Brain Drain:
The Impact of Air Pollution on Firm Performance

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Abstract

We hypothesize that firms located in more polluted areas are less able to recruit and retain quality human capital. First, using Baidu's Search Volume Index, we document that people exhibit an intention to look for jobs in less polluted areas on days when air pollution occurs in the area where they are located. Second, exploiting the exogenous variation in air pollution caused by China's central heating policy, we show that air pollution reduces the accumulation of executive talent and high-quality employees. This brain drain effect is more pronounced when people have concerns about their health triggered by air pollution. Third, firms located in polluted areas have poorer performance. This effect is more pronounced when firm performance has a greater dependence on human capital.

JEL Classification: O3, Q5, J3

Keywords: Air pollution, Brain Drain, Human Capital, Firm Performance, China

1. Introduction

"The last few years of living in such a singular environment [in Beijing] have taken a huge toll on my life and started affecting my health," Hugo Barra, the former vice president of Xiaomi's international business, wrote in a Facebook post announcing his departure in January 2017, hinting that a factor in his decision to move was Beijing's air pollution.[1] Not long afterward, the World Health Organization released its 2018 report, which revealed that 90% of the world's population breathe polluted air.[2] The worsening air quality in recent years, especially in developing countries, has provoked great public concern, and may drive skilled individuals to leave, impeding economic growth. Hugo Barra's post raises the question of whether his case is merely anecdotal or actually the tip of the iceberg. In this paper, we try to answer this question.

Ambient air pollution is known to cause an adverse impact on human physical and mental health.[3] Financial economists recognize that participants in financial markets are not immune to unhealthy air quality. For example, recent studies show that air pollution intensifies investors' and financial analysts' behavioral biases (Chang, Huang and Wang, 2018; Dong *et al.*, 2019; Huang, Xu and Yu, 2019; Li *et al.*, 2019). Thus far, most studies focus on the *short-term* costs of air pollution, and there is little evidence regarding the *long-term* impact of air pollution on firms. Given that corporate human capital is an essential element of value creation and the success of firms, we study whether and how air pollution affects the accumulation of corporate human capital and firm performance.

Our intuition rests on Tiebout's (1956) model, which proposes that individuals have heterogeneous preferences for public goods and sort themselves into localities that most closely match those preferences. People living in areas with poor air quality can adopt defensive behaviors to prevent exposure to air pollution. If these provisional defensive behaviors cannot assure health or are too costly in the long run, people will ultimately seek to settle in areas with better air quality. While such insights can apparently be applied to the whole population, in fact not everyone has

[1] "Ex-Android executive quits Chinese smartphone maker Xiaomi," *Financial Times*, January 23, 2017. Available at: https://www.ft.com/content/2d8be270-e148-11e6-8405-9e5580d6e5fb

[2] "9 out of 10 people worldwide breathe polluted air, but more countries are taking action," World Health Organization, May 2, 2018. Available at: https://www.who.int/news-room/detail/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action

[3] An extensive scholarly literature finds that ambient air pollution may cause adverse impacts on human health, such as premature death and shortened lives (Chen *et al.*, 2013; Tanaka, 2015); it is listed as the single largest environmental health risk (see European Environment Agency, 2015).

the flexibility to "vote with their feet." We expect air pollution to have a more detrimental effect on skilled labor.

Skilled individuals tend to be a high-income group and are more likely to have higher quality of life requirements. They have a greater economic ability to sort themselves into locations where better air quality is capitalized into housing prices (Chay and Greenstone, 2005). Moreover, skilled and highly educated people have more knowledge and understanding of the harmful effects of air pollution and have lower costs in searching for jobs (Arntz, 2010). As a result, firms located in more polluted areas are less able to recruit and retain high-quality individuals, leading to the loss of corporate human capital. We call this view *the brain drain hypothesis*. We test the brain drain effect of air pollution in China and examine how such an effect eventually impacts firm performance. To the best of our knowledge, this paper is the first to assess the effect of environmental pollution on corporate human capital.

To illuminate the influence of individuals' sorting response to air pollution on corporate human capital, we start by examining how people decide on their intended places of work when air pollution occurs. We use the Search Volume Index of Baidu, the largest search engine in China, to measure people's intended places of work. We find that, on days when air pollution occurs in a region (e.g., Chengdu, the provincial capital of Sichuan), people located in the region exhibit an increased intention to work in less polluted areas (e.g., Shenzhen) but a reduced intention to work in more polluted areas (e.g., Beijing). Moreover, the tendency is stronger in regions where people's concern for health is more sensitive to air pollution. This finding suggests that air pollution induces people to choose relatively less polluted areas as their intended workplace.

We then study how such an air pollution effect on people's sorting decisions is compounded into firms' human capital formation. Empirical tests at the firm level tend to be challenging because ambient air pollution is associated with local business activities, which in turn affect labor market opportunities and the labor supply to an individual firm. To deal with potential endogeneity problems, we use a regression discontinuity design (RDD) that exploits discontinuous variation in air pollution created by an arbitrary policy at the Qinling-Huai River (QH) boundary in China (Almond *et al.*, 2009).

The Chinese government established a free coal-based central heating system in the 1950s–1980s. Due to budgetary constraints, free heating is only provided to households living in regions on the north side of the QH boundary. Because the combustion of coal releases massive particulate matter and other pollutants, the areas where the policy applies have a significantly higher level of air pollution (Almond *et al.*, 2009; Chen *et al.*, 2013). Therefore, air pollution has discontinuous variation in areas across the QH boundary, which provides us with a means to test the impact of air pollution on corporate human capital.

To gauge corporate human capital, we consider both firm managers and employees, who enter the production function and influence firm performance distinctly (Gennaioli *et al.*, 2013). Specifically, we check whether a firm's top executives (i.e., CEO and board chairman) were born or obtained college degrees outside the region where the firm is domiciled, or whether they studied or worked abroad. Managers with diverse backgrounds and foreign experience are found to lead to better firm performance (Giannetti, Liao and Yu, 2015; Chemmanur *et al.*, 2019). We also calculate the proportion of highly educated employees and the proportion of skilled employees. Highly educated and skilled workers are important corporate human capital and significantly contribute to the improvement of firm productivity (Haltiwanger, Lane and Spletzer, 1999; Ashraf and Ray, 2017).

We use the sample of firms publicly listed on the Shanghai and Shenzhen stock exchanges from 2000 to 2016. Consistent with *the brain drain hypothesis*, we show that being located on the heating side of the QH boundary leads to a 23% decline in the probability of having a non-locally born top executive, a 19% decline in the probability of having a non-locally educated top executive, and a 7% decline in the probability of having a top executive with overseas experience. Moreover, the proportion of firm employees holding a bachelor's degree or above in heating areas is 20% lower than in non-heating areas, and the proportion of technical or skilled employees in heating areas is lower by 15%. Interestingly, there is no significant distinction in the proportion of employees with low levels of education and non-technical employees between the heating and non-heating sides of the QH boundary.

We conduct additional tests to further mitigate concerns related to omitted regional factors. Specifically, we re-estimate our models by focusing on regions within a narrow margin along the QH boundary. We still find that firms located on the heating side of the QH boundary by a small margin have a lower level of skilled executives and employees than those located on the non-heating side. The results are robust for the use of different bandwidths of margin. In addition, we re-estimate our models by controlling for city fixed effects based on where firms are domiciled and find consistent evidence.

Furthermore, we provide more explicit evidence to show that the loss of human capital is attributable to air pollution. First, we estimate a difference-in-differences (DID) model by exploiting the soaring difference in air pollution between the heating and non-heating sides of QH from 2012 to 2015. We find that the brain drain effect in heating areas becomes more pronounced as compared to non-heating areas when the difference in air pollution between the two areas is greater. Second, we estimate a two-stage least squares (2SLS) regression where the level of air pollution is instrumented by the notation of regions where the heating policy applies. Moreover, we follow Chen, Oliva and Zhang (2017) and use the strength of thermal inversion in a region as an instrument for the level of air pollution. Both tests show that poor air quality is associated with less accumulation of high-quality firm executives and employees. Third, we find that the negative effect of air pollution on corporate human capital is stronger in regions where air pollution is more likely to trigger people's attention to health, suggesting that air pollution affects corporate human capital through the channel of environmental health risk.

In the last part, we examine whether the brain drain effect of air pollution manifests itself in firm performance. Previous studies suggest that top management quality and employee skills are important determinants of corporate innovation and productivity (Haltiwanger, Lane and Spletzer, 1999; Ashraf and Ray, 2017; Chemmanur *et al.*, 2019). Following this notion, we investigate how air pollution affects corporate innovation and productivity. We first show that firms located on the heating side of the QH boundary have a significantly lower level of patent efficiency (patents/employees) and total factor productivity than those on the non-heating side. We further examine the impact of air pollution on firm value and sales growth. Indeed, firms located in the heating regions also have a lower Tobin's Q and sales growth. Our results thus suggest that air pollution can impede corporate innovation and productivity and impair firm value and operating performance.

To tighten the link between the brain drain effect and firm performance, we examine whether the effect of air pollution on firm performance is more pronounced in firms that rely more on human capital. We estimate the dependence of firm performance on human capital by regressing each of the four performance measures (innovation, productivity, firm value, and sales growth) on either the measure of executive talent or the proportion of high-quality employees in each industry over the past five years, respectively. We find that the effect of air pollution on firm performance is more pronounced in industries with a higher estimated dependence on human capital. Moreover, we find that the effect of air pollution on firm performance is stronger in firms with higher average employee compensation or in those in innovative industries. These results are consistent with the human capital channel through which air pollution affects firm performance.

This paper contributes to two strands of the literature: that on corporate human capital and that on the economic consequences of environmental pollution. To the literature on corporate human capital, we document an important non-economic factor that affects the accumulation of corporate human capital, while previous studies, mainly relying on regional analysis, focus on economic factors such as local wages and land rents (Rauch, 1993), organizational change (Bresnahan, Brynjolfsson and Hitt, 2002), financial deregulation (Philippon and Reshef, 2012), and local productivity change (Diamond, 2016). Moreover, we provide micro evidence that the stock of talent with respect to both management and employees is essential for the improvement of corporate innovation, productivity, and shareholder value, while prior studies primarily focus on the role of human capital in regional growth and development.

This paper also adds to the literature on the economic consequences of environmental pollution. Millions of households in developing countries are facing extremely high levels of air pollution. However, the extant studies show that people's willingness to pay for air quality improvement is low (Smith and Huang, 1995; Greenstone and Gallagher, 2008; Sullivan, 2016), which puzzles economists and sociologists. We shed light on this puzzle by proposing that migration sorting is an alternative defensive behavior to prevent exposure to air pollution, especially for skilled labor. Furthermore, recent finance studies have explored the *short-term* impact of air pollution on capital market participants, such as its effect on investor trading behavior (Heyes, Neidell and Saberian, 2016; Meyer and Pagel, 2017; Huang, Xu and Yu, 2019; Li *et al.*, 2019) and analyst forecasts (Dong *et al.*, 2019). However, the *long-term* impact of air pollution on corporate decision-makers and key employees remains unknown. Understanding this effect is important, given the significance of the economic outputs of publicly listed firms.

Finally, our study provides a timely policy implication. At the 2009 United Nations Climate Conference, many countries refused to commit to mandatory emissions reduction targets.[4] A key source of contention is to what extent air pollution affects their economic growth. Regulators raise

[4] "The UN Climate Change Conference, 2009 (COP 15)", ACCA, August 2009. Available at: https://research-repository.st-andrews.ac.uk/bitstream/handle/10023/3767/ACCA-2009-UN-Climate-Change.pdf?sequence=1&isAllowed=y

the concern that environmental regulations may hurt firms' competitiveness. This study documents that the accumulation of corporate human capital is an important channel through which environmental regulation can actually benefit an economy.

2. Hypothesis development and background

2.1. The role of human capital in firm performance

The role of human capital in economic growth has been of constant interest to economists and social scientists. The concentration of talent and skilled workers in a particular place reduces the costs of transmitting knowledge and sharing information, which leads to the "diffusion and growth of knowledge" (Jovanovic and Rob, 1989). The accumulation of human capital generates positive externalities that enhance productivity and economic growth (Lucas, 1988). As a result, the economic growth in a region crucially depends on its ability to attract and retain "brains."

A large body of literature has documented that a high level of human capital (e.g., labor with higher education and richer work experience) is associated with high regional income and productivity (Rauch, 1993; Black and Lynch, 1996). In particular, using a large dataset of 110 countries, Gennaioli *et al.* (2013) study the determinants of regional development such as geography, natural resources, institutions, human capital, and culture. They find that the level of education of workers and entrepreneurs emerges as the most consistently important determinant of regional income and productivity.

While human capital plays a vital role in regional development, the study of its corporate impact is still in its infancy, probably due to the difficulty of measuring corporate human capital. Corporate human capital refers to both firm employees and managers. Among early studies of firm employees, Haltiwanger, Lane and Spletzer (1999) use demographic and firm information from the U.S. Census Bureau and show that firm productivity is significantly higher when there is a higher fraction of highly educated workers, consistent with the human capital model that holds that skilled workers make firms more productive.

Ashraf and Ray (2017) examine the reduction in the quota of H-1B visas in 2004 as a shock to skilled immigrant workers and find that firm-level innovation outcomes decline for immigrant-dependent firms in the post-period of the policy. Consistent with this study, Kerr and Lincoln (2010) find that H-1B admissions increase the employment of science and engineering workers and patenting by Chinese and Indian inventors in cities and firms dependent on the H-1B visa program. The important role of employee human capital in corporate performance has also been highlighted across various aspects including employee incentives (Chang *et al.*, 2015), employee age (Ouimet and Zarutskie, 2014), tolerance for failure (Tian and Wang, 2014), and labor law and unionization (Acharya, Baghai and Subramanian, 2013; Bradley, Kim and Tian, 2017).

Recent studies have started to look at the impact of managerial human capital on corporate performance using managers' characteristics extracted from their resumes. For example, Chemmanur *et al.* (2018) construct an index based on the top management's education and past experience. They find that higher quality managers are able to select better projects and thus have superior operating performance and, consequently, higher firm value and stock returns. Using the same managerial quality index, Chemmanur *et al.* (2019) find that higher quality managers have better foresight into the potential value of innovation opportunities and create a failure-tolerant environment that attracts skilled workers. In line with this view, Custódio, Ferreira and Matos (2017) find that CEOs with general skills have better external job opportunities and thus have a greater tolerance for failure. Moreover, CEOs with skills transferable across firms and industries help to create a firm without boundaries that is beneficial for knowledge transfer.

Notwithstanding, firm workers and managers may influence firm production functions; it has been suggested that both, in different ways, are key factors that drive the economic performance of a firm (Gennaioli *et al.*, 2013). Given its substantial influence, it is important to understand the factors that affect the accumulation of corporate human capital. Previous studies suggest that the accumulation of human capital is shaped by a number of economic and financial factors such as local wages and land rents (Rauch, 1993); firms' technical changes, such as the adoption of information technology; complementary workplace reorganization; the introduction of new products and services (Bresnahan, Brynjolfsson and Hitt, 2002); financial deregulation (Philippon and Reshef, 2012); the introduction of policies to attract talented immigrants (Giannetti, Liao and Yu, 2015), and local productivity change (Diamond, 2016). However, the impact of non-economic factors is under-investigated.

2.2. The impact of air pollution on corporate human capital

Air pollution imposes high health risks on humans. Medical studies have shown that air pollution can cause numerous health problems such as respiratory and cardiovascular illnesses (Seaton *et al.*, 1995), heart disease (Dominici *et al.*, 2006), stroke (Hong *et al.*, 2002), and lung cancer (Kabir, Bennett and Clancy, 2007). Recent studies find that air pollution may increase infant mortality (Tanaka, 2015) and reduce life expectancy (Chen *et al.*, 2013). Moreover, air pollutants such as particulate matter can be absorbed into the bloodstream and travel into the central nervous system, eventually causing cerebrovascular damage (Genc *et al.*, 2012). Exposure to air pollution can damage brain function and reduce individuals' cognitive skills (Lavy, Ebenstein and Roth, 2014).

Given the high environmental risks of air pollution for human health, people facing high exposure to air pollution may adopt defensive behaviors, such as purchasing air purifiers (Ito and Zhang, 2019). However, householders' willingness to invest in these defensive behaviors is estimated to be low in developing countries (Smith and Huang, 1995; Greenstone and Gallagher, 2008; Sullivan, 2016). An alternative defensive behavior is re-location and migration. This intuition is built on the most popular and influential model of individual location sorting, that developed by Tiebout (1956). His model suggests that people "vote with their feet" to find the community that provides them with the optimal bundle of public goods. Banzhaf and Walsh (2008) provide empirical evidence to support this model. Given that not everyone has the flexibility to move around, we expect air pollution to have a more relevant impact on skilled labor.

Skilled and highly educated people are more likely to be a high-income group. They tend to have higher quality of life requirements and are more sensitive to air pollution. They also have a greater economic ability to move to cities where better air quality is capitalized into housing prices (Chay and Greenstone, 2005). Moreover, they have better knowledge on the harmful effects of air pollution and thus lower tolerance for poor air quality. They could also have more information on job opportunities and face lowers costs in searching for new jobs (Arntz, 2010). In line with this view, Levine, Lin and Wang (2018) find that firms exposed to toxic plant openings are more likely to experience CEO turnover. As a result, firms located in more polluted areas are less likely to recruit and retain high-quality individuals, leading to the loss of human capital and poor firm performance. This prediction is named *the brain drain hypothesis*:

H1. Air pollution is negatively associated with a firm's human capital and performance.

2.3. Air pollution in China

The rapid economic growth of China in the past three decades has lifted more than 600 million people out of poverty. However, great economic achievement comes at the expense of environmental pollution. The particulate matter concentration in China is seven times the level in the U.S. and is also higher than that in India (Greenstone and Hanna, 2014). A recent green paper published by the Chinese Academy of Social Sciences indicates that the problem of haze and fog in China has hit a record level and that China is currently facing its worst air pollution problems since 1961.

The problem of haze in China has risen rapidly since the beginning of this century (Gao, 2008). A study of 1,701 monitoring stations in China shows that the annual average number of haze days increased from 6 in 2000 to 18 in 2012 (Han *et al.*, 2016). More than 92% of residents in China have been exposed to PM2.5 concentration exceeding 10 μg/m3 since 2000. This exposure rate increased to 98% in 2012. During the same time, Western countries such as the U.K. and the U.S. have experienced a significant decline to levels below 20% (Hsu *et al.*, 2014).

In particular, from 2013, the regularly occurring haze in the winter and spring began to draw extensive public attention. Many cities, especially those in the north, have experienced very serious haze. In December 2013, China suffered a severe bout of air pollution with thick haze stretching from Beijing to Shanghai, a distance of 750 miles. The levels of PM2.5 in Beijing peaked at 35 times the World Health Organization's (WHO) recommended limit and were stuck at tremendous levels for weeks (Zhang, Liu and Li, 2014). Direct consequences were observed: residents were seen wearing face masks; schools and airports were closed; children were kept indoors; hospital admissions for respiratory problems increased, and social networks exploded with complaints about the heavy blanket of smog.

The terrible air pollution is also leading to an exodus of expatriates fleeing China.[5] Many companies complain that it is harder to recruit talent from outside to work in northern China.[6] Executive recruitment firms also state that it is getting harder to attract top talent to China, including both expatriates and Chinese nationals educated abroad.[7] The availability of computers or smartphones allows anyone to match their data with the choking clouds in front of them. It is reported that strategies for leaving Beijing have become a hot topic on Weibo (China's Twitter).[8]

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[5] See "Why leave job in Beijing? To breathe", *The Wall Street Journal*, April 14, 2013. Available at: https://www.wsj.com/articles/SB10001424127887324010704578418343148947824

[6] "Airpocalypse' drives expats out of Beijing", *Financial Times*, April 1, 2013. Available at: https://www.ft.com/content/46d11e30-99e9-11e2-83ca-00144feabdc0

[7] See, "Execs fleeing China because of bad air", CBS News, January 29, 2013. Available at: https://www.cbsnews.com/news/execs-fleeing-china-because-of-bad-air/ .

[8] "Smog dents Beijing's expat appeal", *Financial Times*, April 5, 2013. Available at: https://www.ft.com/content/b29afeae-9dc9-11e2-bea1-00144feabdc0

Coal consumption is considered to be a significant source of air pollution. According to data from the U.S. Energy Information Administration, coal consumption in China accounts for approximately 70% of the country's total fuel consumption since the 1980s. China is by far the largest coal consumer, accounting for 49% of global coal consumption in 2012. Coal and coal gas are the primary sources for the central heating system. During each winter, cities in northern China rely on the central heating system. Together with the specific climate conditions, the increasing pollutants from the fossil fuel combustion of the central heating system intensify the haze in northern China. For example, in 2013, the central heating system was activated on November 15 in Beijing, Tianjin, Jinan, and Shijiazhuang, and on November 31 in Taiyuan. Just after that, a serious haze occurred and lasted for more than one week at the beginning of December in Beijing and northern China.

3. Air pollution and intended places of work

3.1. Search volume index

We start with our analysis of whether air pollution has an influence on individuals' intended places of work. Specifically, we examine how people's intentions with respect to their place of work change when air pollution occurs in the region in which they are located.

To conduct the test, we first identify the emergence of air pollution in each region (a municipal city). We measure air pollution using AQI, which is published by the Chinese Ministry of Environmental Protection (MEP). AQI synchronizes various types of air pollution, including SO_2, NO_2, PM_{10} (suspended particulates with a diameter of 10 μm or less), $PM_{2.5}$ (suspended particulates with a diameter of 2.5 μm or less), CO, and O_3. A higher AQI level means a higher level of air pollution. Air quality is considered to be good when the AQI is below 100. An AQI above 100 indicates pollution.

Some studies suggest that AQI data are subject to manipulation by city governments at the margin of 100 because they are motivated by the blue-sky award (a blue-sky day is defined as a day with AQI below 100) (Ghanem and Zhang, 2014). To mitigate this concern, we conduct a McCrary density test (McCrary, 2008) based on daily AQI from 2000 to 2016.[9] The results are shown in Figure IA.1. We find that the distribution of AQI is smooth, and the manipulation at the

[9] Published by the Chinese Ministry of Environmental Protection (MEP) since 2000.

margin of 100 is negligible.[10] To identify the emergence of air pollution in a region, we examine whether there is a large increase in AQI. Specifically, a region is identified as experiencing an air pollution day if the increase in daily AQI exceeds a one standard deviation change in daily AQI in the past year in the region.

We measure people's intended places of work using Baidu's Search Volume Index (SVI, similar to Google SVI). As the largest search engine in China, Baidu started to reveal the SVI of words for which people commonly search online in 2011. It provides SVI for a specific word at both country and city levels. We use the city-level SVI to measure the intention of people from one city to work in another city. Specifically, we use the word of "$城市找工作" (to work in $city), where $city is one of the top cities where people intend to work in China based on a study conducted by the ChinaHR Research Institute in 2018.[11] In such, $SVI_{r,d}$, indicates the daily SVI of people in city r who are hoping to work in city d. r refers to the Chinese city in which people reside, and d denotes one of the top work-destination cities. We collect the daily SVI and AQI data and conduct the analysis for the period from 2011 to 2016.

In Panel A of Figure 1, we plot the average searches for information about finding work in Beijing and Shenzhen around air pollution days (Day 0) across all cities. Beijing and Shenzhen are selected for comparison for two reasons: 1) the two cities are the dream work destinations for many young people in China; 2) the two cities have a substantial difference in air quality (the average AQI of Beijing and Shenzhen from 2011 to 2016 is 106 and 54, respectively). Interestingly, we find that, when air pollution occurs at their location, people increase their search for job opportunities in Shenzhen while decreasing such searches with respect to Beijing. Specifically, the level of searches for job opportunities in Shenzhen (Beijing) increases (decreases) by around 12% (6%) from day 0 to day 3 as compared to the average level from day -16 to day -6.

To show a more general pattern, we plot the search volume for more workplaces with various levels of air pollution. Specifically, we divide the top work-destination cities into more and less polluted city groups based on their average AQI during our sample period. The more polluted city group includes the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian), and the less polluted city group includes the five least polluted cities (Shenzhen, Shanghai, Guangzhou,

[10] The results are similar for the sample period from 2011 to 2016.

[11] ChinaHR Research Institute, 2019. "The 16th China college student best employers survey." The top cities where people intend to work in China include Beijing, Shanghai, Guangzhou, Hangzhou, Shenzhen, Chengdu, Wuhan, Tianjin, Nanjing, Xian, Chongqing, Jinan, Zhengzhou, Changsha, and Shenyang.

Hangzhou, and Chengdu). The average search for job opportunities in the two city groups is presented in Panel B. The pattern is similar. The figure shows that, when air pollution occurs in a city, people search more often for work in places that have less pollution while searching less often for work in places that have more pollution.

3.2. Regression analysis

We then conduct a more formal analysis by running regressions with city characteristics controlled. The model is specified as follows:

$$SVI_{r,t} = \alpha_1 + \alpha_2 Pollution\ days_{r,t} + City_r + Date_t + Control_{r,t} + \epsilon_{r,t}, \quad (1)$$

where the dependent variable ($SVI_{r,t}$) denotes the intention of people in city *r* on day *t* to work in another city, including Beijing ($To\ work\ in\ Beijing_{r,t}$), Shenzhen ($To\ work\ in\ Shenzhen_{r,t}$), the more polluted city group ($To\ work\ in\ more\ polluted\ cities_{r,t}$), and the less polluted city group ($To\ work\ in\ less\ polluted\ cities_{r,t}$).

$Pollution\ days_{r,t}$ indicates a five-day window following an air pollution day in city *r*. Specifically, it takes a value of one for days *t*, *t+1*, *t+2*, *t+3*, and *t+4* if city *r* experiences air pollution on day *t* and zero otherwise. We include city fixed effects ($City_r$) and date fixed effects ($Date_t$) in the model. As a result, the coefficient on $Pollution\ days_{r,t}$ (α_2) is a difference-in-difference (DID) estimate. The first difference is the difference in SVI in a city between pollution and non-pollution days, and the second difference is the difference in SVI between cities experiencing air pollution and those not experiencing air pollution.

We control for city-level economic and demographic characteristics that may relate to people's searches for places of work. These variables include a city's *GDP growth*, *GDP per capita*, *Education expenditure* (government expenditure on education/GDP), and *Population* (log of population size). We also control for climate characteristics in a city, including *Temperature*, *Relative humidity*, *Precipitation*, and *Sunshine hours*. Table IA.1 provides detailed definitions and sources for these variables. We estimate Equation (1) based on the sample period from 2011 to 2016. The summary statistics for variables used in this analysis are reported in Panel A of Table 1.

[Insert Table 1]

The estimates of Equation (1) are presented in Table 2. We find that the coefficient on $Pollution\ days_{r,t}$ in Column (1) (Column 2) is significantly negative (positive), suggesting that people reduce (increase) their search for job opportunities in Beijing (Shenzhen) during air pollution days. The results in Columns (3) and (4) suggest that people's intention to work in more (less) polluted cities declines (increases) when air pollution occurs in their location. The DID estimates thus confirm the pattern, as shown in Figure 1.

To ensure that the pattern we identify is falsifiable, we conduct a placebo test by making random assignments of air pollution days to each city. The assignments are made such that the frequency of randomly assigned air pollution days is the same as the frequency of true air pollution days. We create a variable $Pollution\ days\ (random)_{r,t}$, referring to a five-day window following the randomly assigned air pollution day in a city. We re-estimate Equation (1) using $Pollution\ days\ (random)_{r,t}$. The results are presented in Table 3. We find that the coefficients on $Pollution\ days\ (random)_{r,t}$ are not significantly different from zero. The results suggest that our findings, as shown in Table 2, are genuine and falsifiable.

[Insert Tables 2 and 3]

3.3. The impact of concern for health

We conduct additional tests to understand the mechanism behind the pattern we identify. As air pollution may have a large negative impact on human health, we examine whether people change their intended places of work due to concern for their health. With this conjecture, we expect to see a stronger effect of air pollution on intended workplaces in cities where air pollution is more likely to trigger people's concern about their health.

To test the conjecture, we estimate the sensitivity of SVI of health to air quality in a city. Specifically, we regress the percentage change in the daily SVI of the word, "健康" (health), on the percentage change in daily AQI in each city in each year. The estimated beta on the change in AQI is our measure of people's intensity of pollution-induced concern for their health, notated by $Health\ Beta_{r,t}$. A more positive beta means that people's attention to health increases when air pollution emerges, thus indicating a greater concern with health. We add the interaction term between $Health\ Beta_{r,t}$ and $Pollution\ days_{r,t}$ in Equation (1) and re-estimate the model. The results are presented in Table 4.

[Insert Table 4]

We find that the coefficients on the interaction term are significant and have the same sign as the standalone $Pollution\ days_{r,t}$. The results thus suggest that people reduce (increase) their intentions of working in a more (less) polluted place when their concerns for health are more sensitive to air pollution. The results thus lend support to our argument that air pollution has an influence on individuals' workplace decisions by way of environmental health risks.

4. Air pollution and corporate human capital

Given the evidence above that air pollution has an influence on individuals' workplace decisions, in this section, we examine whether the effects are compounded into companies' human capital formation.

4.1. Corporate human capital measures

To measure corporate human capital, we consider both top management and firm employees. We gauge the quality of top management by assessing whether the CEO or chairman in a firm was born or obtained a college degree outside the location where the firm is domiciled, or whether they had work or study experience abroad.

Specifically, we define *Non-locally born executives* as a dummy that equals one if the CEO or chairman was born in a region outside the province where the firm is domiciled and zero otherwise; *Non-locally educated executives* as a dummy that equals one if the CEO or chairman obtained a degree from a university or college in a region outside the province where the firm is domiciled and zero otherwise, and *Executives with overseas experience* as a dummy that equals one if the CEO or chairman has experience studying or working overseas and zero otherwise.

We measure the strength of a firm's employees based on the composition of employees by their education levels and job functions. Specifically, we define *% of highly educated employees* as the number of employees with a bachelor's degree or above scaled by the total number of employees; *% of employees with a low level of education* as the fraction of employees whose highest education level is either high school or below; *% of skilled employees* as the fraction of technical employees; *% of production and sales employees* as the number of production and sales employees, and *% of financial and administrative employees* as the fraction of financial, HR, and administrative employees.[12]

We collect the background information of the CEO and board chairman from the China Corporate Figure Characteristics Series database (GTA_TMT) in China Stock Market and Accounting Research (CSMAR) for the period from 2000 to 2016. For those with missing information, we manually search firms' annual reports, company websites, and other online sources (e.g., Google.com and Baidu.com). We collect the information on employee composition from the Wind Financial Database (WIND). Chinese listed firms started to disclose their employee structure information since 2011. For this reason, we reduce our sample for the analysis of employee human capital to the period from 2011 to 2016. The human capital variables are filled with a missing value if there is no information.

4.2. Regression discontinuity design

To examine the effect of air pollution on corporate human capital, the conventional approach is to estimate the following model using the ordinary least squares (OLS) in a firm-year panel:

$$y_{i,t} = \beta_1 + \beta_2 AQI_{i,t} + X_{i,t} + u_{i,t}, \quad (2)$$

where i indexes firm and t indexes year. The dependent variable is one of our corporate human capital measures. $AQI_{i,t}$ is the AQI in the city where a firm is located. X is a vector of observable firm and city characteristics. However, a concern with this regression is that AQI may be correlated with unobservable firm characteristics and city factors that may also influence firms' human capital, in which case the estimate of β cannot be interpreted as a causal effect of air pollution. To deal with the identification problem, we use a regression discontinuity design (RDD) that exploits the discontinuous variation in air pollution created by China's central heating policy.

China's central heating policy (or the Huai River policy) was established to provide winter heating in northern China during the central planning period from the 1950s to the 1980s. When initiating the policy, the Chinese government arbitrarily divided the territory into northern and southern China by the line formed by the Qinling Mountains and the Huai River, which follows the January 0 ℃ average temperature line (see Figure 2). Free heating was provided to cities north

[12] Please note, the sum of *% of highly educated employees* and *% of employees with low levels of education* is not 100% since employees in the middle level of education, such as those having associate degrees, are also included. The sum of the employee percentage by job function is also not 100% since some employees are not classified by the job function.

of the line. The reason for choosing this dividing line was that the Chinese government faced a budgetary constraint and was not able to supply free heating to all areas of China. This heating system has worked for more than 50 years and is still in operation today.

The centralized heating system rests on the use of coal-based hot water boilers, which is inflexible and energy inefficient. Hot water needs to travel a certain distance from the heating provider to each household in a city, causing substantial energy loss. The incomplete combustion of coal in boilers releases a significant amount of air pollutants, especially particulate matter, which leads to haze. It also leads to the release of total suspended particulates (TSP), SO_2, and NO_2. Almond *et al.* (2009) find that the central heating policy has led to a discontinuously higher level of TSP in the heating area. Using this discontinuous change in air quality, Chen *et al.* (2013) find that people living in the heating area have, on average, a 5.5-year shorter life expectancy than those in the non-heating area.

With a view to precision, we strictly follow Almond *et al.* (2009), Chen *et al.* (2013), and Ito and Zhang (2019) and estimate the following reduced-form regression:

$$y_{i,t} = \gamma_1 + \gamma_2 QH_{i,t} + f(Lat_{i,t}) + X_{i,t} + T + I + L + u_{i,t}, \quad (3)$$

where $QH_{i,t}$ equals one if firm *i* is located in the heating area formed by the QH boundary in year *t* and zero otherwise.[13] $f(Lat_{i,t})$ denotes a smooth control function for the latitude of firm location, allowing for different polynomials of the distance between firm location and the QH boundary.[14]

We control for a variety of firm and city characteristics ($X_{i,t}$). Specifically, we control for firm characteristics that may affect firms' demand for human capital (Hirshleifer, Low and Teoh, 2012; Bradley, Kim and Tian, 2017). These include *Firm size* (log(total assets)), *Leverage* (total liability/total assets), *Cash flow* (operating income before depreciation and amortization/total assets), *Capital expenditure* (Capex/total assets), *Firm age*, *Executive age* (average age of CEO and board chairman), and *SOEs* (state-owned enterprises indicator).

We include the same set of city controls as used in Section 3. In particular, we control for economic and demographic characteristics (*GDP growth*, *GDP per capita*, *Education expenditure*, and *Population*), because they may relate to employment opportunities and human capital supply in firms' location. We also control for city climate characteristics (*Temperature*, *Relative humidity*,

[13] We use historical firm location information. A firm may move from the heating area to the non-heating during our sample period, and vice versa. As we show next, our results are robust for including the firm location city fixed effects.
[14] We use the cubic polynomial of distance between firm location and the QH boundary. We also alternatively use the quadratic polynomial and find consistent results.

Precipitation, and *Sunshine hours*) in firms' location, because prior studies suggest that weather and climate conditions may affect people's sorting decisions (Jessoe, Manning and Taylor, 2017). We further control for year fixed effects (vector *T*) and industry fixed effects (vector *I*). To reduce the scope of unobserved factors on either side of the heating border spanning from the west to the east, we include the fixed effects of longitude decile (vector *L*).

A negative estimated γ_2 would indicate that firms located in more polluted regions have a lower level of human capital accumulation. This design can also be used to develop the following two-stage least squares (2SLS) to estimate the impact of the level of air pollution on corporate human capital:

$$AQI_{i,t} = \gamma_0 + \gamma_1 QH_{i,t} + f(Lat_{i,t}) + X_{i,t} + T + I + L + u_{i,t}, \tag{4.1}$$

$$y_{i,t} = \theta_0 + \theta_1 \widehat{AQ}I_{i,t} + f(Lat_{i,t}) + X_{i,t} + T + I + L + u_{i,t}. \tag{4.2}$$

Following Ito and Zhang (2019), we define *AQI* as the average of daily AQI in the winter months (Oct, Nov, Dec, Jan, Feb, and Mar) in a firm's location.[15] The intuition of this 2SLS is as follows: if the heating policy influences corporate human capital through its impact on air pollution, it is valid to run Equation (4.1) to obtain the variation of *AQI* caused by the policy and then relate the fitted values of *AQI* to human capital outcomes using Equation (4.2). An important appeal of the 2SLS approach is that it produces the estimated units of the impact of *AQI* on corporate human capital.

A valid RDD requires that 1) the heating policy cause the change in the assignment of pollution, and 2) the assignment *per se* be independent of firm outcomes. To assess the first condition, we first plot out the average *AQI* from 2000 to 2016 in each Chinese city. As shown in Figure 2, we find the areas with *AQI* above 100 (shaded in red) and the areas with *AQI* below 100 (shared in green) are well partitioned by the QH boundary, suggesting a significant difference in air pollution at the central heating border.

We also plot the average *AQI* by year in Figure 3. We find that *AQI* in the heating area is higher than that in the non-heating area, with the difference gradually narrowing in the 2000s but abruptly broadening since 2014. We further make the regression discontinuity plots of *AQI* in Figure 4. We find that the level of *AQI* on the heating side of the boundary is about 20 units (or

[15] The central heating system operates in the winter months only. Our results are robust when the whole year average of AQI is used.

25%) higher than that on the non-heating side. The results suggest that the arbitrary heating policy indeed causes a discontinuous change in ambient air pollution.

To verify the second condition, we examine whether there is a discontinuity in other covariates that are correlated with corporate human capital and firm performance at the boundary. In Panel A of Table IA.2, we present the differences in firm and regional characteristics between the two sides of the heating boundary by a small margin (two degrees around the QH boundary). We find that there are no significant differences in firm characteristics (except *SOEs*) and GDP growth. The heating side has higher expenditure on education but lower GDP per capita than the non-heating side, with the net effects on human capital unclear.

Moreover, we test the differences in expected corporate human capital between the two sides. Specifically, we regress human capital variables on firm and regional covariates. The fitted values obtained from the regressions are our measures of expected human capital. We find that, as shown in Panel B, the expected human capital measures are not significantly different for firms on the two sides. Overall, the diagnostic tests suggest that the determinants of corporate human capital are independent of the treatment assignment.

The definitions and sources for variables used in the RDD are provided in Table IA.1. The summary statistics are provided in Panel B of Table 1.

4.3. Main results

4.3.1. Regression continuity plots

Before reporting the regression estimates, we provide a visualization of the human capital difference for firms across the central heating border. The results are presented in Figure 5, where the average human capital measures of all firms in a region are plotted on the region's latitude distance from the heating border. Panel A provides the plot for the regional average of high-quality executives (i.e., the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*). Panel B shows the plot for the regional average of high-quality employees (e.g., the average of *% of highly educated employees* and *% of skilled employees*).

Each dot is generated by averaging human capital measures for firms across locations within 0.1° latitude. The dots are fitted using a linear line. Areas with a 90% confidence interval around the fitted line are shaded. The x-axis is the latitude distance from the heating border. A positive (negative) degree distance means firms located on the heating (non-heating) side of the border. From the figure, we find that there is a discontinuous drop in high-quality executives and firm employees at the border when moving from the non-heating side to the heating side. Moreover, the fitted line on the heating side is below the shaded area of the estimates on the non-heating side, suggesting that the drop is significant.

4.3.2. The accumulation of executive talent

The RDD estimates of the impact of air pollution on firm management are reported in Table 5. Namely, we estimate Equation (3) using a probit model where the dependent variables are *Non-locally born executives, Non-locally educated executives*, and *Executives with overseas experience*. Standard errors are estimated by clustering at the firm level.

We find that the coefficients on *QH* are negative and statistically significant, suggesting that air pollution indeed has a negative impact on the accumulation of executive talent. The impact is also economically significant. At the bottom of the columns, we report the marginal effect of the estimates, namely, the difference between the probability of having executive talent in the heating area and in the non-heating area. The estimates suggest that being located on the heating side of the QH boundary leads to a 23% decline in the probability of having a non-locally born executive, a 19% decline in the probability of having a non-locally educated executive, and a 7% decline in the probability of having an executive with overseas experience. The results suggest that firms headquartered in polluted areas are less likely to accumulate executive talent from outside or with foreign experience.

Turning to control variables, we find that executives from outside and those who have foreign experience tend to be young and to be more interested in large and mature firms. Moreover, they are more likely to choose to work in non-SOEs and in cities with high GDP per capita, implying that talented executives are tempted by firms or cities with better growth opportunities.

[Insert Table 5]

To show that our identification based on the QH boundary is falsifiable, we artificially assume alternative latitude lines other than the QH boundary. We randomly simulate 1,000 alternative latitude lines. For each simulated line, we re-estimate Equation (3) and record the coefficient on

QH. The distribution of the coefficients for the models of executive talent is reported in Panels A-C of Figure 6.

We find that a large fraction of simulated coefficients has a value equal or close to zero. Importantly, the coefficients estimated based on the true latitude of QH (marked by the solid line) are located on the deep left tail and fall below the 10^{th} percentile (marked by the dashed line), suggesting our setting of QH is falsifiable.

4.3.3. The accumulation of high-quality employees

Table 6 presents the results of RDD estimating the effect of air pollution on employee quality, namely, OLS estimates of Equation (3), where the dependent variable is one of the employee measures by education and job function.

Panel A reports the estimates for employee human capital by education. In Column (1), the dependent variable is *% of highly educated employees*. We find that the coefficient on *QH* is significantly negative. The result is also economically significant: the proportion of firm employees holding a bachelor's degree or above for firms on the heating side is 20% lower (i.e., 0.051/.26) than that for firms on the non-heating side. However, in the model of *% of employees with a low level of education* (Column 2), we find the coefficient on *QH* is insignificant. The results suggest that air pollution only causes a decline in the composition of highly educated employees.

Panel B reports the estimates for employee human capital by job function. We find that the coefficient on *QH* for the fraction of technical employees is significantly negative, while the coefficients for the fractions of the other two types of employees are insignificant. The estimate for the model of technical employees has economic significance. Specifically, it implies that the proportion of technical or skilled employees for firms on the heating side is 15% lower (i.e., 0.028/0.19) than that for firms on the non-heating side. The results indicate that air pollution reduces the accumulation of highly educated and skilled employees.

We also repeat the analysis using artificially assumed alternative latitude lines other than the QH boundary. The distribution of estimated coefficients on *QH* is presented in Panels D and E of Figure 6. We find that our coefficients estimated based on the true latitude of QH is on the left tail and smaller than the 10^{th} percentile, which confirms the falsifiability of our setting.

[Insert Table 6]

4.4. Local RDD and city fixed effects

Although the RDD setting allows us to control for regional factors, we might still miss certain unobservable regional factors that may bias our estimates. We further address this concern by 1) running local RDD by focusing on firms located within a small margin around the QH boundary, and 2) including firm location's city fixed effects.

First, we re-estimate our models by focusing on firms located on either side of the QH boundary by a small distance. We exploit the fact that unobservable factors such as economic conditions and social capital effects are likely to be similar in neighboring regions, whereas air pollution has a sharp difference across the heating border. For the test, we conduct local RDD by focusing on firms located in places with a distance smaller than two degrees in latitude from the QH boundary. The estimated results are reported in Table IA.3.

Panel A presents the results for executive talent measures. We find that the coefficients on *QH* are negative and highly significant, indicating that firms located on the heating side of the QH boundary by a small margin are less likely to have CEOs or chairmen who were born or educated outside or had foreign experience than firms located on the non-heating side. Panels B and C present the estimates for the human capital measures of employees. We again find that the composition of better educated and skilled employees is significantly lower on the heating side than on the non-heating side.

We also estimate local RDD using alternative bandwidths (i.e., different latitudes of distance from the QH boundary). The coefficients on *QH* with different bandwidths are presented in Figure 7. We find that the coefficients are largely negative for a small bandwidth. The coefficients continue to be negative for a larger bandwidth, although the magnitude gets smaller. The figure suggests that our findings are robust for the use of different distances from the QH boundary.

To further mitigate concerns about unobservable regional factors, we re-estimate Equation (3) using the full sample by including firm location's city fixed effects.[16] The results are presented in Table IA.4. We find that the negative effect of the central heating policy on both executive and employee human capital becomes even stronger.

Overall, the results suggest that the brain drain effect of air pollution is robust when we account for unobservable regional factors.

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[16] *QH* is defined based on firms' historical location information. The coding of *QH* for a firm changes when it moves from the heating area to the non-heating during our sample period, and vice versa.

4.5.DID analysis and instrumental variable approaches

In this section, we provide more explicit evidence to show that the loss of human capital is related to air pollution.

First, we examine how the change in air pollution affects corporate human capital. We exploit the abruptly broadened difference in *AQI* between heating and non-heating areas in 2014 (as shown in Figure 3) to conduct a DID analysis over the period from 2012 to 2015. Specifically, we create a variable *Post*, which equals one for years 2014 and 2015 (the post-period of the broadened *AQI* difference) and zero for years 2012 and 2013 (the pre-period of the broadened *AQI* difference). We then interact *Post* with *QH* and re-estimate Equation (3) with city fixed effects included. The results are reported in Table 7. We find that the coefficients on *QH* × *Post* are significantly negative, suggesting that the effect of the central heating policy becomes more pronounced when the difference in *AQI* between heating and non-heating areas increases.

[Insert Table 7]

Second, we estimate 2SLS regressions by relating air quality as instrumented by *QH* to human capital measures. Specifically, we estimate the fitted value of *AQI* using Equation (4.1) and then regress human capital variables on the fitted value using Equation (4.2). The results are reported in Table 8. Panel A shows the estimates for the models of executive talent. The results show that firms located in cities with a high level of pollution are less likely to have a CEO or chairman that is non-locally born, non-locally educated, or has overseas experience (marginally significant). Panels B and C present the estimates for employee composition by education and job function, respectively. We find that a higher level of air pollution is associated with a lower proportion of highly educated employees and technical employees. However, there is no significant relationship between the air pollution level and the proportion of employees with low levels of education and production and sales employees.

[Insert Table 8]

Third, we use thermal inversion patterns as an instrument for *AQI* (Arceo, Hanna and Oliva, 2016; Chen, Oliva and Zhang, 2017) and conduct the analysis without relying on the QH setting. Thermal inversion occurs when the above-ground temperature is higher than the ground temperature in a region. Because air moves from hot to cool regions, when thermal inversion occurs, air pollutants are trapped near the ground, leading to higher air pollution concentrations. As a result, the occurrence of thermal inversion can be used as an IV to capture the variation in air pollution. We measure the strength of thermal inversion using the above-ground temperature minus ground temperature (*TI*). The data are obtained from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the U.S. National Aeronautics and Space Administration (NASA).[17] The data are recorded every six hours for each 0.5 degree × 0.625 degree latitude by longitude grid. We aggregate the data from grid to city and then average to the annual level across winter months.[18] The 2SLS results using *TI* as the IV are reported in Table 9. We find the coefficients on fitted *AQI* are significantly negative for the models of executive talent and highly educated employees. The results suggest that higher levels of air pollution are associated with greater losses of corporate human capital.

[Insert Table 9]

4.6. The impact of concern for health

So far, our findings show that corporate human capital is lost in polluted areas, which is consistent with our *brain drain hypothesis*. In this section, we substantiate this view by examining how the brain drain effect of air pollution varies with regional heterogeneity in individuals' concern for their health. If executive talent and skilled employees leave firms in polluted areas and head to less polluted areas because of concerns over health risks, the brain drain effect will be more pronounced when such concern is more salient.

To conduct the test, we use *Health Beta*, as discussed in section 3.3, to measure the intensity of people's concern for health due to air pollution in a region. A higher *Health Beta* means more attention to health (more searches for health online) when air pollution emerges. We augment the interaction term between *QH* and *Health Beta* into Equation (3) and include firm location's city fixed effects in the model. The results are reported in Table 10.

We find that the coefficients on *QH* × *Health Beta* in the models of quality human capital are significantly negative and the coefficients on *QH* continue to be negative. The results suggest that the brain drain effect of air pollution is stronger in cities that have a stronger sensitivity of attention

[17] The data is collected at: https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_V5.12.4/summary?keywords=Aerosols#.
[18] We alternatively average to annual level across all months and find similar results.

to health, which confirms our view that that air pollution induces concern over health risks and eventually affects firms' human capital accumulation.

[Insert Table 10]

5. Air pollution and firm performance

Thus far, we have obtained robust evidence that air pollution has a negative effect on corporate human capital. Given the importance of human capital for corporate long-term growth and success, in this section, we examine whether air pollution has an impact on firms' performance and whether such impact acts through the channel of human capital.

5.1. Corporate innovation and productivity

Previous studies suggest that top management quality (as indicated by, e.g., education and past experience) and employee skills are important determinants of corporate innovation (Ashraf and Ray, 2017; Chemmanur *et al.*, 2019), and corporate productivity (Haltiwanger, Lane and Spletzer, 1999). To the extent that air pollution hurts corporate human capital, we expect that air pollution would impede corporate innovation and productivity. We conduct the test in this subsection.

We measure corporate innovation using the number of a firm's patent applications, scaled by its total employees (see, Cohen, Diether and Malloy, 2013; Hirshleifer, Hsu and Li, 2013), notated by *Patents*. We estimate a firm's productivity using total factor productivity (*TFP*) as in Levinsohn and Petrin (2003). Table IA.1 provides detailed definitions and sources of the two variables.

We first do a preliminary analysis by making regression discontinuity plots of the two variables. The results are shown in Panels A and B of Figure IA.2. We find that there is a discontinuous reduction in *Patents* and *TFP* when moving from the non-heating area (i.e., below zero degrees) to the heating area (i.e., above zero degrees). We next conduct a comprehensive analysis by re-estimating Equation (3) using *Patents* and *TFP* as the dependent variable. The results are reported in Table 11.

[Insert Table 11]

As shown in Columns (1) and (2), the coefficients on *QH* are negative and significant, suggesting that air pollution indeed impedes corporate innovation and productivity. Specifically, Column (1) suggests that being located on the heating side of the QH boundary leads to a decline of 1.25 in the number of patents per thousand employees. Column (2) suggests that the *TFP* of firms in the heating area is likely to be lower by around 58% (i.e., 0.069/0.12), relative to the average firm in the non-heating area.

We conduct falsifiability tests by re-estimating the models using artificially assumed alternative latitude lines other than the QH boundary. The distribution of the coefficients on *QH* using artificial latitude lines is presented in Figure IA.3. As shown in Panels A and B, the value of most simulated coefficients on *Patents* and *TFP* is either zero or close to zero, and our coefficients based on the true QH latitude are far below the 10^{th} percentile, suggesting that our estimates are falsifiable.

5.2. Firm value and sales growth

Considering the essential role of human capital for firm value creation and performance improvement (Chemmanur *et al.*, 2018), we complement our analysis by examining the impact of air pollution on firm value and operating performance. Firm value is measured by Tobin's Q, defined as the market value of total equity over book value of total equity (*Q*). Operating performance is measured by the annual growth rate of total sales (*Sales growth*).

Panels C and D of Figure IA.2 present the regression discontinuity plots of *Q* and *Sales growth*, respectively. The figure shows that there is a drop in firm value and sales growth when moving from non-heating to heating areas.

The RDD estimate results are reported in Columns (3) and (4) of Table 11. We find that firms located in polluted areas have lower firm value and sales growth. Specifically, firms located on the heating side of the QH boundary have a 14% (i.e., 0.370/2.71) lower Tobin's Q and 33% (i.e., 0.076/0.23) lower sales growth than the average firm located on the non-heating side.

We also re-estimate the models using artificially assumed alternative latitude lines. The results are shown in Panels D and E of Figure IA.3. We find that our estimates based on the true QH latitude are on the deep left tail, far below the 10^{th} percentile. The results suggest that our models based on the QH identification are valid.

5.3. Robustness tests

We conduct additional analyses to further mitigate concern about plausible confounding regional factors. First, we run local RDD using a small sample of firms that are located in regions within two degrees of latitude from the QH boundary. The results are reported in Panel A of Table IA.5. We find that the coefficients on *QH* in the regressions of *Patents*, *TFP*, *Q*, and *Sales growth* all remain significantly negative. We also perform the analysis based on alternative latitude distances. The results are shown in Figure IA.4. We find that the estimates remain negative when different distances are used and that the magnitude is most salient when a short distance is used, suggesting that regional characteristics might not be the driving factors.

We further address the concern about regional factors by including firm location's city fixed effects in regressions. The results are reported in Panel B of Table IA.5. We find that the coefficients on *QH* remain significantly negative (except the model of *Sales growth*). Collectively, the tests suggest that our findings are robust, accounting for unobservable regional factors.

Then, we conduct tests to more explicitly link air pollution to firm performance. First, we exploit the broadened difference in *AQI* between heating and non-heating areas in 2014 and examine whether the effect of the central heating policy on firm performance becomes more salient in the post-period of the broadened difference. The DID estimated results are reported in Panel C. As expected, we find that firms located in the heating area indeed experience greater declines in innovation, productivity, and shareholder value.

Second, we regress firm performance measures on *AQI* instrumented by *QH*, namely re-estimating Equation (4) as specified previously. The results are presented in Panel D. We find that the fitted *AQI* is significantly and negatively related to *TFP*, *Q*, and *Sales growth*. Finally, we re-estimate the 2SLS using thermal inversion strength as the IV. The results are presented in Panel E and largely mirror those in Panel D.

Overall, these results suggest that a high level of air pollution is associated with poorer firm performance.

5.4.Human capital dependence

The previous sections show that air pollution is detrimental to firm performance. In this section, we examine whether this effect indeed acts through the channel of corporate human capital.

First, if air pollution harms firm performance through hurting the accumulation of corporate human capital, the effects of air pollution on firm performance should be more pronounced when firms' performance depends more on human capital. To conduct the test, we estimate the sensitivity of firm performance to human capital to measure firms' human capital dependence.

Specifically, we regress each of the four firm performance measures (*Patents*, *TFP*, *Q*, and *Sales growth*) on management human capital (the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*) and employee human capital (the average of *% of highly educated employees* and *% of skilled employees*), respectively.

We run the regressions within each industry in each year using data over the past five years, with firm characteristics (i.e., *Firm size*, *Leverage*, *Cash flow*, *Capital expenditure*, *Firm age*, *Executive age*, and *SOEs*) included as control variables. The coefficients on the human capital variables proxy for human capital dependence for each industry. They gauge the degree to which firm performance in an industry relies on skilled executives and high-quality employees, with a higher value indicating higher dependence. We then re-estimate the models of firm performance by adding human capital dependence measures and their interaction with *QH*. Firm location's city fixed effects are also included as controls. The estimated results are reported in Table 12.

Panel A presents the estimates when the dependence on managerial human capital is used. We find that the coefficients on the interactions between *QH* and the human capital dependence measures are negative and statistically significant. Panel B presents the estimates when the dependence on employee human capital is used. The coefficients on the interaction terms are also significantly negative. These results suggest that the effect of air pollution on firm performance is most potent when skilled executives and high-quality employees are important to firm performance.

Furthermore, we examine whether the effect of air pollution on firm performance is more pronounced in firms with higher average pay and in innovative industries. Because high-quality individuals are paid higher salaries, higher average employee compensation is a signal of greater dependence on human capital (Ouimet and Zarutskie, 2014). Moreover, innovative industries need the input of talented people to generate creative ideas and thus have a greater reliance on human capital.

To conduct the test, we create *High pay*, which is equal to one if a firm has an average employee compensation above the sample median in a year, and *Innovative industries*, which is equal to one if a firm operates in the industries of information technology, scientific research, and technical service, or health and social work (Ouimet and Zarutskie, 2014). We add the interaction terms between *QH* and the two variables, respectively, in our models. The estimated results are reported in Panels C and D, respectively. As expected, we find that the negative effect of air pollution on firm performance is stronger in firms with higher average compensation and in innovative industries.

[Insert Table 12]

We finally link firm performance to our human capital measures instrumented by *QH*. If air pollution affects firm performance by affecting firms' human capital accumulation, the fitted value of human capital measures from the model of regressing human capital on *QH* should be significantly related to firm performance. The results of the 2SLS estimates are reported in Table IA.6. As expected, we find that the coefficients on the fitted human capital measures are significantly positive, indicating that a reduction in human capital as a result of air pollution might lead to a decline in firm performance.

Overall, the results in this section suggest that air pollution influences firm performance via the channel of human capital.

5.5.Regional performance

All our tests thus far focus on publicly listed firms. To generalize our story to the whole economy, we examine whether air pollution also affects the performance of above-scale enterprises (including non-public firms) in a region. To answer the question, we focus on patent production and new product development for above-scale enterprises in each region of China, with data collected from the enterprise innovation database in CSMAR. The database provides aggregated enterprise information, including the number of patent applications, amount of new product issuance, total R&D expenditure, and total number of R&D researchers in each provincial region since 2008.

We measure a region's patent production using the number of patent applications in the region scaled by the region's total R&D expenditure (*Patents/R&D*), or scaled by the total number of R&D researchers (*Patents/R&D researchers*). We measure regional new product development using the amount of new product issuance in a region scaled by the region's total R&D expenditure (*New products/R&D*), or scaled by the total number of R&D researchers (*New products/R&D researchers*). We estimate our RDD models using region-year panel data, with regional characteristics included as controls.

The RDD estimates are reported in Table IA.7. We find that the coefficients on *QH* in all models are negative and statistically significant. The results suggest that enterprises in polluted areas have a lower level of innovation in terms of patent generation and new product development, which further confirms the detrimental effect of air pollution.

6. Conclusion

This paper examines whether air pollution is detrimental to the accumulation of corporate human capital and impairs firm performance. We develop *the brain drain hypothesis*. The hypothesis is built on Tiebout's location sorting model, which proposes that people have heterogeneous preferences for public goods and seek to settle in locations that match their preferences. To substantiate this argument, we first examine how individuals determine or change their intended places of work in response to air pollution. Consistent with the location sorting model, we find that people increase (decrease) searches for work in less (more) polluted areas when air pollution emerges in their location.

Next, we examine whether the sorting effect of air pollution is compounded into firms' human capital formation. Using a unique regression discontinuity design created by the central heating policy in China, we find that firms located in the heating area are less likely to retain executive talent and high-quality employees than those located in the non-heating area, suggesting that air pollution hurts human capital accumulation. Moreover, this brain drain effect is more pronounced in regions where air pollution is more likely to trigger people's concern about their health.

We finally show that the brain drain effect of air pollution manifests itself in corporate performance. Specifically, firms located in the heating area have a lower level of corporate innovation, total factor productivity, firm value, and sales growth than those located in the non-heating area. Furthermore, this negative relationship between air pollution and corporate performance is more salient in firms that have a greater dependence on human capital, in firms where employees are paid higher, and in industries that are more innovative. The results suggest that human capital is the channel through which air pollution affects firm performance.

Overall, we show that air pollution is a crucial non-economic factor that has a significant impact on corporate performance by influencing the accumulation of corporate human capital.

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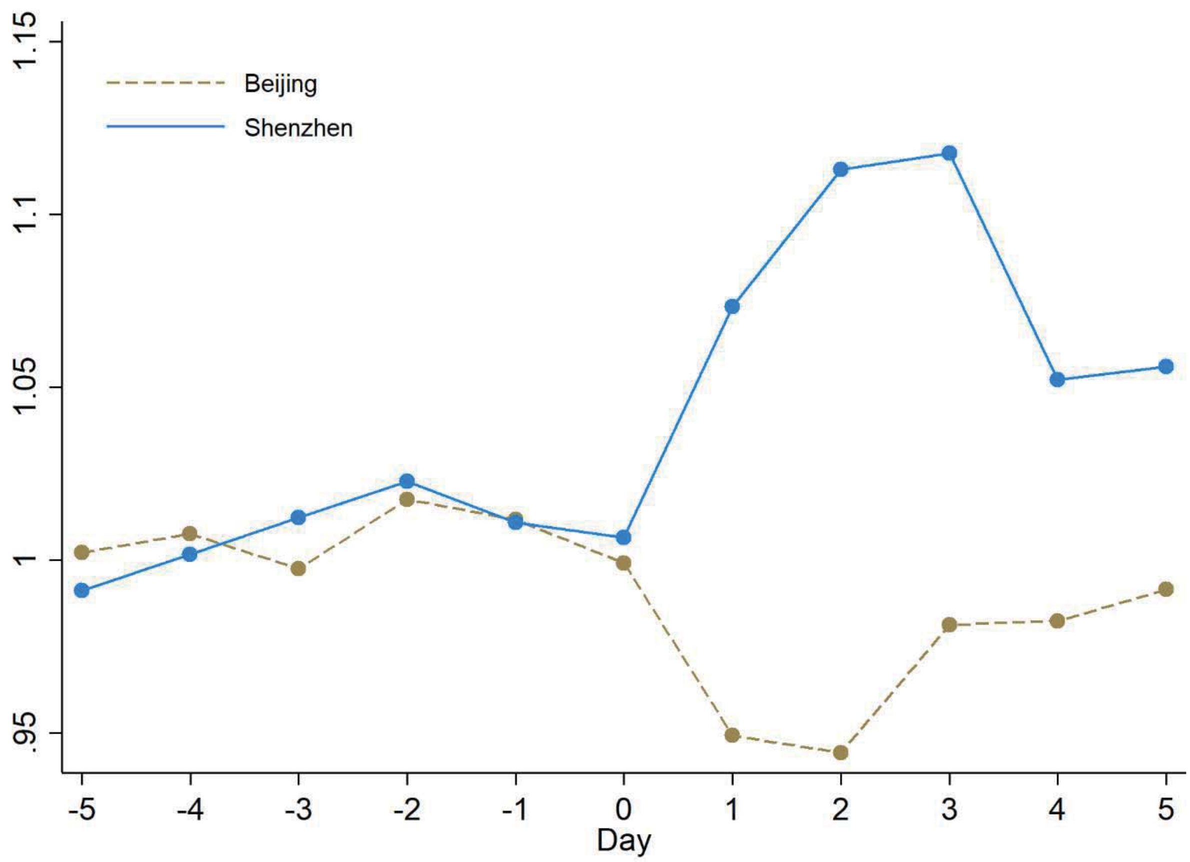
Figure 1: Workplace Searching Activities around Air Pollution Days

This figure plots people's online searches for places of work around air pollution days. A region is defined as experiencing a pollution day (day 0) if the increase in daily AQI exceeds one standard deviation of the daily AQI change in the past year in the region. The y-axis represents the average Baidu Search Volume Index (SVI) across all regions that experience a pollution day. The daily SVI from day -5 to day 5 in a region is scaled by the average daily SVI from day -16 to day -6 in the region. Panel A shows the average SVI for work in Beijing and Shenzhen. The solid line represents the SVI of "北京找工作" (to work in Beijing). The dashed line represents the SVI of "深圳找工作" (to work in Shenzhen). Panel B shows the average SVI for work in top work-intended cities based on a study conducted by the ChinaHR Research Institute in 2018. The solid line represents the average SVI for work in the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou). The dashed line represents the average SVI for work in the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian).

Panel A: SVI for workplaces of Beijing and Shenzhen



Panel B: SVI for work in more and less polluted cities

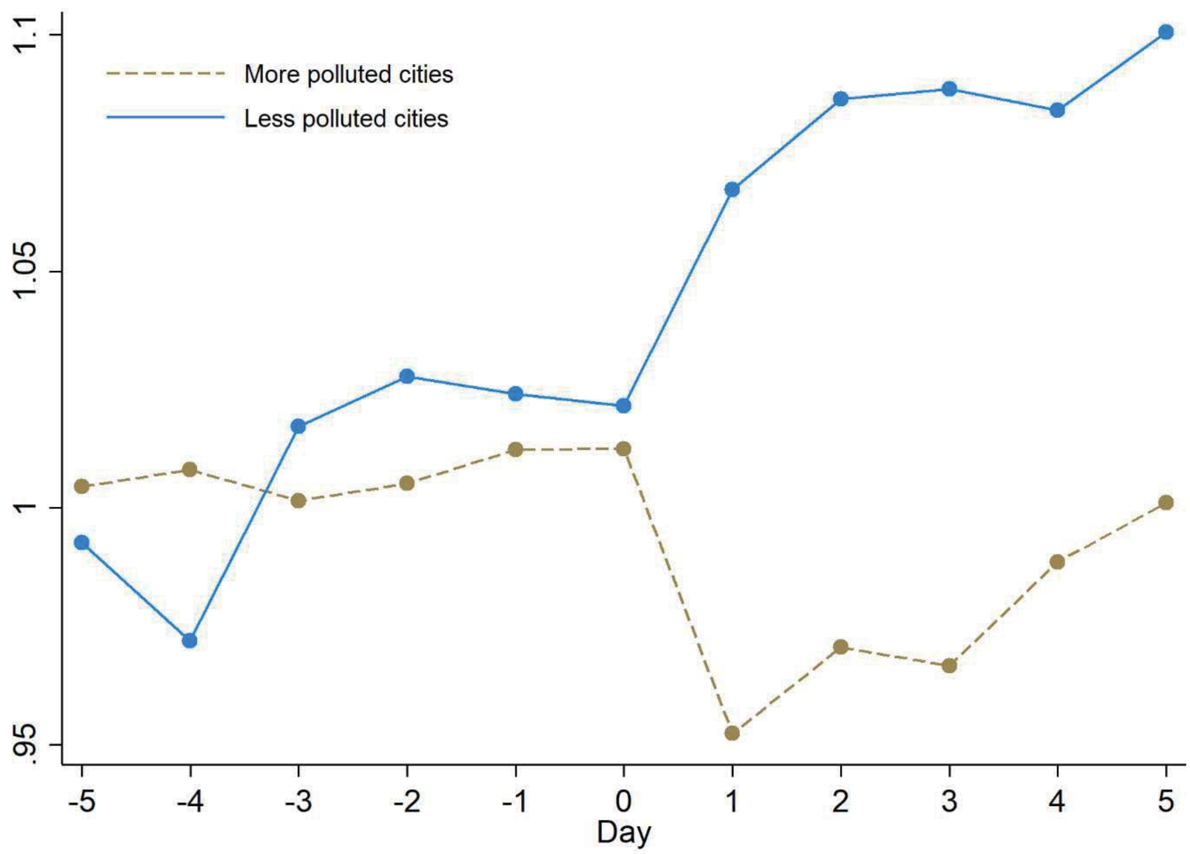


Figure 2: Qinling-Huai River and Air Pollution by Regions in China

The blue line represents the boundary of the Qinling-Huai River. The areas with average Air Quality Index (*AQI*) from 2000 to 2016 above (below) 100 are marked in red (green). The red dots represent cities where listed firms are domiciled. The regions on the north side of the Qinling-Huai River boundary are the heating area, and the regions on the south side of the boundary are the non-heating area.

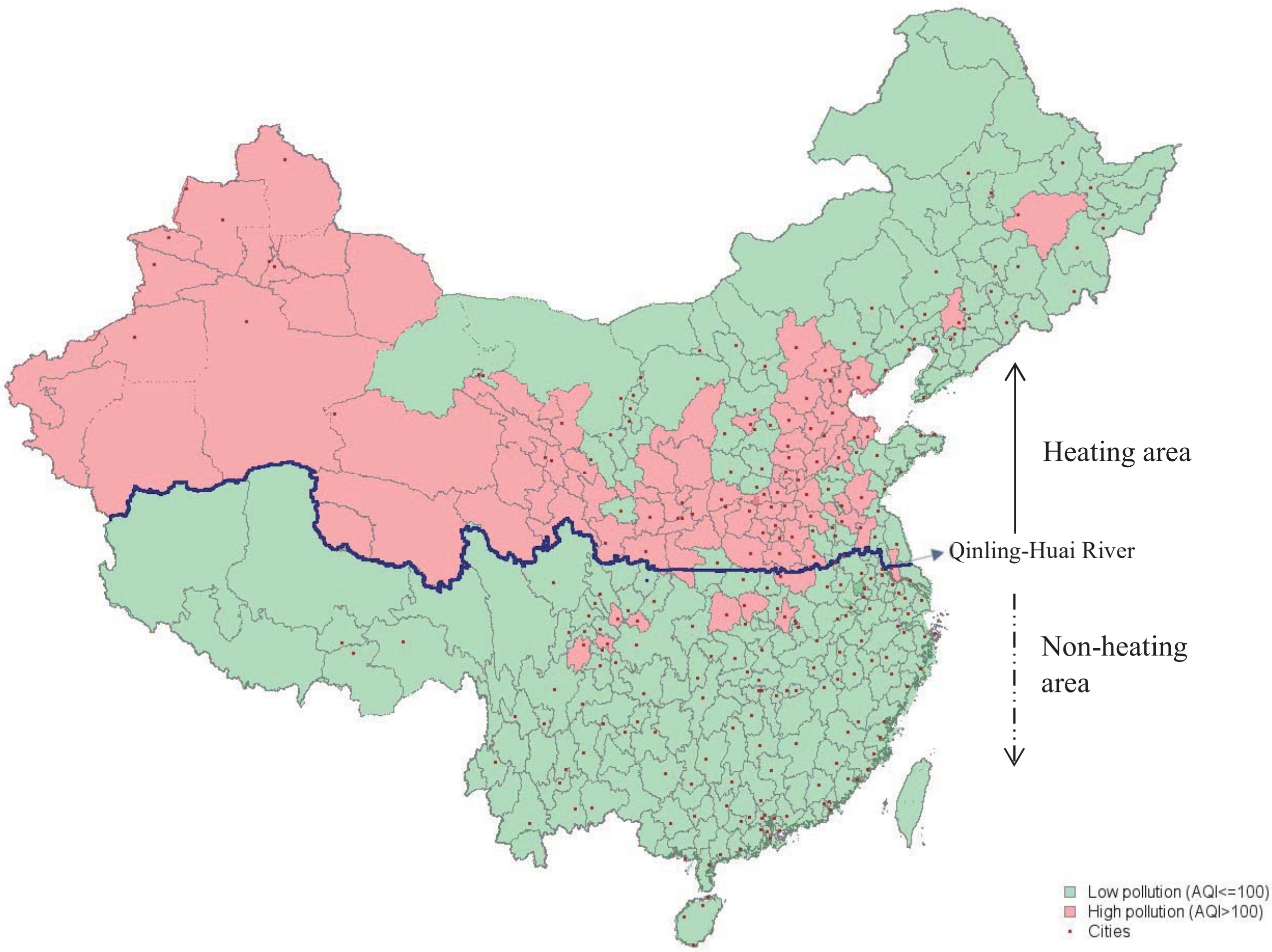


Figure 3: Air Pollution by Year

The bars represent the average Air Quality Index (*AQI*) by year in China. The red-solid (green-dash) line represents the average *AQI* on the heating (non-heating) side of the Qinling-Huai River.

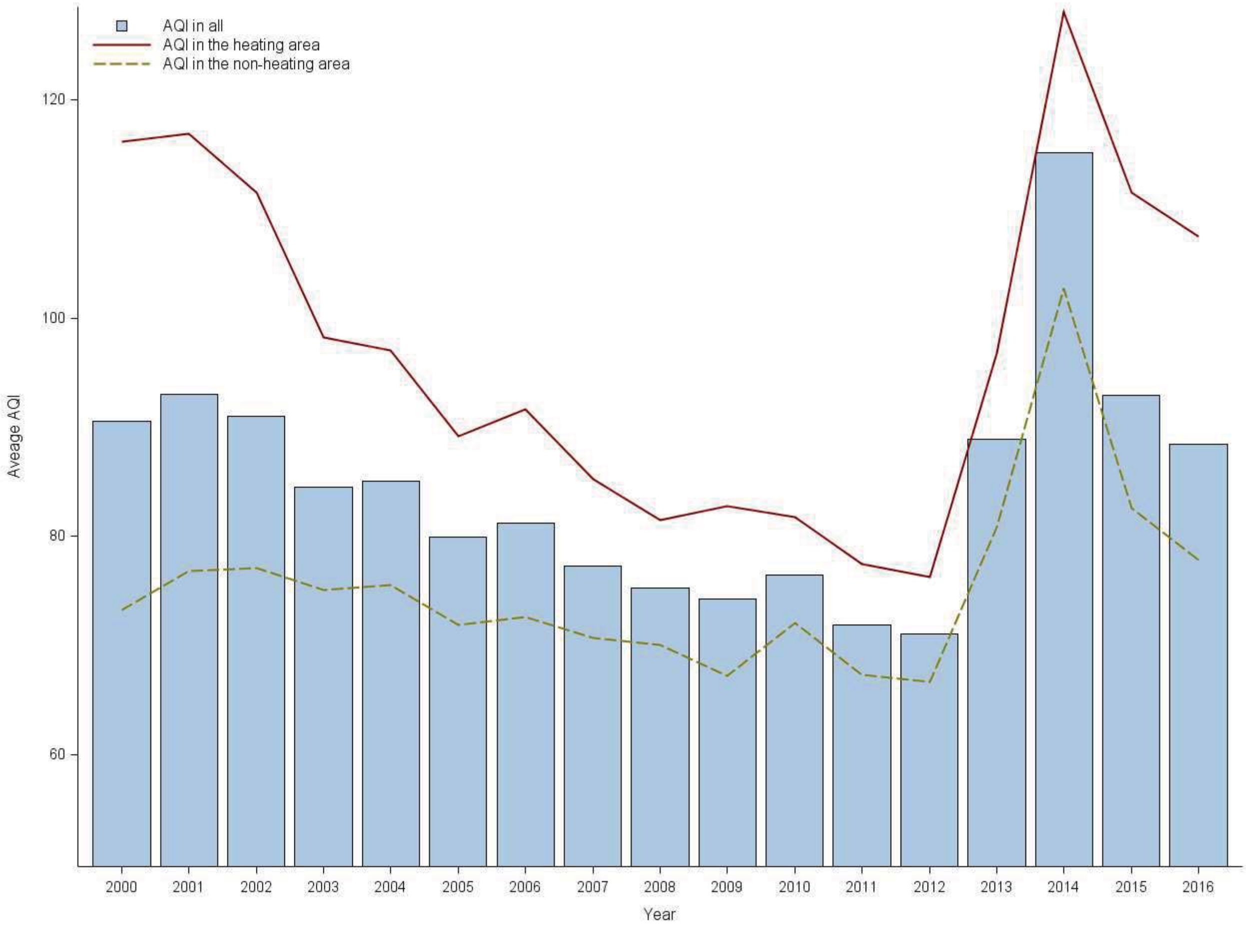


Figure 4: Regression Discontinuity Plots of AQI

This figure plots the Air Quality Index (*AQI*) across the Qinling-Huai River. Each dot is generated by averaging *AQI* across locations within 0.1° of latitude. The x-axis represents the latitude degree, with 0° indicating the latitude of the Qinling-Huai River boundary and positive (negative) degrees indicating areas on the heating (non-heating) side of the boundary. The line represents the fitted values of *AQI* from a linear regression. The shaded area represents a 90% confidence interval around the fitted value.

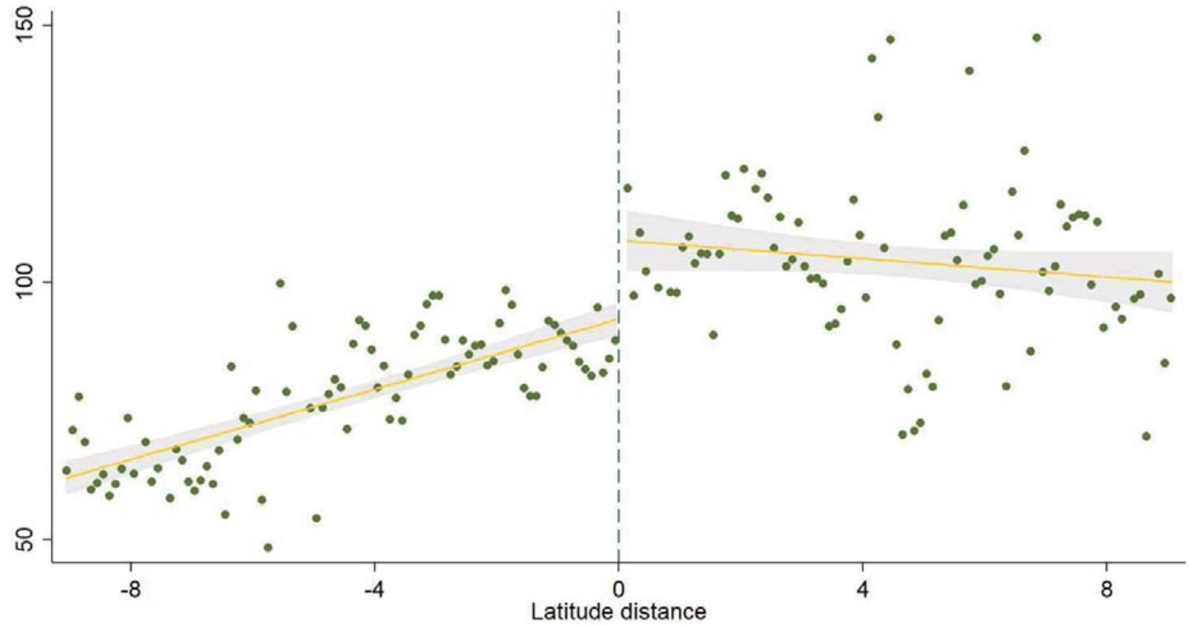
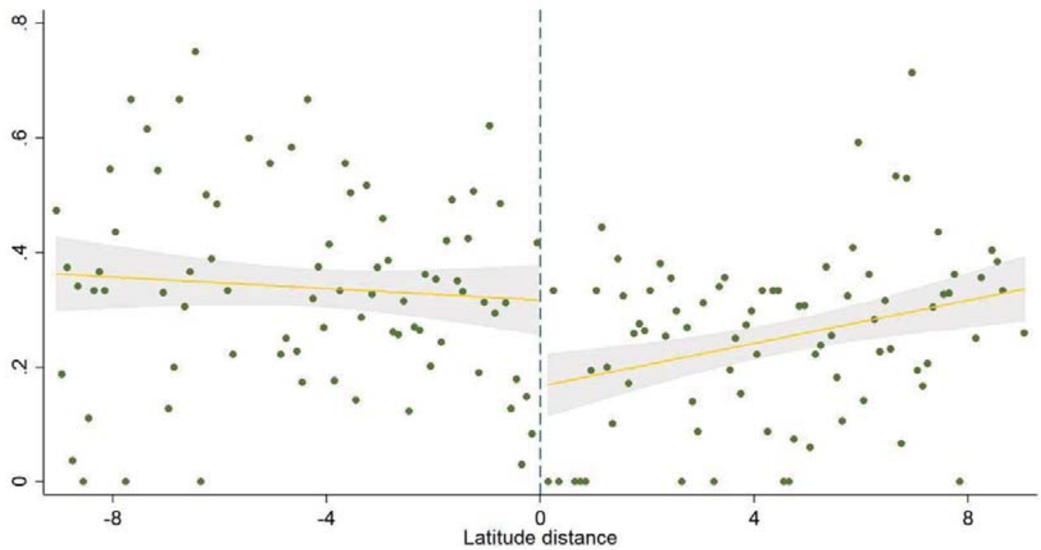


Figure 5: Regression Discontinuity Plots of Human Capital

This figure plots the human capital of firms across the Qinling-Huai River. Panel A plots average executive talent in a region, which is the average of *Non-locally born executives*, *Non-locally educated executives,* and *Executives with overseas experience*. Panel B plots the average percentage of high-quality employees, which is the average of *% of highly educated employees* and *% of skilled employees*. Each dot is generated by averaging the human capital measures of firms across locations within 0.1° of latitude. The x-axis represents the latitude degree, with 0° indicating the latitude of the Qinling-Huai River boundary and positive (negative) degrees indicating areas on the heating (non-heating) side of the boundary. The line represents the fitted values of human capital from a linear regression. The shaded area represents a 90% confidence interval around the fitted value.

Panel A: Executive talent



Panel B: % of high-quality employees

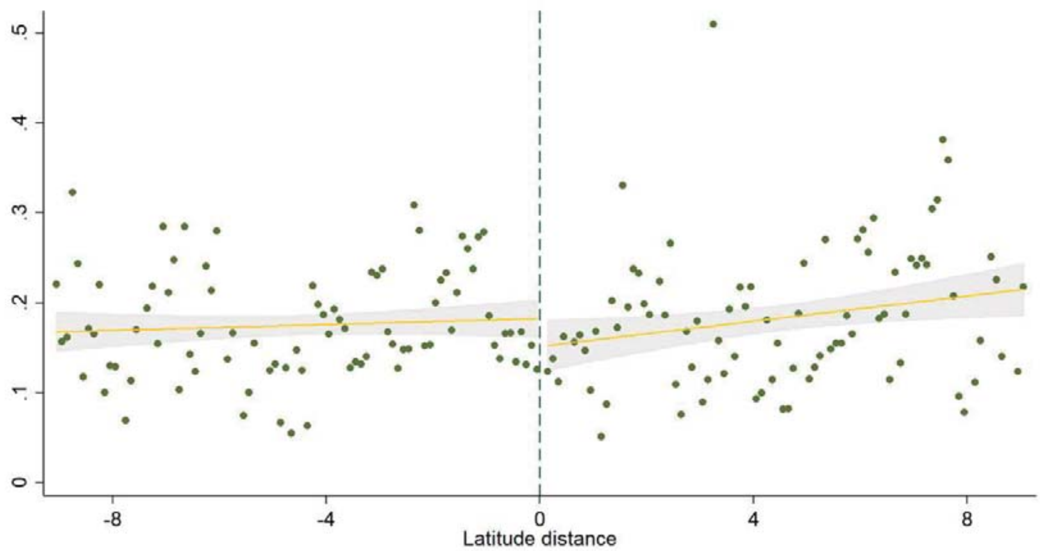


Figure 6: Falsification Tests for the Human Capital Effects

This figure plots the distribution of human capital RDD estimates based on artificially assumed latitude lines. We make 1,000 random assignments of latitude lines other than the Qinling-Huai River. The x-axis is the estimated coefficients on *QH*. The y-axis represents the fraction of the estimates. The solid vertical line is the RDD estimate using the true latitude of the Qinling-Huai River. The dashed line is the 10th percentile estimates.

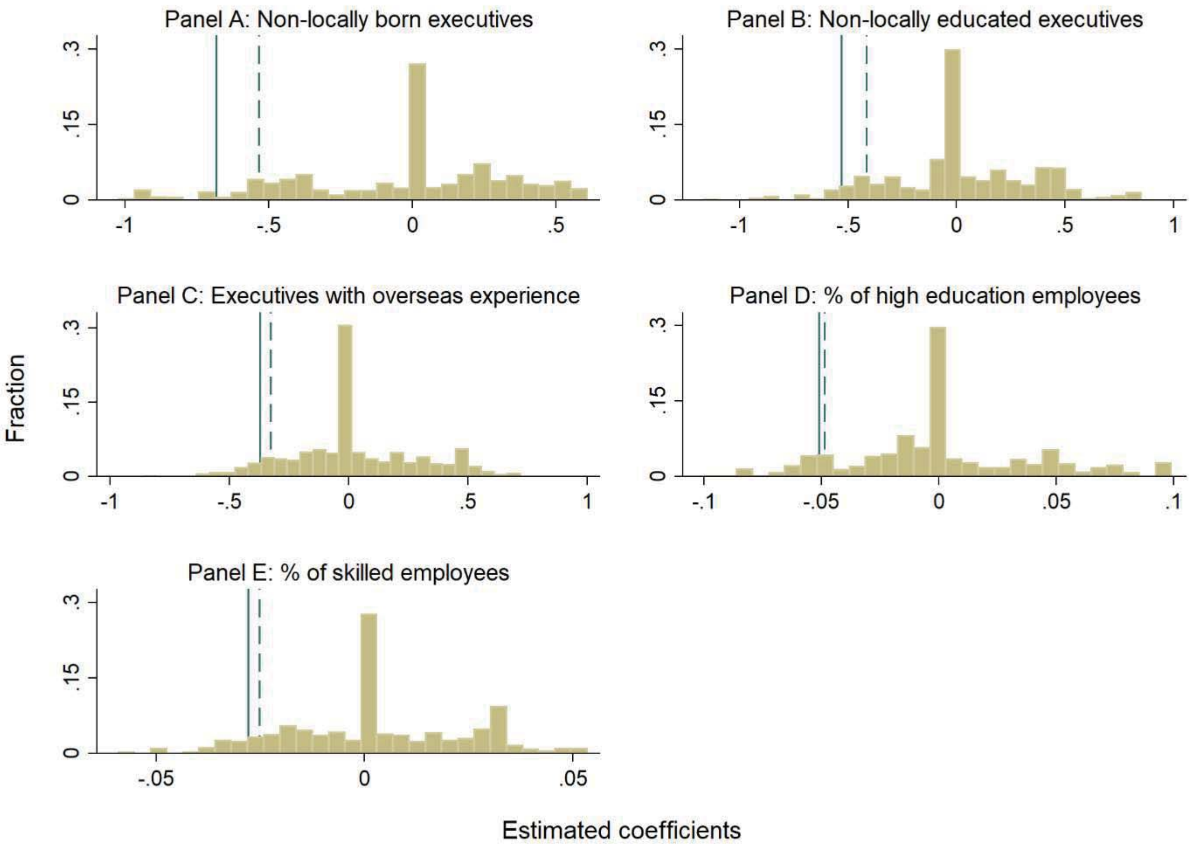


Figure 7: RDD Bandwidths and the Human Capital Effects

This figure plots the local RDD estimates with alternative bandwidths of the distance between firm location and the Qinling-Huai River. The x-axis represents the latitude distance from the Qinling-Huai River. The y-axis represents the estimated coefficients.

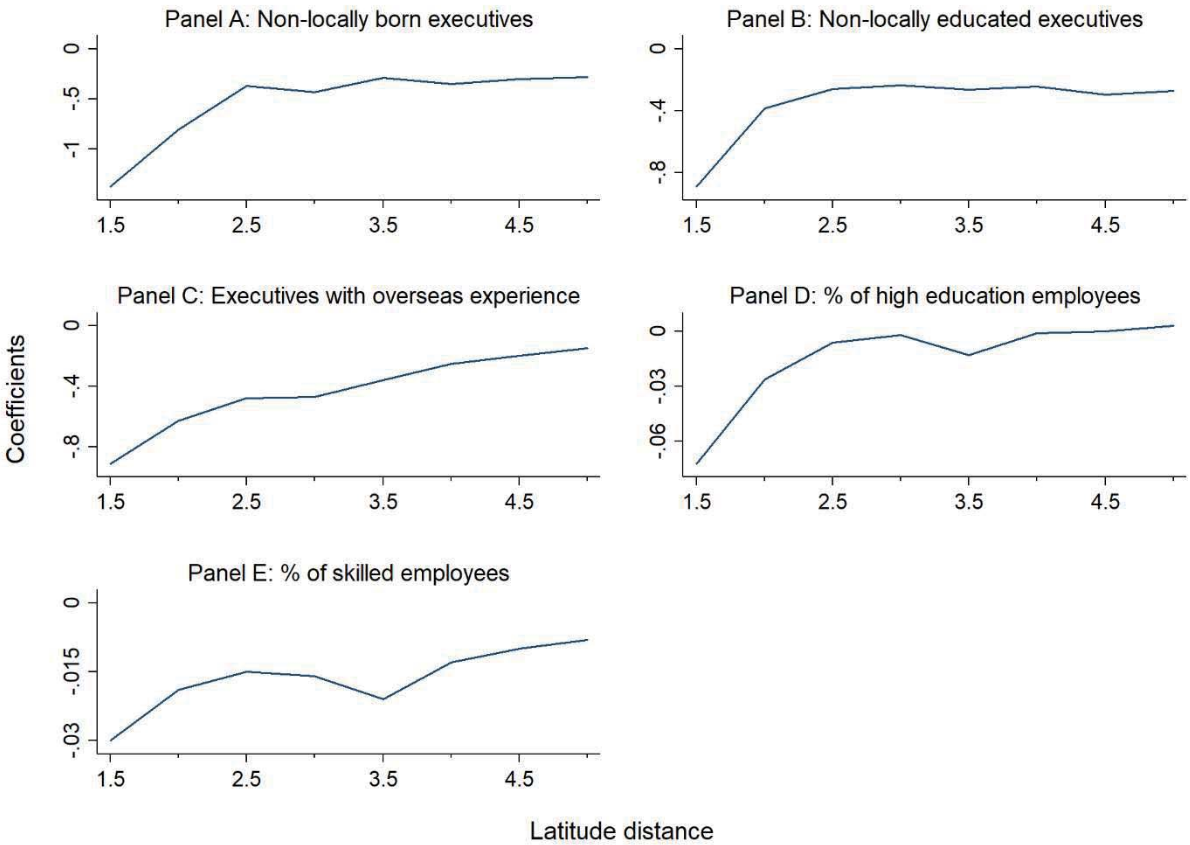


Table 1
Variables Summary Statistics

This table reports the summary statistics of the main variables used in the study. Panel A presents the statistics of variables used in the analysis of intended places of work. Panel B presents the statistics of variables used in the analysis of human capital and firm performance. All variables are defined in Table IA1.

Panel A: the analysis of intended places of work

Variables	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
To work in Beijing	282,630	1.01	1.81	0.00	0.00	0.00
To work in Shenzhen	282,630	0.84	1.69	0.00	0.00	0.00
To work in more polluted cities	282,630	1.07	1.47	0.00	0.00	2.52
To work in less polluted cities	282,630	1.42	1.60	0.00	0.00	2.58
Pollution days	282,630	0.39	0.49	0.00	0.00	1.00
Education expenditure	282,630	0.03	0.05	0.02	0.03	0.04
GDP growth	282,630	0.16	2.33	0.06	0.08	0.11
GDP per capita	282,630	6.10	5.33	2.91	4.54	7.15
Population	282,630	15.21	0.66	14.81	15.23	15.67
Temperature	282,630	15.15	4.56	13.96	16.00	17.42
Relative humidity	282,630	67.93	10.65	58.08	69.17	77.08
Precipitation	282,630	91.66	52.44	47.42	80.67	128.19
Sunshine hours	282,630	157.39	42.79	126.87	155.32	188.35
Health Beta	282,630	0.01	0.13	-0.05	0.01	0.07

Panel B: the analysis of human capital and firm performance

Variables	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
Non-locally born executives	17,952	0.36	0.48	0.00	0.00	1.00
Non-locally educated executives	15,998	0.49	0.50	0.00	0.00	1.00
Executives with overseas experience	19,114	0.09	0.29	0.00	0.00	0.00
% of highly educated employees	14,968	0.26	0.21	0.10	0.19	0.36
% of employees with a low level of education	15,641	0.70	0.42	0.41	0.66	0.92
% of skilled employees	15,109	0.19	0.15	0.09	0.14	0.24
% of production and sales employees	14,542	0.14	0.17	0.03	0.07	0.17
% of financial and administrative employees	14,095	0.14	0.11	0.07	0.12	0.18
Patents	31,776	1.85	15.68	0.00	0.00	0.70
TFP	31,393	0.12	0.29	0.01	0.03	0.09
Q	31,776	2.71	2.13	1.42	2.05	3.17
Sales growth	31,776	0.23	0.74	-0.01	0.11	0.28
QH	31,776	0.36	0.48	0.00	0.00	1.00
AQI	26,366	87.91	26.85	70.27	82.64	98.87
Firm size	31,776	21.68	1.35	20.77	21.50	22.36
Leverage	31,776	0.47	0.25	0.30	0.46	0.62
Cash flow	31,776	0.05	0.07	0.03	0.06	0.09
Capital expenditure	31,776	0.05	0.07	0.00	0.02	0.06
Firm age	31,776	1.91	0.90	1.39	2.08	2.64
Executive age	31,776	3.89	0.11	3.83	3.89	3.96
SOEs	31,776	0.40	0.49	0.00	0.00	1.00
Education expenditure	31,776	0.02	0.01	0.01	0.02	0.03
GDP growth	31,776	0.13	0.07	0.09	0.12	0.17
GDP per capita	31,776	9.59	9.99	2.97	6.51	13.15
Population	31,776	15.57	0.72	15.12	15.67	16.11
Temperature	31,776	16.31	4.17	14.08	16.79	18.22
Relative humidity	31,776	67.80	9.50	59.08	70.25	74.58
Precipitation	31,776	97.44	49.46	58.21	89.75	128.19
Sunshine hours	31,776	155.08	37.91	131.91	150.10	184.26

Table 2
The Impact of Air Pollution on Intended Workplaces

This table presents the results of DID models estimating the effect of air pollution on people's intended workplaces. A day in a municipal region is referred to as a pollution day (day 0) if the increase in daily AQI exceeds one standard of the daily AQI change in the past one year in the region. *Pollution days* refers to a five-day window from pollution day 0 to day 4 in a region. The intention of people in a region to work in a specific city is measured by the Baidu Search Volume Index (SVI). Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. *To work in Beijing* is the log of the daily Baidu SVI of "北京找工作" (to work in Beijing) in a region. *To work in Shenzhen* is the log of the daily Baidu SVI of "深圳找工作" (to work in Shenzhen) in a region. Columns (3) and (4) show the estimates for people's intention to work in the top work-intended cities in China, which are grouped into more and less polluted cities. *To work in more polluted cities* is the log of the average daily Baidu SVI for workplaces of the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian). *To work in less polluted cities* is the log of the average daily Baidu SVI for workplaces of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou). Regional characteristics (*Education expenditure*, *GDP growth*, *GDP per capita*, *Population*, *Temperature, Relative humidity*, *Precipitation, Sunshine hours*) are controlled. Table IA.1 presents detailed variable definitions. The analysis is based on daily observations for all municipal regions in China with data available from 2011 to 2016. In all regressions, city and date fixed effects are included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variables	(1) *To work in Beijing*	(2) *To work in Shenzhen*	(3) *To work in more polluted cities*	(4) *To work in less polluted cities*
Pollution days	**-0.075*** **	**0.045*** **	**-0.074*** **	**0.015*** **
	(-11.86)	**(7.15)**	**(-15.79)**	**(2.86)**
Education expenditure	1.048***	0.705***	0.679***	0.214***
	(13.75)	(10.26)	(12.18)	(3.44)
GDP growth	-0.002	0.002	0.002	-0.006***
	(-1.33)	(1.10)	(1.58)	(-5.91)
GDP per capita	0.168***	0.133***	0.130***	0.049***
	(31.11)	(27.41)	(35.11)	(12.15)
Population	1.515***	0.978***	1.459***	0.920***
	(18.45)	(14.90)	(24.26)	(14.33)
Temperature	0.048***	0.036***	0.053***	-0.028***
	(3.93)	(3.28)	(6.03)	(-3.07)
Relative humidity	-0.001	-0.004***	0.000	-0.005***
	(-0.39)	(-2.87)	(0.36)	(-3.89)
Precipitation	0.000	0.000**	0.001***	0.001***
	(0.92)	(2.41)	(4.25)	(4.80)
Sunshine hours	0.000	0.000	-0.001***	0.001***
	(0.55)	(1.23)	(-4.44)	(4.04)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.380	0.521	0.524

Table 3
Falsification Tests on the Impact of Air Pollution on Intended Workplaces

This table presents the results of falsification tests estimating the effect of air pollution on people's intended places of work. We make random assignments of air pollution days to each regional city. The assignments are made such that the frequency of randomly assigned air pollution days is the same as the frequency of true air pollution days. We create a variable *Pollution days (random)*, referring to a five-day window following the randomly assigned air pollution day in a region. The intention of people in a region to work in a specific city is measured by the Baidu Search Volume Index (SVI). Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. *To work in Beijing* is the log of the daily Baidu SVI of "北京找工作" (to work in Beijing) in a region. *To work in Shenzhen* is the log of the daily Baidu SVI of "深圳找工作" (to work in Shenzhen) in a region. Columns (3) and (4) show the estimates for people's intention to work in the top work-intended cities in China, which are grouped into more and less polluted cities. *To work in more polluted cities* is the log of the average daily Baidu SVI for workplaces of the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian). *To work in less polluted cities* is the log of the average daily Baidu SVI for workplaces of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou). Regional characteristics (*Education expenditure*, *GDP growth*, *GDP per capita*, *Population*, *Temperature, Relative humidity*, *Precipitation, Sunshine hours*) are controlled. Table IA.1 presents detailed variable definitions. The analysis is based on daily observations for all municipal regions in China with data available from 2011 to 2016. In all regressions, city and date fixed effects are included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variables	(1) *To work in Beijing*	(2) *To work in Shenzhen*	(3) *To work in more polluted cities*	(4) *To work in less polluted cities*
Pollution days (random)	**0.005**	**0.006**	**-0.002**	**0.000**
	(0.97)	**(1.03)**	**(-0.52)**	**(0.10)**
Education expenditure	1.030***	0.716***	0.661***	0.217***
	(13.51)	(10.43)	(11.85)	(3.51)
GDP growth	-0.002	0.002	0.002	-0.006***
	(-1.35)	(1.11)	(1.56)	(-5.90)
GDP per capita	0.166***	0.134***	0.128***	0.049***
	(30.87)	(27.64)	(34.76)	(12.26)
Population	1.512***	0.980***	1.456***	0.921***
	(18.44)	(14.90)	(24.26)	(14.33)
Temperature	0.047***	0.036***	0.052***	-0.027***
	(3.81)	(3.37)	(5.87)	(-3.04)
Relative humidity	-0.001	-0.004***	0.000	-0.005***
	(-0.41)	(-2.85)	(0.33)	(-3.88)
Precipitation	0.000	0.000**	0.001***	0.001***
	(1.05)	(2.32)	(4.41)	(4.77)
Sunshine hours	0.000	0.000	-0.001***	0.001***
	(0.85)	(0.99)	(-4.04)	(3.96)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.380	0.520	0.524

Table 4
The Impact of Air Pollution on Intended Places of Work and Pollution-induced Health Concerns

This table presents the results of DID models estimating how the effect of air pollution on people's intended places of work varies with health concern induced by air pollution. The intensity of people's concern for health is measured by *Health Beta*, which is the sensitivity of the change in daily Baidu Search Volume Index of "health (健康)" to the change in AQI in a region in a year. A day in a municipal region is referred to as a pollution day (day 0) if the increase in daily AQI exceeds one standard deviation of the daily AQI change in the past year in the region. *Pollution days* refers to a five-day window from pollution day 0 to day 4 in a region. The intention of people in a region to work in a specific city is measured by the Baidu Search Volume Index (SVI). Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. *To work in Beijing* is the log of the daily Baidu SVI of "北京找工作" (to work in Beijing) in a region. *To work in Shenzhen* is the log of the daily Baidu SVI of "深圳找工作" (to work in Shenzhen) in a region. Columns (3) and (4) show the estimates for people's intention to work in top work-intended cities in China, which are grouped into more and less polluted cities. *To work in more polluted cities* is the log of the average daily Baidu SVI for workplaces of the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian). *To work in less polluted cities* is the log of the average daily Baidu SVI for workplaces of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou). Regional characteristics (*Education expenditure*, *GDP growth*, *GDP per capita*, *Population*, *Temperature, Relative humidity*, *Precipitation, Sunshine hours*) are controlled. Table IA.1 presents detailed variable definitions. The analysis is based on daily observations for all municipal regions in China with data available from 2011 to 2016. In all regressions, city and date fixed effects are included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variables	(1) *To work in Beijing*	(2) *To work in Shenzhen*	(3) *To work in more polluted cities*	(4) *To work in less polluted cities*
Pollution days	**-0.075*** **	**0.043*** **	**-0.074*** **	**0.014*** **
	(-11.77)	**(6.86)**	**(-15.74)**	**(2.61)**
Pollution days × Health Beta	**-0.082** **	**0.106*** **	**-0.052** **	**0.082** **
	(-2.48)	**(2.87)**	**(-1.98)**	**(2.41)**
Health Beta	-0.011	-0.303***	-0.005	-0.229***
	(-0.39)	(-10.00)	(-0.25)	(-8.65)
Education expenditure	1.050***	0.721***	0.680***	0.226***
	(13.78)	(10.49)	(12.20)	(3.64)
GDP growth	-0.002	0.001	0.002	-0.006***
	(-1.37)	(0.91)	(1.55)	(-6.13)
GDP per capita	0.168***	0.135***	0.130***	0.051***
	(31.12)	(27.82)	(35.05)	(12.64)
Population	1.502***	0.926***	1.451***	0.881***
	(18.31)	(14.17)	(24.24)	(13.74)
Temperature	0.048***	0.037***	0.053***	-0.026***
	(3.92)	(3.43)	(6.03)	(-2.94)
Relative humidity	-0.000	-0.003**	0.001	-0.004***
	(-0.25)	(-2.03)	(0.48)	(-3.19)
Precipitation	0.000	0.000**	0.001***	0.001***
	(0.90)	(2.27)	(4.24)	(4.68)
Sunshine hours	0.000	0.000	-0.001***	0.001***
	(0.59)	(1.25)	(-4.41)	(4.06)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.381	0.521	0.525

Table 5
The Impact of Air Pollution on Executive Talent

This table presents the results of RDD probit models estimating the effects of air pollution on executive talent. The dependent variables are *Non-locally born executives, Non-locally educated executives*, and *Executives with overseas experience*. The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. At the bottom of the columns, the marginal effect of being located in the heating area (i.e., the difference in probability of having the respective executive talent in the heating and non-heating areas) is reported. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**-0.682*****	**-0.529*****	**-0.373****
	(-3.60)	**(-3.06)**	**(-2.09)**
Firm size	0.085***	0.063***	0.088***
	(3.58)	(2.90)	(3.62)
Leverage	0.280**	0.045	-0.368***
	(2.13)	(0.41)	(-2.61)
Cash flow	-0.442	0.216	-0.350
	(-1.51)	(0.77)	(-0.88)
Capital expenditure	-0.108	-0.314	0.410*
	(-0.50)	(-1.47)	(1.65)
Firm age	0.092***	0.113***	-0.037
	(2.83)	(3.76)	(-1.17)
Executive age	-0.364*	-0.776***	-0.758***
	(-1.65)	(-3.58)	(-2.78)
SOEs	0.036	-0.200***	-0.324***
	(0.58)	(-3.31)	(-4.86)
Education expenditure	14.924***	4.908	3.301
	(4.24)	(1.48)	(0.80)
GDP growth	0.065	0.021	-0.096
	(0.24)	(0.07)	(-0.27)
GDP per capita	0.020***	0.015***	0.013***
	(5.41)	(4.47)	(3.84)
Population	0.103*	-0.156***	-0.001
	(1.80)	(-3.00)	(-0.01)
Temperature	0.031	-0.038	0.034
	(1.24)	(-1.62)	(1.20)
Relative humidity	-0.006	-0.011*	0.008
	(-1.04)	(-1.90)	(1.23)
Precipitation	-0.000	-0.001	0.000
	(-0.34)	(-1.35)	(0.35)
Sunshine hours	-0.001	-0.004***	-0.000
	(-0.61)	(-3.22)	(-0.15)
Polynomial	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	17,952	15,998	19,114
R-squared	0.087	0.081	0.065
Pr(QH=0|$\bar{X}$))-Pr(QH=1|$\bar{X}$)	23.10%	19.30%	6.82%

Table 6
The Impact of Air Pollution on Employee Human Capital

The results of RDD estimating the effect of air pollution on employee structure. Panel A presents the estimates of the effect on employee structure by education, which are measured by *% of highly educated employees* and *% of employees with a low level of education*. Panel B presents the estimates of the effect on employee structure by job function, which are measured by *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: by education		**Panel B: by job function**		
	(1)	(2)	(3)	(4)	(5)
Dependent variables	*% of highly educated employees*	*% of employees with a low level of education*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
QH	**-0.051*** **	0.034	**-0.028** **	-0.003	-0.005
	(-2.75)	(0.93)	**(-2.13)**	(-0.19)	(-0.50)
Firm size	0.011***	-0.027***	-0.001	0.006***	-0.017***
	(3.86)	(-4.98)	(-0.37)	(2.66)	(-9.68)
Leverage	-0.087***	0.075**	-0.074***	-0.033***	0.018*
	(-5.64)	(2.51)	(-6.78)	(-2.70)	(1.94)
Cash flow	-0.022	-0.321***	-0.017	0.123***	-0.032
	(-0.50)	(-3.67)	(-0.52)	(3.50)	(-1.31)
Capital expenditure	-0.280***	0.240***	-0.113***	-0.153***	-0.099***
	(-9.96)	(4.32)	(-5.59)	(-6.48)	(-6.26)
Firm age	-0.008**	0.048***	-0.008***	-0.007**	0.020***
	(-2.44)	(7.85)	(-3.30)	(-2.39)	(10.40)
Executive age	-0.061**	0.089*	0.029	0.034	-0.037**
	(-2.34)	(1.71)	(1.49)	(1.48)	(-2.56)
SOEs	0.017**	-0.023*	0.006	-0.023***	-0.009**
	(2.30)	(-1.66)	(1.22)	(-3.65)	(-2.26)
Education expenditure	-0.692**	0.998	-0.489**	0.444	0.083
	(-2.22)	(1.54)	(-2.15)	(1.49)	(0.44)
GDP growth	0.207***	-0.415***	0.047	0.150***	0.007
	(4.91)	(-4.60)	(1.51)	(4.04)	(0.27)
GDP per capita	0.001***	-0.001**	0.001**	0.000	-0.000
	(3.41)	(-2.08)	(2.32)	(1.35)	(-0.79)
Population	0.053***	-0.084***	0.026***	0.019***	0.013***
	(10.24)	(-7.90)	(6.92)	(4.37)	(4.84)
Temperature	0.002	-0.007	0.002	0.002	-0.001
	(0.98)	(-1.41)	(1.05)	(1.11)	(-0.95)
Relative humidity	-0.001	0.000	-0.001**	-0.000	-0.000
	(-1.12)	(0.15)	(-1.97)	(-0.53)	(-0.79)
Precipitation	-0.000**	0.000	0.000	-0.000	0.000
	(-2.56)	(1.26)	(1.22)	(-0.07)	(0.11)
Sunshine hours	0.000	-0.001*	-0.000	0.000	-0.000
	(1.10)	(-1.68)	(-0.60)	(1.47)	(-0.17)
Polynomial	Yes	Yes	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes	Yes
Observations	14,968	15,641	15,109	14,542	14,095
R-squared	0.384	0.246	0.319	0.281	0.211

Table 7
The Effect of Substantial Change in Air Pollution on Human Capital

This table presents the results of models estimating the effect of substantial change in air pollution on executive talent and employee structure. We exploit the abruptly broadened difference in *AQI* between heating and non-heating areas in 2014 to conduct a DID analysis based on a period from 2012 to 2015. *Post* equals one for years 2014 and 2015 (the post-period of the broadened difference) and zero for years 2012 and 2013 (the pre-period of broadened difference). We interact *Post* with *QH* and re-estimate Equation (3). Panel A reports the results of the probit model. The dependent variables are measures of executive talent, which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience.* Panels B and C report the results of the OLS model. In Panel B, the dependent variables are the measures of employee structure by education, which include *% of highly educated employees* and *% of employees with a low level of education.* In Panel C, the dependent variables are the measures of employee structure by job function, which include *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at the firm level are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**2.098**	**-3.648*** **	**-2.784** **
	(1.46)	**(-5.62)**	**(-2.32)**
QH* × *Post	**-0.196*** **	**-0.128** **	**-0.039**
	(-3.63)	**(-2.29)**	**(-0.44)**
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	5,502	6,204	6,251
R-squared	0.155	0.103	0.122

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
QH	**-0.081*** **	0.348***
	(-4.25)	(5.95)
QH* × *Post	**-0.008***	0.007
	(-1.83)	(0.56)
Polynomial	Yes	Yes
Firm and regional controls	Yes	Yes
Year, industry, and city FEs	Yes	Yes
Observations	9,912	10,321
R-squared	0.440	0.308

Panel C: Employee structure by job function

Dependent variables	(1) *% of skilled employees*	(2) *% of production and sales employees*	(3) *% of financial and administrative employees*
QH	**-0.111*** **	-0.001	0.032*
	(-5.67)	(-0.02)	(1.91)
QH* × *Post	**-0.006***	0.003	-0.005
	(-1.78)	(0.84)	(-1.59)
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	10,001	9,791	9,393
R-squared	0.364	0.335	0.256

Table 8
2SLS and the Effect of Air Pollution on Human Capital

This table presents the results of 2SLS estimation of the effect of air pollution on executive talent and employee structure. In the first stage, Air Quality Index (*AQI*) is regressed on *QH,* which indicates whether a firm is located in a region where the Qinling-Huai River heating policy applies (yes: one, no: zero). In the second stage, the fitted *AQI* from the first stage is regressed with the measures of executive talent (Panel A), which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*; the measures of employee structure by education (Panel B), which include *% of highly educated employees*, and *% of employees with a low level of education*; and the measures of employee structure by job function (Panel C), which includes *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. The F-statistic of the IV strength test is reported on the bottom of the column. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
Fitted *AQI*	**-7.391****	**-2.673****	**-0.865**
	(-1.98)	**(-2.14)**	**(-1.58)**
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	14,980	13,907	16,751
F-statistic for weak identification	4.479	14.64	13.58

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
Fitted *AQI*	**-0.685****	0.651
	(-2.37)	(1.24)
Polynomial	Yes	Yes
Firm and regional controls	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes
Observations	13,935	14,481
F-statistic for weak identification	26.18	26.98

Panel C: Employee structure by job function

Dependent variables	(1) *% of skilled employees*	(2) *% of production and sales employees*	(3) *% of financial and administrative employees*
Fitted *AQI*	**-0.442****	0.026	-0.223*
	(-2.37)	(0.11)	(-1.70)
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	13,999	13,468	13,079
F-statistic for weak identification	28.69	25.25	24.69

Table 9
Thermal Inversion Strength and the Effect of Air Pollution on Human Capital

This table presents the results of 2SLS estimation of the effect of air pollution on executive talent and employee structure. In the first stage, Air Quality Index (*AQI*) is regressed on thermal inversion strength (*TI*), which is the daily average of above-ground temperature minus ground temperature in the winter (Oct, Nov, Dec, Jan, Feb, and Mar) in a region. In the second stage, the fitted *AQI* from the first stage is regressed with the measures of executive talent (Panel A), which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*; the measures of employee structure by education (Panel B), which include *% of highly educated employees*, and *% of low education employee*; and the measures of employee structure by job function (Panel C), which includes *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. Table IA.1 presents detailed variable definitions. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. The F-statistic of the IV strength test is reported on the bottom of the column. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
Fitted *AQI*	**-1.513****	**-4.215*****	**-3.004*****
	(-2.24)	**(-2.95)**	**(-3.55)**
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	14,980	13,907	16,751
F-statistic for weak identification	26.91	13.99	18.26

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
Fitted *AQI*	**-0.714****	-0.162
	(-2.55)	(-0.36)
Firm and regional controls	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes
Observations	13,935	14,481
F-statistic for weak identification	22.91	29.27

Panel C: Employee structure by job function

Dependent variables	(1) *% of skilled employees*	(2) *% of production and sales employees*	(3) *% of financial and administrative employees*
Fitted *AQI*	**-0.108**	-0.169	-0.017
	(-0.58)	(-0.91)	(-0.13)
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	13,999	13,468	13,079
F-statistic for weak identification	21.03	26.54	23.62

Table 10
The Effect of Air Pollution and Heterogeneity on Concern for Health

This table reports the estimates of regressions examining how the effect of air pollution on human capital varies with heterogeneity in concern for health. The intensity of people's concern for health is measured by *Health Beta*, which is the sensitivity of the change in daily Baidu Search Volume Index for the keyword "health (健康)" to the change in AQI in a region in a year. We re-estimate the RDD regressions of human capital by including the interaction term between *Health Beta* and *QH*. Panel A reports the results of the RDD probit model. The dependent variables are the measures of executive talent, which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*. Panels B and C report the results of the RDD OLS model. In Panel B, the dependent variables are the measures of employee structure by education, which include *% of highly educated employees* and *% of employees with a low level of education*. In Panel C, the dependent variables are the measures of employee structure by job function, which include *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**-4.308*** **	**-3.850*** **	**-3.104*** **
	(-6.19)	**(-6.26)**	**(-5.52)**
QH* × *Health Beta	**-0.836*** **	**-1.490*** **	**-0.746**
	(-2.75)	**(-4.66)**	**(-1.53)**
Health Beta	0.342*	0.180	-0.073
	(1.94)	(1.03)	(-0.28)
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	8,443	9,539	10,887
R-squared	0.152	0.109	0.104

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
QH	**-0.113*** **	0.300***
	(-3.82)	(5.00)
QH* × *Health Beta	**-0.044** **	-0.038
	(-2.04)	(-0.54)
Health Beta	0.001	0.001
	(0.04)	(0.02)
Polynomial	Yes	Yes
Firm and regional controls	Yes	Yes
Year, industry, and city FEs	Yes	Yes
Observations	14,968	15,641
R-squared	0.442	0.304

Panel C: Employee structure by job function

	(1)	(2)	(3)
Dependent variables	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
QH	**-0.099*****	-0.002	0.044***
	(-4.72)	(-0.04)	(2.58)
QH × Health Beta	**-0.035****	-0.018	-0.015
	(-2.07)	(-1.02)	(-0.87)
Health Beta	0.008	0.008	-0.000
	(0.77)	(0.69)	(-0.05)
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	15,109	14,542	14,095
R-squared	0.367	0.331	0.260

Table 11
The Impact of Air Pollution on Firm Performance

This table presents the results of RDD estimation of the effect of air pollution on firm performance (innovation, productivity, firm value, and sales growth). Corporate innovation is measured by the number of invention patent applications filed per thousand employees (*Patents*). Productivity is measured by total factor productivity (*TFP*). Firm value is measured by the market value of total equity over book value of total equity (*Q*). Sales growth is the annual growth rate of total sales (*Sales growth*). The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
QH	**-1.252****	**-0.069*****	**-0.370*****	**-0.076*****
	(-2.23)	**(-4.28)**	**(-2.59)**	**(-2.90)**
Firm size	0.342*	-0.021***	-0.787***	0.004
	(1.96)	(-4.34)	(-25.47)	(0.63)
Leverage	-1.564**	0.064***	0.561***	0.268***
	(-2.35)	(2.96)	(3.12)	(8.71)
Cash flow	1.376	1.054***	3.037***	1.802***
	(1.31)	(19.59)	(7.70)	(19.08)
Capital expenditure	3.472	-0.584***	-0.766***	1.543***
	(1.38)	(-21.70)	(-5.00)	(14.83)
Firm age	0.084	-0.025***	0.002	0.014**
	(0.41)	(-5.84)	(0.08)	(2.05)
Executive age	-0.254	-0.071***	0.094	-0.311***
	(-0.15)	(-2.91)	(0.61)	(-6.71)
SOEs	-0.338	-0.025***	-0.148***	-0.076***
	(-1.11)	(-3.20)	(-3.49)	(-6.97)
Education expenditure	-3.771	1.464***	12.689***	1.755***
	(-0.32)	(3.87)	(4.72)	(2.79)
GDP growth	-1.618	-0.038	0.877***	0.147*
	(-1.14)	(-1.09)	(4.04)	(1.74)
GDP per capita	0.060***	0.002***	0.011***	0.001
	(3.41)	(4.56)	(3.41)	(1.47)
Population	0.831***	0.020***	0.111***	0.015*
	(3.05)	(3.98)	(3.09)	(1.77)
Temperature	-0.093	-0.001	0.009	0.003
	(-1.19)	(-0.33)	(0.51)	(0.73)
Relative humidity	0.006	-0.001**	-0.006	0.004***
	(0.33)	(-2.11)	(-1.29)	(3.06)
Precipitation	-0.002	-0.000	0.001	-0.000
	(-0.60)	(-0.29)	(1.63)	(-0.57)
Sunshine hours	-0.000	-0.000	-0.003***	0.001***
	(-0.04)	(-0.59)	(-3.30)	(3.13)
Polynomial	Yes	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes
Observations	31,776	31,393	31,776	31,776
R-squared	0.018	0.255	0.393	0.066

Table 12
The Effects on Firm Performance and Human Capital Dependence

This table reports the estimates of regressions examining how the effect of air pollution on corporate performance varies with firms' human capital dependence. Panels A and B report the results for the dependence of corporate performance on executive talent and high-quality employees, respectively. Specifically, the dependence of corporate performance on executive talent human capital is the estimated coefficient of the model that regresses each of the firm performance measures (i.e., *Patents*, *TFP*, *Q*, and *Sales growth*) on the executive talent index (i.e. the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*) within an industry over the past five years, with firm characteristics (i.e. *Firm size*, *Leverage*, *Cash flow*, *Capital expenditure*, *Firm age*, *Executive age*, and *SOEs*) included as controls. The estimated dependence of firm performance on executive talent is notated as *Pat-talents sensitivity*, *TFP-talents sensitivity*, *Q-talents sensitivity*, and *SG-talents sensitivity*, respectively. The dependence of corporate performance on high-quality employee human capital is the estimated coefficient of the model that regresses each of the firm performance measures on the high-quality employee index (i.e. the average of *% of highly educated employees* and *% of skilled employees*) within an industry over the past five years, with firm characteristics included as controls. The estimated dependence of firm performance on employee quality is notated as *Pat-employees sensitivity*, *TFP-employees sensitivity*, *Q-employees sensitivity*, and *SG-employees sensitivity*, respectively. The estimated human capital dependence for a particular measure of performance is interacted with *QH* and added to the RDD model that explains that measure of performance. Panels C and D report the results when human capital dependence is measured by average employee compensation (total employee compensation/total number of employees) and industry innovation. A firm is defined as having high human capital dependence if it has an average employee compensation above the sample median in a year (*High pay*=1) or operates in the industries of information technology, scientific research and technical service, or health and social work (*Innovative industries*=1). Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent human capital dependence

Dependent variables	(1) *Patents*	(2) *TFP*	(3) *Q*	(4) *Sales growth*
QH	-0.021	-0.056*	-0.942***	0.007
	(-0.02)	(-1.95)	(-2.65)	-0.11
QH × Pat-talents sensitivity	**-4.492****			
	(-2.27)			
QH × TFP-talents sensitivity		**-0.007****		
		(-2.50)		
QH × Q-talents sensitivity			**-0.021*****	
			(-3.04)	
QH × SG-talents sensitivity				**-0.004****
				(-2.21)
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes
Observations	31,776	31,393	31,117	31,615
R-squared	0.031	0.275	0.413	0.074

Panel B: High-quality employee human capital dependence

Dependent variables	(1) *Patents*	(2) *TFP*	(3) *Q*	(4) *Sales growth*
QH	-0.489	-0.052*	-0.924***	0.009
	(-0.40)	(-1.66)	(-2.63)	-0.14
QH × Pat-employees sensitivity	**-1.129****			
	(-2.15)			
QH × TFP-employees sensitivity		**-0.052****		
		(-2.16)		
QH × Q-employees sensitivity			**-0.039****	
			(-2.24)	
QH × SG-employees sensitivity				**-0.035***
				(-1.71)
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes
Observations	31,776	31,393	31,776	31,776
R-squared	0.031	0.275	0.414	0.074

Panel C: Average employee compensation

Dependent variables	(1) *Patents*	(2) *TFP*	(3) *Q*	(4) *Sales growth*
QH	-0.08	-0.025	-0.831**	0.013
	(-0.07)	(-0.77)	(-2.36)	-0.21
QH × High pay	**-0.161**	**-0.042*****	**-0.118***	**-0.066*****
	(-0.33)	**(-4.12)**	**(-1.71)**	**(-3.34)**
High pay	1.447***	0.066***	0.251***	0.009
	-5.45	-9.8	-5.48	-0.75
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Observations	31,776	31,393	31,776	31,776
R-squared	0.032	0.282	0.416	0.075

Panel D: Innovative industries

Dependent variables	(1) *Patents*	(2) *TFP*	(3) *Q*	(4) *Sales growth*
QH	-0.787	-0.058*	-0.955***	0.007
	(-0.66)	(-1.88)	(-2.73)	-0.1
QH* × *Innovative industries	**-0.169**	**-0.035***	**-0.257****	**-0.054****
	(-0.32)	**(-1.71)**	**(-2.12)**	**(-2.20)**
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes
Observations	31,776	31,393	31,776	31,776
R-squared	0.031	0.276	0.414	0.074

Internet Appendix
“Brain Drain: The Impact of Air Pollution on Firm Performance”

November 2019

Figure IA.1: AQI Distribution

This figure represents the AQI distribution using McCrary density tests on daily AQI for each city during 2000–2016. The y-axis represents the density. The x-axis represents the AQI.

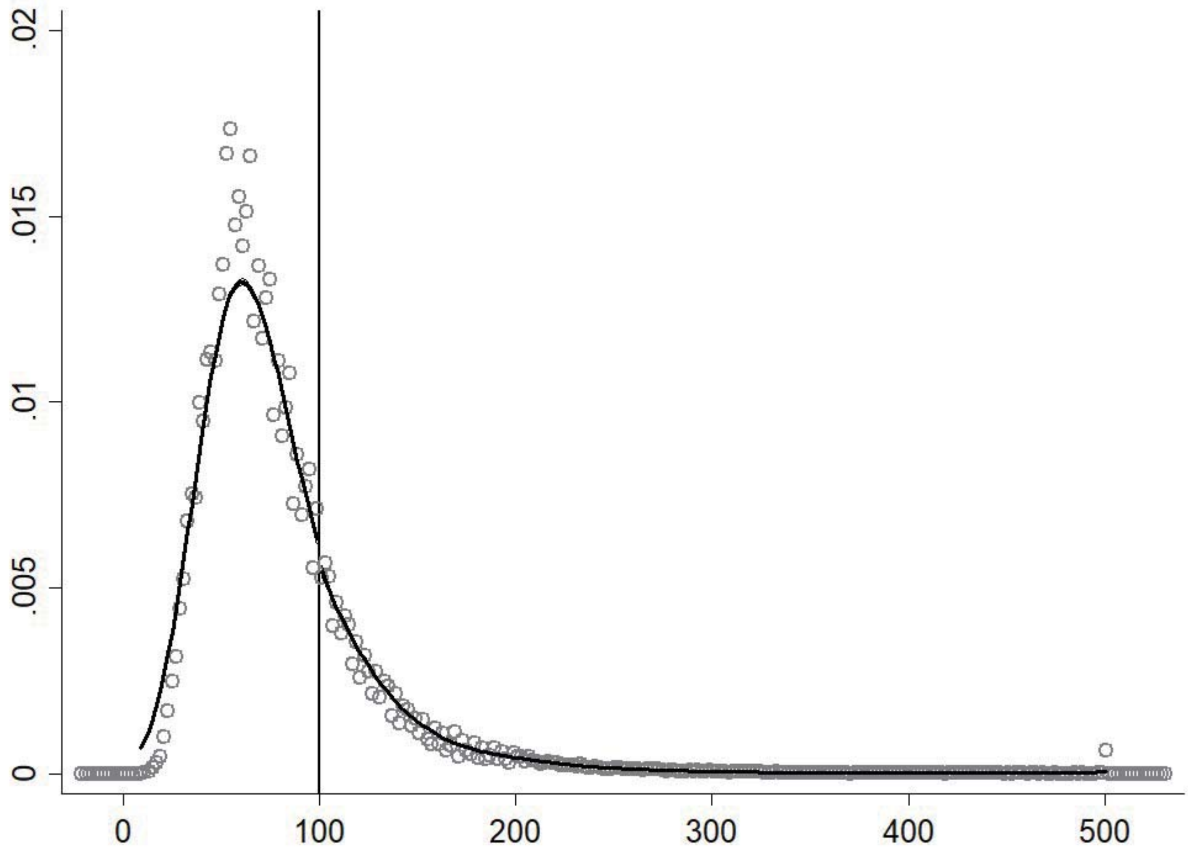


Figure IA.2: Regression Discontinuity Plots of Firm Performance

This figure plots the performance of firms across the Qinling-Huai River. Panel A plots the average *Patents* of firms in a region. Panel B plots the average total factor productivity (*TFP*) of firms in a region. Panel B plots the average firm value (*Q*) of firms in a region. Panel C plots the average total sales (*Sales growth*) of firms in a region. Each dot is generated by averaging outcomes of firms across locations within 0.1° of latitude. The x-axis represents the latitude degree, with 0° indicating the latitude of the Qinling-Huai River boundary and positive (negative) degrees indicating areas on the heating (non-heating) side of the boundary. The line represents the fitted values of outcomes from a linear regression. The shaded area represents a 90% confidence interval around the fitted value.

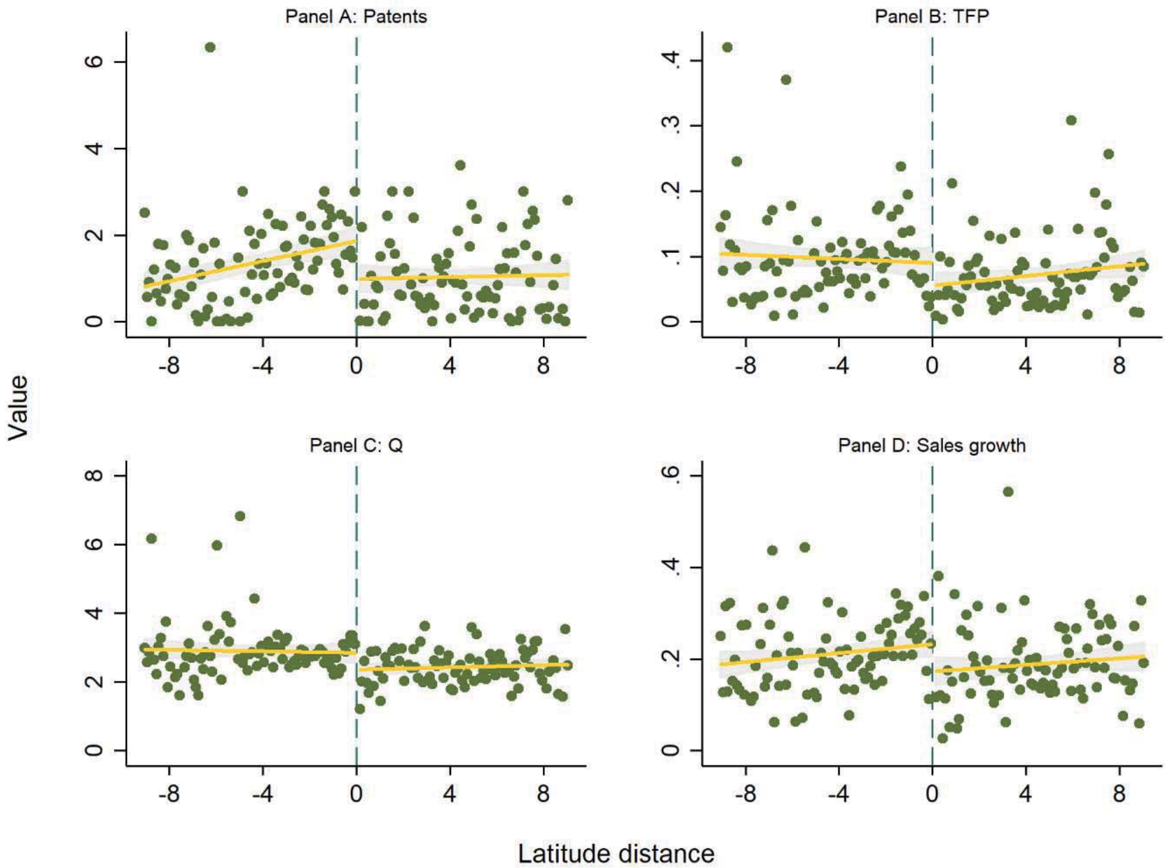


Figure IA.3: Falsification Tests for the Firm Performance Effects

This figure plots the distribution of firm performance RDD estimates based on artificially assumed latitude lines. We make 1,000 random assignments of latitude lines other than the Qinling-Huai River. The x-axis is the estimated coefficients on *QH*. The y-axis represents the fraction of the estimates. The solid vertical line is the RDD estimate using the true latitude of the Qinling-Huai River. The dashed lines are the 10th percentile estimates.

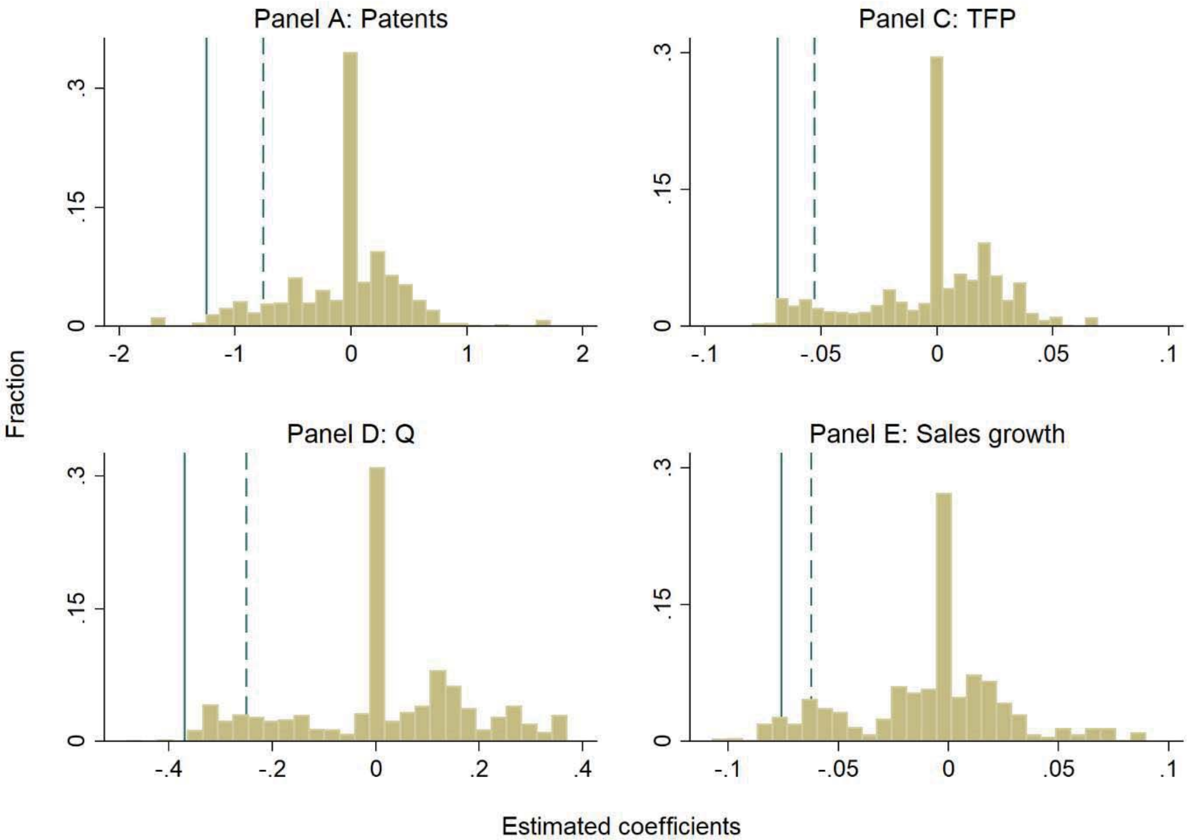


Figure IA.4: RDD Bandwidths and Firm Performance Effects

This figure plots the local RDD estimates with alternative bandwidths of the distance between firm location and the Qinling-Huai River. The x-axis represents the latitude distance from the Qinling-Huai River. The y-axis represents the estimated coefficients.

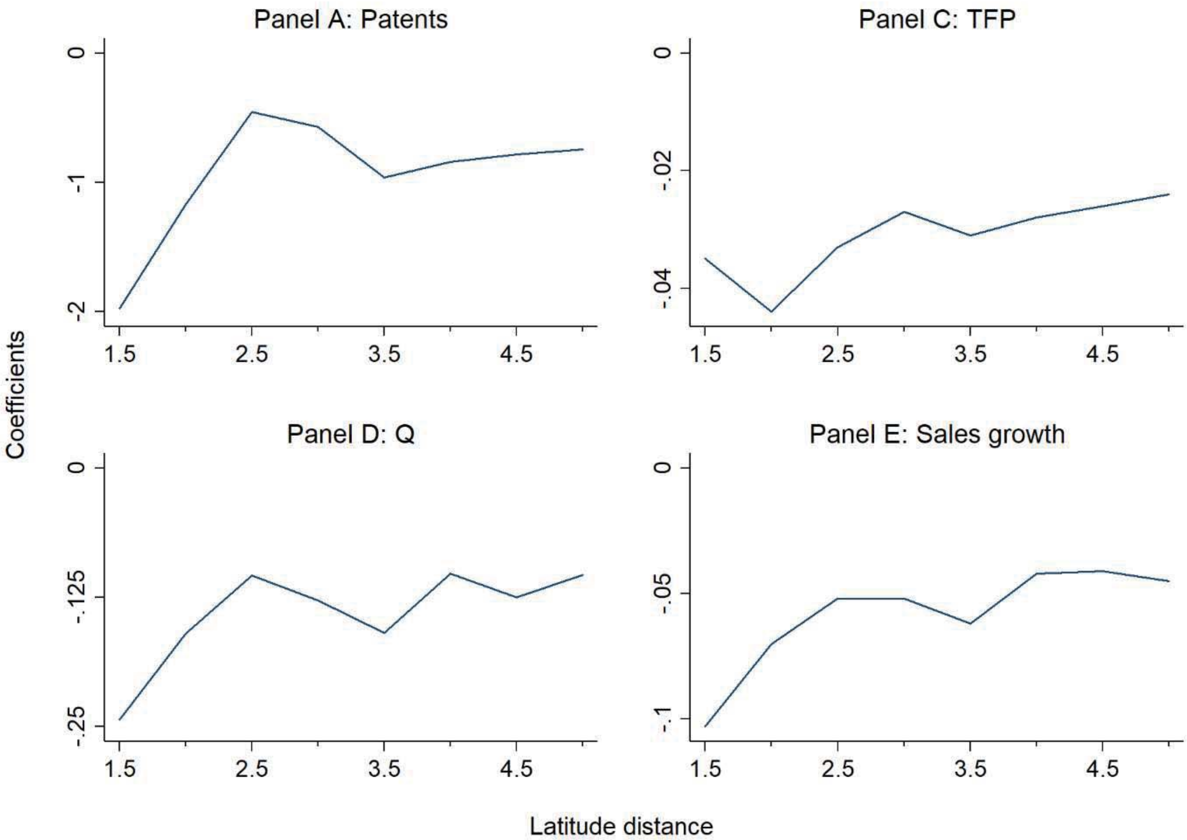


Table IA.1
Variable Definitions and Data Sources

Variables	Definitions	Sources	Period
Human capital variables:			
Non-locally born executives	1 if CEO or chairman was born in a region that is outside the province in which the firm is domiciled and 0 otherwise. It is filled with a missing value if the CEO and chairman's birthplace information cannot be identified.	GTA_TMT/CSMAR, CCXE, and Manually collected	2000–2016
Non-locally educated executives	1 if CEO or chairman received a degree from a university or college in a region that is outside the province in which the firm is domiciled and 0 otherwise. It is filled with a missing value if the CEO and chairman's education information cannot be identified.	GTA_TMT/CSMAR, CCXE, and Manually collected	2000–2016
Executives with overseas experience	1 if the CEO or chairman has study or work experience abroad and 0 otherwise. It is filled with a missing value if the CEO and chairman's education and work information cannot be identified.	GTA_TMT/CSMAR, CCXE, and Manually collected	2000–2016
% of highly educated employees	The number of employees with a bachelor's degree or above, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of employees with a low level of education	The number of employees whose highest education level is high school or below, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of skilled employees	The number of technical employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of production and sales employees	The number of production and sales employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of financial and administrative employees	The number of financial, HR, administrative employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016
Firm performance variables:			
Patents	The number of invention patent applications filed per thousand employees.	GTA_LCPT/CSMAR, Employee structure/Wind	2000–2016
TFP	Total factor productivity, estimated for each firm using the methodology developed by Levinsohn-Petrin (2003) where the output (y) is the firm's net profits (net value added) and firm labor (L) is the number of employees, and firm capital is property, plant, and equipment (PPE).	GTA_FS/CSMAR	2000–2016
Q	The market value of total equity over book value of total equity.	GTA_FS/CSMAR; GTA_TRD/CSMAR	2000–2016
Sales growth	The annual growth rate of total sales.	GTA_FS/CSMAR	2000–2016
Firm explanatory variables:			
QH	1 if a firm is located in a place where the region's latitude distance from the line of Qinling-Huai River (the former - the latter) is positive and 0 otherwise.	SAS Maps, and Manually collected	2000–2016
Firm size	Log(total assets).	GTA_FS/CSMAR	2000–2016
Leverage	Total liability/total assets.	GTA_FS/CSMAR	2000–2016

Cash flow	Operating income before depreciation and amortization/total assets.	GTA_FS/CSMAR	2000–2016
Capital expenditure	Capital expenditure over total assets.	GTA_FS/CSMAR	2000–2016
Firm age	Log of the number of years since the establishment of the firm.	GTA_TRD/CSMAR	2000–2016
Executive age	Log of the average age of firm CEO and chairman of the board of directors.	GTA_TMT/CSMAR	2000–2016
SOEs	1 if the firm is ultimately controlled by the state and 0 otherwise.	GTA_HLD/CSMAR	2000–2016
Regional variables:			
To work in Beijing	Log of the daily Baidu SVI of "北京找工作" (to work in Beijing) in a municipal region.	Index.Baidu.com	2011–2016
To work in Shenzhen	Log of the daily Baidu SVI of "深圳找工作" (to work in Shenzhen) in a municipal region.	Index.Baidu.com	2011–2016
To work in more polluted cities	Log of the average daily Baidu SVI for workplaces of the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian) in a region.	Index.Baidu.com	2011–2016
To work in less polluted cities	Log of the average of the daily Baidu SVI for workplaces of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou) in a municipal region.	Index.Baidu.com	2011–2016
Education expenditure	Government expenditure on education scaled by GDP for a region in a year.	GTA_CRE/CSMAR	2000–2016
GDP growth	GDP growth rate for a region in a year.	GTA_CRE/CSMAR	2000–2016
GDP per capita	Log(GDP per capita) for a region in a year.	GTA_CRE/CSMAR	2000–2016
Population	Log(number of population) for a region in a year.	GTA_CRE/CSMAR	2000–2016
Temperature	The monthly average temperature (℃) in a region in a year.	GTA_RES/CSMAR	2000–2016
Relative humidity	The monthly average relative humidity (%) in a region in a year.	GTA_RES/CSMAR	2000–2016
Precipitation	The monthly average precipitation (mm) in a region in a year.	GTA_RES/CSMAR	2000–2016
Sunshine hours	The monthly average sunshine hours (hrs) in a region in a year.	GTA_RES/CSMAR	2000–2016
AQI	The average daily Air Quality Index for a region in the winter (Oct, Nov, Dec, Jan, Feb, and Mar). China's Ministry of Environmental Protection (MEP) is responsible for measuring the level of air pollution in China and publishing the Air Quality Index.	GTA_CRE/CSMAR	2000–2016
TI	Thermal inversion strength, which is the daily average of above-ground temperature minus ground temperature in the winter (Oct, Nov, Dec, Jan, Feb, and Mar) in a region.	NASA	2000–2016
Health Beta	The estimated beta of the following time-series model: *%Change of Search_Health t*=beta**%Change of AQI t* + FEs + e t where *%Change of Search_Health t* is the percentage change of daily Baidu Search Volume Index by the word of "health (健康)" in a region on day t; *%Change of AQI t* is the percentage change of AQI in a region on day t. FEs are the month, weekday, and Chinese New Year fixed effects. The model is estimated for each municipal region in each year.	Index.Baidu.com, GTA_CRE/CSMAR	2011–2016

Table IA.2
Differences of Characteristics on the Two Sides of the Heating Boundary

This table reports the differences in the characteristics of firms on the two sides of the heating boundary (2 degrees around the line of Qinling-Huai River). Panel A reports the mean and difference of firm and regional characteristics on the heating and non-heating sides of the boundary. Panel B reports the mean and difference of firm expected human capital and performance on the two sides of the boundary. The expected firm outcomes are the fitted values by regressing the outcome variables on firm characteristics (i.e., *Firm size*, *Leverage*, *Cash flow*, *Capital expenditure*, *Firm age*, *Executive age*, and *SOEs*). All variables are defined in Table IA.1. The p-value of testing the difference is reported in Column 4.

	Non-heating side	Heating side	Difference (heating – non-heating)	
	Mean	Mean	Estimate	p-value
	(1)	(2)	(3)	(4)
Panel A: Firm and regional characteristics				
AQI	88.532	100.248	11.715	0.000
Firm size	21.610	21.733	0.123	0.110
Leverage	0.451	0.445	-0.006	0.737
Cash flow	0.056	0.059	0.003	0.569
Capital expenditure	0.048	0.048	-0.001	0.894
Firm age	1.736	1.661	-0.076	0.283
Executive age	3.904	3.910	0.006	0.439
SOEs	0.339	0.492	0.153	0.000
Education expenditure	0.016	0.029	0.014	0.000
GDP growth	0.137	0.130	-0.007	0.102
GDP per capita	8.705	2.509	-6.197	0.000
Population	15.483	15.820	0.337	0.000
Temperature	16.530	16.237	-0.292	0.000
Relative humidity	71.469	68.366	-3.103	0.000
Precipitation	99.966	87.418	-12.548	0.000
Sunshine hours	155.847	154.872	-0.975	0.319
Panel B: Expected firm human capital and performance				
Non-locally born executives	0.191	0.191	0.000	0.947
Non-locally educated executives	0.289	0.283	-0.006	0.276
Executives with overseas experience	0.064	0.060	-0.004	0.203
% of highly educated employees	0.233	0.240	0.008	0.041
% of employees with a low level of education	0.667	0.657	-0.010	0.241
% of skilled employees	0.187	0.189	0.001	0.577
% of production and sales employees	0.127	0.126	-0.001	0.642
% of financial and administrative employees	0.113	0.110	-0.003	0.236
Patents	1.998	1.985	-0.013	0.908
TFP	0.131	0.128	-0.002	0.744
Q	2.804	2.764	-0.040	0.620
Sales growth	0.231	0.217	-0.014	0.217

Table IA.3
Local RDD and the Effect of Air Pollution on Human Capital

This table presents the results of local RDD estimating the effect of air pollution on executive talent and employee structure. Only firms located in regions with a distance smaller than two degrees in latitude from the QH boundary are included. Panel A reports the results of the local RDD probit model. The dependent variables are measures of executive talent, which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience.* Panels B and C report the results of the RDD OLS model. In Panel B, the dependent variables are the measures of employee structure by education, which include *% of highly educated employees* and *% of employees with a low level of education.* In Panel C, the dependent variables are the measures of employee structure by job function, which include *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed variable definitions. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**-0.806***** **(-9.16)**	**-0.384***** **(-5.03)**	**-0.627***** **(-5.09)**
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	4,332	3,799	4,644
R-squared	0.0954	0.0761	0.102

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
QH	**-0.026**** **(-2.33)**	0.039* (1.72)
Firm and regional controls	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes
Observations	4,057	4,212
R-squared	0.344	0.189

Panel C: Employee structure by job function

Dependent variables	(1) *% of skilled employees*	(2) *% of production and sales employees*	(3) *% of financial and administrative employees*
QH	**-0.019**** **(-2.35)**	0.010 (1.21)	0.003 (0.45)
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	4,078	3,984	3,824
R-squared	0.278	0.318	0.267

Table IA.4
The Effects of Air Pollution on Human Capital Controlling for City Fixed Effects

This table presents the results of RDD models estimating the effects of air pollution on executive talent and employee structure, controlling for firm location city fixed effects. Panel A reports the results of the RDD probit model. The dependent variables are the measures of executive talent, which include *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience.* Panels B and C report the results of the RDD OLS model. In Panel B, the dependent variables are the measures of employee structure by education, which include *% of highly educated employees* and *% of employees with a low level of education.* In Panel C, the dependent variables are the measures of employee structure by job function, which include *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed variable definitions. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**-3.964***** **(-6.05)**	**-4.213***** **(-7.38)**	**-2.986***** **(-5.79)**
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	17,952	15,998	19,114
R-squared	0.154	0.124	0.110

Panel B: Employee structure by education

Dependent variables	(1) *% of highly educated employees*	(2) *% of employees with a low level of education*
QH	**-0.113***** **(-3.80)**	0.299*** (5.01)
Polynomial	Yes	Yes
Firm and regional controls	Yes	Yes
Year, industry, and city FEs	Yes	Yes
Observations	14,968	15,641
R-squared	0.442	0.304

Panel C: Employee structure by job function

Dependent variables	(1) *% of skilled employees*	(2) *% of production and sales employees*	(3) *% of financial and administrative employees*
QH	**-0.099***** **(-4.74)**	-0.002 (-0.04)	0.044*** (2.58)
Polynomial	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes
Observations	15,109	14,542	14,095
R-squared	0.367	0.331	0.260

Table IA.5
The Impact of Air Pollution on Firm Performance: Additional Tests

This table presents the results of additional analyses examining the effects of air pollution on corporate performance (innovation, productivity, firm value, and sales growth). Corporate innovation is measured by the number of invention patent applications filed per thousand employees (*Patents*). Productivity is measured by total factor productivity (*TFP*). Firm value is measured by the market value of total equity over book value of total equity (*Q*). Sales growth is the annual growth rate of total sales (*Sales growth*). The key independent variable is *QH*, which indicates whether a firm is located in a region where the central heating policy applies (yes: one, no: zero). Table IA.1 presents detailed definitions of the variables. In Panel A, local RDD is used; only firms located in regions with a distance smaller than two degrees in latitude from the Qinling-Huai River are included. In Panel B, RDD is used and city fixed effects of firm location are included. In Panel B, we exploit the abruptly broadened difference in *AQI* between heating and non-heating areas in 2014 to conduct a DID analysis based on a period from 2012 to 2015. *Post* equals 1 for years 2014 and 2015 (the post-period of broadened difference) and 0 for years 2012 and 2013 (the pre-period of broadened difference). The standalone *Post* is absorbed by the year fixed effects. In Panel D, 2sls RDD is used; Air Quality Index (*AQI*) is instrumented by *QH*, which indicates whether a firm is located in a region where the Qinling-Huai River heating policy applies (yes: 1, no: 0). In Panel E, 2SLS RDD is used; *AQI* is instrumented by thermal inversion strength (*TI*), which is the daily average of above-ground temperature minus ground temperature in the winter (Oct, Nov, Dec, Jan, Feb, and Mar) in a city. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. *t*-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Local RDD

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
QH	**-1.169****	**-0.044*****	**-0.160****	**-0.070****
	(-2.23)	**(-3.67)**	**(-2.25)**	**(-1.97)**
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes
Observations	8,483	8,483	8,483	8,483
R-squared	0.015	0.340	0.377	0.072

Panel B: City fixed effects

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
QH	**-2.790***	**-0.059***	**-0.961*****	**-0.031**
	(-1.75)	**(-1.93)**	**(-2.73)**	**(-0.30)**
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes
Observations	31,776	31,393	31,776	31,776
R-squared	0.031	0.275	0.414	0.074

Panel C: The change in air pollution

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
QH	0.048	-0.027***	0.101	0.017
	(0.17)	(-5.62)	(1.02)	(0.74)
QH × Post	**-0.598***	**-0.013*****	**-0.325*****	**-0.002**
	(-1.83)	**(-3.92)**	**(-2.70)**	**(-0.09)**
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes

Year, industry, and city FEs	Yes	Yes	Yes	Yes
Observations	10,517	10,397	10,517	10,517
R-squared	0.021	0.309	0.425	0.080

Panel D: 2SLS using *QH* as the IV

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
Fitted *AQI*	**-9.822**	**-1.402*****	**-7.010****	**-1.250***
	(-0.83)	**(-2.77)**	**(-2.09)**	**(-1.82)**
Polynomial	Yes	Yes	Yes	Yes
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes
Observations	26,366	25,997	26,366	26,366
F-statistic for weak identification	14.47	14.43	14.47	14.47

Panel E: 2SLS using thermal inversion strength (*TI*) as the IV

	(1)	(2)	(3)	(4)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
Fitted *AQI*	**-4.684**	**-0.877*****	**-5.752*****	**-1.518****
	(-0.35)	**(-2.99)**	**(-3.10)**	**(-2.02)**
Firm and regional controls	Yes	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes
Observations	26,366	25,997	26,366	26,366
F-statistic for weak identification	49.84	48.63	49.84	49.84

Table IA.6
2SLS and the Effects of Human Capital on Firm Performance

This table presents the results of 2SLS estimating the effects of human capital on firm performance. Human capital is measured by executive talent, which includes *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*; and employee quality, which includes *% of highly educated employees* and *% of skilled employees*. Firm performance is measured by *Patents*, *TFP*, *Q*, and *Sales growth*. In the first stage, each of the human capital measures is regressed on *QH*, which indicates whether a firm is located in a region where the Qinling-Huai River heating policy applies (yes: 1, no: 0). In the second stage, the fitted human capital from the first stage is regressed with the measures of firm performance. Table IA.1 presents detailed definitions of variables. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(3)	(4)	(5)
Dependent variables	*Patents*	*TFP*	*Q*	*Sales growth*
Fitted *Non-locally born executives*	3.508***	0.365***	2.054***	0.385***
	(2.84)	(7.50)	(4.58)	(3.86)
Fitted *Non-locally educated executives*	8.829***	0.451***	1.935***	0.625***
	(3.90)	(7.15)	(5.37)	(4.13)
Fitted *Executives with overseas experience*	22.711***	1.445***	8.306***	1.626***
	(3.46)	(6.87)	(4.80)	(2.63)
Fitted *% of highly educated employees*	18.241**	1.107***	9.291***	0.746
	(2.28)	(3.72)	(3.57)	(1.27)
Fitted *% of skilled employees*	29.610*	1.729***	16.225***	0.815
	(1.73)	(3.52)	(4.75)	(0.99)

Table IA.7

The Impact of Air Pollution on Regional Innovation and New Product Development

This table presents the results of RDD estimating the effects of air pollution on regional innovation and new product development. The development of innovation in a provincial region is measured by the number of total patent applications scaled by the total R&D expenditure (10k) of all enterprises in a region in a year (*Patents/R&D*), and the number of patent applications scaled by the total R&D researchers of all enterprises in a region in a year (*Patents/R&D researchers*). The development of new product development in a region is measured by the number of new products issued scaled by the total R&D expenditure (10k) of all enterprises in a region in a year (*New products/R&D*), and the number of new products scaled by the total R&D researchers of all enterprises in a region in a year (*New products/R&D researchers*). Data sources for these four variables are available from 2008 to 2016. Table IA.1 presents detailed definitions of variables. In all regressions, cubic polynomials are included; regional characteristics, year, and longitude fixed effects are included. t-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*Patents/R&D*	*Patents/R&D researchers*	*New products/R&D*	*New products/R&D researchers*
QH	**-0.001*****	**-0.013***	**-0.002*****	**-0.034*****
	(-5.08)	**(-1.87)**	**(-7.71)**	**(-8.33)**
Education expenditure	0.004***	0.358***	-0.006***	0.075***
	(3.02)	(8.23)	(-4.09)	(2.83)
GDP growth	-0.000	-0.001	0.000**	0.001*
	(-0.11)	(-1.28)	(2.03)	(1.68)
GDP per capita	0.000***	0.005***	-0.000***	-0.001***
	(4.56)	(14.88)	(-14.65)	(-3.87)
Population	-0.000***	0.000	-0.001***	-0.005***
	(-3.44)	(0.17)	(-7.32)	(-3.82)
Temperature	-0.000	0.000	-0.000	0.001**
	(-0.50)	(0.27)	(-0.31)	(2.06)
Relative humidity	0.000***	0.004***	-0.000***	0.002***
	(3.81)	(14.33)	(-3.11)	(11.25)
Precipitation	0.000***	0.000***	-0.000***	-0.000***
	(4.24)	(5.28)	(-7.29)	(-8.43)
Sunshine hours	-0.000***	0.000***	-0.000***	-0.000
	(-6.97)	(3.55)	(-10.77)	(-0.90)
Polynomial	Yes	Yes	Yes	Yes
Year and longitude FEs	Yes	Yes	Yes	Yes
Observations	2,862	2,862	2,862	2,862
R-squared	0.351	0.366	0.214	0.207