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Air Pollution and Firm-Level Human Capital, Knowledge and Innovation

EPRG Working Paper 2301

Cambridge Working Paper in Economics CWPE2306

Janeway Institute Working Paper Series 2302

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Keywords Pollution, human capital, knowledge, innovation, China

JEL Classification O15, O30, O44, Q51, Q56

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Publication January 2023

Air Pollution and Firm-Level Human Capital, Knowledge and Innovation*

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January 3, 2023

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This paper investigates the long-run effects of prolonged air pollution on firm-level human capital, knowledge and innovation composition. Using a novel firm-level dataset covering almost all industrial firms engaged in science and technology activities in China, and employing a regression discontinuity design, we show that prolonged pollution significantly diminishes both the quantity and the quality of human capital at the firm level. More specifically, we show that air pollution affects firm-level human capital composition by reducing the share of employees with a PhD degree and master's degree, but instead increasing the share of employees with bachelor's degree. Moreover, the difference in the composition of human capital materially change the knowledge and innovation structure of the firms, with our estimates showing that pollution decreases innovations that demand a high level of creativity, such as publications and inventions, while increasing innovations with a relatively low level of creativity, such as design patents. Quantitatively, on the intensive margin, one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ concentration leads to a 0.188 loss in the number of innovations per R&D employee. Overall, we show that air pollution has created a gap in human capital, knowledge, and innovation between firms in the north and south of China, highlighting the importance of environmental quality as a significant factor for productivity and welfare.

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*We are grateful to Philippe Aghion, Henry-James Hatton, Daniel da Mata, Vítor Possebom, Zhiwei Xu, Rhys Williams and seminar participants at the University of Cambridge, Shanghai Jiao Tong University, and Kunshan Duke University for helpful comments and suggestions. Corresponding author: Hongyu Nian (hongyu.N@sjtu.edu.cn).

1 Introduction

This paper investigates the long-run effects of prolonged air pollution on firm-level human capital, knowledge, and innovation composition. Given the importance of human capital as an engine for economic growth, it is surprising how little evidence there is on how the environment affects human capital accumulation, and its subsequent impacts on knowledge and innovation. Environmental pollution impacts firm-level human capital both at the extensive and intensive margins, by mainly two channels: residential sorting and employees mobility; and the health effects on human capital productivity. At the extensive margin, geographically mobile human capital tends to move from regions with poor environmental amenities to areas with cleaner air and better environmental quality (Hanlon, 2020; Chen et al., 2017; Graff Zivin and Neidell, 2013). The flow of human capital is determined not only by its marginal productivity, but also by many other factors, such as a bundle of amenities and lifestyle options (Bilal and Rossi-Hansberg, 2021). At the intensive margin, environmental pollution might harm the formation of human capital through health and cognitive development (Graff Zivin et al., 2020; Bharadwaj et al., 2017; Ebenstein et al., 2016).

We use a novel Chinese database, *Surveys of Science and Technology Activities of Industrial Firms* (henceforth SSTA). This dataset covers almost all industrial firms that are engaged in science and technology activities in China, reporting comprehensive information on firm-level human capital (e.g. educational levels, profession titles, and gender), knowledge, and innovation (e.g. publication, invention, and trademark). It records detailed information on employees who work on knowledge-producing activities in an independent research and development (R&D) department, such as experimental bases, laboratories, or pilot workshops. The SSTA covers firms that represent more than 90 percent of industrial knowledge and innovation across 46 two-digit industries in China, and are distributed nearly across the whole country. We combine this dataset with information on environmental pollution ($PM_{2.5}$) and thermal inversion, which are obtained from the Earth Observing System (EOS) of National Aeronautics and Space Administration (NASA).

In order to uncover the causal effect of air pollution on firm-level R&D human capital, our empirical strategy uses a spatial regression discontinuity (RD) design, which exploits the spatial discontinuity in air pollution created by China's Huai River heating policy (Ito and Zhang, 2020; Chen et al., 2013; Almond et al., 2009). In the 1950s, due to resource constraints the central Chinese government decided to provide coal-based heating service only for cities in the north of the Huai River. The division was chosen mainly because cities in the north have no less than 90 days when the annual average temperature is below or equal to 5°C.

It was not determined by any other political or economic reasons (Chen et al., 2013). Until today, heating in the north primarily relies on coal-based co-generators and boilers, whereas heating in the south primarily relies on electric power. After several decades, the difference in air quality between the north and the south is substantial (Almond et al., 2009). Since this pollution gap has been accumulated for more than 50 years, it enables us to explore how the pollution stock affects firm-level human capital over a long period. While the north and the south of China differ from each other in many fundamental ways, in our research design, we compare firms in the south and in the north which are immediately adjacent to the Huai River, where the social, economic, and geographic conditions are statistically continuous, and the only existing significant discontinuity is in air pollution. We provide several tests which give support to the validity of our RD exercise (e.g. Lee and Lemieux, 2010).

There are three potential channels of how pollution affects firm-level human capital over the long run. The first two channels comprise the residential sorting of human capital (extensive margin) and the negative effects of pollution on health and cognitive development (intensive margin). Our estimates contain the overall effects. When estimating the intensive margin effect, people's residential sorting can be viewed as a confounding factor, since it is likely to cause non-random assignment of pollution exposure. However, "residential sorting" in this setting functions as a primary vital channel to attract human capital at the extensive margin, which might take decades to affect innovation. In addition, we are interested in the overall effect and not only on the intensive margin channel.

An additional important channel is firm spatial sorting, which may provide another mechanism of how firm-level human capital might differ in regions which are heterogenous in air pollution. For instance, an R&D-oriented firm may observe the negative effects of environmental pollution and relocate itself to the south. This would be problematic for our empirical strategy and the interpretation of our results since firms would be fundamentally different between the north and the south borders of the Huai River. Although firm spatial sorting can be a result of environmental pollution, we empirically test this hypothesis. First of all, we check each firm's address and find that only 207 out of more than 30,000 firms in our sample changed their location between 1998 and 2013, with 81 of them still located in the north. The remaining 126 firms which moved to the south correspond to approximately 0.3 percent of our sample. Second, we test the density of firm distribution across the cutoff, employing the procedure of approximate sign test proposed by Bugni and Canay (2021). The results show that there is statistical continuity of firm distribution at the cutoff, indicating that there is no significant sorting occurring. Last, given that compared with start-up firms, the flexibility of old firms to move across regions is generally greatly reduced, we do further checks by limiting our sample to firms that have been in operation for more than 5, 10, 15 and 20 years, respectively. However, our results remain robust to various sub-samples.

Our estimates show that environmental pollution substantially diminishes both the quantity and the quality of firm-level human capital who work exclusively on R&D activities. More specifically, prolonged air pollution significantly affects firm-level human capital composition, reducing the share of employees with a PhD degree and master's degree, but instead increasing the share of employees with bachelor's degrees. Moreover, the difference in the composition of human capital materially change the knowledge and innovation structure of the firms: with our estimates showing that environmental pollution decrease innovations that demand a high level of creativity (such as publications and inventions) while increasing innovations with a relatively low level of creativity (such as design patents).

While it is relevant to disentangle the extensive margin effects from the intensive margin effects, data and the Huai River setting limit us to do so. In order to shed some light on the importance of the intensive margin, we investigate the impacts of environmental pollution on human capital productivity (innovations per R&D employee) over the short run, exploiting the two-stage least square (2SLS) approach with thermal inversion as an instrument.[1] As a meteorological phenomenon, thermal inversion is correlated with air quality ($PM_{2.5}$) but uncorrelated with firm-level short-run R&D workers' productivity in its neighborhood unless through the air quality channel. In this setting, we are able to investigate the short-run effects of air pollution, controlling for firm fixed effects and any firm-level characteristics formed before the sample period (2011-2013), and considering only within-firm variations.

We find that one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ concentration leads to a 0.188 loss in human capital productivity (number of innovations per R&D employee). Our analysis shows that air pollution heterogeneously dampens human capital productivity varying across the creativity intensiveness. The results indicate that R&D employees engaged in highly knowledge-intensive activities are more prone to productivity losses. Last, the unconditional quantile regression shows that the effects of air pollution exhibit various patterns on quantiles with different levels of human capital productivity. The distributional patterns suggest that the marginal losses of human capital productivity are more sizable and salient in the upper quantiles, implying that top talents suffer more losses at work in response to poor environmental quality. In sum, the findings indicate that air pollution diminishes human capital formation on the intensive margin by reducing human capital's creativity.

In order to rationalize our results, we present in Appendix C a new economic multi-

[1] Thermal inversion occurs when the temperature at the upper atmospheric layer is higher than that of the lower layer, preventing pollutants from dissipating (e.g., Fu et al., 2021; Sager, 2019; Jans et al., 2018).

region geography model, introduced by Helpman (1998). See Redding and Rossi-Hansberg (2017) for an overview of this literature. The model features spatial distribution of economic activity across a set of regions integrated by the trade of goods and labor mobility. Agents in the model move across regions to spatially arbitrage away real wage differences. The real wage depends on the price index for tradeables and the price of a non-tradeable amenity. When air pollution rises in one region, then individuals move away from that region to others, pushing up the price of non-traded amenity in regions with relative better air quality. Economic activity, as well as innovation determined by the measure of varieties M_r, rise in regions with a better non-traded amenity. Air pollution can also cause productivity to fall, moving individuals away from regions with lower labor productivity to those with higher labor productivity. Increasing economic activity and the production of different variety in receiving regions.

This paper contributes to several related strands of literature. To the best of our knowledge, we are the first to study how environmental pollution affects firm-level human capital over the long run. There is a large and growing literature on the negative effects of air pollution on labor productivity (e.g. Fu et al., 2021; Chang et al., 2019; He et al., 2019; Chang et al., 2016; Graff Zivin and Neidell, 2012). The pioneering study by Graff Zivin and Neidell (2012) shows that the exposure to ozone reduces the productivity of agricultural workers. Fu et al. (2021) document that the exposure to $PM_{2.5}$ decreases the productivity of industrial workers. We contribute to this literature by showing how air pollution affects the composition of firm-level human capital and its productivity. We also provide comprehensive evidence on how air pollution negatively affects firm-level knowledge and innovation using different indicators: publications, trademarks, industrial standards, and patents. Among these indicators, patent is the most commonly used by researchers (e.g., Arora et al., 2021; Cui et al., 2020; Cornaggia et al., 2015). However, a patent may not be a sufficient indicator to represent a firm's innovation capability. In addition to applying for patents, firms are also engaged in other knowledge-producing activities, such as publishing papers, registering trademarks, and making industrial standards (e.g., Arora et al., 2021). Moreover, to help us gain a better understanding of firms' innovation quality, rather than looking at total patents, we divide patents into three types: invention, utility model, and design patents. Invention patents are regarded as high-quality innovation because they relate to technological breakthroughs and upgrades in product or production process and are subject to extensive examinations in terms of their originality and novelty prior to approval. In contrast, utility model and design patents do not necessarily go through these examinations. In particular, the design patent, which is usually licensed for a new package, shape, color, and pattern of the product, is regarded as relatively low-quality innovation. Our estimates show that the effects of pollution on the composition of human capital is also reflected on the firm's quality of innovation.

This paper also relates to the literature on the effects of environmental pollution on human capital formation via the cognitive development channel (e.g., Graff Zivin et al., 2020; Bharadwaj et al., 2017; Ebenstein et al., 2016). The pollution-induced decrements in neurological system and lung functioning (e.g., Jans et al., 2018; Power et al., 2015; Schwartz, 2004; Heft-Neal et al., 2018; Chen et al., 2013) may affect human's ability to concentrate and thus decrease their creative ability and work efficiency. This literature mainly focuses on students' examination scores at school, which links to the initial stage of human capital formation. For instance, Bharadwaj et al. (2017) study the impact of fetal exposure to air pollution on 4^{th} grade test scores. Compared with an adult, a child is more susceptible to pollutants because their immune system is more vulnerable (Schwartz, 2004). Until now, there has been very little evidence on the effects on adult human capital's cognitive performance, except for Heyes et al. (2016)'s research on investors' return. Our work focuses on adult human capital who already work for knowledge producing activities, showing that air pollution significantly decreases human capital's innovative ability and productivity. With economic development understandably high on the agenda for emerging and developing countries, they may choose to introduce policies that might sacrifice environmental quality in exchange for economic prosperity. The hope is that pollution can be mitigated after economic development reaches a certain level. We show that this may not be well founded when considering the negative effects of air pollution on firm-level innovation. Overall, our results highlight the importance of environmental quality as a significant factor for productivity and welfare.

The rest of the paper is organized as follows. Section 2 describes our data and the Huai River policy. Section 3 presents the empirical strategy and results, while Section 4 explores various mechanisms. Section 5 conducts heterogeneous analysis and quantile treatment effects. Finally, Section 6 offers concluding remarks.

2 Data and Policy Setting

2.1 Firm-Level Human Capital Data

We combine four datasets: *Surveys of Science and Technology Activities of Industrial Firms* (SSTA), *Annual Survey of Industrial Firms* (ASIF), firm-level *Industrial Patent Database*, and air quality data from NASA. Below we introduce the novel SSTA database, and describe the remaining databases which are widely used in the literature in Appendix A.

SSTA is an annual survey of industrial firms conducted by China's National Bureau of Statistics (NBS). It includes all industrial firms that are engaged in science and technology activities, mainly covering 46 two-digit industries in China. In each year, firms are required to fill in the form of *Scientific and Technological Activities and Related Information of industrial Enterprises* and submit it to China's local NBS. This survey is also the source of *China Statistical Yearbook on Science and Technology*, an authoritative and publicly available statistic. We have access to the SSTA database for the following years: 2011, 2012, and 2013. In *China Statistical Yearbook on Science and Technology*, the number of surveyed firms are 37,467, 47,204 and 54,832, respectively, in year 2011, 2012, and 2013, which are consistent with the SSTA firm-level database. We match the SSTA database with ASIF and 90.4 percent of the sample in the SSTA can be matched. Then, we geocode the geographic location (longitude and latitude) of each firm through the *Amap* interface and compute its distance to the Huai River border. We end up with 24,722, 32,649 and 36,350 observations in year 2011, 2012, and 2013, respectively.

The SSTA database records detailed information on firms' science and technology activities: human capital (educational levels, titles, gender, etc.), R&D human capital's performance (publications, trademarks, patents, etc.), R&D expenditures, and government subsidies. We focus on human capital, knowledge, and innovation in firms' R&D departments, such as R&D institutions, technology centers, laboratories, pilot workshops, or experimental bases. The R&D departments are relatively independent from the production units, and all the employees in these departments work only on science and technology development. Thus, the measure of human capital in this paper does not include those in firms' production and management units. The key variables we use include: the sum of employees in the independent R&D department (or the total number of human capital), the share of human capital with PhD, master's, and bachelor's degrees; the number of publications, registered trademarks, and industrial standards; and government subsidies. See Appendix B for the summary statistics of the main variables, a brief description of the mean value, standard deviation, and numbers of observations for the firm-level and county-level variables.

2.2 The Huai River Policy

In 1958, due to resource constraints, the central government only provided heating services for the cities in the north of the Huai River. The blue line in Figure 1 shows the Huai River and Qinling Mountain, which divides northern China and southern China. The division was chosen mainly because cities in the north have no less than 90 days when the annual average temperature is below or equal to 5°C. It was not determined by any other political or economic reasons (Chen et al., 2013).

The central heating system in north China supplies heating service to residential and office/commercial buildings through pipeline networks, and the heat is mainly generated from coal-based boilers and co-generators (the combined heat and power generators). By the end of 1985, the heat generated by hot water boilers accounted for 75 percent of the heating in the north. In July 2003, China started to commercialize the heating service, requiring users to pay heating bills. According to the National Bureau of Statistics, in 2012, the heat generated by co-generators and boilers accounted for 40.1 percent and 58.8 percent of heating in the cities, respectively. At present, there are basically three conventional heating sources: coal-based boilers, co-generators, and domestic coal-fired stoves in the north. However, heating in the south mainly relies on electric power, either through multi-use air-conditioners or space heaters. Burning coal releases particulate matter (PM), nitrogen dioxides, sulfur dioxides and many other pollutants into the air. In particular, the level of the primary pollutant, particulate matter, is even higher if the coal is not sufficiently burned. Moreover, the boilers and generators in China frequently work under low-load conditions, as a result of which more coal is burned for each unit of heating.

The north-south air pollution gap induced by the coal-based heating policy is substantial. This spatial discontinuity in air provides a favorable quasi-natural experiment for RD design. Although this policy has been explored by some studies (Ito and Zhang, 2020; Chen et al., 2013; Almond et al., 2009), none of them investigate the effects of air pollution on firm-level human capital, knowledge and innovation. As Graff Zivin and Neidell (2013) suggest, due to endogeneity concerns of pollution, finding a reliable design is of first importance to understand the impact of pollution on different economic and social outcomes. North China differs from South China in many fundamental ways. Nevertheless, in the RD design, we compare firms in the south and in the north that are immediately adjacent to the north-south cutoff line, as well as geographically close in the west-east direction. The mean square error (MSE) optimal bandwidth is quite narrow, implying that the south and north firms for computing treatment effects are generally in the same county, where the social, economic, and geographic conditions are statistically continuous at the cutoff, and the only significant discontinuity exists in air pollution. The RD design has been a popular tool of empirical economists, principally because it can be statistically tested as randomized experiments (Lee and Lemieux, 2010). We next formally test the assumptions that establishes the validity of

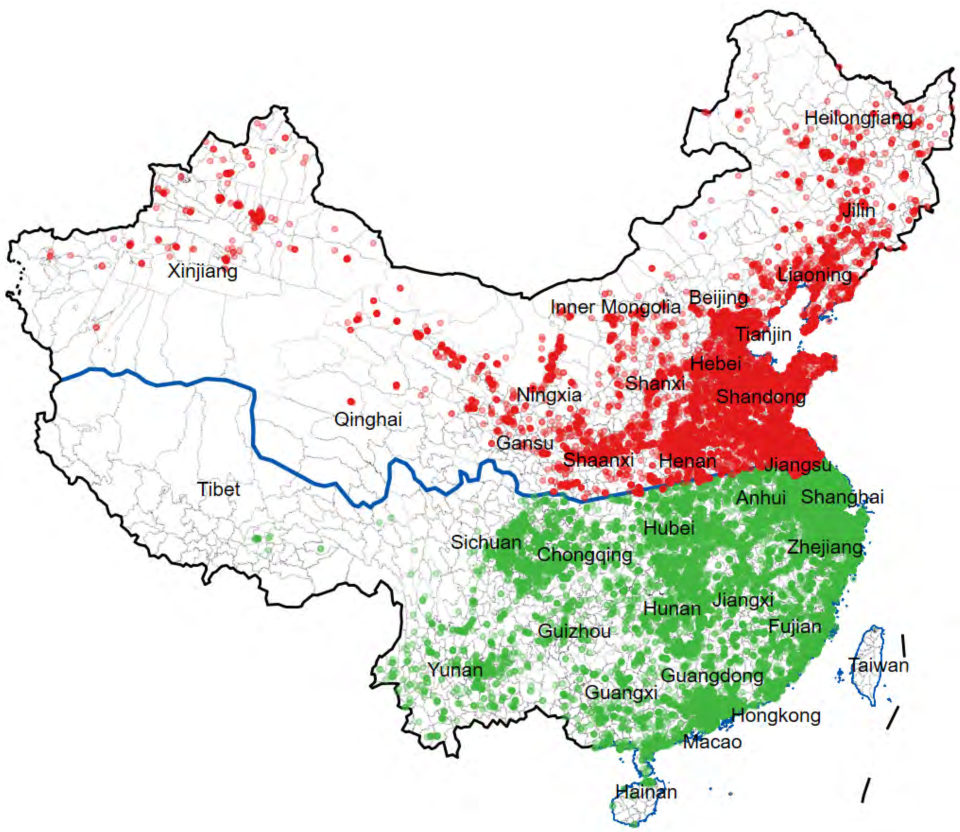


Figure 1: The Huai River Boundary and Firm's Location

Notes: The blue line in the middle of the map is the Huai River and Qinling Mountain. The red dots represent the sampled firms in the north, and the green dots represent the sampled firms in the south.

the RD design.

3 Empirical Strategy and Results

3.1 Spatial RD Design

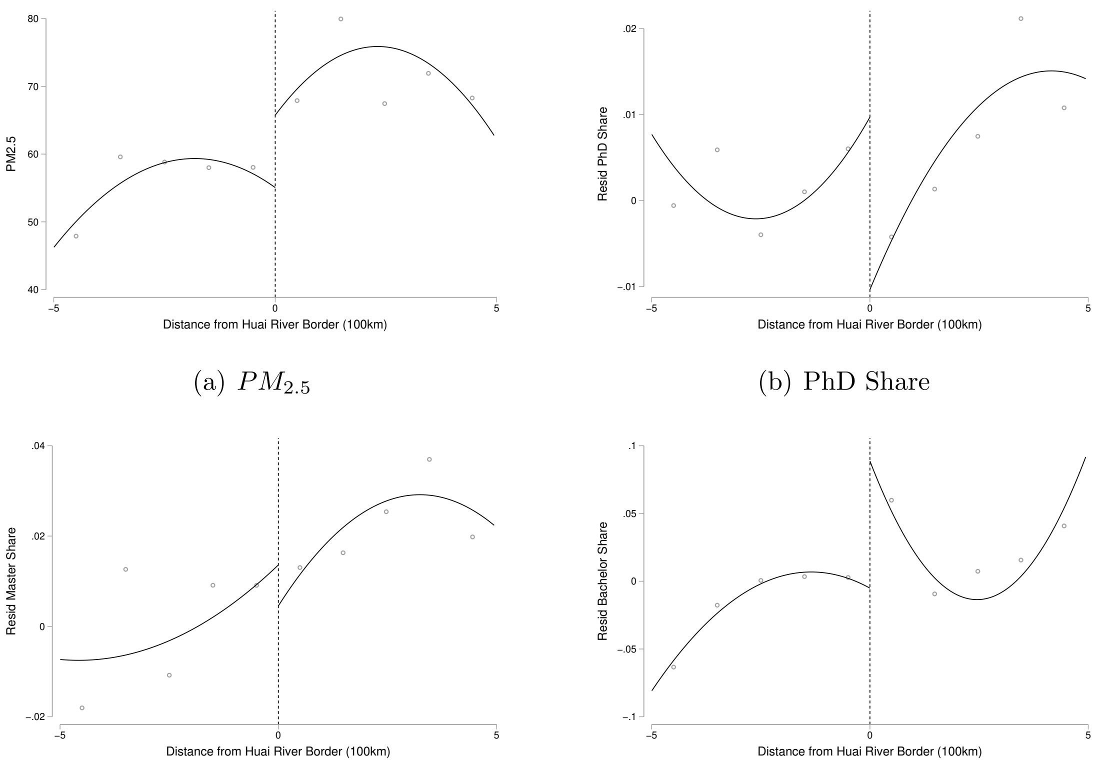
We adopt an RD design to examine the causal effects of air pollution on firm-level R&D human capital, knowledge, and innovation accumulation over the long run. The distance between each firm and the Huai River border serves as the running variable. The specification is defined as

$$\begin{aligned} Y_{ijc} = \alpha_1 North_i + \alpha_2 Dist_i + \alpha_3 North_i \times Dist_i + X_{ijc} + \gamma_j + \delta_c + \epsilon_{ijc}, \\ \text{such that } -h \leq Dist_i \leq h, \end{aligned} \tag{1}$$

where Y_{ijc} represents outcome variables of firm i in industry j at longitude range c. Since the Huai River border stretches from the west to the east of China, it may have systematic differences in the west-east dimension. We divide our sample into ten deciles based on firms' longitudes and include the longitude range fixed effects δ_c. $North_i$ is an indicator that equals 1 if a firm is located in the north, and 0 in the south. $Dist_i$ measures the distance between firm i and the Huai River border (positive if north and negative if south). X_{ijc} is a vector of control variables, including firm age and total assets, and h is the estimated MSE-optimal bandwidth suggested by Calonico et al. (2014). The coefficient of interest, α_1, represents the discontinuous change in Y_{ijc} at the Huai River border. We choose a local linear approach because using a polynomial function of the running variable as a control tends to generate RD estimates that are sensitive to the order of the polynomial and have some other undesirable statistical properties (Gelman and Imbens, 2019).[2] Moreover, industry (γ_j), ownership, and year fixed effects are absorbed. Following Lee and Lemieux (2010), we use a two-step approach to estimate the RD model. We first obtain the residualized outcome variables via the OLS regressions on a set of two-digit industry dummies, ownership dummies, longitude-quartile dummies, and year dummies, and then exploit the RD model with residualized outcome variables. Lee and Lemieux (2010) propose that if the RD design is valid, this procedure provides a consistent estimate of the same RD parameter of interest without causing bias.

[2] We also estimated equation (1) using a polynomial function and our results are robust to the order of the polynomial. These results are not reported here but are available upon request.

3.2 Empirical Results



(a) $PM_{2.5}$ (b) PhD Share

(c) Master Share (d) Bachelor Share

Figure 2: The RD Design at the Huai River Border

Notes: The vertical line in the middle at $Dist_i = 0$ stands for the Huai River border. The horizontal axis represents the distance ($Dist_i$) between firms and the Huai River border. The northern firms are presented on the right-hand side, and the southern firms are presented on the left-hand side. Each dot indicates a mean of the corresponding variable for firms within a bin in a size of 100 kilometers. The solid line that represents the fitted curve of each regression shows the discontinuity around the Huai River border.

3.2.1 Human Capital Accumulation

We begin with a graphical presentation of the spatial RD analysis in Figure 2. The horizontal axis represents the distance ($Dist_i$) between each firm and the Huai River border. The northern firms are presented on the right-hand side, and the southern firms are presented on the left-hand side. The vertical line in the middle at $Dist_i = 0$ represents the Huai River border. Each dot indicates a mean of the corresponding variable for firms within a bin in a size of 100 kilometers. The solid line that represents the fitted curve of each regression shows the discontinuity around the Huai River border.

Table 1: Long-run Effects of Air Pollution on Human Capital Accumulation: North vs. South

	(1) **PhD**	**(2)** **Master**	**(3)** **Bachelor**
Panel A: Control variables			
RD Estimate	-0.016***	-0.013***	0.059***
	(0.002)	(0.005)	(0.010)
Bandwidth	1.735	1.295	1.211
Panel B: Control variables, Longitude-quartile FE, Industry FE, and Year FE absorbed			
RD Estimate	-0.017***	-0.007*	0.078***
	(0.002)	(0.004)	(0.009)
Bandwidth	1.936	1.975	1.310
Panel C: Control variables, Longitude-quartile FE, Industry FE, Year FE, and Ownership FE absorbed			
RD Estimate	-0.017***	-0.009**	0.078***
	(0.002)	(0.004)	(0.009)
Bandwidth	1.732	1.854	1.304
Kernel Type	Triangular	Triangular	Triangular
Observations	85,035	85,035	85,035

Notes: "PhD" represents the share of human capital with PhD degree (the number of human capital with PhD degrees divided by total human capital); "Master" and "Bachelor" are calculated in the same way. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate RD regression. Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

In Figure 2(a), we see a sharp break in $PM_{2.5}$ at the Huai River border of 15.38 $\mu g/m^3$. This is consistent with the findings that air quality in cities north of the Huai River is significantly worse than that in the south (Ito and Zhang, 2020; Ebenstein et al., 2017; Chen et al., 2013; Almond et al., 2009). Notably, the mean $PM_{2.5}$ is 55.14 $\mu g/m^3$ for firms near the south of the border. The RD estimates represent an approximate 27.90% increase in

$PM_{2.5}$. Figures 2(b) and (c) show the RD plot for the residualized share of human capital with PhD and master's degrees, respectively, with industry, ownership, longitude-quartile, and year fixed effects controlled. Given the quantity of human capital, the north has a lower share of firm-level human capital with a PhD degree or a master's degree. Nevertheless, Figure 2(d) shows that firms in the north hire more human capital with bachelor's degrees. It is plausible that the firms in the polluted north have no choice but to hire more employees with bachelor's degrees in their R&D team to make up the deficit in the employees holding a PhD or master's degree.

Table 1 presents results consistent with the findings reported in Figure 2. Panel A presents the RD estimates with firm age and total assets controlled. In order to account for the vast geographical differences along the west-east direction, and the industry-specific and year-specific factors, we use residualized dependent variables with longitude-quartile, industry and year fixed effects absorbed in Panel B. Furthermore, in Panel C, we also control for ownership fixed effects, which teases out confounding impacts stemming from different ownership compositions in the north and south.[3]

Estimates in the three panels of Table 1 are quite similar in magnitude and significance. In Panel C, we compare the differences in the long-run human capital accumulation between the south and the north firms that are not only spatially adjacent to each other along north-south direction, but also geographically close along the west-east direction, belonging to the same industry, observed in the same year, and sharing the same ownership. Columns (1) and (2) show that, immediately adjacent to the Huai River, the share of human capital with PhD degrees and master's degrees of firms in the north are 0.017 and 0.009 lower than those in the south, and these differences are statistically significant. These findings are aligned with the fact that people with high educational levels are more mobile (Hanlon, 2020; Chen et al., 2017). Column (3) of this same table shows that firms in the north tend to hire more R&D workers with bachelor's degrees. In sum, there are important structural differences in the composition of R&D human capital between firms in the north and in the south caused by differences in air pollution.

3.2.2 Knowledge and Innovation Accumulation

Having shown that there are substantial differences in the structure of firm level R&D human capital quality between the south and the north, we now turn to test whether or not this

[3]There are several different types of private firms in our sample: domestic private firms, Hong Kong, Macao, and Taiwan private firms, foreign private firms, collective-owned firms, and other types of private firms.

Table 2: Long-run Effects of Air Pollution on Knowledge and Innovation: North vs. South

	(1) Publication	(2) Trademark	(3) Standard	(4) Patent
Panel A: Control variables				
RD Estimate	-0.250*	-1.634***	-0.320***	1.183**
	(0.129)	(0.583)	(0.079)	(0.590)
Bandwidth	0.766	1.620	1.066	2.337
Panel B: Control variables, Longitude-quartile FE, Industry FE, and Year FE absorbed				
RD Estimate	-0.264**	-1.195**	-0.256***	0.216
	(0.127)	(0.511)	(0.077)	(0.639)
Bandwidth	0.986	2.507	1.117	1.997
Panel C: Control variables, Longitude-quartile FE, Industry FE, Year FE, and Ownership FE absorbed				
RD Estimate	-0.428***	-1.281**	-0.256***	0.387
	(0.136)	(0.518)	(0.075)	(0.643)
Bandwidth	0.831	2.274	1.165	1.971
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	99,496	99,496	99,496	93,898

Notes: "Publication" represents the annual number of papers that are published by human capital at firm level; "Trademark" represents the annual number of registered trademarks that are created by human capital at firm level. "Standard" represents the annual number of national or industrial standards formed by a firm and approved by relevant official departments on the basis of independent R&D activities at firm level. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate RD regression. Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

could result in differences in knowledge and innovation activities.

As for innovation indicators, patents are the most commonly used measure by researchers (e.g., Arora et al., 2021; Cui et al., 2020; Cornaggia et al., 2015). However, the concern is that patents may not be a sufficient indicator to represent a firm's innovation capability. In addition to applying for patents, firms are engaged in various knowledge-producing activities, such as publishing papers. We therefore use the number of publications, registered

Table 3: Long-run Effects of Air Pollution on Patents: North vs. South

	(1) **Invention**	(2) **Utility Model**	(3) **Design**
Panel A: Control variables			
RD Estimate	-0.981***	-0.060	1.107**
	(0.342)	(0.262)	(0.434)
Bandwidth	1.167	2.506	1.981
Panel B: Control variables, Longitude-quartile FE, Industry FE, and Year FE absorbed			
RD Estimate	-0.630**	0.252	1.394***
	(0.312)	(0.246)	(0.398)
Bandwidth	1.438	2.687	2.278
Panel C: Control variables, Longitude-quartile FE, Industry FE, Year FE, and Ownership FE absorbed			
RD Estimate	-0.524*	0.289	1.389***
	(0.300)	(0.254)	(0.398)
Bandwidth	1.602	2.554	2.266
Kernel Type	Triangular	Triangular	Triangular
Observations	93,898	93,898	93,898

Notes: The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate RD regression. Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

trademarks, industrial standards, and patents to measure a firm's knowledge and innovation capability. Columns (1)–(3) of Table 2 show that the numbers of publications, registered trademarks, and industrial standards are significantly smaller (by 0.428, 1.281, and 0.256, respectively) in the north firms than the south ones which are closely distributed along the Huai River border. However, Column (4) shows that there is no statistically significant gap in the total number of patents between firms in the north and the south, except for panel A when controls are not considered.

In order to better assess firms' innovation quality, rather than looking at total patents, we divide patents into three different types: invention, utility model, and design patents according to China's Patent Law. Invention patents are regarded as high-quality innovation because they relate to technological breakthroughs and upgrades in product or production process and are subject to extensive examinations in terms of their originality and novelty prior to approval. In contrast, utility model and design patents do not necessarily go through these examinations. In particular, the design patent, which is usually licensed for a new package, shape, color, and pattern of the product, is regarded as relatively low-quality innovation.

We separately estimate the effects of pollution on each type of patent and present the results in Table 3. Column (1) shows that the number of high-quality innovations (invention patents) is significantly smaller in the north firms than in the south ones within the MSE-optimal bandwidth. However, the difference in utility model patents between the north and the south is not statistically significant. Moreover, Column (3) shows that firms in the north have significantly more low-quality innovations (design patents) than their counterparts in the south. Interestingly, the findings on innovation are structurally consistent with the findings regarding human capital. Tables 2 and 3 suggest that firms in the south outperform those in the north in knowledge and innovation development, not only in terms of the quantity but also in terms of the quality of innovations.[4]

3.3 Validity of the Spatial RD Design

As we use a RD design, our identifying hypothesis is that firms are supposed to be locally randomized at the cutoff of the Huai River border. This implies that observable variables, except for air pollution, that could affect firm-level human capital should change smoothly at the Huai River border.

Table 4 displays a set of geographic and socioeconomic variables in the north and in the south of the Huai River border: temperature, land price, average wage, population density, government spending on education and science, the number of educational institutions, and the number of teachers at educational institutions. Columns (1) and (2) of this table report the means for the north and the south, respectively. Column (3) shows the mean difference between the north and the south. Some of the mean differences are sizable in magnitude, because we compare the whole northern and southern China, rather than the regions adjacent to the cutoff. Then, we adopt the spatial RD regression to obtain RD estimates for those observable characteristics and report the standard errors in brackets in Column (4). It is clear that there is no evidence of discontinuity at the Huai River border for these observed

[4] In Appendix F we also show that government subsidies for R&D activities do not help alleviate the gap in firm-level human capital, knowledge and innovation between the north and the south.

Table 4: Observables: North vs. South of the Huai River

	(1) North	(2) South	(3) Difference in Means	(4) RD Estimates (Local Linear)
$PM_{2.5}$(ug/m^3)	69.434	53.343	16.091	13.383***
				(3.159)
Temperature (°C)	11.904	14.977	-3.073	0.080
				(0.301)
Land price (yuan/m^2)	379.56	752.07	-372.51	24.211
				(36.220)
Average wage (thousand yuan)	63.298	67.952	-4.654	1.756
				(1.938)
Population density (people/square kilometer)	829.080	1207.93	-378.850	69.063
				(64.482)
Government spending on education (millions RMB)	48.873	102.128	-53.256	-1.022
				(12.949)
Government spending on science (millions RMB)	633.131	621.825	11.306	20.605
				(40.209)
Number of higher education institutions	9.341	11.848	-2.507	-0.448
				(0.288)
Number of teachers in higher education institutions	6148.654	8255.307	-2106.701	-230.129
				(207.677)

Notes: $PM_{2.5}$, temperature, land price, average wage, and population density are averaged at the county level. The land transaction information is maintained by the National Department of Natural Resources Development and Utilization. There are 212,735 land transactions that are randomly drawn from the total transactions between 2011 and 2013. Government spending on education and science, the number of high education institutions, and number of teachers in high education institutions are averaged at the city-level. *** denotes significance at the 1% level.

variables. It is reassuring to notice that except for the pollution indicator, other observable variables that could explain firm-level human capital and R&D activity change smoothly in the neighborhood of the Huai River border. Lee and Lemieux (2010) suggest that if the continuity in these baseline covariates is verified, which we do in Table 4, then the underlying identifying assumption of the RD design is verified. In addition, Chen et al. (2013) have shown the continuity in other socio-economic features at the border, such as years of education, share in manufacturing, share of minority, and share of urban population. Finally, Ito and Zhang (2020) have shown that variables, such as years of schooling, fraction of illiterate, fraction of those who have completed high school, fraction of those who have completed college, and house size, are also continuous at the border. These findings give further support to our identifying assumption.

4 Channels

There are three potential channels of how pollution affects firm-level human capital over the long run. The first two channels comprise the residential sorting of human capital (extensive margin) and the negative effects of pollution on health and cognitive development (intensive margin). Our main results represents the overall effects of the two channels. It is noteworthy that when estimating the intensive margin effect, people's residential sorting can be viewed as a confounding factor, because it is likely to cause non-random assignment of pollution exposure. However, "residential sorting" in this setting functions as a primary vital channel to attract human capital at the extensive margin. In addition, another important channel is firm spatial sorting (extensive margin), which may provide another mechanism of how firm-level human capital might differ across regions because of the variations in air pollution.

4.1 Extensive Margin: Firm Spatial Sorting

Firms spatial sorting might be an important mechanism through which air pollution affects firm-level human capital and innovation. A technology-oriented firm may observe the negative effects of environmental pollution and relocate itself to the south. Furthermore, more innovation intensive firms are more likely to do so. This would therefore affect the selection of firms in the north and in the south of the river, which would change the interpretation of our main results. If firms spatial sorting is the main channel explaining our results, then air pollution would generate a north-to-south reallocation of high quality firms but would not directly affect the productivity of firm level human capital. As a result, air pollution would mainly affect human capital and innovation at the extensive margin on the relocation of more innovation intensive firms moving to areas with better air quality.

We introduce three different approaches to assess the importance of firm spatial sorting on our results. First of all, we check each firm's address and find that only 207 firms (out of more than 30,000 firms) in our sample changed their locations between 1998 and 2013, with 81 of those still located in the north. The remaining 126 firms which moved to the south contribute to less than 0.3 percent of our sample. Second, we test the density of firm distribution along the cutoff, using the procedure of approximate sign test proposed by Bugni and Canay (2021). Firms in our database spans approximately 20 longitudes from 103° E to

123°E. The results show that there is a statistical continuity of firm distribution at the cutoff except for the area between longitudes 116° E and 119° E because of the Dabie Mountain just in the south of the border. Therefore, there is no significant firm sorting occurring. Also note that our main results are robust to the exclusion of the firms between these longitudes, see Table D.1 in Appendix D. Last, given that compared with start-up firms, the flexibility of old firms to move across regions is generally considerably lower (and air pollution is not likely to have been a major factor for firm location 20 or 15 years ago), we re-estimate using four different samples: firms that have been in operation for more than 5, 10, 15 or 20 years, respectively. However, our results remain robust to various sub-samples, see Table D.2 in Appendix D for details. Therefore, the evidence suggest that firm spatial sorting is not the key driver of our main results.

4.2 Extensive Margin: Human Capital Residential Sorting

Given that firm spatial sorting does not seem to be the key mechanism underlying our findings on how air pollution affects firm-level human capital and innovation, we now investigate the other two potential channels. More recently, people have become increasingly concerned about environmental quality when choosing where to live or work and have moved away from cities with serious environmental pollution. Different from physical capital, the flow of human capital is determined not only by its marginal production, but also by many other factors that decide the location of individuals who carry human capital, such as the preferences on environmental quality. On the extensive margin, we consider that human capital sorting might be a critical channel because skilled people tend to migrate out of a region with poor environmental amenities and turn to a "clean" city over the long run (Hanlon, 2020; Chen et al., 2017; Graff Zivin and Neidell, 2013). While it is relevant to disentangle the extensive margin effects from the intensive margin effects, data and the Huai River setting limit us to do so. In order to shed some light on the importance of the channels, we instead use an economic geography model developed by Helpman (1998) to discuss how environmental pollution might lead to the losses of human capital through the channel of individual's residential sorting. For the details of our conceptual analysis as well as some model simulations see Appendix C.

4.3 Intensive Margin: Human Capital's Productivity

We next empirically explore the intensive margin channel: how air pollution impacts firm-level human capital's capacity for innovation. The idea is that air pollution can influence not only the composition of firm-level human capital, as we have shown in Table 1, but it can also negatively affect the health and cognitive productivity of the employees. That is, while having more knowledgeable employees can lead to more innovation, their health and well-being can also increase their productivity.

Below we provide evidence on the importance of how air pollution affects firm-level human capital productivity. We consider a different empirical strategy from the previous section, and investigate how temporary changes in air pollution affect human capital productivity (innovations per employees in the firm-level R&D sector) over the short run. We consider the following empirical specification:

$$Y_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 W_{it} + \mu_i + \psi_t + \sigma_{it}, \tag{2}$$

where i and t denote firm and year, respectively; Y_{it} represents human capital productivity,[5] and P_{it} represents air pollution measured by $PM_{2.5}$. Error term (σ_{it}) absorbs unobservable factors varying with year and firm. Air quality in the neighborhood of each firm is obtained and calculated from satellite data. The variation of air pollution is aggregated from grid level to county level and shown in Figure 3. Firm fixed effects (μ_i) control for time-invariant firm-level variables and any firm-level characteristics formed before the sample period (2011-2013), such as the firm's stock of assets, human capital, and innovation. Year fixed effects (ψ_t) are included to control for common shocks like national policies that affect human capital's productivity. W_{it} denotes a vector of firm-level and meteorological controls, including firm age and total assets, hours of sunlight, wind speed, and precipitation.

Endogeneity of air pollution is a critical issue for causal inference of its effects on different socio-economic outcomes. There are unobserved factors which vary with regions and time that could bias the estimates. A region might introduce a more stringent environmental regulation due to pollution, which could also affect innovation. In addition, more productive firms might produce and pollute more, leading to a concern for reverse causality. In order to address the omitted-variable bias and the concern for reverse causality, we use an instrumental variable (IV) approach, which instruments air pollution with thermal inversion.

As a meteorological phenomenon, thermal inversion is correlated with air quality ($PM_{2.5}$) but uncorrelated with firm-level human capital's productivity in its neighborhood unless through the air quality channel. Naturally, atmospheric temperature decreases with the increase of altitude. Thermal inversion occurs when the temperature at the upper atmospheric

[5]Human capital productivity is defined as innovations divided by employees in the R&D sector. Innovations include all the surveyed types of innovation: invention, publication, trademark, and industrial standard. Human capital are those who work exclusively on science and technology activities.

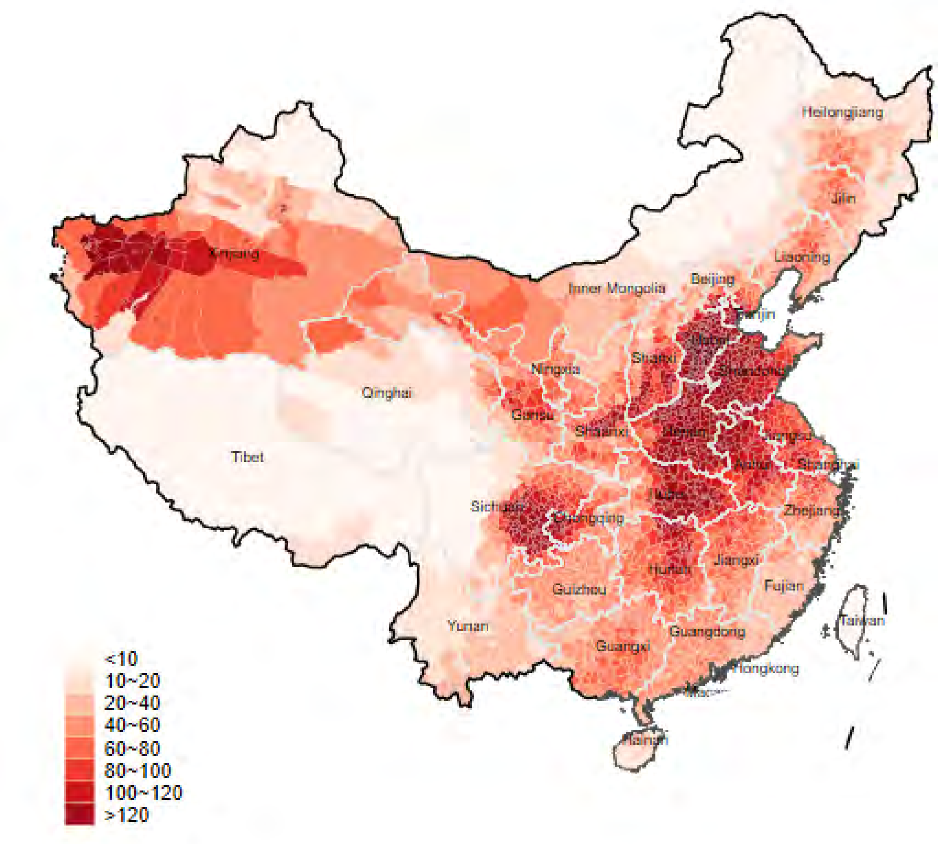


Figure 3: $PM_{2.5}$ ($\mu g/m^3$) Distribution in 2013

Table 5: Short-run Effects of Air Pollution on Human Capital Productivity (2SLS)

First Stage		
Dependent variable	$PM_{2.5}$	
	(1)	(2)
Thermal inversion	0.020***	0.020***
	(0.005)	(0.005)
Second Stage		
Dependent variable	Human capital productivity (innovations per capita)	
	(3)	(4)
$PM_{2.5}$	-0.188***	-0.188***
	(0.082)	(0.082)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm controls	No	Yes
Weather controls	Yes	Yes
KP F-statistic	18.41	18.52
Sample size	74,667	74,667

Notes: Human capital productivity is measured by total innovations divided by human capital stock. Total innovations include all the surveyed types of innovations: invention, publication, trademark, and industrial standard. Human capital are those who work exclusively on science and technology activities and most of them have academic degrees. Thermal inversion is measured by annual days with thermal inversions. Firm controls include firm age and firm total assets, and weather controls include precipitation, temperature, and hours of sunlight. Standard errors are reported in parentheses. *** denotes significance at the 1 percent level.

layer is higher than that of the lower layer. As a result, the denser (cooler) air layer floats below the less dense (warmer) air layer and prevents pollutants from dissipating. During the days with thermal inversion, air pollutants will largely be trapped in the air close to the ground. For this reason, economists widely employ it as a plausible instrument for air pollution (e.g., Fu et al., 2021; Sager, 2019; Jans et al., 2018). Therefore, our empirical strategy explores how exogenous changes in air pollution (e.g. annual days with thermal inversions) affects human capital's productivity at the firm.

We present the 2SLS results in Table 5, with the OLS results reported in Table E.1 of Appendix E. Columns (1) and (2) of Table 5 show that thermal inversion is a strong predictor for $PM_{2.5}$, both when excluding and including firm controls. Columns (3) and (4) present the second-stage estimates, which suggest that one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ significantly reduces firm-level human capital's productivity by 0.188 innovation per RD employee. The total innovation considered here includes all the surveyed types of innovations: invention, publication, trademark, and industrial standard in the SSTA database. Both the sign and the magnitude of the estimate remain unchanged once firm controls are introduced. To further test the validity of the instrument, we carry out the Kleibergen-Paap (KP) Wald rk F-statistic test (Kleibergen and Paap, 2006) and the KP F-statistic is shown in each column. They all corroborate that thermal inversion is a valid instrument for air pollution.

Our findings suggest that air pollution not only change the firm-level R&D composition of human capital (see Table 1) but it also affects the firm-level labor productivity (see Table 5), by reducing innovation per R&D employee.

5 Heterogeneous Analysis and Quantile Treatment Effects

The estimates in Section 3 identify the average effects in the treated samples, but they show little information about the heterogeneous effects of air pollution on R&D activity. In this section, we assess how industrial sectors and R&D activities are differently affected by air pollution.

5.1 Heterogeneous Analysis across Industries

We begin by splitting our sample into various sub-samples based on two-digit industries and also by classifying these industries into two broad categories: low-tech and high-tech intensity following the *OECD ISIC Technology Intensity Definition*. There are good reasons to suspect that the negative effects of air pollution vary across industries because different industries typically conduct research and experiments in different conditions and intensity. In order to investigate how and to what extent different industries are affected, we run separate RD regressions on firm-level innovations and summarize the estimates in Figure 4. The figure clearly shows that the treatment effects are relatively dispersed across industries over the long run (with all significant effects being negative), thereby confirming the heterogenous impacts of air pollution across industries. However, there is no clear pattern in terms of the differential impacts of air pollution on innovation across low vs. high tech industries.

5.2 Heterogeneous Analysis across Creativity

We next investigate the implications of air pollution for human capital productivity across different R&D activities. It could be that the requirements of physical health, mental status, and concentration vary substantially across different types of R&D activity, such as innovation and industrial standard. Hence, the productivity of employees who are employed to work on different R&D projects may be depressed by air pollution differently.

In Table 6, we separately calculate human capital productivity by different types of R&D activities. For instance, firm level human capital's invention productivity is measured by the total inventions in a firm divided by total employment in the firm's R&D department. In Column (1), our estimates show that one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ significantly reduces workers' productivity of invention by 0.174. Columns (2) implies that the effect of air pollution on workers' productivity of publication is negative but statistically insignificant, and similarly, Columns (3) and (4) suggest that the effects of air pollution on workers' productivity of trademark and industrial standard are not statistically different from zero. The estimates in Columns (1)–(4) are consistently negative but differ in statistical significance, suggesting that air pollution heterogeneously dampens R&D workers' productivity across different types of R&D activities.

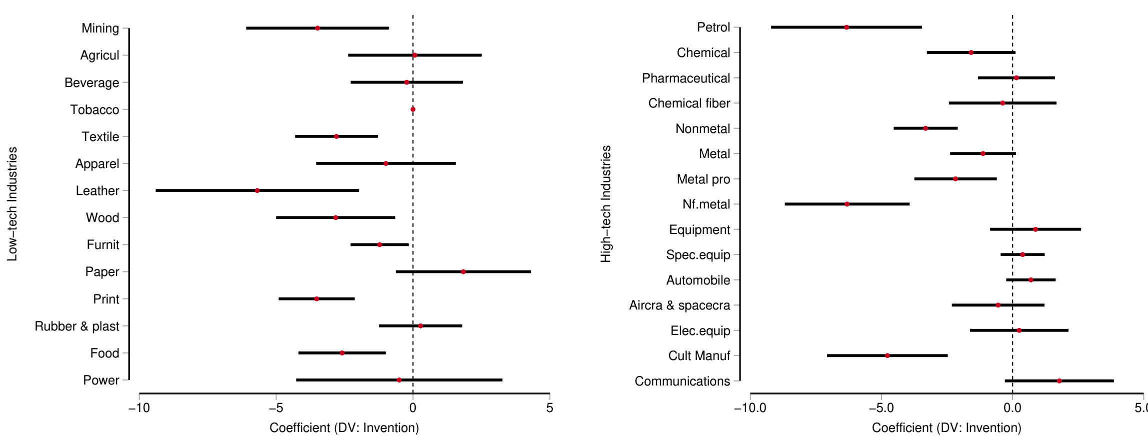


Figure 4: Estimates of the Heterogeneous Effects of Air Pollution Across Industries

Notes: The dependent variable is the number of inventions at firm level. The solid dots represent the coefficients that are separately estimated using samples from low-tech and high-tech industries. The range bars indicate the 90% confidence intervals.

Table 6: Heterogeneous Effects of Air Pollution on Human Capital Productivity Based on Creativity Intensiveness (2SLS)

	(1) **Prod. on invention**	(2) **Prod. on publication**	(3) **Prod. on trademark**	(4) **Prod. on standard**
Instrumented $PM_{2.5}$	-0.174**	-0.004	-0.005	-0.005
	(0.070)	(0.027)	(0.024)	(0.009)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
KP test	37.72	37.72	37.72	37.72
Observations	74,667	74,667	74,667	74,667

Notes: Based on different levels of creativity intensiveness, human capital productivity is measured by invention divided by human capital, publication divided by human capital, trademark divided by human capital, and industrial standard divided by human capital, respectively. Firm controls include firm age and firm total assets, and weather controls include precipitation, temperature, and hours of sunlight. Standard errors in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

5.3 Quantile Treatment Effects

We further explore the distributional effects of air pollution by carrying out unconditional quantile regressions. Recent advances in quantile regression enable us to investigate the effects of air pollution on human capital productivity in different quantiles. The recentered influence function (RIF) regression procedure developed by Firpo et al. (2009) can depict the quantile treatment effects into an unconditional outcome distribution. In practice, the RIF first predicts a couple of thresholds with respect to the specified unconditional quantiles of an outcome variable, and then runs the RIF-2SLS regressions, separately, averaging up the treatment effects on the probability of being above each quantile threshold.

We create 19 RIF-2SLS statistics for each quantile, distributing from the $5th$ to the $95th$ percentiles of the outcome variable. These estimates corresponding to each RIF-2SLS quantile represent the effects of air pollution on the qth quantile of the unconditional distribution of human capital productivity. Intuitively, the effects of air pollution may exhibit various patterns on quantiles with different levels of human capital productivity. Environmental pollution might disproportionately impact human capital productivity because different levels of productivity demand different knowledge intensiveness and workload.

Figure 5 depicts the 19 separate 2SLS estimates on the left panel, and 19 separate OLS regression estimates for comparison on the right panel. The figure presents the effects of air pollution on various quantiles of the unconditional distribution of the outcome variable (human capital productivity). Among the lower quantiles, the confidence intervals almost overlap, suggesting that the treatment effects at the lower quantiles are not statistically different. On the upper quantiles, however, the estimates are more salient, suggesting that to a large extent, the significant negative effects of air pollution on human capital productivity reported in Table 5 are typically attributed to the treatment effects on human capital with high productivity in terms of R&D activities.

6 Concluding remarks

This paper provides comprehensive evidence on the long-run effects of prolonged air pollution on firm-level human capital, knowledge and innovation. Using a novel firm-level dataset covering almost all industrial firms engaged in science and technology activities in China, and employing a spatial regression discontinuity design, we find that prolonged pollution significantly diminishes both the quantity and the quality of human capital at firm level, reducing the share of employees with a PhD degree and master's degree but increasing the

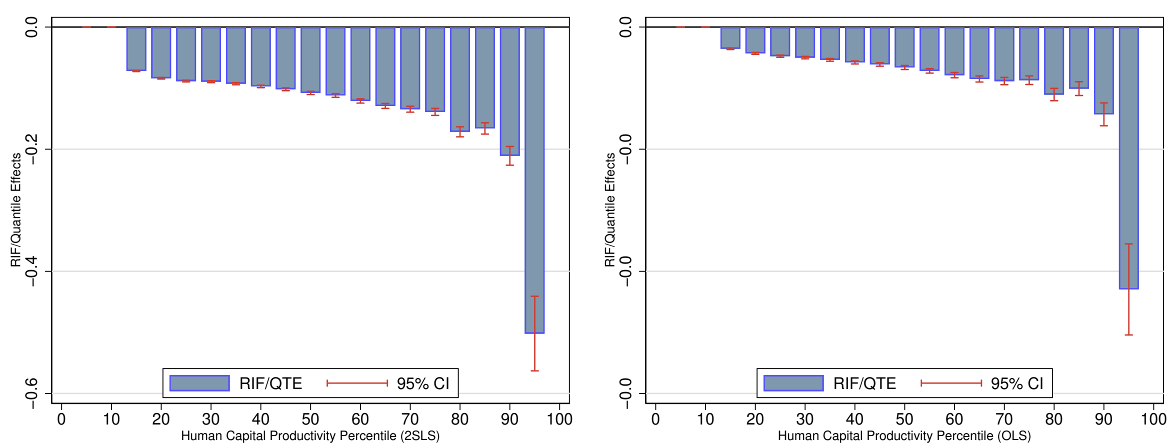


Figure 5: Recentered Influence Function (RIF) Quantile Effects

Notes: The figures are the RIF-2SLS estimates of coefficient β_1 on the left side, and the RIF-OLS estimates on the right side. There are 19 RIF-2SLS statistics for each quantile distributing from the $5th$ to the $95th$ percentiles of outcome variable. The red line represents 95% confidence interval.

share of employees with bachelor's degrees. We also find adverse effects of environmental pollution on knowledge and innovation. More specifically, we show that air pollution decreases firm-level innovation which demand a high level of creativity, such as publications and inventions, while increasing innovations with a relatively low level of creativity, such as design patents. Moreover, using an instrumental variable approach and thermal inversion as an instrument, we also provide evidence that air pollution substantially decreases firm-level human capital productivity in the short run.

With economic development understandably high on the agenda for emerging and developing countries, they may choose to introduce policies that might sacrifice environmental quality in exchange for economic prosperity. The hope is that pollution can be mitigated after economic development reaches a certain level. We show that this may not be well founded when considering the negative effects of air pollution on firm-level innovation. Our findings highlight the importance of environmental quality as a significant factor for productivity and welfare.

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Appendices

A Data Sources

ASIF Database. This database is conducted by China's National Bureau of Statistics (NBS). This annual survey includes private enterprises with annual sales exceeding 5 million RMB and all the SOEs. The output value of firms included in ASIF accounts for approximately 90 percent of the total industrial output value of China, covering 46 two-digit code industries. The ASIF database is widely used in the literature (e.g., Brandt et al., 2012; Song et al., 2011; Hsieh and Klenow, 2009). It contains almost all the information on a firm's major accounting sheets, including more than 100 financial-related variables. We follow the procedure provided by Brandt et al. (2012) to process the data: merge the dataset year by year; correct the mis-recorded firm identifier; and drop observations that apparently violate accounting principles. Based on the ASIF data, we use total assets, interest income, and profits to calculate a firm's ROA (Return on Assets), and include age, two-digit industry code, ownership, and total assets as control variables in the regressions.

County-level air quality. we use publicly available air pollution ($PM_{2.5}$) data monitored by Earth Observing System (EOS), National Aeronautics and Space Administration (NASA) and processed by the Atmospheric Composition Analysis Group of Dalhousie University. We average the $PM_{2.5}$ value at county-year level (about 3000 counties in China). The thermal inversion data is also monitored by NASA and constructed by the Modern-Era Retrospective Analysis for Research and Application (version 2). It reports meteorological temperature for each 50*60 km grid on different atmospheric layers for every six hours. We aggregate the annual average value of thermal inversions from grid level to county level. Since the air quality data from satellite covers the entire China, we are able to include all the firm samples in the SSTA database.

Industrial Patent Database. It is collected and maintained by the State Intellectual Property Office of China. This patent dataset records detailed information on patent type (invention, utility model, and design), abstract, application time, certification time, ID code and address of the owner. We match the patent database with ASIF to control for firm-specific characteristics in the regression analysis of patents. The patents are divided into three types to measure the quality of innovation. The invention patent is regarded as high-quality innovation because it is licensed for technological breakthroughs and upgrades in approach, product, or materials. Additionally, substantive examinations are carried out to examine the originality and novelty of invention patents. According to China's Patent Law, the duration of protection for invention is 20 years, but only 10 years for the utility model and design patents. Additionally, the patent application fee for an invention is seven times higher, and the application duration is two years longer than the utility model and design patents. Comparatively, the threshold for creativity is lower for utility model and design patents, as they do not necessarily go through extensive examinations and are less costly to get granted. In particular, the design patent, which is for instance, related to the package, shape, color, and pattern of the product, is considered a relatively low-quality innovation.

Table B.1: Summary Statistics

	(1) North	**(2) South**	**(3) Difference in Means**
A. Indicators for Human Capital			
Total human capital	52.851	52.616	0.235
Share of human capital with PhD degrees	0.038	0.027	0.011
Share of human capital with master's degrees	0.119	0.079	0.040
Share of human capital with bachelor's degrees	0.569	0.524	0.045
Observations	20,245	64,790	
B. Indicators for Knowledge and Innovation			
Publications	1.518	0.638	0.880
Trademarks	5.261	4.534	0.727
Standards	0.527	0.331	0.196
Observations	21,983	77,513	
C. Patents			
Total patents	8.556	12.451	-3.895
Invention patents	3.540	3.746	-0.206
Utility model patents	3.875	4.619	-0.744
Design patents	1.141	4.086	-2.945
Observations	21,746	72,322	

Notes: All variables are measured at firm level and constructed by the authors using data from *Surveys of Science and Technology Activities of Industrial Firms* and China's *Industrial Patents* databases.

B Summary Statistics

In Table B.1, we report the means and the differences for indicators related to human capital in Panel A, knowledge and innovation in Panel B, and patent in Panel C. Columns (1) and (2) report the sample mean for the north and the south of the Huai River, respectively. Column (3) reports the raw difference between the sample means. In Panel A, we see that firms in northern China have higher human capital quality than those in southern China. Panels B and C show that firms in northern China have more publications, trademarks, and industrial standards but have fewer patents than those in southern China.

In Table B.2, the measures of human capital's productivity are reported at firm-year level, and the $PM_{2.5}$ and thermal inversion values are reported at county-year level. Human capital productivity is defined by total innovations divided by human capital. Total innovation includes all the reported types of innovation in SSTA database, comprising invention,

Table B.2: Summary Statistics on Human capital's Productivity and Pollution

	Mean	**SD**	**Observations**
Firm-level Sample			
Human capital's prod.	0.177	1.133	93,721
(Total innovation/human capital)			
Human capital's invention prod.	0.075	0.802	93,721
(Invention/human capital)			
Human capital's publication prod.	0.016	0.423	93,721
(Publication/human capital)			
Human capital's trademark prod.	0.077	0.603	93,721
(Trademark/human capital)			
Human capital's standard prod.	0.009	0.154	93,721
(Standard/human capital)			
County-level Sample			
Air pollution	56.545	16.270	1990
$PM_{2.5}$ ($\mu g/m^3$)			
Thermal inversion	67.905	22.916	1990
(Annual days with thermal inversions)			

Notes: The firm-level human capital data comes from SSTA database. The county-level air pollution data is reported by Earth Observing System (EOS), National Aeronautics and Space Administration (NASA) and processed by the Atmospheric Composition Analysis Group of Dalhousie University. The thermal inversion data is also monitored by EOS of NASA and constructed by the Modern-Era Retrospective Analysis for Research and Application (version 2).

publication, trademark, and industrial standard. Human capital are those who work only on science and technology activities in the R&D department, and most of them have university degrees (bachelor's degree, master's degree, or PhD's degree). In order to examine the heterogeneous effects, we further separately calculate human capital's productivity in terms of creativity intensiveness. The harmful effects of air pollution on the productivity of human capital are expected to vary across different types of innovation. For instance, invention is viewed as a highly knowledge-intensive activity, which is related to technological breakthroughs and upgrades and subject to extensive examinations in terms of their originality and novelty. Correspondingly, human capital's invention productivity is measured by invention divided by human capital. Likewise, human capital's productivity of publication, trademark, and industrial standard are computed.

C A Conceptual Analysis on Human Capital Sorting

C.1 General Equilibrium Effects

We rationalize our analysis on the channel of human capital sorting with an economic geography model introduced by Helpman (1998). See also Redding and Sturm (2008) and Redding and Rossi-Hansberg (2017).

The economy is populated by a mass of individuals, L. Individuals are endowed with one unit of time, which they supply inelastically in the labor market. They live where they work. Preferences are defined over a consumption index of tradeable varieties, C_r, and consumption of a non-tradeable amenity, H_r with

$$U_r = C_r^{\alpha} H_r^{1-\alpha},\ \alpha \in (0,1).$$

The supply of non-tradeable amenity is given and equal to $H_r > 0$.

For simplicity, assume that there are only two regions: the North (N) region and the South (S) region, such that $r \in \{N, S\}$. Goods consumption index (C_r) is defined over the endogenous measures of differentiated varieties (M_r) supplied by each region with dual price index (P_r^M):

$$C_r = \left(\sum_{i \in \{N,S\}} \int_0^{M_i} c_{ri}(j)^{\rho} dj \right)^{\frac{1}{\rho}};\ P_r^M = \left(\sum_{i \in \{N,S\}} \int_0^{M_i} p_{ri}(j)^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}},$$

where $\sigma = \frac{1}{1-\rho}$ and $-\infty < \sigma < 1$. Goods can be transported from one region to the other without any cost. Varieties are produced under monopolistic competition. To produce a variety $x_r(j)$, a firm must incur a fixed cost F in units of labor and a variable cost in terms of labor that depends on a region's productivity A_r: $l_r(j) = F + \frac{x_r(j)}{A_r}$. Producer of each variety chooses prices to maximize profits subject to its downward-sloping demand curve:

$$p_r(j) = \left(\frac{\sigma}{\sigma - 1} \right) \frac{w_r}{A_r} = p_r. \tag{A.1}$$

Consequently, we have that:

$$P_r^M = \left(M_S p_S^{1-\sigma} + M_N p_N^{1-\sigma} \right). \tag{A.2}$$

Profit maximization and free entry in tradeables imply that $x_r(j) = A_i(\sigma - 1)F = x_r$

and $l_r(j) = \sigma F = \bar{l}$. Labor market clearing requires demand equals the supply for labor, $L_r = M_r\bar{l}$, such that the mass of varieties produced by each region is proportional to its supply of labor

$$M_r = \frac{L_r}{\sigma F}. \tag{A.3}$$

It can also be shown that wages can be written as:

$$w_r = \left(\frac{\sigma - 1}{\sigma}\right)^{\frac{\sigma-1}{\sigma}} A_r(\sigma F)^{-\frac{1}{\sigma}} \left(w_S L_S (P_S^M)^{\sigma-1} + w_N L_N (P_N^M)^{\sigma-1}\right)^{\frac{1}{\sigma}}. \tag{A.4}$$

With a Cobb-Douglas utility function and an inelastic supply of the non-tradeable amenity H_r, the equilibrium price of the non-tradeable amenity depends on its expenditure share, $(1 - \alpha)$ and total expenditure, E_r, such that:

$$P_r^H = \frac{(1-\alpha)E_r}{H_r}. \tag{A.5}$$

Total expenditure is the sum of labor income and expenditure on the non-tradeable amenity which is assumed to be redistributed to the region population, such that $E_r = w_r L_r + (1 - \alpha)E_r$ and

$$E_r = \frac{w_r L_r}{\alpha}. \tag{A.6}$$

With integrated labor markets, individuals move across cities to spatially arbitrage away real wage differences. The real wage depends on the price index for tradeables and the price of the non-tradeable amenity:

$$\omega_r = \frac{w_r}{(P_r^M)^{\alpha}(P_r^H)^{1-\alpha}} = \omega \quad \text{for all} \quad r \in \{N, S\}. \tag{A.7}$$

Equilibrium is characterized by a vector of seven variables $\{w_r, p_r, L_r, M_r, P_r^M, P_r^H, E_r\}$ with $r \in \{N, S\}$. These seven endogenous objects are determined by solving the seven simultaneous equations defined by (A.1)-(A.7).As usual in these type of models, it is not possible to find closed form solutions for equilibrium objects.

Changing units of the non-traded amenity in one region modifies the value of real wage in both regions. In general, when the non-trade amenity falls in one region (air pollution rises), then individuals move away from that region to the other, pushing up the price of the non-traded amenity in the region with relative better amenity. Economic activity, as well as innovation determined by the total measure of varieties M_r, rise in the region with a better non-traded amenity. Table C.1 contains some model simulations showing exactly such results for some parameter values.

Similarly, a fall in individual's productivity (due to the effects of air pollution on health) in one region relative to the other, move workers away from the region experiencing a fall in productivity to another in which productivity is unchanged. This would increase innovation M in the receiving region and the price of its non-traded amenity. This process would continue until the rise in the price of the non-traded amenity equalizes real wages in both regions. See also Table C.1.

C.2 Simulation

Table C.1: Model Simulations

	Symmetric regions $H_S = H_N = 1.7265$, $A_S = A_N = 1$	**Better amenity in the south region** $H_S = 1.7265$, $H_N = 0.9 * H_S$ $A_S = A_N = 1$	**Better prod. in the south region** $H_S = H_N = 1.7265$, $A_S = 1$, $A_N = 0.9$
Labor force, L_S	0.500	0.550	0.640
Labor force, L_N	0.500	0.450	0.360
Amenity price, P_S^H	0.149	0.172	0.179
Amenity price, P_N^H	0.149	0.141	0.123
Variety, M_S	0.125	0.144	0.160
Variety, M_N	0.125	0.106	0.081

Notes: Model is solved with $L = 1$, $\alpha = 0.66$, $\sigma = 4$ and $F = 1$. The first column contains results for the equilibrium with symmetric regions such that $H_S = H_N = 1.7265$ and $A_S = A_N = 1$. The second column contains results for the equilibrium in which amenity H_N is 10% lower in the north relative to the symmetric equilibrium, while all other parameters are the same. The third column contains results for the equilibrium in which productivity A_N is 10% lower in the north relative to the symmetric equilibrium, while all other parameters are the same.

We next provide some simulations, which should not be used as a quantitative exercise but rather to show the mechanisms of the model, which cannot be solved analytically.

We use some common numbers in the literature for some parameters of the model, such as the elasticity of substitution $\sigma = 4$ and the share of expenditure on tradeables $\alpha = 0.66$. See Redding and Sturm (2008). We normalize the total population to one $L = 1$, as well as the fixed cost of production $F = 1$, and the labor productivity factor $A_S = A_N = 1$. We search for values of the amenity (H_S and H_N) in each region such that the real wage is equal to one. In this case $H_S = H_N = 1.7297$. We then decrease the level of amenity in the north by 10% while keeping all the other parameters similar to those of the symmetric equilibrium - results reported in the second column. The third column report results when we decrease the productivity in the north by 10% while keeping all the other parameters similar to those of the symmetric equilibrium.

D Robustness Checks on Firm Spatial Sorting

In section 4.1, in order to assess firm spatial sorting, we exploit an approximate sign test proposed by Bugni and Canay (2021) to test the continuity of firm distribution across to the cutoff. Firms in our database spans approximately 20 longitudes from 103° E to 123° E. Exploiting the approximate sign test, we find that the distribution of firms is continuous at the border except for the area between 116° E to 119° E. This might be affected by an exogenous geographic factor—the location of the Dabie Mountain. As a robustness check, we exclude the observations between 116° E to 119° E and report the results in Table D.1.

In addition, given that compared with start-up firms, the flexibility of old firms to move across regions is generally lower (and air pollution is not likely to have been a major factor for firm location 20 or 15 years ago), we restrict our sample to firms that have been in operation for more than 5, 10, 15, and 20 years, respectively. The corresponding results are presented in Table D.2.

As can be seen from Tables D.1 and D.2, our results remain robust to various sub-samples, which provide further evidence that firm spatial sorting is not the key driver of our results.

Table D.1: Robustness Check: Excluding Firms between 116° E and 119° E

	(1) **PhD**	(2) **Master**	(3) **Bachelor**
Control variables, Longitude-quartile FE, Industry FE, Year FE, and Ownership FE absorbed			
RD Estimate	-0.013***	-0.002	0.190***
	(0.004)	(0.006)	(0.020)
Bandwidth	1.742	2.107	0.679
Kernel Type	Triangular	Triangular	Triangular
Observations	64,021	64,021	64,021

Notes: "PhD" represents the share of human capital with PhD degrees; "Master" and "Bachelor" are calculated in the same way. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate RD regression. Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table D.2: Robustness Check: Firms Operating More than 5, 10, 15, and 20 Years

	(1) PhD	(2) Master	(3) Bachelor
Firms Operating More than 5 Years			
RD Estimate	-0.017***	-0.007*	0.067***
	(0.003)	(0.004)	(0.021)
Bandwidth	1.763	2.001	1.343
Kernel Type	Triangular	Triangular	Triangular
Observations	73,408	73,408	73,408
Firms Operating More than 10 Years			
RD Estimate	-0.013***	-0.007	0.083***
	(0.002)	(0.005)	(0.014)
Bandwidth	2.391	3.131	1.641
Kernel Type	Triangular	Triangular	Triangular
Observations	44,149	44,149	44,149
Firms Operating More than 15 Years			
RD Estimate	-0.009*	-0.009	0.064***
	(0.005)	(0.008)	(0.022)
Bandwidth	2.790	2.449	1.837
Kernel Type	Triangular	Triangular	Triangular
Observations	19,379	19,379	19,379
Firms Operating More than 20 Years			
RD Estimate	-0.003	-0.015*	0.062**
	(0.005)	(0.009)	(0.029)
Bandwidth	2.832	2.910	1.964
Kernel Type	Triangular	Triangular	Triangular
Observations	8,055	8,055	8,055

Notes: Firm level control variables, longitude-quartile, industry, year, and ownership fixed effects are absorbed. "PhD" represents the share of human capital with PhD degrees; "Master" and "Bachelor" are calculated in the same way. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate RD regression. Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

E OLS Estimation

Table E.1: Short-run Effects of Air Pollution on Human Capital Productivity (OLS)

Dependent variable	Human capital productivity (innovations per capita)	
	(1)	(2)
$PM_{2.5}$	-0.001	-0.001
	(0.001)	(0.001)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm controls	No	Yes
Weather controls	Yes	Yes
Sample size	74,667	74,667

Notes: Human capital productivity is measured by total innovation divided by human capital. Total innovations include all the reported types of innovation: invention, publication, trademark, and industrial standard. Firm controls include firm age and firm total assets, and weather controls include precipitation, temperature, and hours of sunlight. Standard errors are reported in parentheses.

Without taking endogeneity of air pollution into account, Table E.1 reports the OLS results from the liner specification in Equation 2. The estimate in Column (1) shows that the effect of air pollution ($PM_{2.5}$) on human capital's productivity is not significantly different from zero. In Column (2), including firm controls does not change this result. However, as discussed in Section 4.3, endogeneity of air pollution is a critical issue for causal inference of its effects on different socio-economic outcomes, therefore, the estimates presented in Table E.1 are likely to be inconsistent. To address this issue, we present the 2SLS results, in which air pollution ($PM_{2.5}$) is instrumented by thermal inversion, in Table 5 from which we can see that one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ significantly reduces firm-level human capital's productivity by 0.188 innovation per RD employee.

F Subsidy Policy Analysis

Our quasi-experimental approach has shown that air pollution has created a gap in human capital, knowledge, and innovation between firms in the north and south of China. The question is whether this gap could be bridged by government R&D subsidies (such as "the war for talent" we have seen recently in China). Following existing work (Giambona and Ribas, 2020; Grembi et al., 2016), we adopt an augmented difference-in-discontinuities specification

$$\begin{aligned} Y_{ijc} =& \alpha North_i + f(Dist_i) + North_i \times f(Dist_i) + \rho North_i \times subsidy_i \\ &+ f(Dist_i) \times subsidy_i + \upsilon_{ijc}, \end{aligned} \tag{A.1}$$

where $subsidy_i$ is a dummy variable equal to 1 if firm i in industry j receives government subsidies for R&D, and 0 otherwise. ρ captures the within-firm changes in the differences in human capital, knowledge, and innovation between the north and the south with the subsidy policy. Y_{ijc} is a set of residualized outcome variables, with firm fixed effects, industry-by-year fixed effects, and longitude-quantile-by-year fixed effects absorbed. υ_{ijc} represents the error term.

Table F.1 reports the difference-in-discontinuities estimates on the long-run human capital accumulation. Columns (1)–(3) show that the firm-level difference of PhD, master's, and bachelor's degree proportions between the north and the south are not significantly different depending on whether they receive government subsidy on R&D. Moreover, Table F.2 shows that the R&D subsidies do not significantly bridge the firm-level knowledge and innovation gap between the north and the south, either. In other words, government subsidies for R&D activities do not help alleviate the gap in firm-level human capital, knowledge and innovation between the north and the south.

Table F.1: Long-run Effects on Human Capital Gap: Difference-in-Discontinuities Estimates

	(1) PhD	(2) Master	(3) Bachelor
$North_{itc} \times subsidy_{it}$	0.003	0.002	0.000
	(0.002)	(0.004)	(0.008)
Bandwidth	4.749	4.138	5.006
Kernel Type	Triangular	Triangular	Triangular
Observations	85,035	85,035	85,035

Notes: All specifications include firm fixed effects, industry-by-year fixed effects, and longitude-quantile-by-year fixed effects; these are absorbed in OLS regressions before the difference-in-discontinuities estimations. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate difference-in-discontinuities estimate: the difference between the human capital gap "with R&D subsidies" and "without RD subsidies". Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates.

Table F.2: Long-run Effects on Knowledge and Innovation Gap: Difference-in-Discontinuities Estimates

	(1) Publication	(2) Trademark	(3) Standard	(4) Patent
$North_{itc} \times subsidy_{it}$	-0.050	0.402	0.010	0.026
	(0.154)	(0.487)	(0.089)	(0.255)
Bandwidth	2.031	1.849	1.352	1.968
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	99,496	99,496	99,496	93,898

Notes: All specifications include firm fixed effects, industry-by-year fixed effects, and longitude-quantile-by-year fixed effects, these are absorbed in OLS regressions before the difference-in-discontinuities estimations. The running variable is the distance between a firm and the Huai River border—positive values for the north and negative for the south. Each cell in the table represents a separate difference-in-discontinuities estimate: the difference between the knowledge and innovation gaps "with RD subsidies" and "without RD subsidies". Following Calonico et al. (2014), we estimate the discontinuities at the Huai River border using locally linear regressions and MSE-optimal bandwidth for the default kernel weighting method. Standard errors are reported in parentheses below the estimates.