Air pollution and elite college graduates’ job location choice: evidence from China

Siqi Zheng1 · Xiaonan Zhang2 · Weizeng Sun3 · Chengtao Lin4

Received: 28 March 2019 / Accepted: 16 August 2019 / Published online: 27 August 2019
© Springer-Verlag GmbH Germany, part of Springer Nature 2019

Abstract
In this paper, we examine the impact of air pollution on the job location choice of a highly educated labor force. Using the administrative job contract records of all graduates from Tsinghua University from 2005 to 2016, we find that air pollution significantly reduces the probability of elite graduates accepting job offers in a polluted city. Specifically, all else equal, if a city’s PM$_{2.5}$ level increases by 10 μg/m$^3$, the share of Tsinghua graduates choosing that city will decrease by 0.23 percentage point (9% of the mean value). This “crowding-out” effect is larger for master’s and doctoral graduates, but insignificant for undergraduates. A placebo test finds this effect does not exist for individuals who had signed a job contract prior to university admission, which strengthens our finding. Heterogeneity analysis indicates that males, students who grew up in cleaner provinces, and students graduating from school of the environment are more sensitive to air pollution. Different levels of preference for clean air and tolerance to pollution, as well as whether having the knowledge of pollution’s harms, can effectively explain the heterogeneous effect of air pollution’s impacts on job location choices of those elites.

* Weizeng Sun
  sunweizeng@gmail.com

Siqi Zheng
sqzheng@mit.edu

Xiaonan Zhang
zhangxiaonant@163.com

Chengtao Lin
lct@tsinghua.edu.cn

1 China Future City Lab, Department of Urban Studies and Planning, and Center for Real Estate, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
2 Hang Lung Center for Real Estate, and Department of Construction Management, Tsinghua University, Beijing 100084, China
3 School of Economics, Central University of Finance and Economics, 39 South College Road, Haidian District, Beijing 100081, China
4 Career Development Center, Tsinghua University, Beijing 100084, China
JEL Classification  Q53 · Q56 · R23

1 Introduction

Severe air pollution brings significant health and social costs to urban residents. Using data from different countries and regions, and focusing on a variety of pollutants (carbon monoxide, sulfur dioxide, nitrogen oxides, ozone, inhalable particulate matter and so on), researchers have found air pollution has significant negative impacts on people’s health in both the short and long term, such as increased mortality (Dockery et al. 1993; Samet et al. 2000; Chay and Greenstone 2003; Pope et al. 2011), reduced birth weight (Bobak 2000; Currie and Neidell 2005; Stieb et al. 2012), increased respiratory diseases and cardiovascular and cerebrovascular diseases (Schwartz and Morris 1995; Wong et al. 1999; Dominici et al. 2006), and shortened life expectancy (Pope et al. 2009; Chen et al. 2013). Studies also find that air pollution tends to reduce people’s life satisfaction (Welsch 2002, 2006; MacKerron and Mourato 2009; Luechinger 2009, 2010; Li et al. 2014), and happiness (Levinson 2012; Zhang et al. 2017a, b; Zheng et al. 2019), and even to lead to mental disorders such as depression (Zhang et al. 2017a, b). In a highly polluted country like China, some studies (Zheng et al. 2014; Sun et al. 2017) have already shown that people may elect to access real-time air pollution information from modern media and adopt avoidance strategies to reduce pollution exposure. Among all population groups, elites with higher human capital have higher willingness to pay to avoid pollution. Various media outlets have reported that severe air pollution in China impedes cities’ capacity to recruit and retain talent. Talented professionals (e.g., transnational company’s executives) often hesitate to accept jobs in China due to concerns over air pollution and other quality of life issues. Local young college graduates also have become more selective when choosing where to work and live, preferring cities with cleaner air. Many city leaders have recognized that blue sky has become their cities’ core competence if they want to attract and retain talent. However, the underlying mechanism that determines how air pollution actually influences workers’ (especially high-skilled workers’) choice of job location, when workers have to make a trade-off between job opportunities and quality of life, remains understudied.

In this paper, we study the impact of air pollution on the job location choice of the highly educated labor force using a unique administrative dataset of job contract data (2005–2016) for graduates from Tsinghua University, one of China’s top 2 universities. Since 2011, China’s severe air pollution has attracted wide attention globally. Some young Beijing-based entrepreneurs are relocating their businesses to

1 See reports in China Business Review (https://www.chinabusinessreview.com/air-pollution-impedes-executive-hiring-in-china/), Reuters (https://www.reuters.com/article/us-china-pollution-survey-idUSBREA21OKU20140319) and Bloomberg (https://www.bloomberg.com/news/articles/2014-04-10/chinas-pollution-costs-companies-in-air-filters-employee-perks).
other cleaner cities, such as Hangzhou, Shenzhen, and Shanghai.² They consider not only the negative impact of dirty air on their own health, but also the risk that their companies will lose talent if they choose to remain in cities, such as Beijing, where there is a low quality of life. When college graduates search for their first jobs, they also regard air quality as a key consideration when choosing which city to work in (and thus live in). To quantify this relationship, we merge air quality data gathered from remote sensing instruments with the job location (city) choice outcomes of Tsinghua graduates by geographic location from 2005 to 2016 to carry out our empirical research.

The job location decisions of college graduates allow us to more accurately identify the impact of urban livability characteristics such as air pollution. Compared with people who have lived in one place for a long time, college graduates face much lower relocation cost, so it is easier to disentangle the effect of air pollution from other factors influencing their job location choice. At the same time, graduates’ job location decisions are mostly made about 9–12 months before their graduation, so we match their choices with the air pollution data at that decision-making time. Among all the universities in mainland China, Tsinghua University is ranked No. 1 in the QS World University Rankings. Those elite graduates have high income and also a strong demand for quality of life. Focusing on this subgroup of elite workers also offers us additional insight regarding how inflow and outflow of highly skilled labor force affects a city’s economic growth potential. In addition to employment information, the dataset also includes many individual characteristics, including gender, major, degree received (undergraduate, master’s, or PhD). This allows us to explore the heterogeneous effects of air pollution on the job location choice of graduates along multiple dimensions.

Based on the employment information of graduates, more specifically which cities their jobs are located, we calculate the proportion of Tsinghua graduates accepting job offers in each city for each year, and this yield a city-year panel dataset. We will use both this panel dataset and individual-level data of all graduates. In order to identify the casual effects of air pollution on job location choice, we introduce city fixed effects and year fixed effects, and control for city’s time-variant local attributes in terms of economic development level, labor demand, living cost, public services, and weather conditions. To address the potential endogeneity issue, we construct an instrumental variable for air pollution by taking advantage of cross-boundary spillovers of air pollution due to long-range transportability, which is widely used in the economic literature (Barwick et al. 2018; Williams and Phaneuf 2019; Zheng et al. 2014).

We find that air pollution has a significantly negative effect on the probability of elite graduates accepting job offers in a city. All else equal, if PM$_{2.5}$ increases by 10 μg/m$^3$, the share of Tsinghua graduates accepting job offers in that city will decrease by 0.23 percentage point (mean: 2.69 percentage points, 9% of the mean value). This “crowding-out” effect is larger and more significant for graduate students than undergraduate students.

² See report: https://www.scmp.com/business/china-business/article/2059320/beijing-start-ups-move-out-hazardous-smog-smothers-capital.
students. The instrumental variable estimation yields similar results—the same direction of impact with a larger magnitude of coefficient than that in the OLS estimation. Our results are robust to various model specifications. Moreover, the placebo test further verifies our finding by showing no effect for those individuals who already signed job contracts prior to their admission to Tsinghua University (ding xiang pei yang). Finally, we also find significant heterogeneous effects among different groups. Males, Tsinghua Environmental School graduates, those who grew up in cleaner provinces, and those who major in engineering care more about the air quality of their future city of residence.

This study makes two main contributions to the literature. First, this is one of the few empirical studies that focuses on the impact of air pollution on job location choice, and thus adds to the growing literature that examines the determinants of job location choice across regions (So et al. 2001; Faggian et al. 2006; Wozniak 2010; Plantinga et al. 2013). Using the national survey data on college graduates from 2012 to 2015 in China, Fan et al. (2018) investigates the impact of air pollution on the job location decisions of college graduates. Their results indicate that a ten-unit increase in PM$_{2.5}$ increases the probability of leaving the city by 6%. In this paper, we expand this research question by further examining the impact of air pollution on college graduates’ job location choice for all optional cities following the framework of Rosen–Roback’s spatial equilibrium theory. Second, this paper also contributes to the studies on the negative impact of air pollution on local economy. Existing papers have found negative effects of air pollution on labor supply (Hanna and Oliva 2015; Zhang et al. 2018), labor productivity (Graff Zivin and Neidell 2012; Li et al. 2015; Chang et al. 2016), and academic outcomes (Currie et al. 2009; Stafford 2015). This paper thus adds to the literature by associating air pollution with a new perspective—the city’s power to retain and attract talent, which has been shown to have significant and positive effects on economic development (McAusland and Kuhn 2011; Vandenbussche et al. 2006; Whalley and Zhao 2013).

The rest of the paper is organized as follows. In Sect. 2, we present the identification strategies and introduce the data. Sections 3 and 4 provide the main empirical results, robustness and placebo tests, and heterogeneous analysis. We conclude the paper in Sect. 5.

2 Empirical strategy

2.1 Model specifications

2.1.1 Binary location decision model

As Tsinghua University is located in Beijing, we adopt a linear probability model (LPM) that uses individual-level data to test the effect of Beijing’s air pollution on graduates’ choice of whether to stay in Beijing. The model specification is as follows:

\[
\text{choice}_{it} = \alpha_1 \cdot \text{relative}_{pmt} + \alpha_2 \cdot X_{t-1} + \alpha_3 \cdot Y_{it} + \varepsilon_{ijt}
\]  

(1)
where \( \text{choice}_{i,t} \) equals 1 if student \( i \) chooses to stay in Beijing after graduation in year \( t \). \( \text{relative} \_\text{pm}_{t-1} \) measures the ratio of Beijing’s average PM\(_{2.5}\) concentration in year \( t-1 \) to the mean value of other large and medium-sized cities in China.\(^3\) Here, we use this relative level indicator, because the job location choice decision is affected by how severe Beijing’s air pollution is, compared with other major cities. Such a “relative” level cannot be fully reflected by the absolute value of concentration. Similarly, we also construct such relative level indicators for Beijing’s other attributes, \( X_{t-1} \), measured as the ratio of Beijing’s GDP per capita, population, the number of high schools per capita, etc., to the mean value of those indicators, respectively, in other large and medium-sized cities.\(^4\) \( Y_t \) controls for student characteristics, including gender, ethnicity, degree and a set of college department dummy variables and home province dummy variables. Department dummies are added to control major-specific fixed effects. Home province dummies are used to control for the “hometown effect,” which takes into consideration that students from certain provinces are more likely to return to their hometown after graduation. To examine the impact of distance between students’ home province and Beijing on the location choice, we use this distance measure instead of home province dummy in some regressions. To deal with the potential problems of serial correlation, we clustered standard errors according to students’ home province.\(^5\)

### 2.1.2 City-level choice model

Besides the binary choice of whether to stay in Beijing (where Tsinghua University is located), a graduate also must decide which specific city he/she will work in, from a menu of many different cities. A panel data model is adopted to test the effect of a destination city’s air pollution on graduates’ probability of accepting job offers in that city. The model specification is as follows:

\[
\text{share}_{jt} = \alpha_1 \cdot \text{pm}_{jt-1} + \alpha_2 \cdot \text{share}_{jt-2} + \alpha_3 \cdot X_{jt-1} + \alpha_4 \cdot w_t + \alpha_5 \cdot \mu_j + \varepsilon_{jt} \tag{2}
\]

where \( \text{share}_{jt} \) refers to the share of students who accept job offers in city \( j \) among all students who graduated in year \( t \). \( \text{pm}_{jt-1} \) measures city \( j \)'s average PM\(_{2.5}\) concentration in year \( t-1 \). In this city-level choice model, we model the choice of the destination city among all potential cities. We are not comparing Beijing with others, instead, we are comparing between those potential cities. Therefore, the absolute

---

\(^3\) There are 35 large and medium-sized cities in China, including Beijing, Tianjin, Shijiazhuang, Taiyuan, Huhehaote, Shenyang, Dalian, Changchun, Harbin, Shanghai, Nanjing, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Xi’an, Lanzhou, Xining, Yinchuan, Urumqi. During our study period, more than 94% of Tsinghua graduates chose to work in one of the large and medium-sized cities in China, which means elite graduates seldom select to work in small cities, and thus we set the large and medium-sized cities as their potential working places.

\(^4\) We also use the ranks of PM2.5 as well as other economic variables of Beijing among the 35 large and medium-sized cities in the graduates’ location choice model, the results are consistent with those using the relative level indicators.

\(^5\) We also try to cluster the standard errors by students’ department (also major) as a robustness check. The results are consistent with the results when clustering the standard errors at the home province level.
air pollution level of each city is an appropriate measure for this purpose. We also include \( \text{share}_{jt-2} \) on the right hand side to control for the cohort network effect, considering later graduates are influenced by earlier cohorts’ job location choices.\(^6\) \( X_{jt-1} \) refers to city \( j \)’s economic and population attributes, as well as weather attributes. The economic and population attributes include GDP per capita, GDP shares of secondary industry and tertiary industry, total population, housing price, Bartik index, as well as the number of primary schools and doctors per capita. The weather variables include average temperature, total precipitation, and the number of days with snow, with storm, with fog and with frost. \( \omega_t \) refers to year dummies, which capture changes in labor demand due to business cycles. \( \mu_j \) refers to city dummies, which control for cities’ time-invariant attributes.

2.1.3 IV design

The negative relationship between PM\(_{2.5}\) concentration and the probability that students choose the city may be generated by omitted factors that vary with years on the level of individual cities. For example, industrial upgrades may cause changes in air pollution and also increase student attraction to a city. In this case, our estimates would be biased in favor of the direct role of pollution in causing a low share of graduates to elect to move to the city. We employ an instrumental variable (IV) approach to address this potential endogeneity issue.

We utilize air pollution from the cities in the upwind direction to construct the instrumental variable. As the wind blows air pollutants from upwind cities to the destination city, this introduces exogenous variation in the destination city’s air pollution (Zhang et al. 2017a, b). This exogenous variable is unlikely to affect the destination city’s local social and economic activities through other channels, so it is an ideal instrumental variable (Bayer et al. 2009; Zheng et al. 2014). Drawing from the method adopted by Barwick et al. (2018), we construct our IV as follows:

\[
IV_{it} = \sum_j \max \left( \cos \theta_{ij}, 0 \right) \times PM_{2.5j_t} / e^{d_{ij}}, \quad 60 \text{ km} < d_{ij} < 300 \text{ km}
\]

where \( PM_{2.5j_t} \) is city \( j \)’s PM\(_{2.5}\) concentration in year \( t \). \( \theta_{ij} \) denotes the angle between the wind direction of city \( i \) and the direction from city \( j \) to city \( i \). We make a simple vector decomposition and assume that the amount of pollutants carried toward city \( i \) from city \( j \) is the larger one between \( \cos(\theta_{ij}) \) and zero. \( d_{ij} \) is the distance (in hundred km) between local city \( i \) and city \( j \). Considering agglomeration economies will lead to the correlation or co-movement of nearby cities’ local economies, we exclude all cities within 60 km from local city \( i \) in the equation. Also, cities that are too far from local city \( i \), setting 300 km as the cutoff, are not included in the calculation.\(^7\)

---

\(^6\) The choice of cohort that is just 1 year earlier, \( \text{share}_{jt-1} \), is not used because it is also highly influenced by the \( \text{pm}_{jt-1} \). For samples in 2005/2006, we use the average share in the whole study period as the 2-year-lag choice share.

\(^7\) As for the choice of cutoffs (60 km and 300 km), we refer to the study of Fan et al. (2018). We also tried different distances and the results are robust.
Refer to Fig. 1 to understand the construction of IV more directly. City A in the middle is our destination city, with its wind direction from the north. The angle between the wind direction of city A and the location of city B, \( \theta_{ab} \), is smaller than 90°, so that the contribution of air pollution from city B to our IV is \( \cos \theta_{ab} \times PM_{2.5 bt} \). Similarly, city C contributes \( \cos \theta_{ac} \times PM_{2.5 ct} \). As \( \theta_{ac} \) and \( d_{ac} \) are larger than \( \theta_{ab} \) and \( d_{ab} \) respectively, the air pollution of city C has less effect on city A. Given that \( \theta_{ad} \) is larger than 90°, \( \cos \theta_{ad} \) is less than 0 and therefore city D will be excluded in the IV calculation. In addition, city E and F are not included because they are either too near or too far.

2.2 Data

Our primary dataset is administrative data from Tsinghua University Graduates Employment Record 2005–2016. Established in 1911, Tsinghua University is located in Beijing, China’s capital. It has been consistently ranked first among all mainland Chinese universities on the QS Global University Rankings over the last 5 years.

The dataset includes every student who graduated from Tsinghua University between 2005 and 2016. In this study, we focus on those students who accepted a job offer upon graduation. The key information for such students contains their graduation year, school, degree received (bachelor’s, master’s, or PhD), and the city where they took employment. In addition, the data contain basic demographic information, such as gender, ethnic minority or not, and hometown province (where students attend the college entrance examination).

In addition, we divide students into two subsamples, depending on whether they already had a labor contract prior to their admission to Tsinghua University (ding xiang pei yang). For those with contracts, jobs are determined prior to entering the university, and their tuition is usually paid by their employers. We exclude these students in the main analysis because they do not search for jobs when they graduate. The placebo test is conducted based on such students.
As for the main explanatory variable, we apply satellite-derived PM$_{2.5}$ concentrations across China for the period from 2004–2016 as developed by Van Donkelaar et al. (2016). By using ArcGIS, the 0.1°×0.1° grid-level PM$_{2.5}$ concentrations are collapsed to the city level. Compared to air pollution levels recorded by monitoring stations, the satellite-derived data have better temporal and spatial coverage and are more objective and accurate (Ghanem and Zhang 2014). Further, it also matches well with station data (Gupta et al. 2006; Kumar et al. 2015).

Our secondary data are city-level statistics. The economic and population attributes come from China City Statistical Yearbooks. Referring to Bartik (1991) and Wozniak (2010), we construct a Bartik index, an indicator of exogenous labor demand shock for each city in each year, as follows:

$$\text{bartik}_{jt} = \frac{\sum_{d=1}^{D} \epsilon_{jd,t-1} (\ln \tilde{E}_{dt} - \ln \tilde{E}_{d,t-1})}{\ln \tilde{E}_{dt} - \ln \tilde{E}_{d,t-1}}$$

(4)

where $d$ indexes industry, $j$ city, and $t$ year. $\epsilon_{jd,t-1}$ is the share of employment for city $j$ in industry $d$ in year $t-1$. $\tilde{E}_{dt}$ is the national employment level in industry $d$ excluding city $j$, and $\tilde{E}_{d,t-1}$ is the same measure but in the previous year. Therefore, the term in parentheses is a measure of national employment growth in industry $d$ except for city $j$. The sum of industry-level products is a proxy for changes in city-level employment driven by industry growth outside the city. Employment data also come from China City Statistical Yearbooks, which covers 19 industries in total.

Station level weather data come from http://www.meteomanz.com/. By linking each city with the nearest weather station, we obtain city-level weather attributes. Tables 1 and 2 present the variable definitions and summary statistics for the linear probability model and panel model, respectively. According to the summary statistics, from 2005 to 2016, about 60% of graduates from Tsinghua University ultimately chose to work in Beijing.

3 Main results

3.1 Whether to stay in Beijing

We utilize the probability model in regression model (1) to examine the effect of Beijing’s air pollution on students’ choice to stay in Beijing. Estimate results are reported in Table 3. In the first three columns, we include the distance between the graduate’s home province and Beijing, instead of hometown fixed effects. In column (1) and (4), we find negative estimates of coefficient of Beijing’s relative PM$_{2.5}$ concentration compared to other large and medium-sized cities, which is statistically significant at the 1% level. This means that when Beijing’s air pollution is much worse than that for other major cities (so a higher relative ratio), it significantly reduces the likelihood that students choose to stay in Beijing after graduation. Specifically, if the ratio of Beijing’s PM$_{2.5}$ concentration to other large- and medium-sized cities’ average level increases by 0.1, which indicates
### Table 1: Variable definitions and summary statistics for linear probability model

| Variables     | Definition                                                                 | Obs.  | Mean  | SD   | Min. | Max. |
|---------------|----------------------------------------------------------------------------|-------|-------|------|------|------|
| choice        | Whether graduates chose to stay in Beijing (stay = 1; leave = 0)           | 34,828| 0.60  | 0.49 | 0    | 1    |
| relative_pm   | The ratio of Beijing’s PM$_{2.5}$ concentration to other large and medium-sized cities’ average level | 34,828| 1.16  | 0.07 | 1.00 | 1.28 |
| gender        | Male = 1; female = 0                                                       | 34,828| 0.68  | 0.47 | 0    | 1    |
| ethnicity     | Minority = 1; other = 1                                                    | 34,828| 0.07  | 0.25 | 0    | 1    |
| degree        | Bachelor = 0; master = 1; doctor = 2                                       | 34,828| 1.05  | 0.60 | 0    | 2    |
| log_dhome     | The logarithm of the distance between graduates’ home province and Beijing  | 34,828| 5.95  | 2.17 | 0    | 7.88 |
| relative_gdppc| The ratio of Beijing’s GDP per capita to other large and medium-sized cities’ average level | 34,828| 1.43  | 0.12 | 1.26 | 1.60 |
| relative_pop  | The ratio of Beijing’s population to other large and medium-sized cities’ average level | 34,828| 1.83  | 0.03 | 1.81 | 1.92 |
| relative_highsch| The ratio of Beijing’s high schools per capita to other large and medium-sized cities’ average level | 34,828| 1.12  | 0.07 | 1.01 | 1.22 |
Table 2  Variable definitions and summary statistics for panel model

| Variables  | Definition                                                                 | Obs. | Mean  | SD    | Min. | Max. |
|------------|-----------------------------------------------------------------------------|------|-------|-------|------|------|
| shareall   | The share of all graduates that accept job offers in the city (%)           | 419  | 2.69  | 9.99  | 0    | 66.45|
| shareunder | The share of undergraduate students that accept job offers in the city (%)  | 419  | 2.55  | 8.36  | 0    | 60.90|
| sharegradu | The share of graduate students that accept job offers in the city (%)       | 419  | 2.72  | 10.36 | 0    | 71.01|
| pm         | PM$_{2.5}$ concentration in the year before graduation ($\mu$g/m$^3$)       | 419  | 44.27 | 15.42 | 14.88| 88.91|
| gdppc      | GDP per capita (10 million RMB)                                            | 419  | 55.16 | 36.36 | 8.48 | 467.75|
| second_gdp | The share of secondary industry by GDP (%)                                 | 419  | 45.39 | 7.83  | 19.25| 61.59|
| third_gdp  | The share of tertiary industry by GDP (%)                                  | 419  | 49.44 | 8.35  | 34.93| 79.65|
| pop        | Total population at the end of year (10 million)                           | 419  | 0.70  | 0.54  | 0.14 | 3.38 |
| resihp     | Residential housing price (10,000 RMB/m$^2$)                              | 419  | 0.61  | 0.42  | 0.14 | 3.37 |
| bartik     | Bartik index                                                               | 419  | 0.05  | 0.07  | −0.08| 0.32 |
| primsch    | Number of primary schools per 10,000 people                               | 419  | 1.50  | 0.72  | 0.38 | 3.59 |
| doctor     | Number of doctors per 10,000 people                                        | 419  | 31.18 | 13.68 | 11.64| 88.45|
| temp       | Average temperature ($^\circ$C)                                            | 419  | 15.06 | 5.36  | 4.5  | 26   |
| prec       | Total precipitation (mm)                                                  | 419  | 944.21| 516.43| 76.5 | 2687.8|
| dayssnow   | The number of days with snow                                              | 419  | 15    | 16.70 | 0    | 79   |
| daysstorm  | The number of days with storm                                              | 419  | 28.44 | 20.67 | 0    | 91   |
| daysfog    | The number of days with fog                                               | 419  | 23.13 | 26.04 | 0    | 156  |
| daysfrost  | The number of days with frost                                             | 419  | 66.80 | 61.67 | 0    | 180  |
worse air quality compared to other cities, the probability of staying in Beijing will decrease by 0.7 percentage point (mean: 60 percentage points, 1.2% of the mean value). This negative effect is even larger for graduate students, which is shown in column (3) and (6). As for undergraduate students, the effect is not significant and much smaller [column (2) and (5)]. One possible explanation for this is that the primary choice of undergraduate students from Tsinghua University is to pursue a graduate program rather than directly entering the job market. The sample of undergraduates in our study is much smaller than the sample of graduates, which may not be large enough to test the effect of air pollution.
The coefficients of demographic variables and city-level attributes are also reasonable. The coefficient of the distance variable is significantly negative, indicating that if the student’s home province gets farther from Beijing, (s)he will have a lower likelihood of choosing to stay in Beijing. Female students, nonminority students, and graduates with higher degrees are more likely to accept a job offer in Beijing. Meanwhile, if the relative level of Beijing’s GDP per capita, population, as well as the number of high schools per capita gets larger, which indicate the condition of Beijing in those aspects gets relatively better compared to other large and medium-sized cities, the probability that students choose to stay in Beijing will increase.8

### 3.2 Choosing among 35 large and medium-sized cities

Table 4 reports the estimated results of Eq. (2) and IV regressions. Similar to results found in Table 3, having a higher level of air pollution is found to have a significantly negative effect on the probability of elite graduates accepting a job offer in a city. If a city’s PM$_{2.5}$ level increases by 10 μg/m$^3$, the share of Tsinghua graduates choosing that city will decrease by 0.23 percentage point (mean: 2.69 percentage points, 9% of the mean value). The crowding-out effect is found to be larger

---

8 We calculate the variance inflation factors (VIFs) for independent variables, which are all less than 3, thus indicating there is little risk of multicollinearity in this model.
and more significant for graduate students than for undergraduate students. When including the instrument variable, the estimation results are similar in direction of influence but larger in magnitude than those in OLS estimations. As air pollution may result from an extensive secondary industry and indicates higher output and higher income, such omitted variables will increase the probability that students choose to work in polluted cities. Therefore, the OLS estimation is biased to the lower bound, and IV results are larger in magnitude and closer to the direct effect of air pollution. The first-stage regression indicates that the instrumental variable, air pollution from upwind cities, has strong explanatory power on the destination city’s air pollution. Further, the large Cragg–Donald Wald F statistic (41.60) indicates that the instrument is acceptable (not weak).9 Besides, we find that the cohort network effect is significant in all regressions. Consistent with our expectation, later graduates are influenced by earlier cohorts’ job location choices. If 2 years ago, the share of Tsinghua graduates choosing that specific city is larger by 1 percentage point (relative to the default city), the share of fresh graduates choosing that city is also larger by about 0.27–0.44 percentage point (relative to the default city) in the current year.

### 3.3 Robustness tests

In the main regression, we utilize PM$_{2.5}$ concentration in the year before graduation as the indicator of a city’s air pollution level. As PM$_{2.5}$ has become the primary air pollutant in China in recent years, the number of news reports and people’s

---

9 Stock et al. (2005) estimate the critical value of the Cragg–Donald statistic to be equal to 16.38 for a model with one endogenous regressors and one instrument.
awareness about its negative health effects has increased rapidly. Therefore, we can reasonably assume that students will take PM$_{2.5}$ concentration into consideration when they are searching for jobs, which occurs at the end of the year before they graduate. To verify the effect is not limited to PM$_{2.5}$ itself, but the air pollution level of target cities, the concentration of SO$_2$ is used as another main air pollutant in columns (1)–(3) in Table 5. The responses of graduates from bachelor, master’s and doctoral degrees are tested separately in each column. In addition, considering the fact that some students make their final job decisions during their graduation year, we also use the PM$_{2.5}$ concentration in the graduation year in place of the year before graduation. These results are reported in columns (4)–(6) in Table 5. The results are very robust showing that on average, air pollution has a significant negative effect on college graduates’ job location choice, and the effect is larger for students with master’s or PhD degrees but not significant for undergraduates.

### 3.4 Placebo test

In this study, we consider air pollution to be an important determinant in college graduates’ job location choice. Through including sufficient control variables and using the IV approach, we have found robust causal effects of air pollution on college graduates’ job location decision. In this part, we further conduct a placebo test on samples who already had labor contracts prior to their admission to Tsinghua University (ding xiang pei yang). As ding xiang pei yang students’ jobs are determined prior to entering the university and they have much higher cost to change their jobs after graduation, we expect air pollution to have no effect on their job location choice. If that is not the case, it might imply an illusory effect of air pollution on college graduates’ job location choice. The estimated results are reported in Table 6. Both OLS and IV estimates show insignificant results, which is consistent with our expectation. This placebo test further verifies that a higher level of air pollution influences the graduates’ job location choice behavior.

### 4 Heterogeneity analysis

#### 4.1 Heterogeneous effects among student groups

Thus far, we have found that on average, air pollution significantly affects college graduates’ job location choice. For different student groups, the degree they care about air pollution may vary according to their personal preference, knowledge about air pollution and so on. To test the heterogeneous effects, we divide the whole sample into groups by gender, the air quality of their hometown, the school they graduated from

---

10 If ding xiang pei yang students refuse to comply with the contract after graduation, they will be charged a high penalty, which is double the amount of the subsidy received during their whole study period. Further, they cannot receive their diploma from Tsinghua University and cannot register for graduation information online for 5 years.
and the major they studied. Table 7 presents the OLS estimates for each group, which illustrates that males, graduates coming from cleaner provinces, those graduating from environmental school, and students majoring in engineering and art care more about the air quality of destination cities. The results are consistent with our expectation. While both are significant, the coefficients are larger for males than for females, which indicates males are more sensitive to air pollution when making location choice. Students from polluted hometowns are more accustomed to poor air quality and have lower sensitivity than those from cleaner hometowns. Those graduating from environmental schools know more about the negative effects of air pollution and thus have a stronger preference for cleaner cities. Tsinghua University has an unbalanced composition of majors. In the whole sample, the ratio of graduates majoring in engineering, art and science is about 10:6:1. The limited number of students majoring in science can explain why the estimated result for this group is less significant. The IV estimates for different groups can be found in Appendix Table 10. Based on these heterogeneous effects, it can be expected that being accustomed to air pollution and recognizing the harm of air pollution could determine job location choice for elites given differing levels of air pollution.

Table 6  Placebo test on ding xiang pei yang students

| Dependents | OLS | IV |
|------------|-----|----|
|            | (1) | (2) | (3) | (4) | (5) | (6) |
| shareall   |     |     |     |     |     |     |
| shareunder|     |     |     |     |     |     |
| sharegradu|     |     |     |     |     |     |
| pm         |     |     |     |     |     |     |
| share_lag  |     |     |     |     |     |     |
| City attributes | Yes | Yes | Yes | Yes | Yes | Yes |
| Weather attributes | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N          | 419 | 383 | 419 | 419 | 383 | 419 |
| R²         | 0.432 | 0.295 | 0.205 | 0.430 | 0.295 | 0.203 |

First-stage regression

| IV        | 0.144*** | 0.144*** | 0.146*** |
|------------|----------|----------|----------|
| Cragg–Donald Wald F statistic | 42.69 | 39.91 | 42.36 |

Note: Heteroscedasticity-robust standard errors in parentheses

*p < 0.1; **p < 0.05; ***p < 0.01
|                  | Panel A: All graduates |                  | Panel B: Undergraduates |                  | Panel C: Graduates |
|------------------|------------------------|------------------|-------------------------|------------------|-------------------|
|                  | (1) Males             | (2) Females      | (3) Polluted hometown   | (4) Clean hometown | (5) Environmental School | (6) Other schools | (7) Engineering | (8) Art          | (9) Science      |
|                  |                       |                  |                         |                  |                   |                   |               |                 |                 |
| pm               | −0.0256***            | −0.0225**        | −0.0141*                | −0.0327***        | −0.0608***        | −0.0218***        | −0.0259***     | −0.0262**      | −0.0147          |
|                  | (0.00901)             | (0.00967)        | (0.00834)               | (0.0113)          | (0.0253)          | (0.00838)         | (0.00958)      | (0.0109)       | (0.0180)         |
| share_lag        | 0.373***              | 0.466***         | 0.0209                  | 0.432***          | 0.144***          | 0.407***          | 0.503***       | 0.0485         | 0.320***         |
|                  | (0.0514)              | (0.0518)         | (0.0548)                | (0.0532)          | (0.0530)          | (0.0517)          | (0.0507)       | (0.0565)       | (0.0525)         |
| N                | 419                   | 419              | 419                     | 419               | 419               | 419               | 419            | 419            | 419              |
| R²               | 0.434                 | 0.472            | 0.152                   | 0.472             | 0.266             | 0.448             | 0.507          | 0.166          | 0.308            |
|                  |                       |                  |                         |                  |                   |                   |               |                 |                 |
| pm               | −0.00645              | −0.0179          | −0.00334                | 0.0150            | −0.0156           | −0.00836          | −0.00457       | −0.0334**      | 0.0418           |
|                  | (0.0156)              | (0.0192)         | (0.0151)                | (0.0199)          | (0.0572)          | (0.0140)          | (0.0189)       | (0.0160)       | (0.0383)         |
| share_lag        | 0.301***              | 0.0591           | 0.119**                 | 0.252***          | −0.412***         | 0.292***          | 0.357***       | 0.0141         | −0.136**         |
|                  | (0.0623)              | (0.0593)         | (0.0563)                | (0.0629)          | (0.0518)          | (0.0630)          | (0.0633)       | (0.0567)       | (0.0562)         |
| N                | 419                   | 419              | 419                     | 419               | 419               | 419               | 419            | 419            | 419              |
| R²               | 0.176                 | 0.065            | 0.092                   | 0.221             | 0.195             | 0.144             | 0.136          | 0.087          | 0.142            |
|                  |                       |                  |                         |                  |                   |                   |               |                 |                 |
| pm               | −0.0327***            | −0.0254**        | −0.0155*                | −0.0417***        | −0.0632***        | −0.0276***        | −0.0335***     | −0.0267**      | −0.0254          |
|                  | (0.0112)              | (0.0108)         | (0.00863)               | (0.0137)          | (0.0255)          | (0.0101)          | (0.0114)       | (0.0121)       | (0.0188)         |
| share_lag        | 0.401***              | 0.488***         | 0.159***                | 0.476***          | 0.271***          | 0.432***          | 0.548***       | −0.00280       | 0.427***         |
|                  | (0.0511)              | (0.0538)         | (0.0544)                | (0.0524)          | (0.0527)          | (0.0520)          | (0.0501)       | (0.0571)       | (0.0491)         |
| N                | 419                   | 419              | 419                     | 419               | 419               | 419               | 419            | 419            | 419              |
| R²               | 0.505                 | 0.493            | 0.298                   | 0.538             | 0.349             | 0.514             | 0.573          | 0.188          | 0.485            |

Note: (1) Control variables include city attributes, weather attributes, city fixed effects, and year fixed effects. (2) Heteroscedasticity-robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01
Since 2011, air pollution has received much attention in China, and this attention has been reflected by more and more news reports about air pollution. We collect the number of news reports for each city and each year with the key words “haze” or “PM2.5” in Baidu, the main search engine in China. By interacting PM2.5 with this variable, we test how information transparency regarding air pollution influences students’ choice. As shown in Table 8, the interaction term is significantly negative for all students and graduates. This indicates that given the PM2.5 concentration level, more new reports will further lower the probability that a city is chosen. This means better information transparency will improve students’ knowledge of air pollution in target cities, and further influence their decision choice.

### Table 8 Heterogeneous effects between different levels of information transparency

| Dependent variables | (1) shareall | (2) shareunder | (3) sharegradu |
|---------------------|--------------|----------------|---------------|
| pm                  | -0.0205**   | -0.0228*       | -0.0227**     |
|                     | (0.00947)   | (0.0132)       | (0.0115)      |
| pm*reports          | -0.00519**  | -0.0769***     | -0.00882***   |
|                     | (0.00225)   | (0.0137)       | (0.00273)     |
| City attributes     | Yes          | Yes            | Yes           |
| Weather attributes  | Yes          | Yes            | Yes           |
| City fixed effects  | Yes          | Yes            | Yes           |
| Year fixed effects  | Yes          | Yes            | Yes           |
| N                   | 419          | 419            | 419           |
| R²                  | 0.365        | 0.234          | 0.435         |

Note: Heteroscedasticity-robust standard errors in parentheses
* p < 0.1; ** p < 0.05; *** p < 0.01

### Table 9 Heterogeneous effects between different years

| Dependant variables | (1) shareall | (2) shareunder | (3) sharegradu |
|---------------------|--------------|----------------|---------------|
| pm                  | -3.628**     | 2.051          | -4.930**      |
|                     | (1.672)      | (2.685)        | (2.036)       |
| pm × year           | 0.00179**    | -0.00102       | 0.00243**     |
|                     | (0.000831)   | (0.00133)      | (0.00101)     |
| City attributes     | Yes          | Yes            | Yes           |
| Weather attributes  | Yes          | Yes            | Yes           |
| City fixed effects  | Yes          | Yes            | Yes           |
| Year fixed effects  | Yes          | Yes            | Yes           |
| N                   | 419          | 419            | 419           |
| R²                  | 0.364        | 0.095          | 0.428         |

Note: Heteroscedasticity-robust standard errors in parentheses
* p < 0.1; ** p < 0.05; *** p < 0.01

#### 4.2 Heterogeneous effects between different levels of information transparency

Since 2011, air pollution has received much attention in China, and this attention has been reflected by more and more news reports about air pollution. We collect the number of news reports for each city and each year with the key words “haze” or “PM2.5” in Baidu, the main search engine in China. By interacting PM2.5 with this variable, we test how information transparency regarding air pollution influences students’ choice. As shown in Table 8, the interaction term is significantly negative for all students and graduates. This indicates that given the PM2.5 concentration level, more new reports will further lower the probability that a city is chosen. This means better information transparency will improve students’ knowledge of air pollution in target cities, and further influence their decision choice.
4.3 Heterogeneous effects among different years

Considering economic agents always behave in a forward-looking way, their response to air pollution may change with time. In Table 9, we try to identify the time trend from our data. The interaction term is significantly positive for all students and graduates, thus indicating that students are becoming less sensitive to air pollution over time. The result is consistent with the finding of Ou and Nam (2019). This may be partly due to the Chinese government’s strong signal to the market on strict pollution regulations. The signal then gives residents an impression that air pollution in urban areas will sooner or later be less of a concern, leading to reduced sensitivity.

5 Conclusion

In this paper, we study the impact of air pollution on elite college graduates’ job location choice in China. By merging air quality data from remote sensing with a unique administrative dataset including all recent graduates’ job contract data from Tsinghua University in China from 2005 to 2016, we construct a city-year panel dataset to examine the causal relationship between air pollution and graduates’ job location choice. We find that severe air pollution has a significantly negative impact on a city’s power to retain and attract top talent. Specifically, 0.1 unit increase in the ratio of Beijing’s PM$_{2.5}$ concentration to other large and medium-sized cities’ average level, which indicates Beijing air quality getting worse compared to other cities, the probability of staying in Beijing will decrease by 0.7 percentage point (mean: 60 percentage points, 1.2% of the mean value). If we consider all the 35 large and medium-sized cities as optional job locations, a 10 μg/m$^3$ increase in annual average PM$_{2.5}$ concentration will decrease the share of Tsinghua graduates choosing that city by 0.23 percentage point (mean: 2.69 percentage points, 9% of the mean value). This negative effect is found to be even larger for master’s and doctoral graduates, but insignificant for undergraduates. Moreover, male graduates are more sensitive to air pollution than female graduates; students coming from cleaner provinces are affected more than those coming from “dirty” provinces, which might be due to their different degrees of adaptation capacity and preferences for a clean environment. We also find that students that graduated from environmental schools care more about the air quality of their work destination, which may because they have more knowledge of the harm of air pollution. Finally, rising information transparency thanks to the internet and modern media amplifies the impacts of air pollution on the job location choice of top talent.

We acknowledge our constraint that we only have data from one university (Tsinghua University), which will lead to possible selection bias. We are unable to conduct Heckman selection bias control because we do not have data from other universities. Actually, since all elite universities need to enroll students through the standard national college entrance examination, student quality does vary significantly among top elite universities. Within a university such as Tsinghua, we do observe some variation in characteristics (gender, quality, etc.) between different
schools with different majors. Therefore, we include major fixed effects in our main specification, and also conduct heterogeneous analysis for student groups, and find the results are robust.

The findings of this paper have important policy implications. On one hand, nowadays many cities both in developed and developing countries are rushing to propose programs to attract top talent, aiming to attract high human capital through higher incomes and better welfare. However, the demand for environmental quality and other urban amenities cannot be ignored. In the long term, improving environmental quality will be more effective for the high-quality urban growth driven by human capital. On the other hand, studies have found that land values increase in value when environmental quality improves (Zheng et al. 2010, 2014). As demonstrated in this paper, the quantitative evidences of air quality’s role in attracting talent and thus improving cities’ competitiveness can help local governments effectively evaluate the social benefit of environmental regulation policies.

Appendix

See Table 10.
Table 10: Heterogeneous effects between different students—IV estimates

| (1) Males | (2) Females | (3) Polluted hometown | (4) Clean hometown | (5) Environmental school | (6) Other schools | (7) Engineering | (8) Art | (9) Science |
|---|---|---|---|---|---|---|---|---|
| pm | $-0.0596^{**}$ | $-0.0470$ | $-0.0304$ | $-0.0865^{**}$ | $-0.0954$ | $-0.0509^{**}$ | $-0.0674^{**}$ | $-0.0455$ | $-0.0000464$ |
| (0.0272) | (0.0288) | (0.0248) | (0.0345) | (0.0742) | (0.0253) | (0.0291) | (0.0323) | (0.0529) |
| share_lag | $0.359^{***}$ | $0.459^{***}$ | $0.0136$ | $0.418^{***}$ | $0.143^{***}$ | $0.394^{***}$ | $0.490^{***}$ | $0.0435$ | $0.323^{***}$ |
| (0.0515) | (0.0507) | (0.0539) | (0.0533) | (0.0511) | (0.0515) | (0.0507) | (0.0551) | (0.0511) |
| N | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 |
| $R^2$ | 0.412 | 0.463 | 0.143 | 0.438 | 0.262 | 0.429 | 0.481 | 0.158 | 0.307 |

Panel A: All graduates

| pm | $0.0475$ | $0.00923$ | $0.0624$ | $0.0678$ | $0.0940$ | $0.0357$ | $0.0484$ | $-0.000991$ | $0.229^{**}$ |
| (0.0465) | (0.0562) | (0.0458) | (0.0583) | (0.168) | (0.0415) | (0.0560) | (0.0470) | (0.117) |
| share_lag | $0.303^{***}$ | $0.0623$ | $0.110^{**}$ | $0.258^{***}$ | $-0.413^{***}$ | $0.296^{***}$ | $0.360^{***}$ | $0.0192$ | $-0.14^{***}$ |
| (0.0608) | (0.0575) | (0.0558) | (0.0614) | (0.0500) | (0.0615) | (0.0615) | (0.0552) | (0.0561) |
| N | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 |
| $R^2$ | 0.148 | 0.060 | 0.044 | 0.205 | 0.187 | 0.120 | 0.117 | 0.076 | 0.084 |

Panel B: Undergraduates

| pm | $-0.0785^{**}$ | $-0.0607^{*}$ | $-0.0425$ | $-0.105^{**}$ | $-0.108$ | $-0.0674^{**}$ | $-0.0833^{**}$ | $-0.0616^{*}$ | $-0.0174$ |
| (0.0340) | (0.0323) | (0.0260) | (0.0416) | (0.0751) | (0.0306) | (0.0346) | (0.0360) | (0.0555) |
| share_lag | $0.388^{***}$ | $0.479^{***}$ | $0.146^{***}$ | $0.464^{***}$ | $0.269^{***}$ | $0.418^{***}$ | $0.536^{***}$ | $-0.0109$ | $0.429^{***}$ |
| (0.0511) | (0.0531) | (0.0542) | (0.0523) | (0.0509) | (0.0519) | (0.0500) | (0.0561) | (0.0481) |
| N | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 |
| $R^2$ | 0.482 | 0.478 | 0.278 | 0.510 | 0.343 | 0.492 | 0.550 | 0.169 | 0.485 |

Panel C: Graduates

Note: (1) Control variables include city attributes, weather attributes, city fixed effects, and year fixed effects. (2) Heteroscedasticity-robust standard errors in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01
References

Bartik TJ (1991) Who benefits from state and local economic development policies? Kalamazoo, MI: WE Upjohn Institute for Employment Research

Barwick PJ, Li S, Rao D, Zahur NB (2018) The morbidity cost of air pollution: evidence from consumer spending in China (no. w24688). National Bureau of Economic Research

Bayer P, Keohane N, Timmins C (2009) Migration and hedonic valuation: the case of air quality. J Environ Econ Manag 58(1):1–14

Bobak M (2000) Outdoor air pollution, low birth weight, and prematurity. Environ Health Perspect 108(2):173

Chang T, Graff Zivin J, Gross T, Neidell M (2016) Particulate pollution and the productivity of pear packers. Am Econ J Econ Policy 8(3):141–169

Chay KY, Greenstone M (2003) Air quality, infant mortality, and the Clean Air Act of 1970 (no. w10053). National Bureau of Economic Research

Chen Y, Ebenstein A, Greenstone M, Li H (2013) Evidence on the impact of sustained exposure to air pollution on life expectancy from China’s Huai River policy. Proc Natl Acad Sci 110(32):12936–12941

Currie J, Neidell M (2005) Air pollution and infant health: what can we learn from California’s recent experience? Q J Econ 120(3):1003–1030

Currie J, Hanushek EA, Kahn EM, Neidell M, Rivkin SG (2009) Does pollution increase school absences? Rev Econ Stat 91(4):682–694

Dockery DW, Pope CA, Xu X, Spengler JD, Ware JH, Fay ME, Ferris BG Jr, Speizer FE (1993) An association between air pollution and mortality in six US cities. N Engl J Med 329(24):1753–1759

Dominici F, Peng RD, Bell ML, Pham L, McDermott A, Zeger SL, Samet JM (2006) Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA 295(10):1127–1134

Faggian A, McCann P, Sheppard S (2006) An analysis of ethnic differences in UK graduate migration behaviour. Ann Reg Sci 40(2):461–471

Fan H, Lai W, Song H, Wang H (2018) Air pollution and brain drain: evidence from job location choices of college graduates. Working paper

Ghanem D, Zhang J (2014) ‘Effortless perfection:’ Do Chinese cities manipulate air pollution data? J Environ Econ Manag 68(2):203–225

Graff Zivin J, Neidell M (2012) The impact of pollution on worker productivity. Am Econ Rev 102(7):3652–3673

Gupta P, Christopher SA, Wang J, Gehrig R, Lee YC, Kumar N (2006) Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmos Environ 40(30):5880–5892

Hanna R, Oliva P (2015) The effect of pollution on labor supply: evidence from a natural experiment in Mexico City. J Public Econ 122:68–79

Kumar P, Morawska L, Martani C, Biskos G, Neophytou M, Di Sabatino S, Bell M, Norford L, Britter R (2015) The rise of low-cost sensing for managing air pollution in cities. Environ Int 75:199–205

Levinson A (2012) Valuing public goods using happiness data: the case of air quality. J Public Econ 96(9–10):869–880

Li Z, Folmer H, Xue J (2014) To what extent does air pollution affect happiness? The case of the Jinchuan mining area, China. Ecol Econ 99:88–99

Li T, Liu H, Salvo A (2015) Severe air pollution and labor productivity (no. 8916). IZA discussion papers

Luechinger S (2009) Valuing air quality using the life satisfaction approach. Econ J 119(536):482–515

Luechinger S (2010) Life satisfaction and transboundary air pollution. Econ Lett 107(1):4–6

MacKerron G, Mourato S (2009) Life satisfaction and air quality in London. Ecol Econ 68(5):1441–1453

McAusland C, Kuhn P (2011) Bidding for brains: intellectual property rights and the international migration of knowledge workers. J Dev Econ 95(1):77–87

Ou Y, Nam K (2019) Impacts of air pollution on urban housing prices in China. In Western Regional Science Association (WRSA) Annual Conference (Napa, CA)

Plantinga AJ, Détang-Dessendre C, Hunt GL, Piguet V (2013) Housing prices and inter-urban migration. Reg Sci Urban Econ 43(2):296–306

Pope CA III, Ezzati M, Dockery DW (2009) Fine-particulate air pollution and life expectancy in the United States. N Engl J Med 360(4):376–386
Pope CA III, Burnett RT, Turner MC, Cohen A, Krewski D, Jerrett M, Gapstur SM, Thun MJ (2011) Lung cancer and cardiovascular disease mortality associated with ambient air pollution and cigarette smoke: shape of the exposure–response relationships. Environ Health Perspect 119(11):1616
Samet JM, Dominici F, Curriero FC, Coursac I, Zeger SL (2000) Fine particulate air pollution and mortality in 20 US cities, 1987–1994. N Engl J Med 343(24):1742–1749
Schwartz J, Morris R (1995) Air pollution and hospital admissions for cardiovascular disease in Detroit, Michigan. Am J Epidemiol 142(1):23–35
So KS, Orazem PF, Otto DM (2001) The effects of housing prices, wages, and commuting time on joint residential and job location choices. Am J Agr Econ 83(4):1036–1048
Stafford TM (2015) Indoor air quality and academic performance. J Environ Econ Manag 70:34–50
Stieb DM, Chen L, Eshoul M, Judek S (2012) Ambient air pollution, birth weight and preterm birth: a systematic review and meta-analysis. Environ Res 117:100–111
Stock JH, Yogo M, Andrews DW, Stock JH (2005) Identification and inference for econometric models: essays in honor of Thomas Rothenberg. Cambridge University Press, Cambridge
Sun C, Kahn ME, Zheng S (2017) Self-protection investment exacerbates air pollution exposure inequality in urban China. Ecol Econ 131:468–474
Van Donkelaar A, Martin RV, Brauer M, Hsu NC, Kahn RA, Levy RC, Lyapustin A, Sayer AM, Winker DM (2016) Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. Environ Sci Technol 50(7):3762–3772
Vandenbussche J, Aghion P, Meghir C (2006) Growth, distance to frontier and composition of human capital. J Econ Growth 11(2):97–127
Welsch H (2002) Preferences over prosperity and pollution: environmental valuation based on happiness surveys. Kyklos 55(4):473–494
Welsch H (2006) Environment and happiness: valuation of air pollution using life satisfaction data. Ecol Econ 58(4):801–813
Whalley J, Zhao X (2013) The contribution of human capital to China’s economic growth. China Econ Policy Rev 2(1):1350001
Williams AM, Phaneuf DJ (2019) The morbidity costs of air pollution: evidence from spending on chronic respiratory conditions. Environ Resource Econ. https://doi.org/10.1007/s10640-019-00336-9
Wong TW, Lau TS, Yu TS, Neller A, Wong SL, Tam W, Pang SW (1999) Air pollution and hospital admissions for respiratory and cardiovascular diseases in Hong Kong. Occup Environ Med 56(10):679–683
Wozniak A (2010) Are college graduates more responsive to distant labor market opportunities? J Hum Resour 45(4):944–970
Zhang Q, Jiang X, Tong D, Davis SJ, Zhao H, Geng G, Feng T, Zheng B, Lu Z, Streets DG, Ni R (2017a) Transboundary health impacts of transported global air pollution and international trade. Nature 543(7647):705
Zhang X, Zhang X, Chen X (2017b) Happiness in the air: How does a dirty sky affect mental health and subjective well-being? J Environ Econ Manag 85:81–94
Zhang Z, Hao Y, Lu ZN (2018) Does environmental pollution affect labor supply? An empirical analysis based on 112 cities in China. J Clean Prod 190:378–387
Zheng S, Kahn ME, Liu H (2010) Towards a system of open cities in China: home prices, FDI flows and air quality in 35 major cities. Reg Sci Urban Econ 40(1):1–10
Zheng S, Cao J, Kahn ME, Sun C (2014) Real estate valuation and cross-boundary air pollution externalities: evidence from Chinese cities. J Real Estate Finance Econ 48(3):398–414
Zheng S, Wang J, Sun C, Zhang X, Kahn ME (2019) Air pollution lowers Chinese urbanites’ expressed happiness on social media. Nat Hum Behav 1:237

Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.