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The impact of exposure to air pollution on cognitive performance

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This paper examines the effect of both cumulative and transitory exposures to air pollution for the same individuals over time on cognitive performance by matching a nationally representative longitudinal survey and air quality data in China according to the exact time and geographic locations of the cognitive tests. We find that long-term exposure to air pollution impedes cognitive performance in verbal and math tests. We provide evidence that the effect of air pollution on verbal tests becomes more pronounced as people age, especially for men and the less educated. The damage on the aging brain by air pollution likely imposes substantial health and economic costs, considering that cognitive functioning is critical for the elderly for both running daily errands and making high-stake decisions.

aging | cognitive decline | air pollution | gender difference | China

While a large body of literature has shown that air pollution harms human health, in terms of life expectancy (1), illness and hospitalization (2), child health (3), health behavior (4), and dementia (5–7), knowledge about the potential consequences of air pollution on cognitive abilities is more limited. A few existing studies on the impact of air pollution on cognition have mainly focused on young students (8–11). It is unclear whether their findings hold for the whole population or not, in particular for older cohort. Our paper fills this knowledge gap by examining the pollution–cognition relationship by age in China based on a nationally representative longitudinal dataset at the individual level.

We find that air pollution impairs verbal tests, and the effect becomes stronger as people age, especially for less educated men. Cognitive decline or impairment are risk factors of Alzheimer's disease and other forms of dementia for elderly persons. As the most expensive form of cognitive decline, Alzheimer's disease alone costs $226 billion of health services and 18 billion labor hours of unpaid caregiving in 2015 (6). Moreover, given that senior citizens have to make a host of complex high-stake economic decisions, such as purchasing health insurance and planning retirement, the decay in cognitive ability induced by air pollution will likely impair the quality of the important decisions (12). The damage on the aging brain by air pollution likely imposes substantial health and economic cost, which has been neglected in the policy discourse. Therefore, the finding on the detrimental effect of air pollution on the aging brain has important policy implications.

On the technical level, our paper has tried to overcome several common challenges facing this strand of empirical studies. First, we address the potential problem of omitted variables, which may be correlated with both cognition and exposure to air pollution, on estimation bias by using a panel data at the individual level. Most studies, except for those of Ebenstein et al. (10) and Marcotte (13), fail to account for individual-level heterogeneity due to data limitation. For instance, Ham et al. (8) only control for school-grade fixed effects; Bharadwaj et al. (14) include only sibling fixed effects. In this study, because we have access to a longitudinal dataset, the China Family Panel Studies (CFPS), we can remove individual-level unobservable factors.

Second, we have matched exposure to local environmental stressors with individual cognitive performance according to the exact time of test taking. This is more precise than in previous studies, for instance, that of Ham et al. (8), who match yearly air pollution with average standardized test scores at the school-grade level. Third, most existing studies consider either the effects of transitory or cumulative exposure to air pollution, but rarely both effects simultaneously, except for Marcotte (13). For example, Ham et al. (8) and Ebenstein et al. (10) focus on contemporaneous exposure; Bharadwaj et al. (14), Molina (15), and Sanders (16) examine the effect of cumulative exposure. We are among the first to examine the cognitive impact of cumulative exposure to air pollution while controlling for contemporaneous exposure. By controlling for the latter, we can evaluate the relative importance of transitory and accumulative effects. We find that the accumulative effect dominates.

Given that cognitive ability shapes human behavior and decision making, our result provides supporting evidence on the findings about the negative effect of air pollution on decision making (7, 17), risk attitude (11), and behavior (11, 18). The damage on cognitive ability by air pollution also likely impedes the development of human capital. In fact, a few studies have found that exposure to air pollution lowers educational attainment (10, 16) and results in lower labor productivity (19–22).

Air pollution is a ubiquitous problem in developing countries. According to the global ambient air pollution database compiled

Significance

Most of the population in developing countries live in places with unsafe air. Utilizing variations in transitory and cumulative air pollution exposures for the same individuals over time in China, we provide evidence that polluted air may impede cognitive ability as people become older, especially for less educated men. Cutting annual mean concentration of particulate matter smaller than 10 μm (PM10) in China to the Environmental Protection Agency's standard (50 $\mu g/m^3$) would move people from the median to the 63rd percentile (verbal test scores) and the 58th percentile (math test scores), respectively. The damage on the aging brain by air pollution likely imposes substantial health and economic costs, considering that cognitive functioning is critical for the elderly for both running daily errands and making high-stake decisions.

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SUSTAINABILITY SCIENCE

by the World Health Organization (www.who.int/phe/health_topics/outdoorair/databases/cities/en/), the top 20 most polluted cities are all in developing countries. Almost all of the cities (98%) in low- and middle-income countries with more than 100,000 residents fail to meet World Health Organization air quality guidelines. Therefore, the research findings on China, the largest developing country with severe air pollution, can also shed light on other developing countries.

The remainder of the paper is organized as follows. *Data Sources* describes the data, and *Econometric Model* lays out the empirical strategy. *Empirical Results* presents our main findings. *Conclusions* provides some conclusions. In *SI Appendix*, we also discuss the scientific background of this study and potential mechanisms in detail.

Data Sources

The dataset for this analysis is based on several sources. The cognitive test scores come from the CFPS, a nationally representative survey of Chinese families and individuals. The waves 2010 and 2014 contain the same cognitive ability module, that is, 24 standardized mathematics questions and 34 word-recognition questions. All of these questions are sorted in ascending order of difficulty, and the final test score is defined as the rank of the hardest question that a respondent is able to answer correctly. The survey also provides exact information about the geographic locations and dates of interviews for all respondents, which enables us to match test scores with local air quality data more precisely.

Air quality is measured using the air pollution index (API), which is calculated based on daily readings of three air pollutants, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter smaller than 10 μm (PM10). The API ranges from 0 to 500, with larger values indicating worse air quality. Daily API observations are obtained from the city-level air quality report published by the Chinese Ministry of Environmental Protection. The report includes 86 major cities in 2000 and covers most of the cities in China in 2014.

Our analysis also includes rich weather measures on the interview date, enabling us to separate the impact of air pollution from general weather patterns. The weather data are derived from the National Centers for Environmental Information of the US National Oceanic and Atmospheric Administration. The dataset contains daily records of rich weather conditions from 402 monitoring stations in China.

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 readings as the county's readings. If a CFPS county is not located in any cities with API readings, we match it to the nearest API reporting city within a radius of 40 km according to the distance between the CFPS county centroid and the city boundaries. In *SI Appendix, Part 2: Description of Data*, we show the results are robust to a wide range of matching radiuses and alternative matching strategies. The final dataset used in this study includes 31,959 observations. *SI Appendix* describes the data and the matching procedure in greater detail.

Econometric Model

Our baseline econometric specification is as follows:

$$\mathrm{Score}_{ijt} = \alpha_1 P_{jt} + \alpha_2 \cdot \frac{1}{k} \sum_{n=0}^{k-1} P_{j,t-n} + X'_{ijt}\beta + W'_{jt}\phi + T'_{jt}\gamma + \lambda_i + \delta_j + \eta_t + f(t) + \varepsilon_{ijt}. \quad [1]$$

The dependent variable Score_{ijt} is the cognition test scores of respondent i in county j at date t. P_{jt} is the contemporaneous air quality measure at date t. The key variable $(1/k)\sum_{n=0}^{k-1} P_{j,t-n}$ is the mean API reading in the past k days, which measures cumulative exposure. X_{ijt} is a set of the observable demographic correlates of the respondents. We also control for a vector of contemporaneous weather conditions W_{jt} and a vector of county-level characteristics T_{jt} to account for factors that are correlated with both test scores and air quality. λ_i denotes individual fixed effects. δ_j represents county fixed effects, which cannot be wiped out by individual fixed effects since some respondents do not live in the same counties across the two waves. η_t indicates month, day of week, and postmeridiem 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. SEs are clustered at the county level.

By conditioning on the individual fixed effects, 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. *SI Appendix*, Fig. S1 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. There is a concern that the results are mainly driven by the skewed sample distribution in the summer months, when air pollution is not as serious as in winter. *SI Appendix*, Fig. S11 and Table S12 also show that our findings still hold if giving an interview in winter greater weight than that in nonwinter so that the two periods share the same weight. The study was approved by the institutional review board (IRB) at Peking University (Approval IRB00001052-14010). All participants gave informed consent in accordance with policies of the IRB at Peking University.

Empirical Results

Estimates of the Effect of Air Pollution on Cognitive Test Scores. *SI Appendix*, Table S1 reports the results for estimation of Eq. **1** using seven windows of air pollution exposure, that is, 1-d, 7-d, 30-d, 90-d, 1-y, 2-y, and 3-y exposures. Panel A presents the estimates for the verbal test scores, while panel B displays the results for the math test scores. Three findings are apparent from the table. First, in general, air pollution inhibits respondents' test performance. Except for the effects of 1-d and 7-d air pollution exposure on math test scores (first and second columns in panel B), all of the coefficients for mean APIs over a longer period are negative and statistically significant. Second, the damage of air pollution on cognitive performance is more sizable when using longer window of exposure measure. As shown at the bottom in panel A, an increase in the 7-d-mean API by 1 SD lowers verbal test scores by 0.278 point (0.026 SD), while a 1 SD increase in average API over 3 y before the interview is associated with 1.132 points (0.108 SD) drop in verbal test scores. Third, air pollution exposure appears to exert a more negative effect on verbal test performance than math test performance. The changes in SDs in the parentheses presented at the bottom of panel A for verbal test scores are more pronounced than the corresponding ones in panel B for math test scores. *SI Appendix*, Table S11 further confirms that the baseline results are robust to alternative specifications without controlling for potentially endogenous variables or individual fixed effects.

Fig. 1 visualizes our baseline results obtained from *SI Appendix*, Tables S2a and S2b. Fig. 1*A* refers to the results for verbal tests, while Fig. 1*B* is for math test scores. Each figure presents the estimated coefficients for different windows of the mean API readings, together with their 95% and 99% confidence intervals, for the male and female subsamples, respectively. As shown in Fig. 1*A*, exposure to air pollution is associated with lower verbal test scores for both men and women regardless of the length of exposure. In general, the effect becomes larger as the duration of exposure to air pollution increases. Men are more vulnerable to air pollution than women. The gender difference is statistically significant, as shown by the asterisks in Fig. 1*A*. As illustrated in *SI*

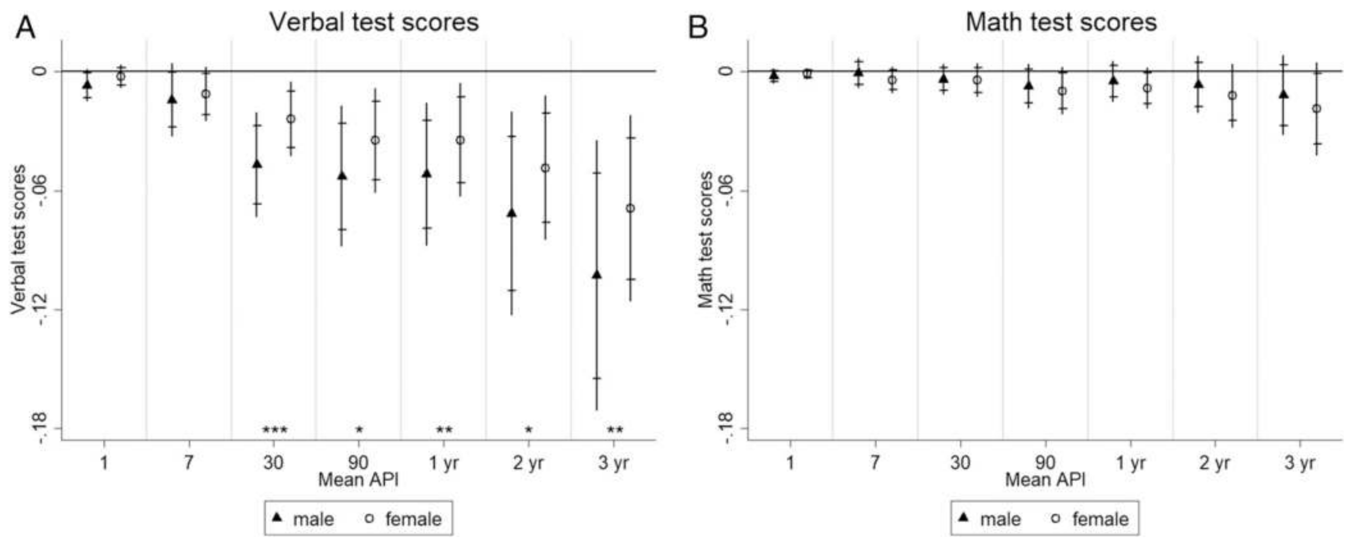

Fig. 1. The figures plot the estimated coefficients on air pollution for the male and female subsamples with 95% and 99% confidence intervals based on the estimates in *SI Appendix*, Tables S2a and S2b. *A* and *B* refer to verbal and math test scores, respectively. Air pollution data are matched between each CFPS county centroid and its nearest API reporting city boundary within a radius of 40 km (i.e., 25 miles). The asterisks in the figure indicate the significance of the male–female difference denoting the results of Wald tests: *10% significance level; **5% significance level; ***1% significance level.

Appendix, Part 6: Scientific Backgrounds and Potential Mechanisms, this gender gap is likely caused by their different sizes of white matter activated, which can be reduced by air pollution.

As presented in Fig. 1*B*, the effect on math tests is more muted than that on verbal tests. *SI Appendix, Part 6: Scientific Backgrounds and Potential Mechanisms* speculates that the observed patterns are probably associated with gender difference in white matter and gray matter. Air pollution has a stronger effect on white matter (required more by verbal tests) than on gray matter (required more by math tests). 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.

Estimates of the Age-Cohort Effect of Air Pollution on Cognitive Test Scores. To understand how air pollution affects cognition as people age, we examine the accumulative effects for verbal and math test scores, respectively, for different age cohorts. The age cohort effects are measured by the interaction terms between 3-y-mean API and age cohort dummies 25–34, 35–44, 45–54, 55–64, and 65+ in 2014. The age band 10–24 is the reference category. Fig. 2 plots the estimated coefficients on the interaction terms for the male and female subsamples coupled with 95% and 99% confidence intervals. The numerical results are shown in *SI Appendix*, Table S3. In Fig. 2, A and B present results for verbal and math tests, respectively. Compared with younger age cohorts, the negative effect on the verbal test performance is more

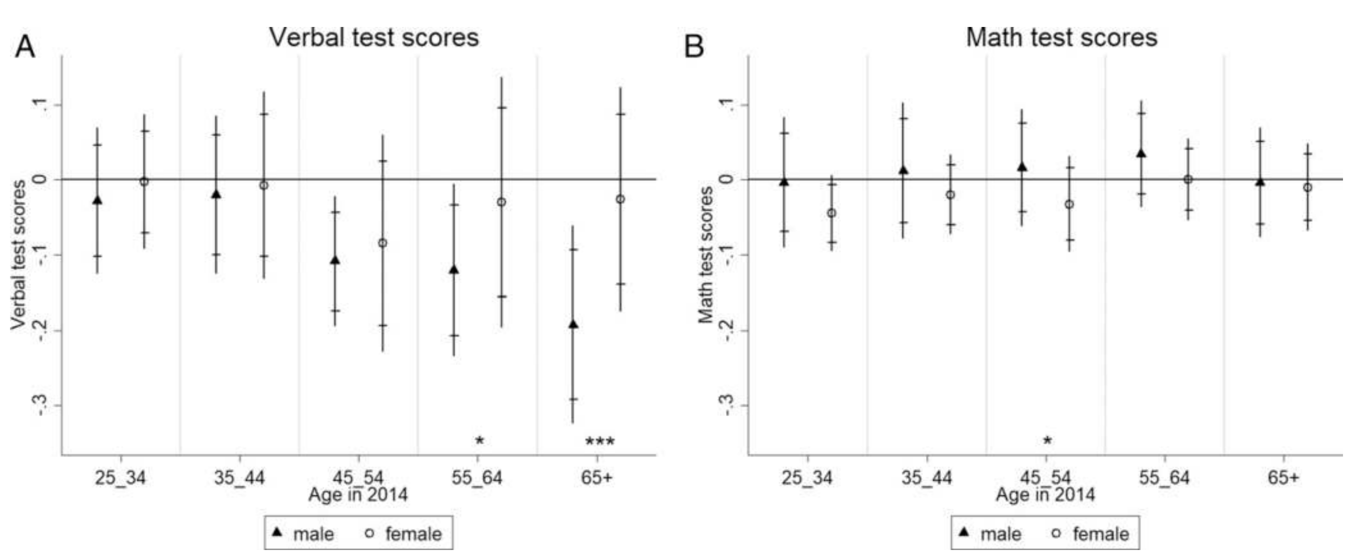

Fig. 2. The age cohort effects of air pollution on cognitive test scores include interaction terms between 3-y-mean API and age cohort dummies 25–34, 35–44, 45–54, 55–64, and 65+ in 2014. The age band 10–24 is the reference category. The figures plot the estimated coefficients on the interaction terms for the male and female subsamples with 95% and 99% confidence intervals based on the estimates in *SI Appendix*, Table S3. *A* and *B* refer to verbal and math test scores, respectively. Air pollution data are matched between each CFPS county centroid and its nearest API reporting city boundary within a radius of 40 km (i.e., 25 miles). The asterisks in the figure indicate the significance of the male–female difference denoting the results of Wald tests: *10% significance level; **5% significance level; ***1% significance level.

pronounced for the older cohorts, especially among males. As a result, the gender gap in the decline of verbal skills widens as people age. Such pattern, however, is less noticeable for the math tests.

Estimates of the Age-Cohort Effect of Air Pollution on Cognitive Test Scores by Educational Attainment. We repeat the exercises in Fig. 2 to identify potential heterogeneous effects of air pollution on verbal test scores by educational attainment, that is, primary school or below versus middle school or above. Fig. 3 and *SI Appendix*, Table S4a display the estimated coefficients on the interaction terms for the male and female subsamples, together with 95% and 99% confidence intervals across age cohorts. As shown in Fig. 3*A*, the effect for men over 44 y old with primary school education or below is highly negative. Among the more educated subsample (Fig. 3*B*), the negative effect only shows up for men aged 65 and above. Such pattern, however, is not evident for older women regardless of their education. *SI Appendix*, Table S4b further displays age cohort effects of air pollution on math test scores by educational attainment. There is no clear difference.

Falsification Tests. Some time-variant unobserved factors, such as migrating to a different city with more ambient air and better-paying job between 2012 and 2014, may affect both cognitive test scores and exposure to air pollution even after controlling for individual fixed effects. To address this concern, *SI Appendix*, Fig. S10 reports a falsification test, examining whether API readings on the days after cognitive tests affect test scores. If the time series of API readings embody some unobserved factors that are correlated with the outcome variables, using the API readings after the test to replace the current and past API readings in regressions would yield similar results. However, for the whole sample as well as the male and female subsamples, all of the coefficients are not statistically different from zero, largely dismissing the concern about potential omitted variables. It is worth noting that the coefficients in this falsification test are smaller in size than the main effects.

Robustness. People may become more impatient or uncooperative when exposed to more polluted air. Therefore, it is possible that the observed negative effect on cognitive performance is due to behavioral change rather than impaired cognition. To check this possibility, we examine the impact of exposure to air pollution and patience and cooperation during the interview in *SI Appendix*, Table S13. None of the coefficients for API is significant, largely dismissing this channel. Changes in the brain chemistry or composition are likely more plausible channels between air pollution and cognition. It is beyond the scope of this paper to test the exact mechanism, so we leave it as agenda for future research.

Our baseline results are also robust to a wide variety of specification checks. *SI Appendix*, Fig. S12 and Table S14 document that migration is unlikely to significantly bias our estimates. *SI Appendix*, Fig. S13 and Table S15 show that the results are qualitatively unchanged after excluding polluted occupations. Furthermore, as revealed in *SI Appendix*, Table S16, the baseline results are robust to controlling for province-by-year fixed effects and clustering SEs at the province level.

Interpretation. *SI Appendix, Part 5: Estimating Movement in the Test Distribution Using the Coefficient Estimates* calculates movement in test distribution using the coefficient estimates. Reducing the population-weighted annual mean concentration of PM10 over 2014 in China to levels below the National Ambient Air Quality Standards published by the US Environmental Protection Agency will on average lift verbal test scores by 2.41 points (or the movement of people from the median to the 63rd percentile in the verbal test distribution) and math test scores by 0.39 point (or the movement of people from the median to the 58th percentile in the math test distribution).

The effect is particularly large for less educated men older than 64. A 1 SD decrease in 3-y-mean API leads to an increase in verbal test scores by 9.18 points (or the movement of people from the median to the 87th percentile in the verbal test distribution) for this group relative to the cohort younger than 25. The effect remains sizable for more educated older men. A 1 SD decrease in 3-y-mean API is associated with an increase in verbal test scores by 1.88 points (or the movement of people from the

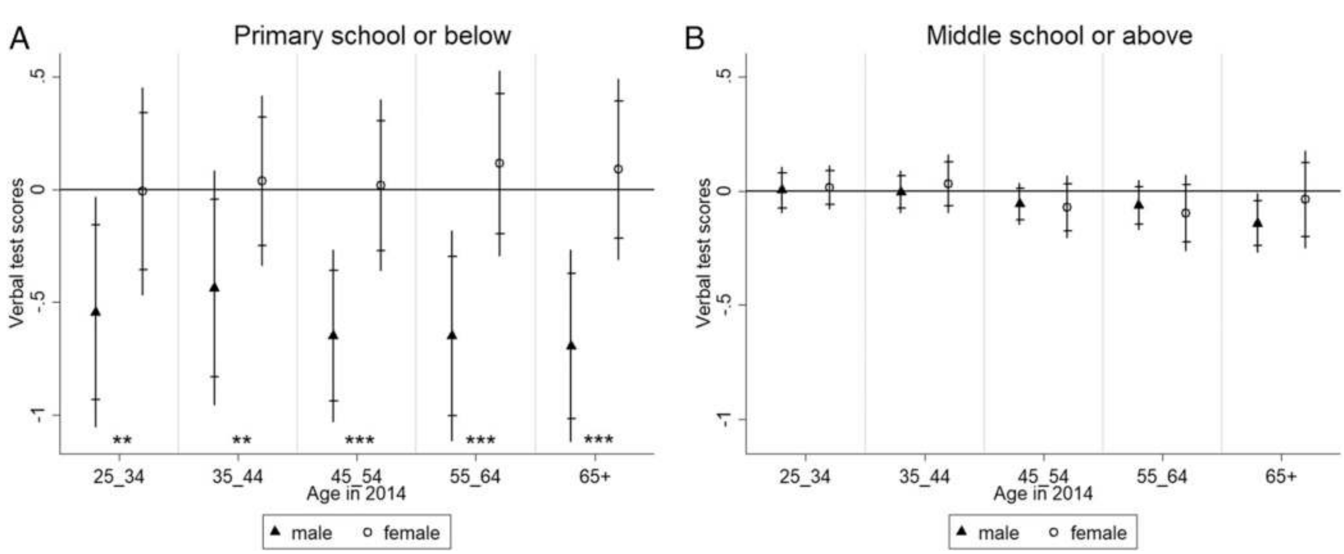

Fig. 3. The age cohort effects of air pollution on verbal test scores by educational attainment include interaction terms between 3-y-mean API and age cohort dummies 25–34, 35–44, 45–54, 55–64, and 65+ in 2014. The age band 10–24 is the reference category. The figures plot the estimated coefficients on the interaction terms for the male and female subsamples with 95% and 99% confidence intervals based on the estimates in *SI Appendix*, Table S4a. *A* refers to the subsample with education level at the primary school or below, while *B* includes the subsample with middle school education or above. Air pollution data are matched between each CFPS county centroid and its nearest API reporting city boundary within a radius of 40 km (i.e., 25 miles). The asterisks in the figure indicate the significance of the male–female difference denoting the results of Wald tests: *10% significance level; **5% significance level; ***1% significance level.

median to the 69th percentile in the verbal test distribution) for them relative to their younger counterpart.

Conclusions

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 according to the exact dates and locations of the interviews. We find that accumulative exposure to air pollution impedes verbal test scores. As people age, the negative effect becomes more pronounced, especially for men. The gender gap is particularly large for the less educated.

Our findings about the damaging effect of air pollution on cognition, particularly on the aging brain, imply 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 pollution.

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