The impact of indoor air pollution on health outcomes and cognitive abilities: Empirical evidence from China

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Abstract

This paper investigates the health impact of indoor air pollution caused by household use of solid fuels for heating or cooking for middle-aged and elderly people, using data from the 2013 China Health and Retirement Longitudinal Study. Using a propensity score matching method, we find that indoor air pollution significantly increases the likelihood of being diagnosed with respiratory diseases and cardiovascular diseases (e.g., lung disease, heart disease, hypertension) and self-reporting poor health. We also find a significant adverse impact on cognitive abilities, including short-term memory and mathematical reasoning. These results suggest that indoor air pollution poses a great environment health risk.

Keywords: indoor air pollution; health outcomes; cognitive abilities; propensity score matching

JEL code: Q50, I10

1. Introduction

Outdoor air pollution, which imposes substantial health and economic burdens on many people in China, has received tremendous interest from scientists, policymakers, and the public. However, much less attention has been paid to indoor air pollution, although nearly half the Chinese people still rely on solid fuels (such as coal and wood residue) for cooking and heating (Baumgartner et al. 2014). Exposure to household air pollution is a major health risk for people in China and other developing countries.[1] According to the World Health Organization (WHO), 4.3 million people a year die from exposure to household air pollution (Ghosh Banerjee et al. 2014; WHO 2016). Indoor air pollution is also harmful to cognitive abilities (Calderón-Garcidueñas et al. 2008; Fonken et al. 2011; Ailshireand Crimmins 2014; Gatto et al. 2014), which in the long run can defer human capital accumulation, reduce lifetime earnings, and decrease social welfare. Therefore, a thorough evaluation of the health impact of indoor air pollution caused by household use of solid fuels is needed to inform health public policy. The existing literature, however, provides limited evidence on this important question.

This paper fills the gap in existing literature by estimating the impact of indoor air pollution on physical health outcomes and cognitive abilities. We consider an individual exposed to indoor air pollution if he or she lives in a household that uses solid fuels for heating or cooking. Using data from the 2013 China Health and Retirement Longitudinal Study (CHARLS), we apply a propensity score matching (PSM) method to address the selection bias due to heterogeneity between households that use solid fuels and those that do not. Our estimates are conditional on a wide set of explanatory variables that are considered to be correlated with the choice of heating and cooking power sources and health outcomes.

[1] Pollutants from household combustion of solid fuels include TSP, SO_X, NO_X, PAH_S, Hg, Pb, F, As, etc.

We find that household use of solid fuels has a significant negative effect on both health outcomes and cognitive abilities. In terms of physical health, respondents in households that use solid fuels are 1.3% and 4.7% more likely to be diagnosed with chronic lung disease and heart disease, respectively. They are also 5.0% and 2.7% more likely to experience left chest pain and be diagnosed with hypertension, respectively. In addition, they are 8.1% more likely to report poor health. In terms of cognitive abilities, we find that people in households that use solid fuels recall 0.08 fewer words (out of 10) in a word-memorizing test and score 0.26 fewer points (out of 5) in a numerical calculation test. Additionally, they are 3.2% less likely to report having a good memory. These findings are consistent with the epidemiological literature that some air pollutants (such as fine particulate matters) may penetrate deeply into the lungs and affect blood flow and oxygen circulation (Clark and Sokoloff 1999; Wilker et al. 2015; Ebenstein, Lavy, and Roth 2016), thereby adversely affecting cognitive abilities.

Furthermore, there is significant heterogeneity in the health impact of indoor air pollution across the region. We find that indoor air pollution has a larger impact on health outcomes and cognitive abilities in southern China, where outdoor air pollution is much less severe. The health impact is also heterogeneous across gender. Our results show that female respondents suffer more from indoor air pollution on self-reported poor health, heart disease, left chest pain, and numerical calculation ability. This is consistent with the fact that women are primarily responsible for preparing meals or doing housework, and thus more likely to have prolonged exposure to indoor air pollution.

As a robustness check, we examine the effect of indoor air pollution on self-reported diagnosis of some other diseases (e.g., stomach or digestive disease, dyslipidemia, and diabetes) that are less likely to be influenced by air pollutants from the incomplete combustion of biomass.

We find no significant impacts on all these diseases, suggesting that our results are driven by indoor air pollution instead of other factors, such as water pollution.

This study makes several contributions. First, this paper contributes to the economic literature on air pollution and health outcomes (Chay and Greenstone 2003; Janke, Propper, and Henderson 2009; Chen et al. 2013). This paper adds to the economic literature that evaluates the effects of indoor air pollution on health outcomes. Although epidemiological studies have examined the health impact of indoor air pollution, they often rely on small samples or focus on small geographic areas (Ezzati and Kammen 2001; Baumgartner, Schauer, et al. 2011; Baumgartner, Zhang, et al. 2014). Some economic studies have also investigated the relationship between indoor air pollution and health outcomes, but they mostly focus on the impact on children or have limited health outcomes (respiratory health for children five and under (Yu 2011); acute respiratory infections for children under six (Barron and Torero 2017); in perinatal deaths and low-birth-weight infants (Xue 2017); computed Physical Component Summary for adults (Mueller et al. 2013)).

We complement existing studies by using a nationwide survey of middle-aged and elderly people in China that has a much larger sample size and includes rich information of health outcomes and cognitive abilities, which leads to greater statistical power and more general conclusions.

Second, this paper contributes to economic and medical literature on the impact of air pollution on brain structure, cognitive abilities, and productivity (Calderón-Garcidueñas et al. 2008; Fonken et al. 2011; Ailshireand Crimmins 2014; Gatto et al. 2014; Stafford 2015; Chang et al. 2016; Ebenstein, Lavy, and Roth 2016). Although studies have started to look at the impact of air pollution in an indoor environment (Stafford 2015), few studies focus on air pollutants from indoor combustion of solid fuels.

Third, by using the CHARLS data, which focuses on middle-aged and elderly people, this paper highlights the impact of air pollution on older populations, who are especially vulnerable to hazards in their living environment. Population aging is taking place in most countries of the world, and China has the largest aging population. It is projected that by 2050 more than 30% of the population (440 million) will be age 60 or older in China (UN 2009). A focus on China's older population is vital to economic and health policy design because the aging population imposes a substantial burden on medical care and the economy.

The remaining sections of the paper are organized as follows. The next two sections describe the data and empirical strategy. Section 4 reports the results and robustness checks. The final section provides the conclusion.

2. Data and summary statistics

2.1 Data

We use data from the CHARLS, which is a nationally representative sample of people age 45 and older. The CHARLS, which began in 2011, is a biannual panel survey that includes about 17,500 individuals and 10,000 households in 150 counties in 28 (out of 31) provinces in China. This survey collects extensive information on demographic and socioeconomic characteristics, family and household characteristics, health status and functioning, employment, wealth, and so on. The CHARLS is particularly suitable for investigating the health impact of indoor air pollution because it has rich information on physical health and cognitive outcomes and, more important, on the type of fuel each household uses for heating and cooking.

Our dependent variables include indicators of physical health outcomes and cognitive abilities. For physical health outcomes, we construct a set of dummy variables indicating whether the respondent has been diagnosed with a certain type of chronic disease. These include respiratory diseases (asthma and chronic lung diseases), cardiovascular diseases (heart disease, stroke, and hypertension), and other diseases (dyslipidemia, diabetes, cancer, liver diseases, kidney diseases, stomach diseases). We additionally create a dummy variable of experiencing chest pain during physical activity because chest pain is a symptom of cardiovascular diseases. Finally, we create a dummy variable of self-reported poor health to measure perceived general health, and it is equal to one if the respondent rates his or her health as poor or very poor.

Regarding cognitive abilities, we construct several measures of memory and mathematical reasoning utilizing the results from a simple memory and math test. The memory test asks each respondent to recall as many words as possible after a list of 10 words is read to them. As a result, we use the number of words correctly recalled as a measure of short-term memory ability. We also create a dummy variable of self-reported good memory if the respondent rates his or her current memory as good, very good, or excellent. For mathematical reasoning, each respondent is asked to perform a series of simple numerical calculation problems. We then use the resulting number of numerical calculation problems correctly answered as a measure of mathematical reasoning.

Our key explanatory variable of interest, *IAP*, is a dummy variable indicating household use of coal, crop residue, or wood for heating or cooking. These kinds of fuel are a major source of indoor air pollution because they are likely to produce health-damaging pollutants such as fine particles, compared to natural gas, liquefied petroleum gas, and electricity. We also include a rich set of demographic and socioeconomic variables including age, gender, marital status, education level, income, an indicator of agricultural *hukou*[2], and usage of running water in the residence. We additionally control for individual drinking and smoking behavior and social activities because these are important determinants of health outcomes. Lastly, we merge the city-level air quality index (AQI) to the CHARLS data to control for the outdoor air pollution level.[3]

We use the 2013 CHARLS data in this study, and exclude 497 respondents under 45. After excluding respondents with missing information on explanatory variables, our final sample includes 15,637 observations.

2.2 Summary statistics

(Here insert Table 1)

Table 1 reports the pre-matching summary statistics of the outcome and explanatory variables. Column (1) and (2) of Table 1 present the sample means for respondents in households that use and do not use solid fuels, respectively. Column (3) shows the difference in means between these two groups, and Column (4) reports the corresponding *t*-values of the test of whether the mean difference is statistically different from zero. We see that solid fuel households are older, have a higher number of males, and are less likely to be married than non-solid fuel households. In terms of socioeconomic status, not surprisingly, solid fuel households have lower education and earn less than comparison households. They are also more likely to hold agricultural *hukou* and less likely to have access to running water in their home. With respect to lifestyle, solid fuel households have a higher percentage of smokers, a lower percentage of

[2] *Hukou* is a household registration system used in China.

[3] Gathered from the Ministry of Environmental Protection of the People's Republic of China, AQI is an indicator of the densities of several air pollutants, including SO_2, NO_2,PM_{10},$PM_{2.5}$,O_3, and CO. Specifically, we use the average pollution level from 2014 to 2016 because earlier air quality data are not available for a number of cities in the CHARLS. Although we do not have the 2013 data, the 2014–2016 average can be a good proxy for long-term air pollution levels because air pollution levels are highly correlated over time.

drinkers, and are less likely to engage in social activity, compared to non-solid fuel households. In addition, respondents in solid fuel households are exposed to more serious outdoor air pollution than those in non-solid fuel households. It is notable that most of these differences are statistically significant as shown in Column (4), suggesting that respondents in households that use and do not use solid fuels are quite different in observed characteristics. This motivates us to use the PSM method to estimate the impact of indoor air pollution.

3. Methodology

The objective of this paper is to examine the effect of indoor air pollution on health outcomes for middle-aged and elderly people. One empirical challenge to estimating this impact is that household use of solid fuels for heating or cooking is not randomly assigned. Thus, the estimated health impact may be biased due to the neglected heterogeneity between households that use and do not use solid fuels, i.e., the selection bias. For instance, as shown in Table 1, individuals with lower socioeconomic status are more likely to live in households that use solid fuels and may have worse health outcomes, in which case the health impact is overestimated.

To deal with the selection bias, we use a PSM method to uncover the causal relationship between indoor air pollution and health outcomes by constructing a proper control group with similar observed characteristics to the treatment group.[4] A key assumption of this method is the conditional independence assumption (CIA), which assumes no confounding factors between the treatment and matched control groups conditional on observables. Under this assumption, the differences in health outcomes between these two groups can be attributed to indoor air pollution.

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[4] PSM method has been used in studies examining the relationship between indoor air pollution and health outcomes (e.g., Yu 2011; Mueller et al. 2013; Silwal and McKay 2013).

Let Y_{1i} and Y_{0i} represent the potential outcomes of individual *i* in a household that uses and does not use solid fuels for heating or cooking, respectively. The average treatment effect on the treated (ATT) can be written as

$$ATT = E[Y_{1i} \mid IAP_i = 1] - E[Y_{0i} \mid IAP_i = 1], \qquad (1)$$

where *IAP* indicates indoor air pollution caused by household use of solid fuels. However, the potential outcomes of individuals in households that use solid fuels had they not used ($E[Y_{0i} \mid IAP_i = 1]$) are not observed. To identify the ATT, one strategy is to assume the CIA holds so that the outcomes of individuals in non-solid fuel households conditional on observables ($E[Y_{0i} \mid X_i, IAP_i = 0]$) can be used to represent these missing counterfactual outcomes. Namely,

$$E[Y_{0i} \mid X_i, IAP_i = 1] = E[Y_{0i} \mid X_i, IAP_i = 0]. \qquad (2)$$

Empirically, the propensity score $p(X_i)$ — the probability of household use of solid fuels given the observed characteristics—is used in the matching process because direct matching becomes impractical as the number of explanatory variables increases (Rosenbaum and Rubin 1983). Therefore, Equation (2) can be rewritten as

$$ATT = E[Y_{1i} \mid p(X_i), IAP_i = 1] - E[Y_{0i} \mid p(X_i), IAP_i = 0]. \qquad (3)$$

Another assumption required for the PSM method is the overlap or common support assumption, which ensures a positive probability of being treated and untreated for individuals with the same observed characteristics:

$$0 < p(IAP_i = 1 \mid X_i) < 1 \qquad (4)$$

This assumption requires sufficient overlap in observed characteristics for treatment and control groups so that there are adequate comparable untreated individuals for the treated individuals.

In this paper, we first estimate a *probit* model of household use of solid fuels based on observed characteristics and then use the estimated propensity score to construct the control group. We apply the commonly used nearest neighbor matching method, which selects one or more individuals from the control group whose propensity scores are close enough to each individual in the treatment group. Here we select ten untreated individuals whose propensity score is within 0.1 range of each treated individual. To test the sensitivity of our results, we also report the results using the kernel matching method with Gaussian kernel function and a bandwidth of 0.06.[5] Additionally, as a second sensitivity check, we implement a weighted least square (WLS) regression using the previously estimated propensity scores as sampling weights (Hirano and Imbens 2001; Imbens and Rubin 2015).[6]

3.1 Propensity Score Estimation and Covariate Balancing Test

Before examining the estimated health impact of indoor air pollution, we present the results of a *probit* model of household use of solid fuels in Appendix Table A2. All estimated coefficients are statistically different from zero except *drinker*. It is worth noting that socioeconomic variables are important determinants of the use of dirty power. For example, individuals with higher income or education are less likely to use solid fuels in their household. In addition, individuals with agriculture *hukou* are more likely to use solid fuels.

(Here insert Figure 1)

Now we move to the discussion of matching quality. We first examine the degree to which the estimated propensity scores for the treatment and control groups overlap. Figure 1 plots the

[5] The kernel matching method calculates a weighted average of outcomes of all untreated individuals as the counterfactual outcome for each treated individual. It is also commonly used in matching literature and has an advantage of lower variance over other matching estimators (Caliendo and Kopeinig 2008).

[6] Specifically, we apply the inverse of propensity scores to a weighted regression of outcome on treatment and explanatory variables. This approach is another way to account for selection bias based on observables, and it has an advantage of resulting in doubly robust estimates (Imbens and Rubin 2015).

histograms of propensity scores for the treatment and control groups, and it shows a sufficient overlap between these two groups. Therefore, the overlap or common support assumption is satisfied for PSM. We then move to assess the covariate balancing.

(Here insert Table 2)

Table 2 presents the results of the covariate balancing test using the nearest neighbor matching method. Column (3) of Panel A reports the difference in means between individuals in households that use and do not use solid fuels for each explanatory variable, and the corresponding *t*-value in Column (4) indicates whether the mean difference between these two samples is significantly different. We also report the percentage reduction in bias in Column (5).[7] Overall, these tests suggest a good matching quality, as only four variables remain significantly different (*age*, *male*, *drinker*, and *agricultural hukou*), and there is a considerable reduction in bias for nearly every explanatory variable.

Panel B reports the overall test of balancing quality. Column (1) shows that the pseudo R-squared from the *probit* model estimation decreases substantially from 0.184 using the unmatched sample to 0.002 using the matched sample.[8] This low pseudo R-squared when using the matched sample suggests no systematic differences between individuals in households that use and do not use solid fuels because the explanatory variables fail to explain the variation in household use of solid fuels. Lastly, Column (2) presents the likelihood-ratio test of joint significance of all explanatory variables, and Column (3) and (4) report the mean and median of absolute bias, respectively. It is evident that the bias decreases considerably after matching, but the matching is not perfect, as the likelihood-ratio test remains statistically significant.

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[7] Specifically, the reduction in bias is calculated as the change in mean difference before and after matching divided by the pre-matching mean difference.

[8] Sianesi (2004) suggests the use of pseudo R-squared from the probit model estimation as an indicator of matching quality.

4. Estimation Results

4.1 Main results

(Here insert Table 3)

Table 3 reports the estimation results for physical health outcomes and cognitive abilities. Column (1) and (2) present estimated ATT using the nearest neighbor matching method and kernel matching method, respectively. For comparison, we report the results from the WLS regression in Column (3). The results are quite similar, suggesting that our results are insensitive to the choice of matching method. Below we discuss the results using the nearest neighbor matching method.

Indoor air pollution has a significant impact on respiratory diseases. Respondents in households that use solid fuels are 1.3% more likely to be diagnosed with chronic lung disease, compared to those in households that do not use solid fuels. Interestingly, the health impact is stronger on cardiovascular diseases. Respondents in solid fuel households are 4.7% and 2.7% more likely to be diagnosed with heart disease and hypertension than comparison households, respectively. They are also 5.0% and 8.1% more likely to experience chest pain during physical activity and report poor health, respectively. Overall, these results are consistent with existing literature studying the health impact of air pollution. For example, Chen et al. (2013) find that exposure to higher $PM_{2.5}$ increases the likelihood of having heart disease.

Turning to cognitive abilities, the results show that household use of solid fuels has a significant, adverse impact on both short-term memory and mathematical reasoning. On average, respondents in households that use solid fuels recall 0.08 fewer words than those in households that do not use solid fuels. Additionally, they are 3.2% less likely to self-report having good memory. For mathematical reasoning, we find that solid fuel households are less likely to answer the numerical calculation problems correctly. On average, they score 0.26 fewer points compared to non-solid fuel households. These findings are consistent with literature studying the impact of air pollution on cognitive ability. For example, Ebenstein, Lavy, and Roth (2016) find that transitory $PM_{2.5}$ exposure is associated with a significant decline in cognitive performance in high-stakes exams.

4.2 Subgroup analysis

Our main analysis demonstrates that indoor air pollution caused by household use of solid fuels has an adverse impact on both physical health status and cognitive abilities. However, it is likely that the health impact differs by subgroups. For example, individuals who spend more time at home may suffer more from indoor air pollution than others due to prolonged exposure. To provide a more comprehensive analysis, we move to examine the impact of indoor air pollution for different groups.

We first examine whether the impact is heterogeneous across north and south regions, divided by the *Qin Mountain-Huai River* line. Northern China is notorious for its severe outdoor air pollution due to the provision of central heating, and studies have found that outdoor air quality becomes significantly worse north of this line (Almond et al. 2009; Chen et al. 2013). It is possible that people in the south region have a larger marginal opportunity to be affected by indoor air pollution because outdoor air pollution is much less severe in the south region.

(Here insert Table 4)

Column (1) and (2) in Table 4 report the results using the north and south samples, respectively, and these results are consistent with our expectation. We find that indoor air pollution has a larger impact in southern China. In this region, respondents in households that use solid fuels are 7.5%, 3.1%, and 11.4% more likely to experience left chest pain, be diagnosed with chronic lung disease, and report poor health, respectively. Similarly, they recall 0.36 fewer words in a word-memorizing test and score 0.37 fewer points in a numerical calculation test, respectively. They are also 4.3% less likely to report having good memory. On the contrary, the impact on health outcomes and especially cognitive abilities is much smaller in northern China, except for heart disease and hypertension. For example, the impact on experiencing left chest pain (3.8%) in northern China is half of that in southern China. These significant results in southern China also corroborate our main results because outdoor air pollution is much less severe in this region. Thus, statistically, it would be easier to detect the impact of indoor air pollution using the southern China sample.

We also examine the heterogeneous effect of indoor air pollution for male and female respondents, respectively. Because women are primarily responsible for preparing meals and doing housework, they are more likely to have prolonged exposure to indoor air pollution than men. Thus, we expect to see a larger impact for female respondents. The results in Column (3) and (4) of Table 4 confirm this prediction. Indoor air pollution has a larger impact on nearly every outcome except self-reported good memory for female respondents.[9] For example, the female respondents in households that use solid fuels are 5.1% more likely to be diagnosed with heart disease (3.9% for males); they are also 7.8% more likely to report poor health conditions (7.1% for males). Regarding numerical calculation ability, female respondents also exhibit a larger negative impact than male respondents. On average, female respondents in solid fuel households answer 0.27 fewer questions correctly (relative to non-solid fuel households), while

[9] The estimated IAP impact on hypertension is only slightly higher for female respondents, but it is only significant at the 10% level.

male respondents in solid-fuel households answer 0.18 fewer questions correctly. These results suggest that, in the long run, indoor air pollution can increase gender inequality because health outcomes and cognitive abilities are important factors in human capital accumulation.

4.3 The results for other diseases

So far, we focus on respiratory diseases and cardiovascular diseases because they are more likely to be affected by air pollution. Other types of chronic diseases, although possible, are much less likely to be influenced by air pollution. We thus examine whether indoor air pollution affects other types of chronic diseases including dyslipidemia, diabetes or high blood sugar, cancer or malignancy, liver disease, kidney disease, and stomach or digestive disease. These results also serve as a robustness check. Table 5 reports the estimation results for these diseases. Not surprisingly, all these diseases are not significantly affected by indoor air pollution. These results are quite similar using the nearest neighbor matching or kernel matching method.

(Here insert Table 5)

5. Conclusion

Air pollution imposes a substantial health and economic burden on many people living in China. However, compared with outdoor air pollution, indoor air pollution has received much less attention. This paper seeks to strengthen our understanding of the impact of indoor air pollution caused by household use of solid fuels on both physical health outcomes and cognitive abilities for the middle aged and elderly people in China. We use a PSM method to carefully construct the balanced treatment and control groups using many social demographic variables which are likely important factors of the choice of fuel and health outcomes following the literature (Mueller et al. 2013). Consistent with existing literature, we find that indoor air pollution has a significant negative impact on health outcomes and cognitive abilities. These results are insensitive to different specifications. In particular, we show that indoor air pollution significantly increases the likelihood of being diagnosed with respiratory diseases and cardiovascular diseases, experiencing chest pain during physical activities, and self-reporting poor health. Our findings also show that indoor air pollution has an adverse impact on short-term memory and mathematical reasoning. We do not find a significant impact for all other chronic diseases that are less likely to be affected by air pollution, suggesting that our findings are driven by indoor air pollution instead of other factors. Moreover, the health impact of indoor air pollution is heterogeneous across regions. Our findings show that the health effect is much stronger in southern China, where outdoor air pollution is less severe. We also find that the health impact differs by gender, with a larger impact on nearly every health outcome for female respondents. Taken together, these results suggest that household use of solid fuels is a major cause of both health and cognition impairment, highlighting a need for households to switch to cleaner fuels.

To promote public health, China in recent years has implemented several policies, such as the dissemination of efficient biomass and improved coal stoves (Sinton et al. 2004; Mueller et al. 2013) and gas subsidies which encourages the use of natural gas or electricity for heating and cooking. In addition, China has made significant progress toward expanding electricity and natural gas infrastructure, especially in rural areas where solid fuels are the major source of energy. Despite these significant efforts, there are not many studies on the impact of these policies. Given that indoor air pollution is a major health risk, future studies should collect more recent data on more dimensions (e.g. accurate measurements of indoor air quality) and assess the effectiveness of these policy interventions.

On the other hand, although utilizing the exogenous variation of indoor air quality brought about by some policy change may appear an ideal way of identifying the causal effect of indoor air pollution, it is often infeasible to find perfectly exogenous policy change or government programs that are suitable for research on this topic or relavant data sets.[10] For example, both Yu (2011) and Mueller et al. (2013) mention that the interventions used in their research may not have been completely random and be correlated with both health outcomes and demographic information. Thus, a thorough understanding of the background of those programs and balancing the treatment and control groups is necessary before the policy evaluation analysis (Yu 2011; Mueller et al. 2013). In this sense, our estimation results after careful matching can still be helpful for informing future public policy on improving indoor air quality.

Disclosure statement

The authors report no potential conflict of interest.

[10] An exception is Barron and Torero (2017).

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Appendix Table 1. Variable definition

Variables	Definition	Mean	S. D.	N
Outcome variables				
Asthma	1 if diagnosed with asthma, 0 otherwise	0.040	0.197	15601
Chronic lung disease	1 if diagnosed with lung disease, 0 otherwise	0.121	0.327	15536
Heart disease	1 if diagnosed with heart disease, 0 otherwise	0.140	0.347	15576
Left chest pain	1 if experiencing chest pain during physical activity, 0 otherwise	0.208	0.406	15580
Stroke	1 if diagnosed with stroke, 0 otherwise	0.027	0.161	15603
Hypertension	1 if having hypertension, 0 otherwise	0.289	0.453	15551
Poor health	1 if reporting poor health, 0 otherwise	0.267	0.442	15608
Word recall score	Number of words correctly recalled	2.990	2.097	15637
Numerical test score	Number of numerical calculation questions correctly answered	2.776	1.989	15637
Good memory	1 if reporting good memory, 0 otherwise	0.168	0.374	15438
Explanatory variables				
IAP	1 if a household uses coal, wood, or crop residue for heating or cooking, 0 otherwise	0.612	0.487	15637
Age	Age in years	59.968	9.547	15637
Male	1 if male, 0 otherwise	0.478	0.500	15637
Married	1 if married, 0 otherwise	0.873	0.333	15637
Illiterate	1 if illiterate, 0 otherwise	0.260	0.439	15637
Elementary	1 if highest degree is elementary school, 0 otherwise	0.400	0.490	15637
Junior high	1 if highest degree is junior high school, 0 otherwise	0.211	0.408	15637
Senior high	1 if highest degree is senior high school, 0 otherwise	0.128	0.334	15637
Income	Total personal income ($1,000 RMB)	7.594	14.886	15637
Drinker	1 if the respondent drinks more than once a month in the past year, 0 otherwise	0.267	0.442	15637
Smoker	1 if smokes 1 or 2 packs a day, 0 otherwise	0.422	0.494	15637
Social activity	1 if participating in social activities in the past month, 0 otherwise	0.402	0.490	15637
Agricultural hukou	1 if the household holds an agricultural hukou, 0 otherwise	0.765	0.424	15637
Running water	1 if the residence has running water, 0 otherwise	0.717	0.450	15637
AQI	Average air quality index between 2014 and 2016 at city level	84.250	25.355	15637

Appendix Table 2. *Probit* estimates for indoor air pollution

Variable	Coefficient	Standard error
Age	0.008 ***	0.001
Male	0.078 **	0.034
Married	0.088 **	0.036
Elementary	-0.194 ***	0.030
Junior high	-0.290 ***	0.037
Senior high	-0.355 ***	0.046
Income	-0.014 ***	0.001
Drinker	-0.021	0.028
Smoker	0.133 ***	0.032
Social activity	-0.064 ***	0.023
Agricultural *hukou*	0.773 ***	0.031
Running water	-0.718 ***	0.027
AQI	0.007 ***	<0.001
Constant	-0.666 ***	0.115
Log-likelihood value	3850.550	
Pseudo R^2	0.184	
Sample size	15,637	

Note: ***p < 0.01; **p < 0.05; *p < 0.10.

Table 1. Sample statistics (before matching)

Variables	With indoor air pollution Mean (1)	Without indoor air pollution Mean (2)	Differences (1) - (2) Mean (3)		Differences (1) - (2) t-statistic (4)
Outcome variables					
Asthma (0/1)	0.044	0.034	0.010	***	-3.201
Lung disease (0/1)	0.133	0.103	0.031	***	-5.742
Heart disease (0/1)	0.146	0.129	0.017	***	-3.045
Left chest pain (0/1)	0.230	0.173	0.056	***	-8.442
Stroke (0/1)	0.026	0.027	-0.001		0.220
Hypertension (0/1)	0.290	0.287	0.004		-0.526
Poor health (0/1)	0.315	0.191	0.124	***	-17.294
Word recall score	2.759	3.353	-0.594	***	17.420
Numerical test score	2.535	3.156	-0.622	***	19.266
Good memory (0/1)	0.143	0.209	-0.066	***	10.758
Explanatory variables					
Age	60.466	59.185	1.280	***	-8.191
Male (0/1)	0.478	0.477	0.001		-0.125
Married (0/1)	0.870	0.878	-0.008		1.439
Illiterate (0/1)	0.317	0.170	0.147	***	-20.688
Elementary (0/1)	0.422	0.366	0.057	***	-7.045
Junior high (0/1)	0.185	0.253	-0.067	***	10.040
Senior high (0/1)	0.075	0.211	-0.136	***	25.392
Income ($1,000)	4.009	13.243	-9.233	***	39.653
Drinker (0/1)	0.263	0.273	-0.011		1.449
Smoker (0/1)	0.439	0.396	0.043	***	-5.288
Social activity (0/1)	0.381	0.434	-0.053	***	6.591
Agricultural *hukou* (0/1)	0.893	0.564	0.328	***	-50.970
Running water (0/1)	0.610	0.886	-0.275	***	39.037
AQI	86.102	81.332	4.770	***	-11.513
Sample size	9,566	6,071			

Note: ***p < 0.01; **p < 0.05; *p < 0.10.

Table 2. Covariate balancing tests from the nearest-neighbor matching method

Panel A. Test of balancing property for explanatory variables

Variables	With indoor air pollution Mean (1)	Without indoor air pollution Mean (2)	Differences (1) - (2) Mean (3)	t-statistic (4)	% reduction bias (5)
Age	60.461	60.013	0.448 ***	3.22	65.0
Male (0/1)	0.478	0.494	-0.016 *	-2.27	-1502.1
Married (0/1)	0.870	0.870	0.000	-0.09	94.3
Elementary (0/1)	0.422	0.419	0.004	0.5	93.7
Junior high (0/1)	0.185	0.185	0.001	0.12	99.0
Senior high (0/1)	0.075	0.075	0.000	-0.02	100.0
Income ($1,000)	4.010	4.216	-0.205	-1.42	97.8
Drinker (0/1)	0.263	0.275	-0.012 *	-1.82	-11.1
Smoker (0/1)	0.439	0.449	-0.010	-1.46	75.6
Social activity (0/1)	0.381	0.392	-0.011	-1.56	79.2
Agricultural *hukou* (0/1)	0.893	0.909	-0.016 ***	-3.71	95.1
Running water (0/1)	0.610	0.619	-0.009	-1.28	96.7
AQI	86.089	85.782	0.307	0.81	93.6

Panel B. Overall test of balancing property

Sample	Pseudo R^2	LR chi^2	Mean bias	Median bias
Unmatched	0.184	3850.55***	25.5	13.4
Matched	0.002	48.32***	1.9	2.1

Note: ***p < 0.01; **p < 0.05; *p < 0.10.

Table 3. The effect of indoor air pollution

Outcome	Nearest neighbor matching (1)	Kernel matching (2)	Weighted Least Square (3)
Panel A. Physical health			
Asthma	<0.001	-0.001	0.002
	[0.004]	[0.004]	[0.004]
Number of observations	15599	15599	15601
Chronic lung disease	0.013*	0.016**	0.017***
	[0.007]	[0.007]	[0.006]
Number of observations	15534	15534	15536
Heart disease	0.047***	0.047***	0.041***
	[0.008]	[0.007]	[0.006]
Number of observations	15574	15574	15576
Left chest pain	0.050***	0.050***	0.053***
	[0.009]	[0.008]	[0.008]
Number of observations	15578	15578	15580
Stroke	0.001	<0.001	-0.002
	[0.004]	[0.004]	[0.003]
Number of observations	15601	15601	15603
Hypertension	0.027***	0.027***	0.020**
	[0.01]	[0.01]	[0.009]
Number of observations	15549	15549	15551
Poor health	0.081***	0.076***	0.078***
	[0.009]	[0.009]	[0.009]
Number of observations	15606	15606	15608
Panel B. Cognitive functioning			
Word recall score	-0.081*	-0.093**	-0.065*
	[0.049]	[0.046]	[0.037]
Number of observations	15635	15635	15637
Numerical test score	-0.257***	-0.264***	-0.25***
	[0.045]	[0.042]	[0.035]
Number of observations	15635	15635	15637
Good memory	-0.032***	-0.027***	-0.033***
	[0.009]	[0.009]	[0.007]
Number of observations	15436	15436	15438

Note: ***p < 0.01; **p < 0.05; *p < 0.10. Standard errors are in brackets.

Table 4. The effect of indoor air pollution by subgroup, nearest-neighbor matching

	By region		By gender	
	North	South	Male	Female
Outcome	(1)	(2)	(3)	(4)
Panel A. Physical health				
Asthma	-0.008	0.005	-0.002	-0.001
	[0.007]	[0.005]	[0.007]	[0.006]
Number of observations	7360	8237	7453	8144
Chronic lung disease	-0.003	0.031***	0.009	0.018*
	[0.012]	[0.009]	[0.011]	[0.009]
Number of observations	7339	8193	7420	8112
Heart disease	0.049***	0.011	0.039***	0.051***
	[0.016]	[0.008]	[0.01]	[0.012]
Number of observations	7354	8218	7440	8132
Left chest pain	0.038**	0.075***	0.044***	0.055***
	[0.016]	[0.011]	[0.012]	[0.013]
Number of observations	7343	8233	7436	8140
Stroke	-0.001	0.002	0.001	<0.001
	[0.006]	[0.005]	[0.006]	[0.005]
Number of observations	7363	8236	7449	8150
Hypertension	0.042**	0.001	0.026*	0.023
	[0.019]	[0.012]	[0.015]	[0.015]
Number of observations	7344	8203	7428	8119
Poor health	0.057***	0.114***	0.071***	0.078***
	[0.016]	[0.012]	[0.013]	[0.014]
Number of observations	7361	8243	7457	8147
Panel B. Cognitive functioning				
Word recall score	-0.059***	-0.359***	-0.067	-0.096
	[0.084]	[0.058]	[0.067]	[0.07]
Number of observations	7373	8260	7467	8166
Numerical test score	-0.198***	-0.365***	-0.181***	-0.27***
	[0.075]	[0.055]	[0.06]	[0.063]
Number of observations	7373	8260	7467	8166
Good memory	-0.016***	-0.043***	-0.038***	-0.020*
	[0.016]	[0.011]	[0.014]	[0.012]
Number of observations	7292	8142	7373	8061

Note: ***p < 0.01; **p < 0.05; *p < 0.10. Standard errors are in brackets.

Table 5. The effect of indoor air pollution, kernel matching

Outcome	10-nearst neighbor matching (1)	Kernel matching (2)	Weighted Least Square (3)
Dyslipidemia	-0.003	<0.001	-0.006
	[0.008]	[0.008]	[0.006]
Number of observations	15307	15307	15309
Diabetes or high blood sugar	-0.005	-0.003	-0.008
	[0.006]	[0.006]	[0.005]
Number of observations	15508	15508	15510
Cancer or malignancy	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]
Number of observations	15579	15579	15581
Liver disease	-0.002	-0.003	-0.003
	[0.005]	[0.005]	[0.004]
Number of observations	15553	15553	15555
Kidney disease	0.002	0.004	0.006
	[0.006]	[0.005]	[0.005]
Number of observations	15557	15557	15559
Stomach or digestive disease	0.006	0.004	0.013
	[0.010]	[0.009]	[0.009]
Number of observations	15595	15595	15597

Note: ***p < 0.01; **p < 0.05; *p < 0.10. Standard errors are in brackets.

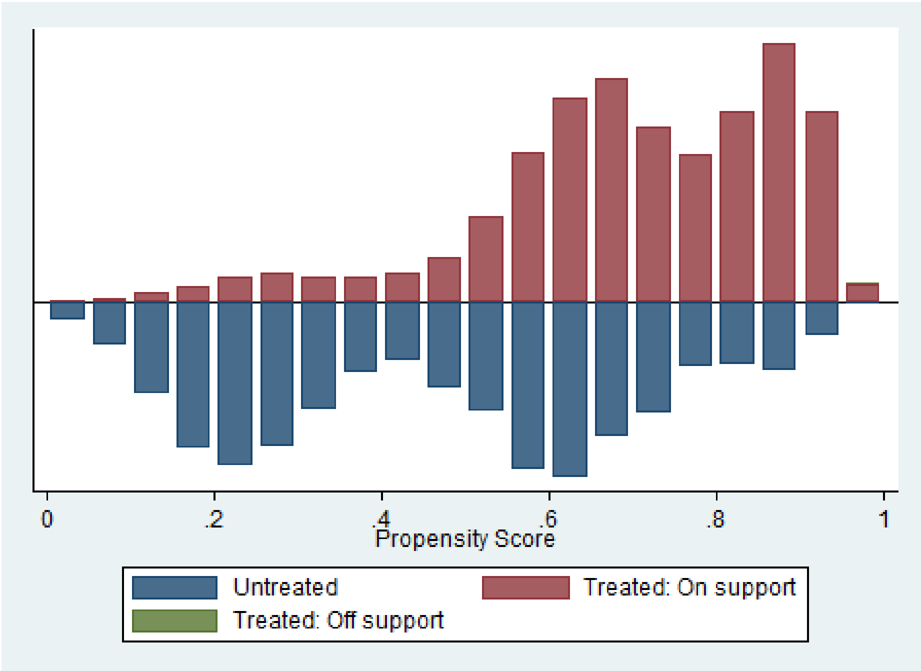

Figure 1. Distribution of propensity scores for the treatment and control groups