution on cognitive performance based on a nationally representative survey in China. By merging a longitudinal sample at the individual level with local air-quality data according to the exact dates and counties of interviews, we find that contemporaneous and cumulative exposure to air pollution impedes both verbal and math scores of survey subjects. Interestingly, the negative effect is stronger for men than for women. Specifically, the gender difference is more salient among the old and less educated in both verbal and math tests.

JEL Classification: I24, Q53, Q51, J16

Keywords: cognitive performance, air pollution, gender difference

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1. Introduction

While a large body of literature has shown that air pollution poses a significant threat to human health,[1] knowledge about the potential consequences of air pollution on cognitive abilities is more limited. Poor cognitive function may have profound social, economic and health implications (Lang et al. 2008). While recent studies have explored the link between air pollution and cognition (Sanders 2012; Bharadwaj et al. 2014; Ham, Zweig, and Avol 2014; Molina 2016; Marcotte 2016; Ebenstein, Lavy, and Roth 2016), several challenges plague the empirical identifications.

First, omitted variables correlated with both cognition and exposure to air pollution may bias estimations. Most studies, except for Ebenstein, Lavy, and Roth (2016) and Marcotte (2016), do not account for individual-level heterogeneity. For instance, Ham, Zweig, and Avol (2014) only control for school-grade fixed effects, and Bharadwaj et al. (2014) include sibling fixed effects. In this study, we are able to remove individual-level unobservable factors by using a longitudinal dataset – the China Family Panel Studies (CFPS).

Second, most existing studies consider either the effects of transitory or cumulative exposure to air pollution but rarely both effects simultaneously, with the exception of Marcotte (2016). For example, Ham, Zweig, and Avol (2014) and Ebenstein, Lavy, and Roth (2016) focus on contemporaneous exposure; Bharadwaj et al. (2014), Molina (2016) and Sanders (2012) examine cumulative exposure. We are among the first to examine both contemporaneous and cumulative exposure to air pollution on cognitive performance. By simultaneously studying both effects, we are able to determine the degree to which human beings can adapt to air pollution in the long run. In addition, the relative importance of the two effects has policy implications. In the case of test taking, if transitory effects dominate, resources could be directed toward limiting pollution near test sites or rescheduling high-stakes exams in the event of severe air pollution. However, these short-term interventions may be less effective than more drastic actions to cut air pollution if cumulative effects

[1] The literature includes but is not limited to studies on the effect of air pollution on life expectancy (Chay and Greenstone 2003), illness and hospitalization rates (Pope, Bates, and Raizenne 1995; Cohen et al. 2005), child health (see an excellent review by Currie et al. 2014), and health behavior (Graff Zivin and Neidell 2009; Zheng, Sun, and Kahn 2015).

dominate.

Third, most cognitive tests in previous studies were administered to young cohorts, such as students (Ham, Zweig, and Avol 2014; Stafford 2015; Ebenstein, Lavy, and Roth 2016). It is not clear whether the findings inferred from these specific groups hold true for the population as a whole. The cognitive tests in our nationally representative sample cover nearly all ages above 10, which enable us to test if there is age heterogeneity in cognition.

Fourth, most economic studies have been silent about gender gap in cognitive performance. We provide the first attempt to explicitly testing how air pollution may affect males differently from females and explain the potential mechanisms at work. Understanding the gender gap in cognitive performance as a result of environmental stressors may bear implications for gender equity in schooling and allocative efficiency in the labor market.

Fifth, most previous studies do not match exposure to local environmental stressors with individual cognitive performance according to the exact time of test taking. For instance, Ham, Zweig, and Avol (2014) match yearly air pollution with average standardized test scores at the school-grade level. Measures of yearly air pollution capture the accumulative effect but not the instantaneous effect of air pollution on cognitive performance at the time of the exams. Using information on the exact time and location of the interview for each survey subject, we can match test scores and local air pollution levels more precisely than what was possible in previous studies.

We find that contemporaneous and cumulative exposure to air pollution lowers both verbal and math test scores of survey subjects, and the effect on verbal abilities is larger than the effect on math skills. The effect is more pronounced for men than for women, i.e., men perform worse than women on both tests when exposed to the same dose of air pollution. Our calculation suggests that males' verbal test scores on a day with hazardous air pollution (API $\geq$ 301) are on average 0.30 standard deviations lower than their scores on a day without air pollution (API $\leq$ 50). In addition, the gender difference is more salient among the old and less educated in both tests.

The large gender gap in cognitive abilities probably has something to do with gender difference in the composition of gray matter (information processing centers) and white matter (the connections between these processing centers) in brain's central nervous system.

The gray matter is highly associated with mathematical skills. The white matter is mainly responsible for coordinating communication between different brain regions and largely determines language skills. It has been found that air pollution mainly reduces the density of white matter (Calderón-Garcidueñas et al. 2008; Wilker et al. 2015). This explains why air pollution affects verbal test scores more than math test scores. Given men's relatively smaller volume of white matter activated during general intelligence tests than women do (Haier et al. 2005), it is not surprising that air pollution exposure has a more negative effect on men, as shown by its effect on their verbal test scores.

Our study also relates to the broader literature on the effect of air pollution on a wide variety of topics which range from happiness and mental well-being (Luechinger 2009; Levinson 2012; Zhang, Zhang, and Chen 2015) to labor productivity (Graff Zivin and Neidell 2012; Chang et al. 2014, 2016; He, Liu, and Salvo 2016). Given the importance of human capital as a principal engine of economic growth, the relationship between air pollution and cognition reveals an important but underexplored channel through which environmental stressors may affect economic well-being.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 lays out the empirical strategy. Section 4 presents our main findings. Section 5 concludes. In the Appendix B, we discuss the scientific background of this study and potential mechanisms in detail.

2. Data

2.1. Cognitive Tests

We utilize cognitive test scores from the CFPS, a nationally representative survey of Chinese families and individuals conducted in 2010, 2012, and 2014. The CFPS includes questions on a wide range of topics for families and individuals from 162 counties in 25 provinces of China, including their economic activities, education outcomes, family dynamics and relationships, health, and cognitive abilities.[2]

[2] The CFPS is funded by Peking University and carried out by the university's Institute of Social Science Survey. The CFPS uses multistage probability proportional to size sampling with implicit stratification to better represent Chinese society. The 2010 CFPS baseline sample is drawn through three stages (county, village, and household) from 25 provinces. The 162 randomly chosen counties largely represent Chinese society (Xie and Hu 2014).

The CFPS is suitable for our study for several reasons. First, the survey includes several standardized cognitive tests. Second, exact information about the geographic locations and dates of interviews is available to us for all respondents, enabling us to precisely match individual test scores in the survey with local air-quality data. Third, the longitudinal data allow us to remove unobserved individual factors that may bias estimates. Further, the survey embodies rich information at multiple levels, allowing us to control for a wide range of covariates. Finally, because the cognitive tests are administered to all age cohorts older than 10, we can study the effects of air pollution on different age groups.

CFPS 2010 and CFPS 2014 contain the same cognitive ability module, i.e., 24 standardized mathematics questions and 34 word-recognition questions. All these questions are obtained from standard textbooks and are sorted in ascending order of difficulty. The starting question depends on the respondent's education level.[3] The test ends when the individual incorrectly answers three questions in succession. The final test score is defined as the rank of the hardest question a respondent is able to answer correctly. If the respondent fails to answer any questions during the test, his or her test score is assigned as the rank of the starting question minus one. For example, a respondent with middle school education begins with the 9th question in the verbal test. If the hardest question he is able to correctly answer is the 14th question, then his verbal test scores would be 14. However, if he fails the 9th, 10th, and 11th questions consecutively, his verbal test scores would be 8.[4]

2.2. Weather and Pollution Measures

We measure air quality using the air pollution index (API), which is aggregated based on daily readings for three atmospheric pollutants, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter smaller than 10 micrometers (PM10).[5] The API

[3] Specifically, those whose education level is primary school or below start with the 1st question; those who attended middle school begin with the 9th question in the verbal test and the 5th question in the math test; and those who finished high school or above start with the 21st question in the verbal test and the 13th question in the math test.

[4] The respondents did not know the rules before they were interviewed. So they did not have the incentive to fail the tests on purpose.

[5] We use the Chinese Ministry of Environmental Protection's (MEP's) breakpoints table (see Table A1) and the following formula to generate the API measurement: $I_P = ((I_{HI} - I_{LO}) / (BP_{HI} - BP_{LO})) * (C_P - BP_{LO}) + I_{LO}$, where I_P is the index for pollutant P, C_P is the rounded concentration of pollutant P, BP_{HI} is the breakpoint

ranges from 0 to 500, with larger values indicating worse air quality.[6] Daily API observations are taken from the city-level air-quality report published by the Chinese Ministry of Environmental Protection (MEP). The report includes 86 major cities in 2000 and covers all the cities in 2014.[7] Figure A1 plots the daily API in China from 2010 to 2014.

We also include rich weather data in our analysis to help isolate the impact of air pollution from the impact of overall weather patterns. The weather data comes from the National Climatic Data Center (now known as the National Centers for Environmental Information) of the US National Oceanic and Atmospheric Administration. The dataset contains daily records of weather conditions, such as temperature, precipitation, wind speed, and indicators for bad weather, from 402 monitoring stations in China.[8]

We match city-level API with CFPS samples in the following way. If a CFPS county is within an API reporting city, we use the city's API reading as the county's reading. If it does not lie in any API cities, we use the API readings of the nearest available city within 40 kilometers according to the distance between the centroid of the CFPS county to the boundaries of nearby API reporting cities. Our baseline results are robust if we restrict the sample to only respondents living in API reporting cities.[9] Following the convention of the literature (Levinson 2012), we use the radius of 40 km in our analyses to ensure precise match and retain greater number of observations. The weather conditions are obtained as the inverse distance-weighted average of all monitoring stations within a radius of 100 kilometers of the county centroid.[10] The binary indicator for bad weather comes from the

that is greater than or equal to C_P, BP_{LO} is the breakpoint that is less than or equal to C_P, I_{HI} is the API value corresponding to BP_{HI}, and I_{LO} is the API value corresponding to BP_{LO}. The API represents the highest index value calculated for each pollutant.

[6] Carbon monoxide (CO), ozone, and particulate matter smaller than 2.5 micrometers (PM2.5) were not added to the basket of the index until 2014. Because all the cognitive tests were administered between 2010 and 2014, we transform the air quality index (AQI) to the API in 2014 and use the API based on SO_2, NO_2, and PM10 in our paper.

[7] If the government indeed manipulates the API data as suggested by Chen et al. (2012) and Ghanem and Zhang (2014), using the official API data would underestimate the true impact of air pollution. In this case, our estimates would represent a lower bound.

[8] Bad weather includes fog, rain/drizzle, snow/ice pellets, hail, thunder, and tornadoes/funnel clouds.

[9] The results are available upon request.

[10] The matching radius is comparable to those used in Deschenes, Greenstone, and Guryan (2009) and Deschenes and Greenstone (2011). Our baseline results are robust to alternative weights, including inverse of the square root distance or squared distance between the monitoring stations and the county centroids. The results are available upon request.

nearest monitoring station.

The CFPS surveyed a balanced panel of 25,485 individual respondents over age 10 in 2010 and 2014, for a total of 50,970 observations.[11] Of the individuals surveyed in both waves, 181 are missing values for cognitive test scores. Among the remaining 50,789 observations, 37,918 observations could be matched to API and weather data.[12] Due to some missing values for household demographics, the final dataset used in this study includes 31,959 observations. Figure A2 displays the percentage of respondents who took the cognitive tests and the hourly pollutant concentration. Most of the cognition tests were conducted in the afternoon and evening. Among the three major pollutants, PM10 is a dominant one throughout the day.

3. Empirical Strategy

Our baseline econometric specification is as follows:

$$Score_{ijt} = \alpha \cdot \frac{1}{k}\sum_{n=0}^{k-1} P_{j,t-n} + X'_{ijt}\beta + W'_{jt}\phi + T'_{jt}\gamma + \lambda_i + \delta_j + \eta_t + f(t) + \varepsilon_{ijt} \qquad (1)$$

The dependent variable $Score_{ijt}$ is the cognition test scores of respondent i in county j at date t. The key variable $\frac{1}{k}\sum_{n=0}^{k-1} P_{j,t-n}$ is the mean API readings in the past k days. It indicates the air quality measure at date t if k equals 1. We control for a set of demographic correlates X_{ijt}, including gender, age and its square and cubic terms, log form of household per capita income, years of education and an indicator of cross-county migration.[13] We also control for a vector of rich weather conditions W_{jt}, involving a set of temperature bins (that is, <25°F, 25–45°F, 45–65°F, 65–85°F, and >85°F), total precipitation, mean wind

[11] The attrition rates for consecutive waves, that is, 2010–2012 and 2012–2014, are 19.3 percent and 13.9 percent, respectively. We compare the attrition rate of the CFPS with that of the UK Household Longitudinal Survey (UKHLS). The two surveys were conducted during the same period and followed similar interview methods, so the UKHLS serves as a good benchmark for the CFPS. Compared to the UKHLS, the CFPS's attrition rate is reasonable. The key reason for using the 2010 and 2014 waves is that the two waves included exactly the same test modules, whereas the short memory and logic tests employed in the 2012 wave are not comparable with the tests used in the other two waves.

[12] Counties unmatched to any API report cities within 40 kilometers or weather stations within 100 kilometers are dropped. The matching rate of 74.7 percent (37,918 out of 50,789) is within a reasonable range compared with other studies. For example, Levinson (2012) was able to maintain 52.3 percent of the observations when matching the US General Social Survey with PM10 readings from the Environmental Protection Agency's Air Quality System.

[13] Our baseline results are robust if using nonmigrants only. The results are available upon request.

speed, and a dummy for bad weather on the day of the interview, and a vector of county-level characteristics T_{jt}, including gross domestic product (GDP) per capita (deflated to 2010 yuan), population density, and industrial value share, to account for factors that are correlated with both test scores and air quality.[14] λ_i denotes individual fixed effects. δ_j represents county fixed effects. η_t indicates month, day of week, and post meridiem hour fixed effects. *f(t)* is the quadratic monthly time trend that ranges from 1 (January, 2010) to 60 (December, 2014). ε_{ijt} is the error term. Standard errors are clustered at the county level.[15] Table 1 describes key variables and their summary statistics.

[Insert Table 1 here.]

By conditioning on the full set of fixed effects listed above, the key parameters are identified by making use of variations in exposure to air pollution for the same respondent in the 2010 and 2014 surveys. Figure A3 displays the monthly distribution of interview times in the two waves of the CFPS survey. Although a majority of interviews were conducted in July and August when college students were employed as numerators, the survey spans all months and seasons, providing us with large temporal variations.[16]

The validity of our empirical strategy also hinges on one key assumption: that variations in an individual's exposure to air pollution at the time of the tests between the two waves have little to do with unobserved time-varying factors that may also affect cognitive performance. We have checked some other potential factors, such as the assignment of interviewers and the days of the week on which cognition tests were implemented, and found that these variables are random.

4. Results

Figure 1 plots residuals from regressions of verbal and math test scores on years of

[14] Graff Zivin, Hsiang, and Neidell (2015) find that high temperature is associated with significant decreases in cognitive performance on math in the short run. Here we have controlled for a set of temperature bins to capture the effect.
[15] Our results are robust to controlling for province-by-year fixed effects and clustering standard errors at the province level.
[16] Besides, we divide the sample into two groups with equal weight. Respondents in group one were interviewed at least once in winter months (November, December and January), while respondents in group two were only interviewed in non-winter months (from February to October). The weighted regression indicates that the results are robust, i.e., the size of the effects is similar to that estimated in the baseline results. Hence, the underestimation of the effect of air pollution, if any, is small. The results are available upon request.

education versus age cohort for males and females in polluted and less polluted areas. As revealed in Panel A (verbal test scores) and Panel B (math test scores) of Figure 1, women and men perform equally well in both verbal and math tests before age 20. Both math and verbal test scores decline steadily with age afterwards for men and women, but the speed of decline is faster for women than men. As a result, the gender gap between males and females in cognitive scores widens as people become older. The large gender difference in test scores masks the difference in test scores between people living in more polluted and less polluted areas.

[Insert Figure 1 here.]

Considering that the gender difference may also result from some covariates other than air pollution, we use a difference-in-differences approach to remove these systematic factors. Specifically, we first obtain gender differences in test scores for polluted and less polluted areas, respectively, and then gauge the differences in the gender gap between more polluted and less polluted areas. Panel C displays the results. The difference-in-differences in test scores is negative for most cohorts, indicating that men are generally more vulnerable to air pollution than women.

However, Figure 1 does not consider many other factors that may affect test scores, such as interpersonal differences. Next, we conduct more rigorous regression analyses by controlling for more individual-level factors. Table 2 presents regression estimates on the effect of air quality on verbal test scores (Panel A) and math test scores (Panel B) based on equation (1). In each panel, we test the impacts of contemporaneous exposure (Columns 1 and 2) and cumulative exposure (Columns 3 through 7), respectively.[17]

Three findings are apparent from Table 2. First, in general, air pollution negatively affects respondents' test performance as shown by the negative coefficient for the pollution variable in all the regressions. Except for the effect of one-day air pollution exposure on math test scores (first column in Panel B), all the coefficients for air pollution variable are statistically significant. The impact is economically significant. For example, the estimate in Column (5) of Panel A indicates that a one-unit increase in the annual mean API leads to a 0.043-point decline in verbal scores. Second, the impact of cumulative exposure on

[17] In Table A2, we further display results that add individual fixed effects and demographic controls step-by-step.

test scores is larger than that of contemporaneous exposure. As shown in the last row of Panel A and Panel B, an increase in the mean API on the interview date by one standard deviation (SD) lowers verbal test scores by 0.131 point (0.012 SD), while a one SD increase in average API over three years prior to the interview is associated with an up to as 1.139 points (0.109 SD) drop in verbal test scores. Third, air pollution exposure appears to have a more negative effect on verbal test performance than math test performance. It is evident that the changes in SDs in the parentheses presented at the bottom of Panel A for verbal test scores are more prominent than the corresponding ones in Panel B for math test scores. Given that the cognitive tests we used might be easier and less challenging than the college entrance exams, our identified contemporaneous effects are a little smaller than those obtained in Ebenstein, Lavy, and Roth (2016). For example, Ebenstein, Lavy, and Roth (2016) find that a one SD reduction in air pollution leads to an increase in *Bagrut* scores by 0.038 SD. However, our estimated cumulative effects are larger than their contemporaneous effects.

[Insert Table 2 here.]

To further explore potential differential effects on men and women, Panel A and Panel B in Tables A3 and A4 present separate regressions on verbal and math test scores for males and females. Panel C combines the male and female subsamples and uses an interaction term between a dummy for males and pollution concentration to identify gender differences in the effect of exposure to air pollution on test scores.

Figure 2 visualizes the key estimates obtained from Tables A3 and A4. Panel A is for verbal tests, while Panel B is for math test scores. In each panel, the left part presents the estimated coefficients for API, as well as their 95 percent confidence intervals, for men and women, respectively; the right part is drawn based on the estimates of the interaction term between air pollution and a gender dummy in the whole sample. As shown in the left part of Panel A, exposure to air pollution lowers verbal test scores for both men and women regardless of the length of exposure (with the exception of females' one-day exposure). In general, the effect increases with the duration of exposure to air pollution. Men are more vulnerable to air pollution than women. The gender difference is statistically significant, as shown in the right part of Panel A.

[Insert Figure 2 here.]

As shown in Panel B, the effect on math tests is more muted than the effect on verbal tests. Although the coefficients for the API are negative in all 14 regressions in the left part of Panel B, they are only statistically significant in four regressions using the subsamples. Interestingly, the gender difference persists. All the seven coefficients for the interaction term between gender and level of air pollution as presented in the right part of Panel B are statistically significant at the 5 percent level. Once again, in accordance with the findings of Ebenstein, Lavy, and Roth (2016), men's math performance is more significantly affected by exposure to polluted air than women's performance.

To understand how the aging brain may affect the gender differences in the effect of air pollution on cognition, we repeat the exercises above to estimate the effect for different age groups, i.e., children (age 20 and under), young adults and the middle-aged (age 21 to 59), and seniors (60 and above). Figure 3a displays the estimated coefficients for API and their 95 percent confidence intervals in regressions on verbal test scores for different age groups. As revealed in Panel A, the negative effect of air pollution on verbal test scores is minimal for children with no obvious differential impact by gender. As shown in Panel B, for young adults and the middle-aged, air pollution has a detrimental effect on verbal scores for both men and women without showing a significant gender difference. For seniors (Panel C), air pollution is strongly associated with worse verbal test scores for males but not for females.

[Insert Figure 3a here.]

Figure 3b repeats the exercises but plots the coefficients and their confidence intervals in regressions on math test scores. Similar to the verbal test scores, there is a salient gender difference among the old cohorts.

[Insert Figure 3b here.]

We repeat estimations in Figure 2 by running separate regressions on verbal tests for three subgroups based on education level—primary school and below, middle school, and high school and above, to identify potential heterogeneous effects by education. Figure 4a displays the coefficients for API across various windows of exposure. Overall, exposure to air pollution negatively affects verbal test scores, especially for less educated men, as shown in Panel A and Panel B. The effect is much weaker for the more educated (Panel C), probably because these individuals are more likely to work indoors or because they are more knowledgeable about the negative effects of air pollution. Figure 4b reports the same analysis for math test scores. Among the less educated group (middle school and below), men perform worse than women in the presence of air pollution.

[Insert Figures 4a and 4b here.]

In Table A5, we further explore the heterogeneous effects by income and workplace. Comparing the coefficients for the API in Panel A (income level below median) and Panel B (income level above median), air pollution has a greater adverse effect on the low-income group than on the high-income group. Another comparison between Panel C (working outdoors) and Panel D (working indoors) reveals that the negative effect of air pollution is greater on people working outdoors than those working indoors. The gap widens when measuring the API over a longer period, suggesting a lasting, more negative effect of exposure to air pollution on men.

Some time-variant unobserved factors may affect both cognitive test scores and exposure to air pollution even after controlling for individual fixed effects. In a falsification test, we employ a strategy similar to Bensnes (2016). If concerns about such unobserved factors are valid, we would expect to see API readings on the days after cognitive tests also affect test scores. Figure 5 presents the estimated coefficients with their 95 percent confidence intervals from a regression of test scores on API readings one to six days into the future. For both men and women, all the coefficients are statistically indifferent from zero, largely dismissing the concern about potential omitted variables.

[Insert Figure 5 here.]

Table A6 estimates a more flexible nonlinear functional form to capture potentially heterogeneous effects at various intervals of pollution concentrations.[18] We assign several indicators to capture the interval bins of APIs and leave "API $\leq$ 50" as the reference bin. Since very few observations fall into the long-term average API > 100, we combine API readings from 101 to 200 as one bin when examining 90-day and longer interval exposures. We identify the impact of contemporaneous exposure in Panel A and Panel B and cumulative exposure in the remaining panels. Our results consistently show that males are more affected by both contemporaneous and cumulative air pollution exposure, while females are largely immune to the effect of short-term pollution during cognitive tests. Our

[18] Figure A4 reveals the distribution of API readings with these cutoffs.

back-of-the-envelope calculation suggests that men score 2.840 points (0.301 SD) lower on a day with hazardous air pollution (API ≥ 301) than on a day with good air (API ≤ 50). According to the relationship between test scores and education years revealed in Figure A5, 2.840 points corresponds to approximately 0.9 year of education.

Furthermore, Panel A and Panel B of Table A7 in the appendix estimate verbal and math test scores, respectively, by simultaneously controlling for contemporaneous exposure as well as cumulative exposure. It is apparent from the table that cumulative exposure to air pollution plays a greater role in lowering verbal test scores than contemporaneous exposure.

5. Conclusion

This paper estimates the contemporaneous and cumulative impacts of air pollution on cognition by matching the scores of verbal and math tests given to people age 10 and above in a nationally representative survey with local air-quality data for the exact dates and locations of the interviews. Contemporaneous and cumulative exposure to air pollution significantly lowers both the verbal and math test scores of survey subjects. In general, men perform worse than women when exposed to the same dose of air pollution. The gender difference is more salient among the old and less educated in both tests.

The population-weighted annual mean concentration of PM2.5 over 2014 in China is 68 $\mu g/m^3$, much higher than the primary and secondary standards in the NAAQS published by the U.S. Environmental Protection Agency (EPA).[19] Reducing the annual mean PM2.5 to levels below the secondary standard, which corresponds to 44 units in one-year-mean API, will lead to a sizable increase in verbal test scores by 1.89 points (or 0.63 education year) and math test scores by 0.26 point (or 0.16 education year).

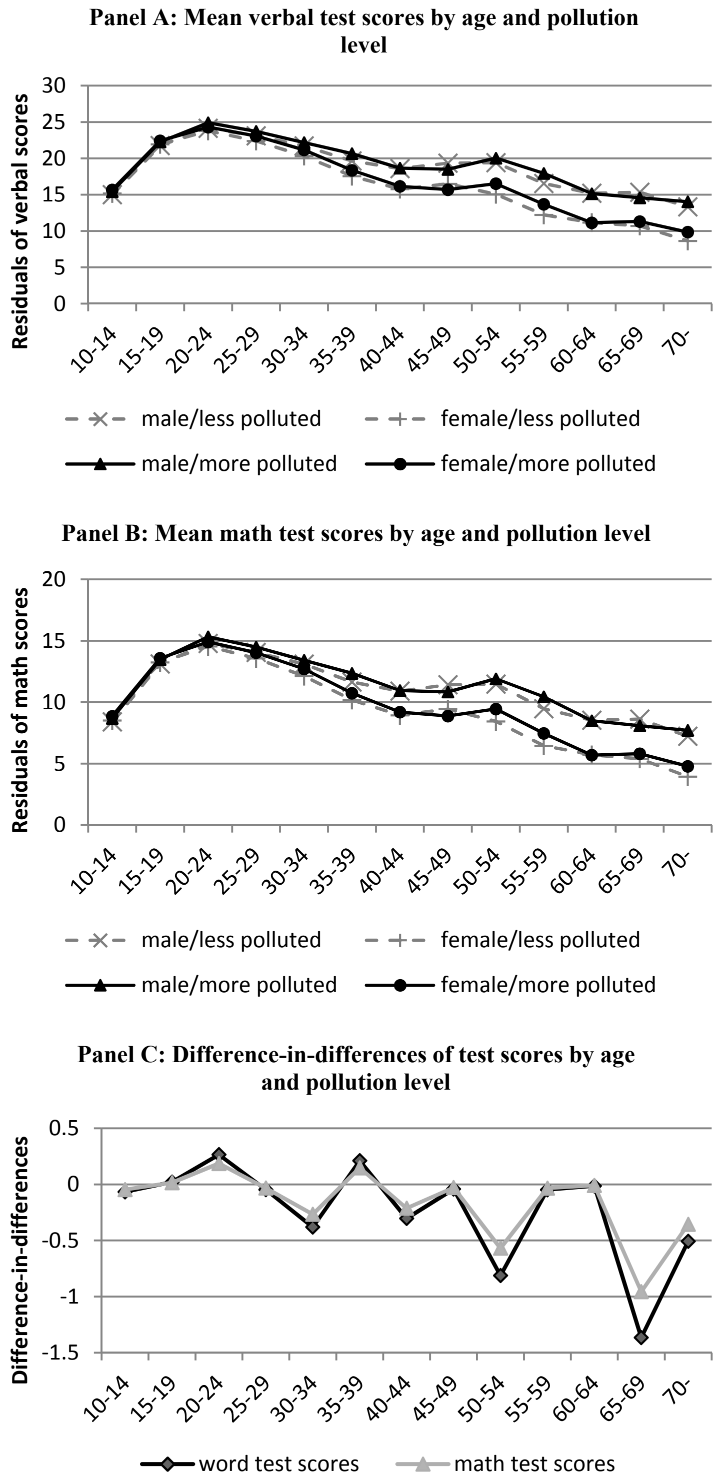
As cognitive functioning is critical to everyday activities, human capital formation, and productivity, our finding about the negative effect of air pollution on cognition implies that the indirect effect on social welfare could be much larger than previously thought. A narrow focus on the negative effect on health may underestimate the total cost of air

[19] The annual mean PM2.5 data at the city level are obtained from the *China Environmental Statistical Yearbook 2015*, and the population data (for the weighting purpose) come from *China City Statistical Yearbook 2015*. The primary and secondary standards of annual mean PM2.5 published by the EPA are 12 $\mu g/m^3$ and 15 $\mu g/m^3$, respectively. Source: https://www3.epa.gov/ttn/naaqs/standards/pm/s_pm_history.html.

pollution.

In Appendix B, we hypothesize that differences in brain composition may help explain why men appear more sensitive to the negative effects of air pollution. It is beyond the scope of this paper to formally test this mechanism. We leave it as a future research topic.

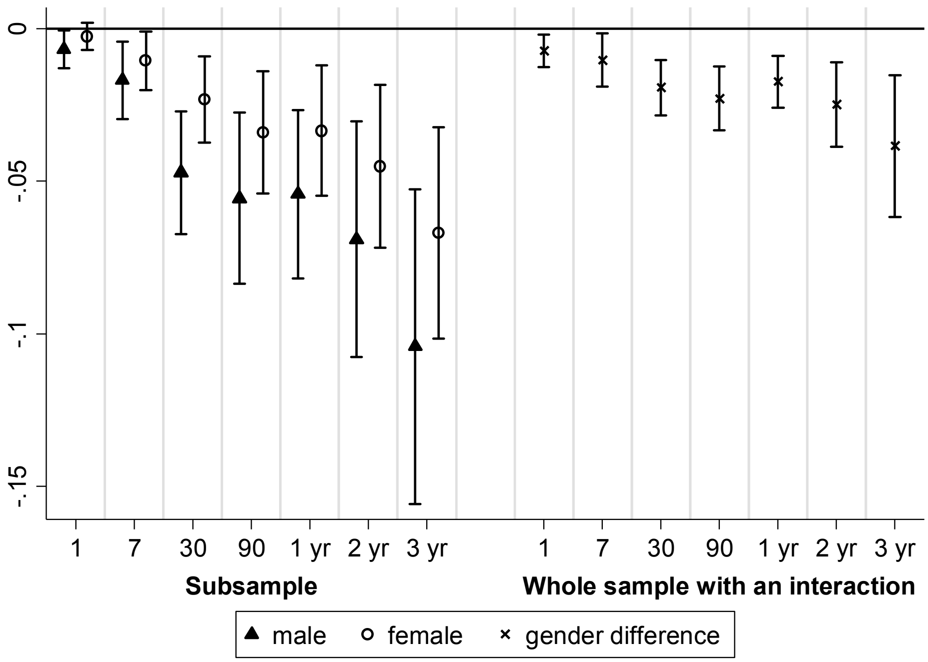
Figure 1: Mean test scores by age and pollution level



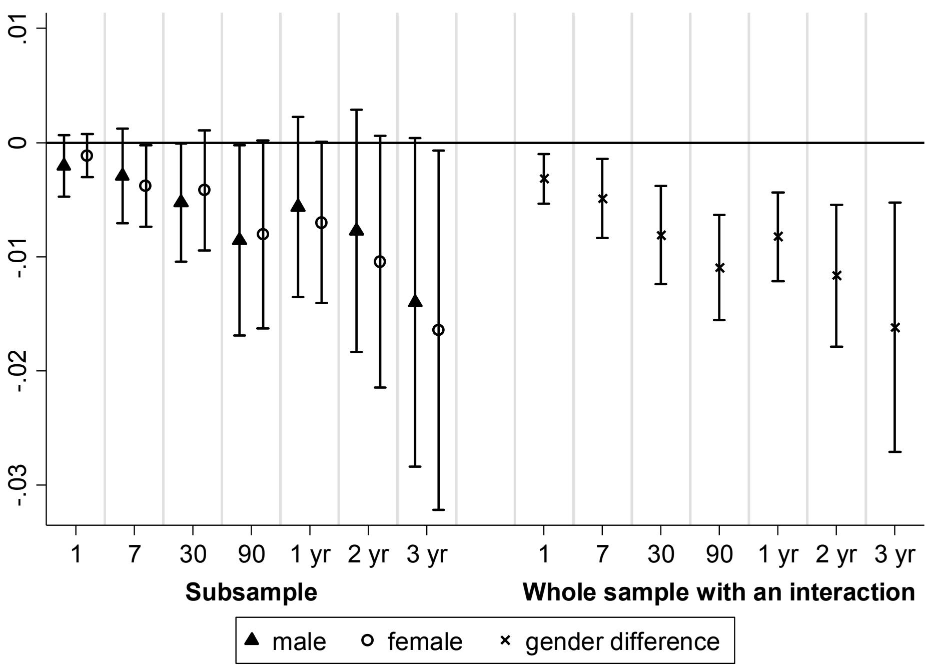
Source: Authors' calculations using CFPS survey 2010 and 2014.
Note: The residuals are generated from regressions of test scores on education years. The less polluted and more polluted areas are divided by the median of the pollution level in the past year. The difference-in-differences is generated by the gender difference (male-female) in differences in test scores between polluted and less polluted areas.

Figure 2: Effects of air pollution on test scores, by gender

Panel A: Verbal test scores



Panel B: Math test scores

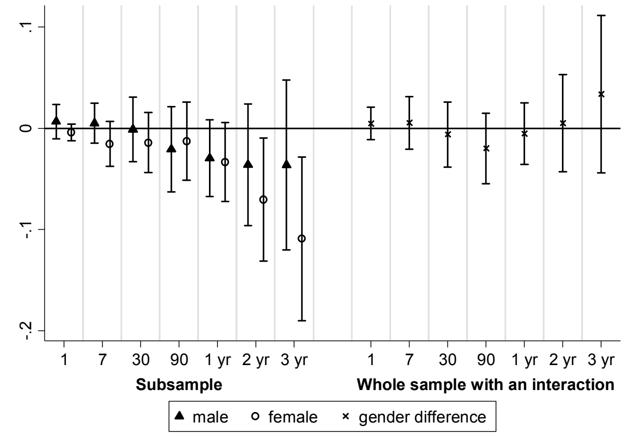


Source: Authors' estimations using CFPS survey 2010 and 2014.

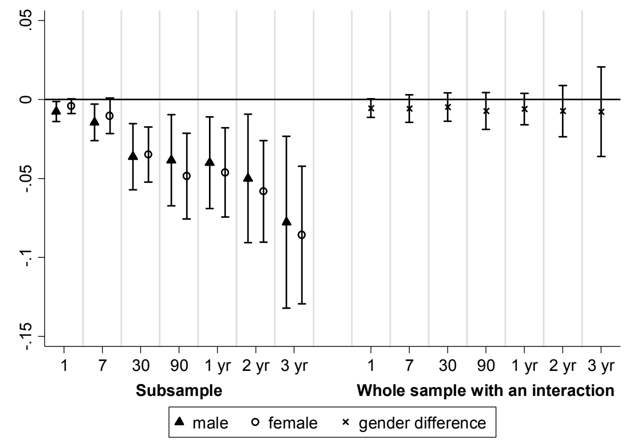
Note: The figures plot the estimated coefficients with 95% confidence intervals based on the estimates in Tables A3 and A4. In each panel, the left part presents the coefficients on air pollution for males and females in the subsample; the right part is drawn based on the estimates of the interaction term between air pollution and a male dummy in the whole sample.

Figure 3a: Effects of air pollution on verbal test scores, by age

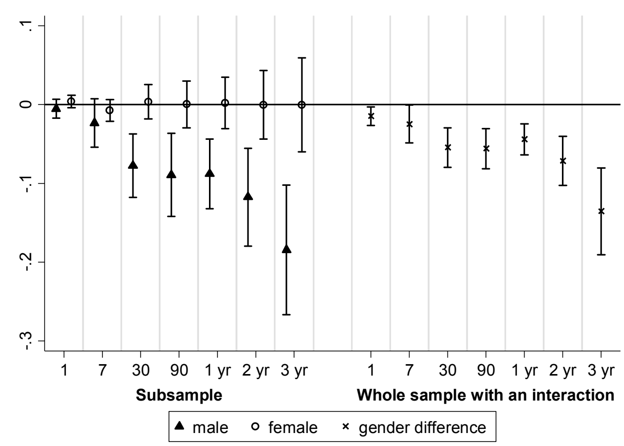
Panel A: Age 20 and under



Panel B: Age 21 to 59



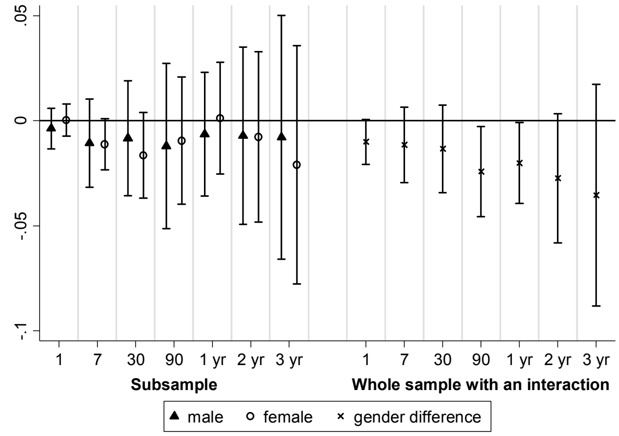
Panel C: Age 60 and over



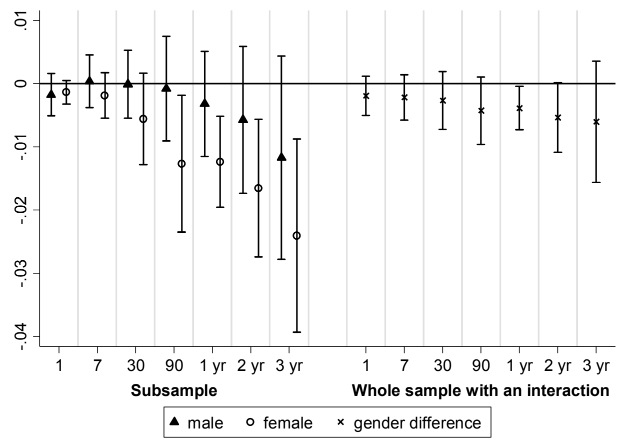
Source: Authors' estimations using CFPS survey 2010 and 2014.
Note: In each panel, the left part presents the estimated coefficients with 95% confidence intervals on air pollution for males and females in the subsamples; the right part is drawn based on the estimates of the interaction term between air pollution and a male dummy in the whole sample.

Figure 3b: Effects of air pollution on math test scores, by age

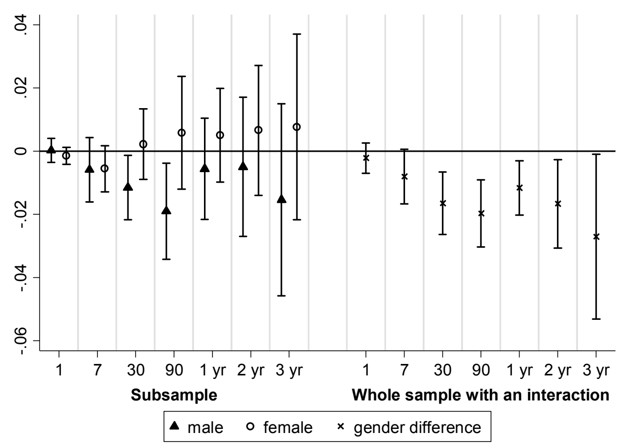
Panel A: Age 20 or under



Panel B: Age 21 to 59



Panel C: Age 60 or over

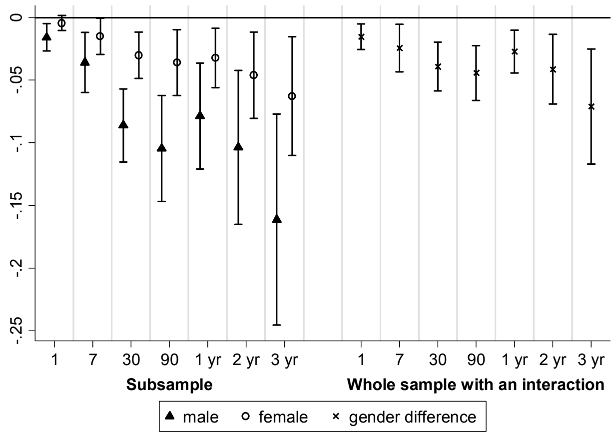


Source: Authors' estimations using CFPS survey 2010 and 2014.

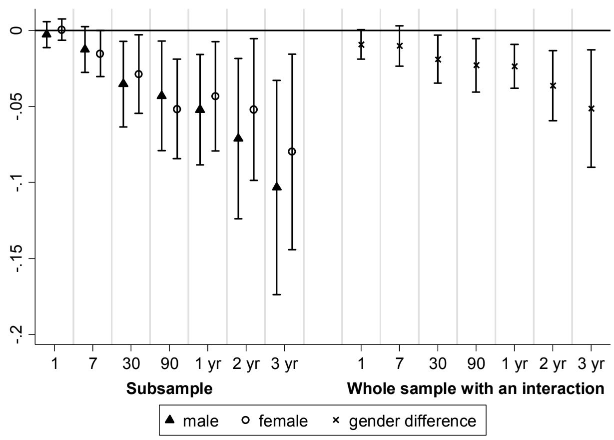
Note: In each panel, the left part presents the estimated coefficients with 95% confidence intervals on air pollution for males and females in the subsamples; the right part is drawn based on the estimates of the interaction term between air pollution and a male dummy in the whole sample.

Figure 4a: Effects of air pollution on verbal test scores, by education level

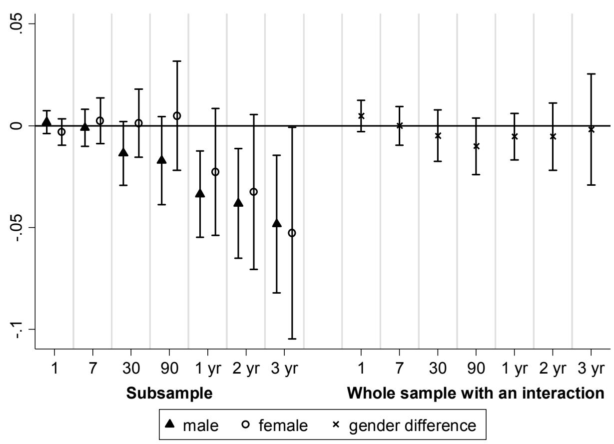
Panel A: Primary school or below



Panel B: Middle school



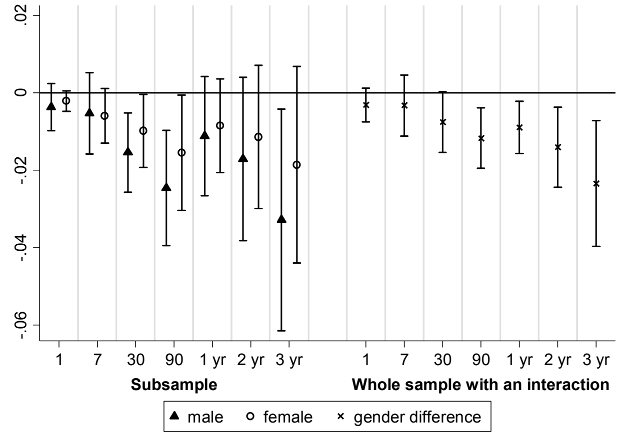
Panel C: High school or above



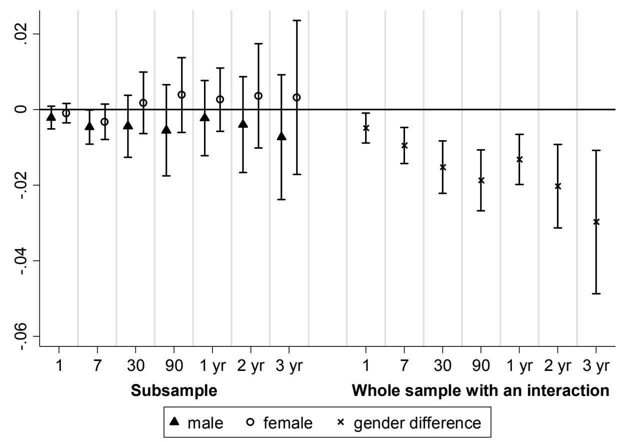
Source: Authors' estimations using CFPS survey 2010 and 2014.
Note: In each panel, the left part presents the estimated coefficients with 95% confidence intervals on air pollution for males and females in the subsamples; the right part is drawn based on the estimates of the interaction term between air pollution and a male dummy in the whole sample.

Figure 4b: Effects of air pollution on math test scores, by education level

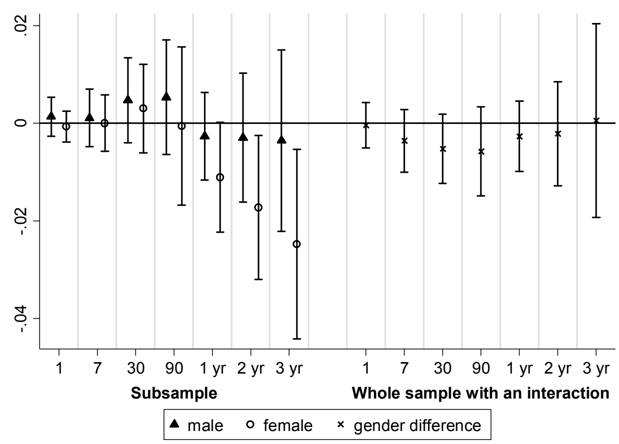
Panel A: Primary school or below



Panel B: Middle school



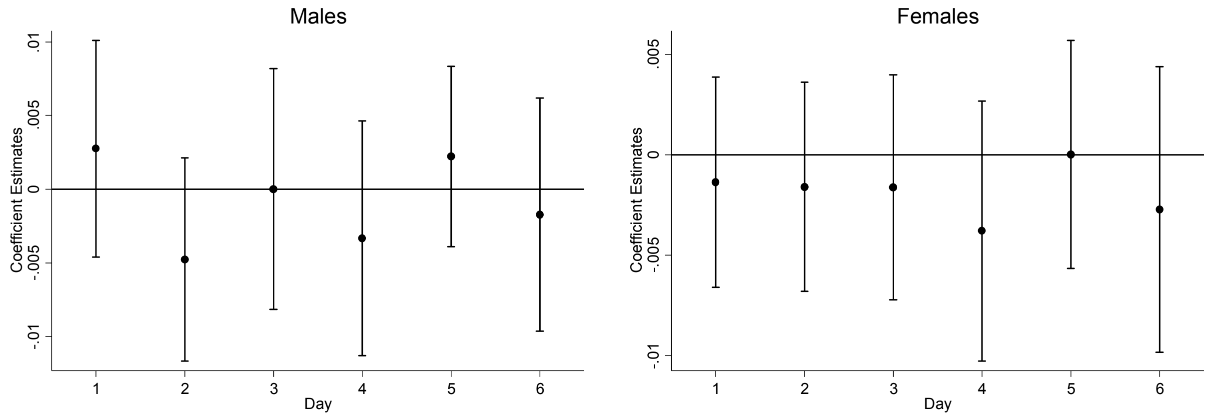
Panel C: High school or above



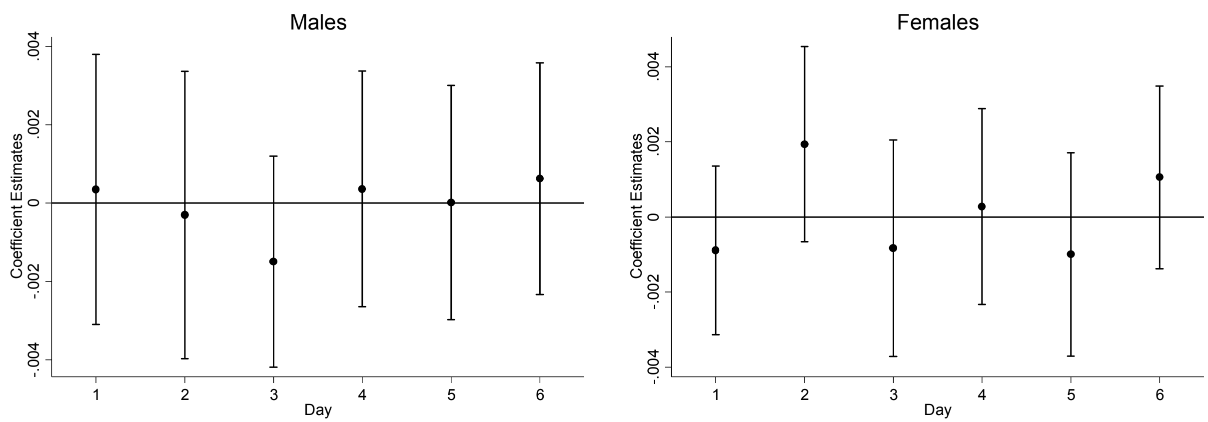
Source: Authors' estimations using CFPS survey 2010 and 2014.
Note: In each panel, the left part presents the estimated coefficients with 95% confidence intervals on air pollution for males and females in the subsamples; the right part is drawn based on the estimates of the interaction term between air pollution and a male dummy in the whole sample.

Figure 5: Placebo tests: Effects of air pollution on test scores in the days after the interview

Panel A: Verbal test scores



Panel B: Math test scores



Source: Authors' estimations using CFPS survey 2010 and 2014.

Note: The figure plots the coefficients with 95% confidence intervals from a regression of test scores on air pollution index (API) readings in the days after the interview. Other controls and fixed effects are the same as those presented in Table 2.

Table 1: Summary statistics

Variable	Description	All		Male		Female	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Verbal scores	verbal scores	18.115	10.488	19.728	9.431	16.629	11.171
Math scores	math scores	10.438	6.403	11.497	5.924	9.464	6.667
API	API	73.519	32.683	73.203	31.714	73.810	33.549
API_7	7-day mean API	72.907	21.360	72.641	21.108	73.151	21.588
API_30	30-day mean API	73.012	17.125	72.822	17.086	73.187	17.160
API_90	90-day mean API	75.529	16.179	75.359	16.129	75.686	16.223
API_1y	1-year mean API	84.009	20.804	83.832	20.865	84.172	20.747
API_2y	2-year mean API	78.386	16.245	78.223	16.329	78.536	16.167
API_3y	3-year mean API	75.284	13.397	75.110	13.462	75.443	13.335
Household per capita income (log)	log form of household per capita income (Chinese *yuan*)	8.874	1.154	8.891	1.153	8.858	1.155
Age	age	44.738	17.893	44.920	18.160	44.572	17.643
Education years	education years	7.187	4.657	7.938	4.309	6.497	4.854

Source: Authors' estimations using CFPS survey 2010 and 2014.

Note: API = air pollution index; SD = standard deviation.

Table 2: Effects of air pollution on cognitive test scores

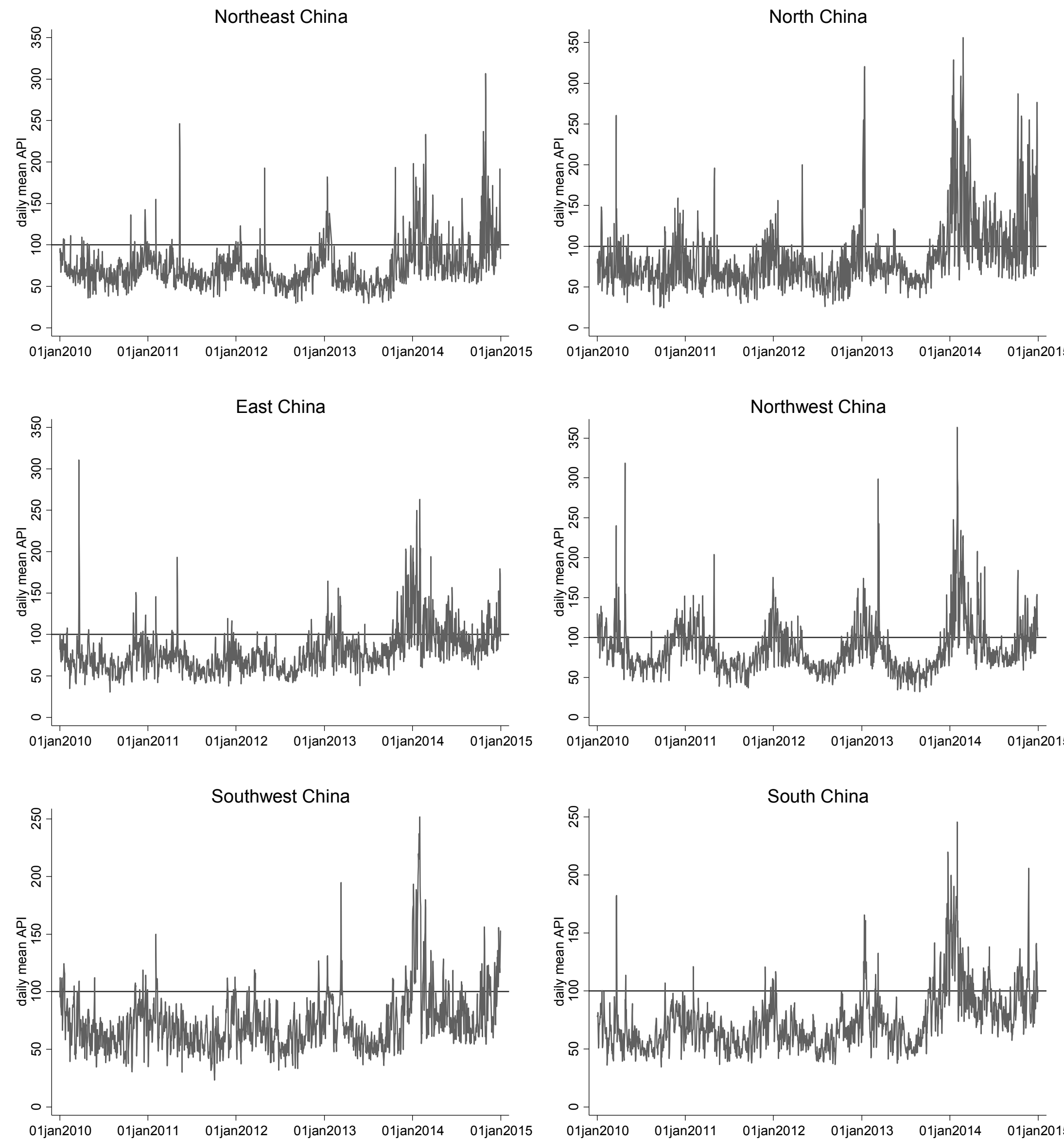
	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Verbal test scores							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.004*	-0.014***	-0.035***	-0.044***	-0.043***	-0.057***	-0.085***
	(0.002)	(0.005)	(0.008)	(0.011)	(0.012)	(0.016)	(0.020)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.280	0.278	0.282	0.338	0.283	0.286	0.321
Impact of a one SD reduction in mean API on test scores (SDs of test scores)	0.131	0.299	0.599	0.712	0.895	0.926	1.139
	(0.012)	(0.029)	(0.057)	(0.068)	(0.085)	(0.088)	(0.109)
B. Math test scores							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.001	-0.003**	-0.005**	-0.008**	-0.006**	-0.009**	-0.015**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.667	0.664	0.663	0.707	0.672	0.684	0.693
Impact of a one SD reduction in mean API on test scores (SDs of test scores)	0.033	0.064	0.086	0.129	0.125	0.146	0.201
	(0.005)	(0.010)	(0.013)	(0.020)	(0.019)	(0.023)	(0.031)

Source: Authors' estimations using CFPS survey 2010 and 2014.

Note: $\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$ indicates the mean of API readings in the past *k* days, where *k* equals 1, 7, 30, 90, 365, 730, and 1,095, respectively. All the regressions include individual fixed effects; county fixed effects; year, month, day of week, and post meridiem hour fixed effects; and a quadratic monthly time trend. Demographic controls include gender, age and its square and cubic terms, household per capita income, years of education, and an indicator for migration. Weather controls include 20°F indicators for temperature bins (that is, <25°F, 25–45°F, 45–65°F, 65–85°F, and >85°F), total precipitation, mean wind speed, and a dummy for bad weather. County-level characteristics include gross domestic product (GDP) per capita, population density, and industrial value share. Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index; SD = standard deviation. *10% significance level; **5% significance level; ***1% significance level.

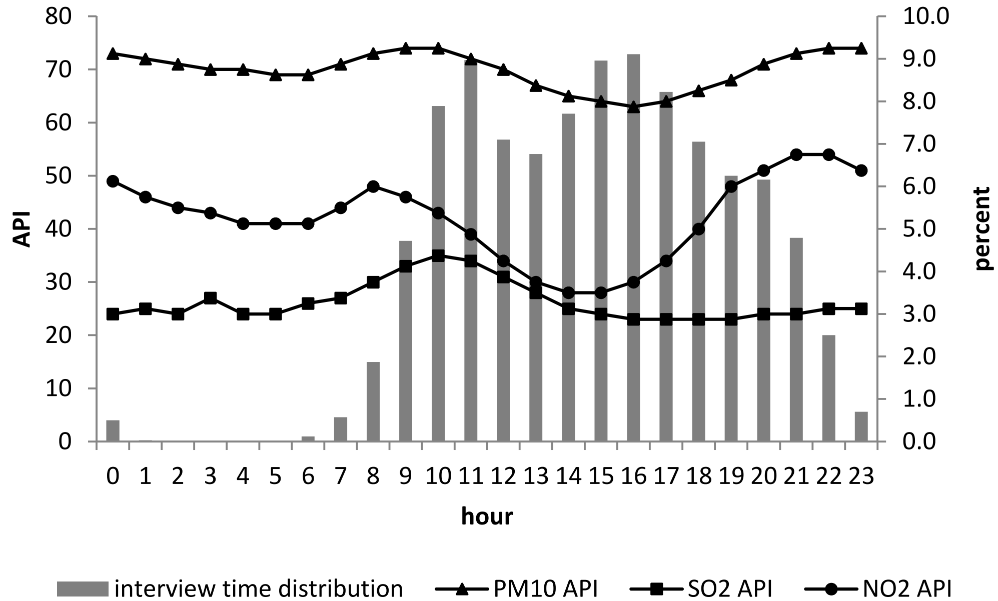
Appendix A: Supplementary Figures and Tables

Figure A1: Daily air pollution index (API) in China, 2010–2014



Source: Daily air-quality report, Ministry of Environmental Protection of the People's Republic of China.
Note: The daily mean API is calculated by finding the weighted average of all the API report cities within the region, where the weights are the yearly population in each city. The US National Ambient Air Quality Standard for fine particulate matter smaller than 10 micrometers is 0.15 mg/m^3, which corresponds to API = 100 in China. Northeast China includes Heilongjiang, Jilin, and Liaoning. North China includes Beijing, Hebei, Inner Mongolia, Shanxi, and Tianjin. East China includes Anhui, Fujian, Jiangsu, Jiangxi, Shandong, Shanghai, and Zhejiang. Northwest China includes Gansu, Ningxia, Qinghai, Shanxi, and Xinjiang. Southwest China includes Guizhou, Sichuan, Tibet, Yunnan, and Chongqing. South China includes Guangdong, Guangxi, Hainan, Henan, Hubei, and Hunan.

Figure A2: PM10 API, SO_2 API, and NO_2 API during the day, 2014



Source: Hourly air-quality report, Ministry of Environmental Protection of the People's Republic of China.

Note: The hourly mean pollution concentrations are calculated using the average values from all the monitoring stations in China. The left axis indicates the pollutant API that converts the corresponding pollutant measure in micrograms per cubic meter ($\mu g/m^3$) into an API score ranging from 0 to 500 using a formula devised by the MEP. The right axis indicates the interview time distribution (percent). This detailed air-quality dataset is only available for 2014, so we cannot use it in our main empirical analysis. API = air pollution index; NO_2 = nitrogen dioxide; PM10 = particulate matter 10 micrometers or less in diameter; SO_2 = sulfur dioxide.

Figure A3: Distribution of interviews by month in 2010 and 2014

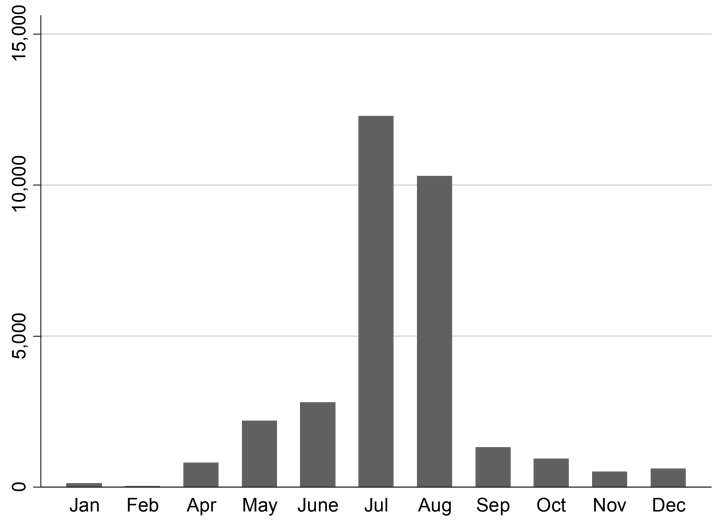
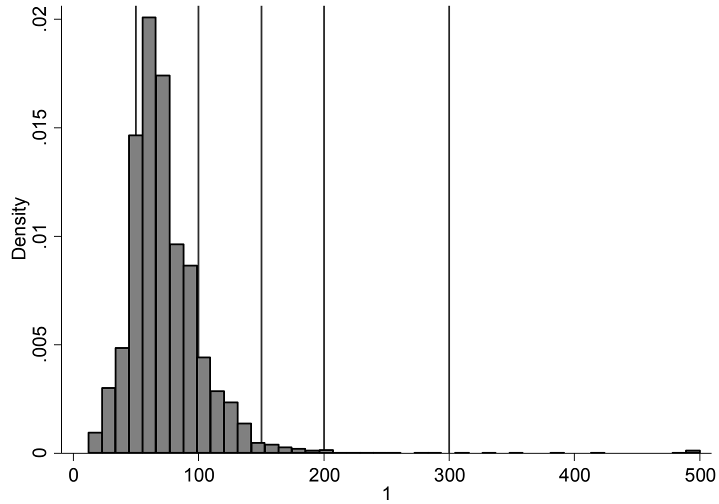
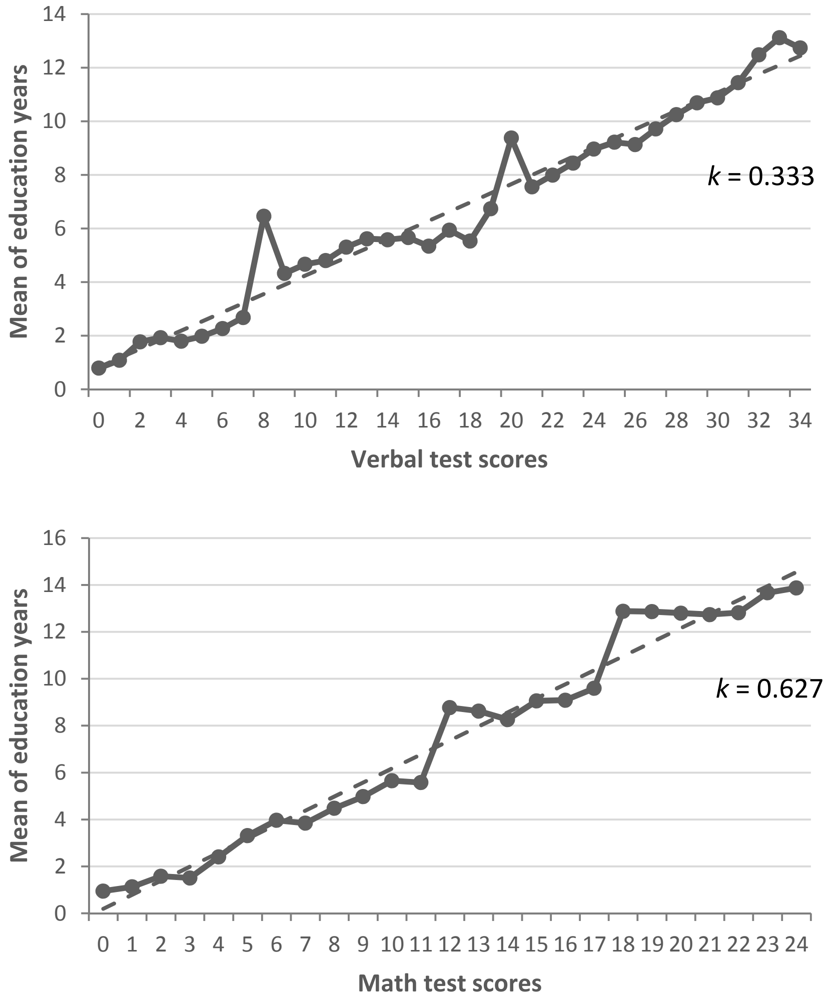


Figure A4: Distribution of API, 2010 and 2014



Note: API = air pollution index.

Figure A5: Relations between test scores and mean of education years



Note: *k* values indicate the coefficients from regressing mean of education years on verbal test scores/math test scores.

Table A1: Breakpoints for API value calculation

API index value	PM10 ($\mu g/m^3$)	SO_2 ($\mu g/m^3$)	NO_2 ($\mu g/m^3$)
0	0	0	0
50	50	50	40
100	150	150	80
150	250	475	180
200	350	800	280
300	420	1600	565
400	500	2100	750
500	600	2620	940

Note: API = air pollution index; NO_2 = nitrogen dioxide; PM10 = particulate matter 10 micrometers or less in diameter; SO_2 = sulfur dioxide.

Table A2: Robustness checks: Adding controls step-by-step

A: Verbal test scores

	1-day mean			7-day mean			1-year mean		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.002	-0.003	-0.004*	-0.010***	-0.011**	-0.014***	-0.033***	-0.048***	-0.043***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)	(0.011)	(0.012)	(0.012)
Income per capita	0.353***		0.148*	0.353***		0.145*	0.355***		0.155*
	(0.043)		(0.084)	(0.043)		(0.084)	(0.042)		(0.080)
Years of education	1.393***		0.693***	1.394***		0.692***	1.393***		0.678***
	(0.020)		(0.108)	(0.020)		(0.108)	(0.020)		(0.106)
Individual fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County-level characteristics	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R2	0.351	0.351	0.351	0.340	0.340	0.340	0.327	0.327	0.327

B: Math test scores

	1-day mean			7-day mean			1-year mean		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.001	-0.001	-0.001	-0.002	-0.002	-0.003**	-0.006*	-0.010**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.003)
Income per capita	0.094***		0.014	0.094***		0.013	0.094***		0.015
	(0.026)		(0.040)	(0.026)		(0.040)	(0.026)		(0.039)
Years of education	1.113***		0.998***	1.113***		0.997***	1.113***		0.995***
	(0.009)		(0.049)	(0.009)		(0.049)	(0.009)		(0.049)
Individual fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County-level characteristics	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R2	0.714	0.714	0.714	0.698	0.698	0.698	0.693	0.693	0.693

Note: $\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$ indicates the mean of the air pollution index (API) in the past k days, where k equals 1, 7, and 365, respectively. All the regressions include county fixed effects; year, month, day of week, and post meridiem hour fixed effects; and a monthly quadratic time trend. Demographic controls include gender, age and its square and cubic terms. Weather controls include 20°F indicators for temperature bins (that is, <25°F, 25–45°F, 45–65°F, 65–85°F, and >85°F), total precipitation, mean wind speed, and a dummy for bad weather. County-level characteristics include gross domestic product (GDP) per capita, population density, and industrial value share. Robust standard errors, clustered at the county level, are presented in parentheses. *10% significance level; **5% significance level; ***1% significance level.

Table A3: Effects of air pollution on verbal test scores, by gender

Dependent variable verbal scores	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Male subsample							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.007**	-0.017***	-0.047***	-0.056***	-0.054***	-0.069***	-0.104***
	(0.003)	(0.006)	(0.010)	(0.014)	(0.014)	(0.020)	(0.026)
Observations	15,318	15,318	15,318	15,318	15,318	15,318	15,318
Overall R^2	0.252	0.249	0.247	0.249	0.244	0.244	0.243
B. Female subsample							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.003	-0.010**	-0.023***	-0.034***	-0.033***	-0.045***	-0.067***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.011)	(0.013)	(0.018)
Observations	16,641	16,641	16,641	16,641	16,641	16,641	16,641
Overall R^2	0.450	0.449	0.456	0.460	0.440	0.437	0.444
C. Whole sample with an interaction							
Male $\times \frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.007***	-0.010**	-0.019***	-0.023***	-0.017***	-0.025***	-0.038***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.012)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.277	0.293	0.335	0.330	0.285	0.277	0.311

Note: See the notes to Table 2.

Table A4: Effects of air pollution on math test scores, by gender

Dependent variable math scores	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Male subsample							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.002	-0.003	-0.005**	-0.009**	-0.006	-0.008	-0.014*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
Observations	15,318	15,318	15,318	15,318	15,318	15,318	15,318
Overall R^2	0.512	0.524	0.514	0.517	0.534	0.513	0.537
B. Female subsample							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.001	-0.004**	-0.004	-0.008*	-0.007*	-0.010*	-0.016**
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.008)
Observations	16,641	16,641	16,641	16,641	16,641	16,641	16,641
Overall R^2	0.692	0.697	0.688	0.701	0.692	0.683	0.689
C. Whole sample with an interaction							
Male $\times \frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.003***	-0.005***	-0.008***	-0.011***	-0.008***	-0.012***	-0.016***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.671	0.705	0.699	0.691	0.671	0.670	0.677

Note: See the notes to Table 2.

Table A5: Heterogeneous effects of air pollution on verbal test scores, by income and workplace

Dependent variable verbal scores	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Income level 0-50%							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.006*	-0.014**	-0.037***	-0.053***	-0.061***	-0.093***	-0.127***
	(0.003)	(0.006)	(0.011)	(0.012)	(0.014)	(0.019)	(0.026)
Observations	13,019	13,019	13,019	13,019	13,019	13,019	13,019
Overall R^2	0.338	0.338	0.338	0.338	0.338	0.338	0.338
B. Income level 50-100%							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.003	-0.013**	-0.033***	-0.040***	-0.033***	-0.036**	-0.060**
	(0.002)	(0.006)	(0.009)	(0.013)	(0.012)	(0.017)	(0.023)
Observations	18,213	18,213	18,213	18,213	18,213	18,213	18,213
Overall R^2	0.357	0.357	0.357	0.357	0.357	0.357	0.357
C. Working outdoors							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.006*	-0.009	-0.039***	-0.046***	-0.055***	-0.082***	-0.121***
	(0.003)	(0.007)	(0.012)	(0.015)	(0.015)	(0.018)	(0.024)
Observations	13,029	13,029	13,029	13,029	13,029	13,029	13,029
Overall R^2	0.277	0.277	0.277	0.277	0.277	0.277	0.277
D. Working indoors							
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	-0.003	-0.016***	-0.031***	-0.040***	-0.032***	-0.036**	-0.055**
	(0.002)	(0.005)	(0.008)	(0.012)	(0.011)	(0.015)	(0.022)
Observations	18,930	18,930	18,930	18,930	18,930	18,930	18,930
Overall R^2	0.328	0.328	0.328	0.328	0.328	0.328	0.328

Note: See the notes to Table 2.

Table A6: Nonlinear effects of air pollution on verbal test scores

Dependent variable verbal scores	A: 1-day mean			B: 7-day mean			C: 30-day mean		
	all	male	female	all	male	female	all	male	female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0-50 *(reference)*	--	--	--	--	--	--	--	--	--
51–100	0.112	-0.106	0.327	-0.327	-0.592	-0.054	-0.664	-1.162*	-0.166
	(0.286)	(0.336)	(0.293)	(0.382)	(0.481)	(0.368)	(0.481)	(0.595)	(0.434)
101–150	-0.078	-0.215	0.027	-0.861*	-1.108*	-0.622	-1.684**	-2.160**	-1.234**
	(0.329)	(0.404)	(0.366)	(0.495)	(0.614)	(0.499)	(0.687)	(0.849)	(0.605)
151–200	-0.121	0.074	-0.286	-1.543	-2.068	-1.016	-6.901***	-8.421***	-5.176***
	(0.542)	(0.825)	(0.669)	(0.941)	(1.278)	(1.164)	(1.009)	(1.283)	(0.909)
201–300	-1.241	-3.878**	0.700	-3.108	-3.908	-2.248	--	--	--
	(1.557)	(1.569)	(1.380)	(1.878)	(3.016)	(1.518)			
301–500	-0.715	-2.840**	0.585	--	--	--	--	--	--
	(1.145)	(1.247)	(1.278)						
Observations	31,959	15,318	16,641	31,959	15,318	16,641	31,959	15,318	16,641
Overall R^2	0.453	0.453	0.453	0.446	0.446	0.446	0.452	0.452	0.452

Dependent variable verbal scores	D: 90-day mean			E: 1-year mean			F: 2-year mean		
	all	male	female	all	male	female	all	male	female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0-50 *(reference)*	--	--	--	--	--	--	--	--	--
51–75	-1.352**	-1.878**	-0.828	-1.694*	-2.695**	-0.750	-0.931	-1.851*	0.032
	(0.656)	(0.737)	(0.661)	(1.000)	(1.220)	(0.789)	(0.993)	(1.102)	(0.920)
76–100	-1.821**	-2.309**	-1.329*	-2.025*	-3.100**	-0.996	-1.584	-2.478**	-0.615
	(0.789)	(0.897)	(0.780)	(1.076)	(1.324)	(0.846)	(1.048)	(1.181)	(0.969)
101–200	-2.197**	-2.806***	-1.625*	-2.934**	-4.281***	-1.667*	-3.033***	-4.186***	-1.840*
	(0.933)	(1.062)	(0.911)	(1.183)	(1.485)	(0.930)	(1.123)	(1.259)	(1.059)
Observations	31,959	15,318	16,641	31,959	15,318	16,641	31,959	15,318	16,641
Overall R^2	0.446	0.446	0.446	0.447	0.447	0.447	0.431	0.431	0.431

Note: See the notes to Table 2.

Table A7: Contemporaneous and cumulative exposure

A. Verbal test scores

Dependent variable verbal scores	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
API_t	-0.004*	-0.001	-0.000	-0.002	-0.002	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$		-0.013**	-0.035***	-0.043***	-0.042***	-0.055***	-0.083***
		(0.005)	(0.008)	(0.011)	(0.012)	(0.015)	(0.020)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.284	0.284	0.284	0.284	0.284	0.284	0.284

B. Math test scores

Dependent variable math scores	Contemporaneous		Cumulative				
	1-day	7-day	30-day	90-day	1-year	2-year	3-year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
API_t	-0.004*	-0.001	-0.000	-0.002	-0.002	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$		-0.003	-0.004*	-0.007**	-0.006*	-0.009*	-0.015**
		(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
Observations	31,959	31,959	31,959	31,959	31,959	31,959	31,959
Overall R^2	0.680	0.680	0.680	0.680	0.680	0.680	0.680

Note: See the notes to Table 2.

Appendix B: Scientific Background and Potential Mechanisms

Broadly speaking, according to the existing medical literature, air pollution may affect cognition through physiological and psychological pathways.

A few of these physiological pathways have been documented in the literature (Block and Calderón-Garcidueñas 2009). First, multiple pollutants (or toxic compounds bonded to the pollutants) may directly affect brain chemistry. For example, ozone in the air can react with body molecules to create toxins, causing asthma and respiratory problems (Sanders 2012).[20] Particulate matter (PM), especially fine particles, can carry toxins through small passageways and directly enter into the brain. There is evidence that suggests that exposure to high PM concentrations may compromise cognitive performance even for people working indoors (Braniš, Řezáčová, and Domasová 2005).[21]

Second, people breathing polluted air are more likely to be subject to oxygen deficiency, which in turn impairs their cognitive abilities (Amitai et al. 1998; Kampa and Castanas 2007). Carbon monoxide (CO), one important element of air pollution, prevents the body from releasing adequate oxygen to vital organs, in particular to the brain, which consume a large fraction of total oxygen intake. Third, air pollution could also damage the immune system, hinder neurological development, and impair neuron behavior, all of which contributeto long-term memory formation (Perera et al. 2009). Fourth, long-term exposure to pollution leads to the growth of white-matter lesions, potentially inhibiting cognition (Calderón-Garcidueñas et al. 2008). Further, exposure to highly concentration air pollution can be linked to markers of neuroinflammation and neuropathology that are associated with neurodegenerative conditions, such as Alzheimer's disease (Calderón-Garcidueñas et al. 2004; Levesque et al. 2011).

In addition to physiological pathways, air pollution could also disrupt cognitive

[20] Ozone is formed through a chemical reaction between nitrogen oxides, sunlight, and various gaseous pollutants.

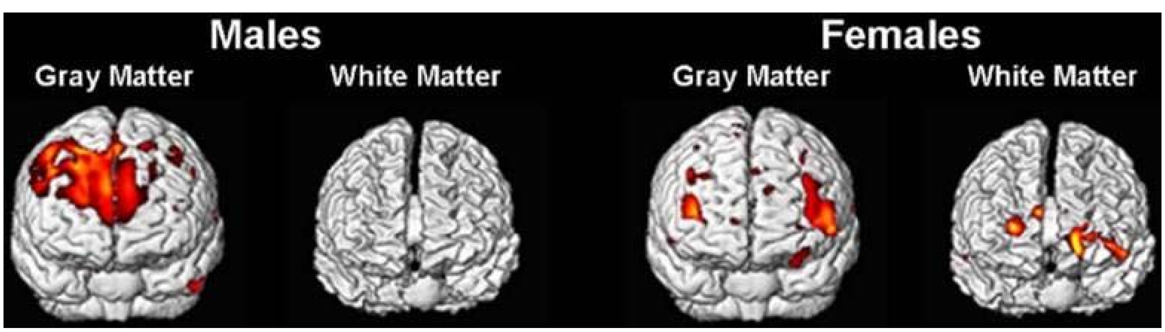
[21] PM is generated by power plants, factories, vehicles, dust, pollen and forest fires.

functioning through some psychological pathways. For example, high concentrations of CO and nitrogen dioxide (NO_2) are significantly associated with headache, eye irritation, and respiratory problems (Nattero and Enrico 1996).[22] High levels of ozone and sulfur dioxide (SO_2) have also been found to cause psychiatric distress (Rotton and Frey 1984).[23] Exposure to high concentrations of CO, NO_2, SO_2, ozone, and PM may also increase the risk of depression (Szyszkowicz 2007).

Our central nervous system has two important tissues: gray matter and white matter. Gray matter represents information processing centers, and white matter represents the networking of – or connections between – these processing centers. Mathematics abilities, which require more local processing, mainly depend on gray matter. While language skills, which require integrating and assimilating information from distributed gray-matter regions in the brain, mainly rely on white matter.[24]

A brain scanning study conducted by Haier et al. (2005) reveals that men have approximately 6.5 times the amount of gray matter activated during general intelligence tests than women do, but women have nearly 10 times the amount of white matter activated during general intelligence tests than men do. Please see Figure B1 for a front view of grey and white matter activation during IQ tests. This finding may help explain why men tend to excel in math tests, while women tend to excel in verbal tests.

Figure B1: Front view of grey and white matter activation during IQ tests



Source: Haier et al. (2005).

[22] NO_2 and CO are emitted by coal-burning power plants and the burning of fossil fuels.
[23] SO_2 is mainly emitted by coal-burning power plants.
[24] University of California, Irvine. "Intelligence in Men and Women Is a Gray and White Matter." Science Daily. www.sciencedaily.com/releases/2005/01/050121100142.htm [accessed January 25, 2017].

A large body of literature has proven that air pollution can reduce the density of white matter in the brain (Calderón-Garcidueñas et al. 2008, 2011; Wilker et al. 2015), which may directly explain why air pollution appears to have a larger effect on verbal test than on math test scores. Besides, since men have a much smaller amount of white matter activated during intelligence tests, their cognitive performance, especially in the verbal domain, tends to be more affected by exposure to air pollution.

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