Does Air Pollution Hurt Innovation? Evidence from China[*]

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Abstract

We examine the effect of air pollution on innovation activity by studying city-level patenting activities and Air Pollution Index (API) in China. We adopt a novel quasi-natural experiment of China's Huai River policy, which provides subsidy of winter heating to cities north of the Huai River but not to cities to the south, to estimate the impact of air pollution on innovation performance. Based spatial regression discontinuity design, we find that API is 8.565 higher in the north and the number of patents per city is 29.1% lower in the north. Further analysis shows that one unit increase in API is associated with 6.7% reduction in the number of patent per city, suggesting that air pollution significantly impedes innovation activities.

JEL classification: O30; Q53.

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1. Introduction

Air pollution has become a major environment problem over the world, and the issue is particularly critical in China since 1980s of Chinese industrialization. Air Pollution Index (API) in China far exceed World Health Organization (WHO) recommended levels that are considered as a safe standard to public health. For example, in 2016 the annual median exposure to Fine Particulate Matter (PM 2.5) in China was 48.8 μg/m3, which is about four times higher than the WHO recommended levels.[1] High levels of air pollution in China lead to more than 350 thousands of premature deaths each year.[2] Chen et al. (2013) find that life expectancies in the north of China are about 5.5 years lower than that in the south of China because the north is exposed to severer air pollution.[3] Smoking bans help innovators create new ideas and know-how (Gao et al., 2020), thus air pollution could significantly impede innovation activity. Therefore, as the purpose of this paper, we examine the real effect of air pollution on innovation activity in China.

The ambient air pollution could hurt innovation activity in at least three ways. First, long-term exposure to air pollution has been proved to related to many non-communicable diseases, such as respiratory mortality, coronary heart disease, ischemic heart diseases, cerebrovascular diseases, kidney diseases and diabetes (see, for example, Zhou et al. 2015; Lin et al. 2016; Bowe et al. 2017; Bowe et al. 2018; Chen, 2017; Lin et al. 2017; Chen and Bloom, 2019). Innovators who suffer disproportionally from air pollution driven diseases could have frequent sick leaves, early retirements, or even sudden deaths, and accordingly the innovation activities would drop. Second, ambient air pollution impairs cognitive functioning of people (Huang et al., 2020; Li, et al., 2020), and innovators who exhibit behavioral biases in decision making

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[1] https://www.who.int/china/news/detail/02-05-2018-who-issues-latest-global-air-quality-report-some-progress-but-more-attention-needed-to-avoid-dangerously-high-levels-of-air-pollution

[2] http://news.bbc.co.uk/2/hi/asia-pacific/6265098.stm.

[3] Other papers also suggest that ambient air pollution is harmful to human health; for example, Brunekreef and Holgate (2002), Pope et al. (2009; 2013), Tanaka (2015), Ebenstein et al. (2017), and Ito and Zhang (2020).

process may lower their innovation productivities. Conversely, a healthy environment helps innovators create new ideas and technologies (Gao et al., 2020). Third, skilled people, who have better labor market mobility, tend to avoid working in polluted areas (Xue et al., 2019). When air pollution drives away these people, lack of skilled innovators would lower average innovation capability of an institute.

In order to study the impact of ambient air pollution on innovation activity, we collect 7,089 patents from 151 cities in China that filed to (and eventually granted by) United States Patent and Trademark Office (USPTO) between 2000 and 2010. [4] While we propose a negative impact of ambient air pollution on innovation, an endogeneity problem may occur that cities experiencing stronger economic growths generate more air pollution and innovation outputs. In an ordinary least squared (OLS) regression analysis for innovation on API, we find a positive coefficient of API, which seems to be opponent to our argument about damage of air pollution.[5] To further understand the real impact of air pollution on innovation, a way that could address endogeneity concern is needed.

We follow Chen et al. (2013), Ebenstein et al. (2017) and Li et al. (2020) to address the endogeneity concern and adopt the quasi-natural experiment of China's Huai River policy, which provides subsidy of winter heating to cities north of the Huai River but not to cities to the south, to estimate the impact of air pollution on innovation performance. During 1950-1980, China government establishes free winter heating for people who live in northern Chinese cities as their basic rights. The government provides them unlimited heating between November 15 and March 15 via the provision of free coal for fuel boilers, where the combustion of coal in boilers is highly related to the release of air pollutants. In southern Chinese cities, there is no

[4] Following Ma et al. (2009) and Wu and Mathews (2012), we focus on patents filed to USPTO but not to Chinese State Intellectual Property Office because U.S. patents are usually regarded with better technological capability and reliability.
[5] One possible explanation is the revised causality that firms and institutes innovate more to alleviate the damage from air pollution (e.g., Marinova and McAleer, 2006; Popp, 2006).

centralized winter heating in the south because the government does not build up heating infrastructure there (Almond et al., 2009). Residents in southern cities rely on their own means to stay warm such as electric blankets, oil column heaters, hot water bottle, air conditioners, etc. They are much more environmentally friendly than central heating fueld by coal boilers. Even though the Chinese government issued a heating reform that changed the payment system from free provision to flat-rate billing to northern Chinese cities in July 2003 (World Bank 2005)[6], government centralized winter heating for the north continues to generate a significant gap between the level of air pollution between northern and southern China (Chen et al., 2013). Northern and southern China are usually identified by the Huai River (or known as the Huai River/Qinling Mountain Range), where the average January temperature is about 0° Celsius along this line (Almond et al., 2009). We test the difference in API and difference in innovation performance per city across the two sides of the Huai River boundary. We then use a spatial regression discontinuity design (RDD) to identify the causal effect of air pollution on innovation because discontinuous variation in air pollution exists across the Huai River and corresponding line.

We firstly separately test whether the Huai River policy causes a discontinuous jump in API and drop in innovation to the north of the river. We find API is 8.565 higher in the north and the difference explains more than half of the API standard deviation, a result consistent with Chen et al (2013), who suggest that the air pollution is more severe in northern China due to the Huai River policy. More importantly, we find that the number of patents per city is 29.1% lower in the north. We also perform a two-stage spatial RDD analysis, and we uncover that a unit increase in API is associated with 6.7% reduction in the number of patent per city. Our

[6] See World Bank. (2005) *China Heat Reform and Building Energy Efficiency Project*. Tech. report, World Bank Group, Washington, DC. http://documents.worldbank.org/curated/en/458551468770148424/China-Heat-Reform-and-Building-Energy-Efficiency-Project

findings remain qualitatively same after two robustness checks: i) restricting our sample to a narrower bandwidth by only including cities located within 10 degree of latitude, approximately 1000 km, both to the north and the south of the Huai River, and ii) using the number of patents scaled by city population as alternative measure of innovation. Our results generally suggest that given serious air pollution in northern China, air pollution significantly hurts patent-based innovation activity.

This paper contributes the literature in two ways. First, our study answers the question how air pollution may damage economic growth. Brown et al. (2009) and Chen et al. (2020) both argue that innovation activities of firms and public sectors remarkably contribute to economic growth and productivity improvement. Hence, air pollution, which impedes innovation, could accordingly hurt economic growth. This finding is also related to a long-term debate about a trade-off between pollution and economic growth (e.g., Gradus and Smulders, 1993; Bovenberg and De Mooij, 1997; Kågeson, 2012). While some scholars argue that pollution prevention policy increases cost of production and slows down the economic growth, our paper suggests that reduced pollution leads to more innovations, which is good for economic growth. Second, recent innovation papers widely investigate the role of firm characteristics and key workers' incentives in innovation (e.g., Belenzon and Berkovitz, 2010; Hirshleifer et al., 2012; He and Tian, 2013; Fang et al., 2014; Bradley et al., 2017; Fassio et al., 2019). Our study further shows that not only firm and institutional factors but also environmental factors (i.e., ambient air pollution in our study) may influence the innovation activity.

The reminder of this paper is organized as follows. Section 2 introduces the Huai River policy. In Section 3, we describe our data sources, variables, and summary statistics. Section 4 presents the methodology. Section 5 provides empirical results. Finally, Section 6 concludes.

2. Huai River policy

Since 1950s, Chinese central government established free central heating policy for northern part of China in winter. The division of the north and south is along the Huai River /Qinling Mountain Range as shown in Figure 1 (January 0° Celsius isotherm). Central heating is not implemented south of this line while residents in the south can only use air conditioning, electric heaters, and other means to stay warm in winter. The centralized heating system is based on large-scale coal burning. Combustion of coal in boilers emits large amounts of air pollutants, deteriorating air quality in China. In 2003, China had a heating reform in northern cities from free heating provision to flat-rate billing. However, the way of winter heating remains unchanged.

While residents in northern part of China enjoy centralized heating policy in winter, the cost is unavoidable. Chen et al. (2013) pointed out that China's Huai River policy greatly increases air pollution, causing the average life expectancy of northern residents 5.5 years lower in the north than in the south owing to cardiorespiratory mortality. Ito and Zhang (2020) find that a household is willing to pay $32.7 annually to eliminate the pollution induced by the Huai River heating policy.

In this paper, we use ArcGIS to draw the Huai River/Qinling Mountain Range based on its major waterway, which originates in Tongbai Mountain in Henan province, flows through southern Henan, northern Anhui, and northern Jiangsu, and then finally enters the Yangtze River at Yangzhou in Jiangsu Province. This Huai River/Qinling Mountain Range is also used in several other studies, such as Almond et al. (2009), and Chen et al. (2013), and Ebenstein et al. (2017).

3. Data and variables

3.1. Innovation measure

Our innovation data come from the Harvard Business School (HBS) patent and inventor database.[7] This database identifies the names, city name, latitude and longitude data of individual inventors who are covered by United States Patent and Trademark Office (USPTO) and the National Bureau of Economic Research (NBER) utility patent database from 1975 to 2010.[8] Thus it enables us to track inventors' city location. We then compute natural logarithm of one plus number of patents of each city as our main innovation measure. Though inventors file patents applications to USPTO, not all of them come from the U.S. Our paper only limits inventors who were in mainland China and applied (and eventually granted) at least one U.S. patent between 2000 to 2010.

One challenge we face to apply this database to the Chinese context is the use of "Pinyin" for city names in HBS patent and inventor database rather than the use of Chinese characters. Some Chinese cities share the same Pinyin, but have different Chinese characters, hence should correspond to different sets of latitude and longitude. Another challenge we face is that some location names in this database are not city names; instead they are the names of provinces where the cities locate or names of city district where inventors live in. To solve these problems, we use Google map to identify the city's longitude and latitude. Then we only select cities whose longitude and latitude information are exactly the same under both Google map and HBS patent and inventor database. This procedure reduces our sample to 484 city names. This does not mean we have 484 unique inventor cities because some cities have multiple names in

[7] Available at: https://dataverse.harvard.edu/dataverse/patent. Also see Li et al. (2014) for a detailed description.
[8] The inventor data generated by Li et al. (2014) correct inconsistent reports of individual inventors among different patent documents. They also distinguish different inventors who have same names. The way they identify inventors is a disambiguation algorithm, which considers all pairs of inventor-patent cases and then determine whether any two paired inventor's names are subject to the same inventor career.

HBS patent and inventor database.[9] For example, for the city of Guangzhou, it appeared as "Guangzhou", "Guangzhou Gangdong", "Guangzhou Guangdong Province, PR", "Guangzhou Guangdong Province", "Guangzhou Province" in this database. All of those city names have the same latitude of 23.12911 and longitude of 113.26439. To minimize the cost of losing observations, in our merging process at later stage, we do not use the city name to merge data. Instead we use latitude and longitude of 484 city names to merge other spatial data.

3.2. Air pollution measure

Our air pollution data is from China Stock Market & Accounting Research (CSMAR) Global Warming Research Database. CSMAR is a widely used commercial database on the Chinese capital market. This database covers daily API of Chinese cities, released by the Chinese Ministry of Environmental Protection (MEP). API characterizes the degree of air pollution. It is determined by the concentration and duration of several major air pollutants near to the ground. The items included in the API are sulfur dioxide (SO_2), nitrogen oxides (NO_2) and inhalable particle matter (PM10) or total suspended particulates. The API is divided into six levels of air quality: 0-50, 51-100, 101-150, 151-200, 201-300, and greater than 300. The larger the index, the higher the level, indicating more air pollution. There are 120 monitoring stations of API. The API data is daily data. We average the daily API to get annual API data for each monitoring station.

3.3. Regional controls

We use data from China City Statistical Yearbook (2000 to 2010) to get the list of cities that have complete data series of GDP and population to control for regional differences. We have 294 cities with full GDP and population data from 2000 to 2010. It includes all provincial

[9] One should notice that we identify the location of an inventor rather than the location of a patent applicant, in particular they could be different from each other when the inventor is hired by the firm that files the patent to USPTO. For example, if an inventor X (who lives in Hangzhou) is hired company A (located in Shanghai), then we identify the location of the inventor X as Hangzhou.

capital cities, some prefecture-level and county-level cities. We use Google Maps to get the GPS geographic coordinates of those cities.

Recent literature suggests that temperature has an impact on people's emotional states cognitive performance (Connolly, 2013; Noelke et al., 2016; Baylis et al., 2018; Dai et al., 2016; Graff Zivin et al., 2018), which can affect innovation activities. We obtain the temperature data from the National Meteorological Information Center of China.[10] This dataset is derived from nationwide digitalized CLIMAT files from various provincial meteorological bureaus. The dataset provides the annual values of climate data from 194 weather stations in 1951-2010. We use annual values of average temperature for each station. Every weather station site has latitude and longitude.

3.4. Creating a panel data set at city-level

Before the merging process, we ensure all data such as patent, API, GDP, population, and temperature have their corresponding latitude and longitude information. We use the latitude and longitude of inventor city names as the base and perform distance matching with API, GDP, population, temperature information within a 150 km radius of inventor cities' geographic coordinates. This process leads our final sample to 151 unique cities. Then we compute natural logarithm of one plus number of patents of each city j in each year t as our main innovation measure. Figure 1 plots the geographic locations of our sample cities. Each dot represents one inventor city. We can see that they are well scattered across China, covering a large sample of important cities (including nearly all provincial capitals and second-tier cities). We do not see a dot (inventor city) in Tibet, Qinghai, and Xingjiang provinces. Qinghai-Tibetan Plateau across both Tibet and Qinghai. Their habitable areas are mainly for pastoral zones. Xinjiang is mostly mountain ranges and basins with poor public transportation access. In Figure 1, coloring

[10] Data is available from here:
http://data.cma.cn/en/?r=data/detail&dataCode=SURF_CLI_CHN_MUL_YER_CES

corresponds to interpolated API levels at the 12 nearest monitoring stations, where green, yellow, and red indicate areas with relatively low, moderate, and high levels of API, respectively. As shown in Figure 1, the areas shaded in red versus the areas shared in yellow and green are well partitioned by the Huai River/Qinling Mountain Range , suggesting a significant difference in air pollution at the central heating border.

<Figure 1 here>

4. Methodology

To examine the effects of air pollution on innovation, we begin our analysis by estimating the ordinary least squares (OLS) model:

$$Innovation_{j,t} = \beta_0 + \beta_1 API_{j,t} + X_{j,t} + \zeta_j + \varepsilon_{j,t} \ , \qquad (1)$$

where $\mathrm{Innovation}_{j,t}$ is the innovation measure, i.e., natural logarithm of one plus the number of patents, for city j in year *t*, and $API_{j,t}$ is the air pollution index for city j in year *t*. ζ_j is the year fixed effect. Vector X stacks a list of city-level time varying observable characteristics (i.e. temperature, GDP growth and natural logarithm of GDP per capita in our study) that might influence city innovation activities other than air pollution. $\varepsilon_{j,t}$ is a disturbance term. In equation (1), the coefficient β_1 measures the effect of air pollution exposure on city innovation after controlling for some covariates.

Consistent estimation of β_1, which can be used for causal effect analysis, requires that unobserved determinants of innovation do not vary with air pollution after adjustment for X. However, one concern about this regression is that the innovation and air pollution may be spuriously correlated because air pollution may be correlated with some unobservable covariates that may also influence the innovation (omitted variable bias). This makes the estimate of β_1 cannot be interpreted as a causal effect of air pollution. To address this endogeneity concern, we leverage a spatial regression discontinuity design (RDD) implicit in the China's Huai River policy. Specifically, we separately test: 1) whether the Huai River policy causes discontinuous changes in air pollution and innovation across the Huai River; and 2) whether determinants of innovation change smoothly as they cross the river. If these two conditions are satisfied, we may implement the RDD, which removes all potential sources of bias and allow us to obtain reliable causal inference.

We firstly perform RDD estimation for innovation to learn to what extent the innovation changes cross the boundary of the Huai River. Specifically, following the model framework of Chen et al. (2013), Ebenstein et al. (2017) and Li et al. (2020), we estimate the RDD model as follows:

$$Innovation_{j,t} = \delta_0 + \delta_1 N_j + f(L_j) + N_j f(L_j) + X_{j,t} + \zeta_t + \varepsilon_{j,t}, \quad (2)$$

where N_j is an indicator variable that takes a value of one if city *j* is located north of the Huai River line and zero otherwise; $f(L_j)$ is a *k*-order polynomial in degrees of the northern latitude of city *j* relative to that of the Huai River line; $N_j f(L_j)$ is included to allow latitude to affect outcomes differently north and south of the Huai River; The estimate of $\delta_1$shows the impact of Huai River on innovation.

Next we use the following two-stage least squares (2SLS) RDD model to estimate the impact of air pollution on innovation. Specifically, we treat the location to the north of the Huai River as an instrument of air pollution, which is measure by API, in the first stage, and regress the innovation on the instrumented API in the second stage. Our 2SLS RDD model is as follows:

The first stage equation is

$$API_{j,t} = \alpha_0 + \alpha_1 N_j + f(L_j) + N_j f(L_j) + X_{j,t} + \zeta_t + u_{j,t} \quad (3)$$

The second stage equation is

$$Innovation_{j,t} = \beta_0 + \beta_1 \widehat{API}_{j,t} + f(L_j) + N_j f(L_j) + X_{j,t} + \zeta_t + \varepsilon_{j,t} \quad (4)$$

By using this 2SLS approach, we offer a way of solving the confounding or omitted variables problem associated with the estimation of effect of air pollution on innovation. The estimate of α_1 indicates the impact of Huai River policy on air pollution. We expect that α_1 is significantly positive, suggesting cities located to the north of the Huai River/Qinling Mountain Range have a higher air pollution level. The estimate of β_1 in equation (4) can be used to interpret the causal effect of air pollution on innovation activity. A significantly negative β_1 suggests that air pollution hurts innovation activities in China.

5. Empirical results

5.1. Diagnostic tests of the validity of the Huai River RDD

Firstly, we test whether Huai River policy causes a drastic change in innovation activities and air pollution. Table 1 presents some preliminary testing results. It clearly indicates that the cities located to the south of the Huai River exhibit a significantly higher level of innovation than cities locate to the north of the Huai River. Meanwhile, we also find that air pollution in cities located to the north of the Huai River is significantly more serious than cities located to the south of the Huai River.

< Table 1 here >

We further make the RDD plots for innovation and air pollution. In Figure 2, we plot our innovation measure at the city level against degrees north of the Huai River. This figure graphically illustrates the general trend of the innovation based on quadratic specification. The x-axis indicates a city's degree of latitude with respect to the Huai River, with 0 indicating the latitude of the Huai River and positive (negative) degrees indicating the degrees north (south) with respect to the Huai River. The y-axis indicates the innovation performance (i.e., natural logarithm of one plus the number of patents) aggregated at the city level. The discontinuity in the innovation is illustrated in a very intuitive way in Figure 2, which clearly shows that innovation jumps up when we move from the north to the south across the Huai River. Specifically, we uncover a striking discrete drop in innovation at the border, suggesting that innovation is lower in the north than in the south around the border of the Huai River.

< Figure 2 here>

To examine whether Huai River policy causes a drastic change in air pollution, we make the RDD plot of API against degrees north of the Huai River in Figure 3. The plotted line in the figure presents the fitted values of API obtained from a quadratic specification. This figure provides a graphical assessment of the Huai River policy's impact on air pollution. Specifically, it reveals a discontinuous upward jump in API to the north of the river. Specifically, we find that there is a sharp discrete jump in API about 15 at the border, implying that API is about a standard deviation higher in the north than in the south around the border of the Huai River.

< Figure 3 here>

Overall, the 2 figures above provide strong evidence that innovation and air pollution changes drastically across the discontinuity point. More explicitly, cities located to the north of the Huai River exhibit a significantly higher pollution and lower innovation.

Secondly, we examine whether city characteristics (i.e., GDP growth, GDP per capita and temperature), which are correlated with innovation, change smoothly as they cross the Huai River. Specially, we perform two tests: i) we test whether these covariates are significantly different between the two sides of the Huai River by a small margin (one degree both south and north around the Huai River); ii) we regress our innovation measure on these city characteristics to get the fitted innovation, which is the expected innovation. Then we test whether the expected innovation is significantly different between the south and north one degree around the Huai River. Table 2 presents these testing results. We find that all these covariates have insignificant differences between the two sides. Moreover, the expected innovation is not significantly different for cities in the south and north as well. Overall, our testing results suggest that the determinants of innovation are independent from the Huai River policy.

< Table 2 here>

To sum up, the diagnostic test results presented in this subsection support the validity of implementing the Huai River RDD, which removes all potential sources of bias and allow us to obtain reliable causal inference.

5.2. Results for OLS and RDD estimations

In this subsection, we proceed to implement our RDD. Before we present our RDD estimation results, we report our OLS estimation results with and without control variables in Table 3. Our results show that air pollution has significantly positive impact on innovation. As we discussed above, this finding may be spurious because air pollution may be correlated with unobservable covariates that may also influence the innovation.

< Table 3 here>

Table 4 presents RDD estimation for innovation, which is measured by natural logarithm of one plus the number of patents. The RDD model is estimated based on quadratic specification. In Model (1), we find that the coefficient estimate on indicator variable North (N_j) is negative and significant at the 1% level, meaning that innovation drops cross the boundary of the Huai River/Qinling Mountain Range. In Model (2), we further control for other city-level variables. Once again, the coefficient estimate on indicator variable North (N_j) is negative (equal to -0.344) and significant at the 1% level. To interpret the economic effect, based on equation (2), we obtain 29.1% ($e^{-0.344}$ - 1= -0.2911) percentage changes in the number of patents. Therefore, we conclude that innovation is about 29.1% lower in the north.

< Table 4 here>

Table 5 presents our 2SLS RDD estimation results. We report the first-stage regression with API as the dependent variable and the instrument variable (IV), indicator variable North (N_j), as the independent variable (column 1 and column 3). The coefficient estimate on North (N_j), is positive and significant at the 1% level, suggesting that the North (N_j) is positively associated with API. We find there is a significant increase in API at the Huai River: at the boundary, compared with the API of southern China, the API is 14.158 (column 1) and 8.565 (column 3) higher in the northern China. To interpret the economic effect, based Model (2), we find that API is 8.565 higher in the north, which is more than half of the API standard deviation indicated in Table 1. Overall, consistent with the literature, our first stage estimation results provide evidence that the Huai River policy has created a discontinuity in air pollution and it made air pollution more serious in the northern China area.

< Table 5 here>

Column 2 and column 4 displays our estimated results for the second stage regression. We find that instrumented air pollution negatively affects the innovation. This effect is highly significant no matter we include control variables or not, lending strong support to a causal interpretation of the negative impact of air pollution on the innovation in China. Specifically, the column (4) shows that one unit increase in API is associated with a reduction in the number of patent per city by 6.7% ($e^{-0.069}$ - 1= -0.067).

5.3. Robustness checks and additional analyses

In addition to the above estimations, we have conducted two robustness checks and additional analyses.

5.3.1. Estimation results for a sample closer to Huai River

In the first set of additional analyses, we restrict our sample to a narrower bandwidth by only including cities located within 10 degree of latitude, approximately 1000 km, both to the north and the south of the Huai River line. We apply the same OLS and 2SLS RDD estimation methods to this sample with narrower bandwidth.[11]

In unreported results from the OLS estimation, we find same results as what we demonstrated in Table 3, air pollution has significantly positive impact on innovation. But as discussed above, this finding may be spurious. Next, we perform RDD estimation. Table 6 presents our new results from the 2SLS RDD estimation. Consistent with Table 5, the coefficient estimate on the dummy variable North (N_j) obtained from the first stage estimation, is positive and significant at the 1% level, suggesting that air pollution gets worse in the northern China. We find there is a significant increase in API crossed the Huai River, and the API rises by 23.505 and 16.606 in column 1 and column 3, respectively. Column 2 and column 4 display our estimated results for the second stage regression. Consistent with Table 5, we find that instrumented air pollution negatively affects the innovation.

< Table 6 here>

5.3.2. Estimation results using patent numbers scaled by city population

We also apply the same spatial RDD specified by equation (3) and equation (4) to the patent number scaled by city population. We adopt this measure to address the concern that big cities (like Shanghai) tend to generate more patents because of more potential inventors. We report our estimation results in Table 7 using this new innovation measure. Our new results are

[11] Same as what we do in the previous section, we also perform diagnostic tests for the validity of the RDD design for our robustness checks and additional analyses. Our test results show that the conditions to apply the RDD are satisfied. To save space, we do not report these test results here, but they are available upon request.

consistent with our findings in Table 5 reports. The column 1 and column 3 show that the coefficient estimate on North (N_j), is positive and significant at the 1% level, suggesting that the Huai River policy has created a discontinuity in air pollution, and cities located to the north of the Huai River have higher pollution levels. As we can find from the column 2 and column 4 of Table 7, the instrumented air pollution (API_hat) is significantly negative. Therefore, we conclude that air pollution impedes the innovation in China even we scale the innovation performance by city population.

< Table 7 here>

6. Conclusion

In this paper, we study the impact of ambient air pollution on innovation activity by using 151 cities in China between 2000 and 2010. To address the endogeneity problem, we adopt the quasi-natural experiment of China's Huai River policy, which provides subsidy of winter heating to cities north of the Huai River but not to cities to the south, to estimate the impact of air pollution on innovation performance. We use a spatial regression discontinuity design (RDD) to identify the causal effect of air pollution on innovation due to the discontinuous variation in air pollution across the Huai River/Qinling Mountain Range.

Our empirical results show that Huai River policy causes a discontinuous jump in API and drop in innovation to the north of the river. The API is 8.565 higher in the north, and the difference explains more than half of the API standard deviation. The number of patents per city is about 29.1% lower in the north. We also perform a two-stage spatial RDD analysis, and uncover that a unit increase in API is associated with 6.7% reduction in the number of patent per city. Therefore, our results generally suggest that air pollution hurt innovation activity.

Our paper suggests one important policy implication to a long-term debate about a trade-off between pollution and economic growth (e.g., Gradus and Smulders, 1993; Bovenberg and De Mooij, 1997; Kågeson, 2012). Although air pollution prevention increases cost of production, the reduced air pollution could also stimulate innovation as well as economic growth. Therefore, governments should emphasize more on environmental protection without concerning about the cost of air pollution preventions.

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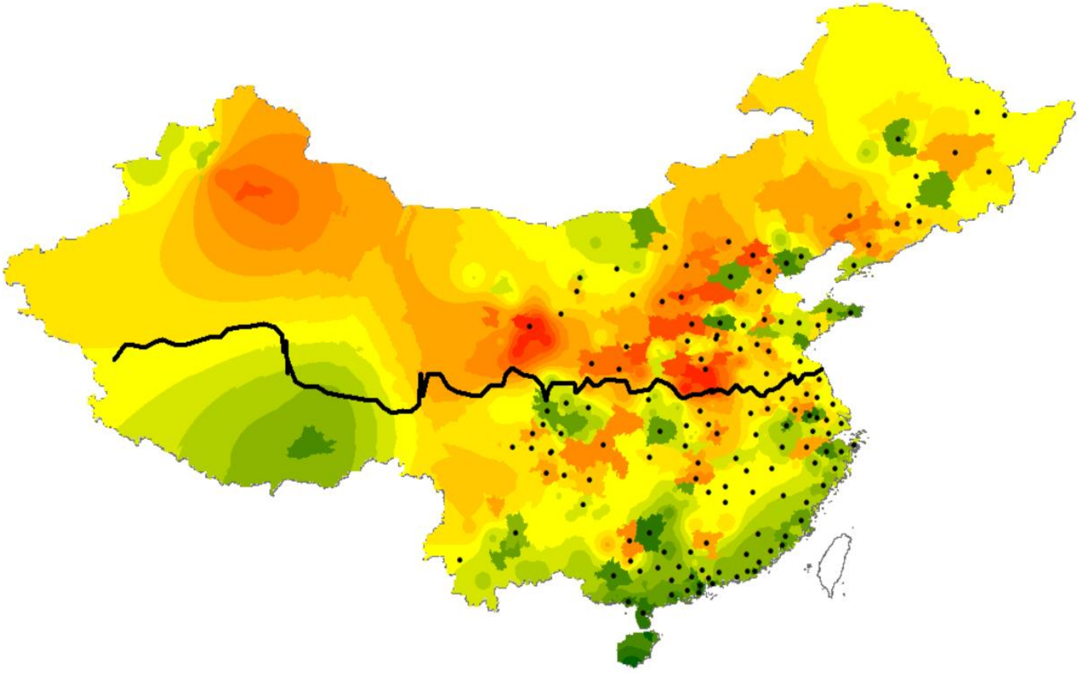

Figure 1. Huai River/Qinling Mountain Range and Air Pollution Index

Notes: This line in the middle of the map is the Huai River/Qinling Mountain Range. Each dot represents one inventor city. Coloring corresponds to interpolated API levels at the 12 nearest monitoring stations, where green, yellow, and red indicate areas with relatively low, moderate, and high levels of Air Pollution Index (API). An area left in white is not within the range of the API station.

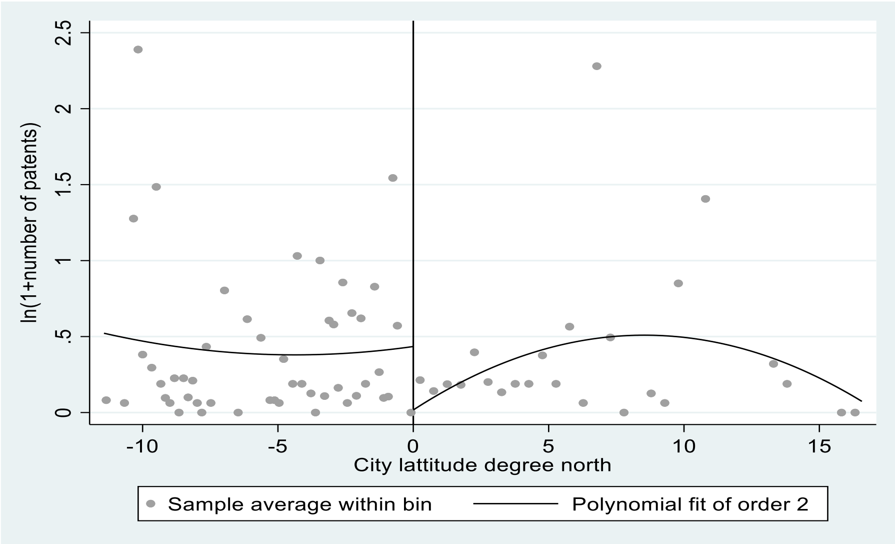

Figure 2. Regression Discontinuity Plot of Innovation at City Level

Notes: This figure plots innovation against degrees north of the Huai River/Qinling Mountain Range, where innovation is measured as natural logarithm of one plus the number of patents filed to USPTO by individuals and institutes of cities. The x-axis represents the latitude degree, with 0 indicating the latitude of the Huai River and positive (negative) degrees indicating the degrees north (south) with respect to the Huai River. Each dot represents the average within each bin. The line presents the fitted values of natural logarithm of one plus the number of patents from a quadratic specification.

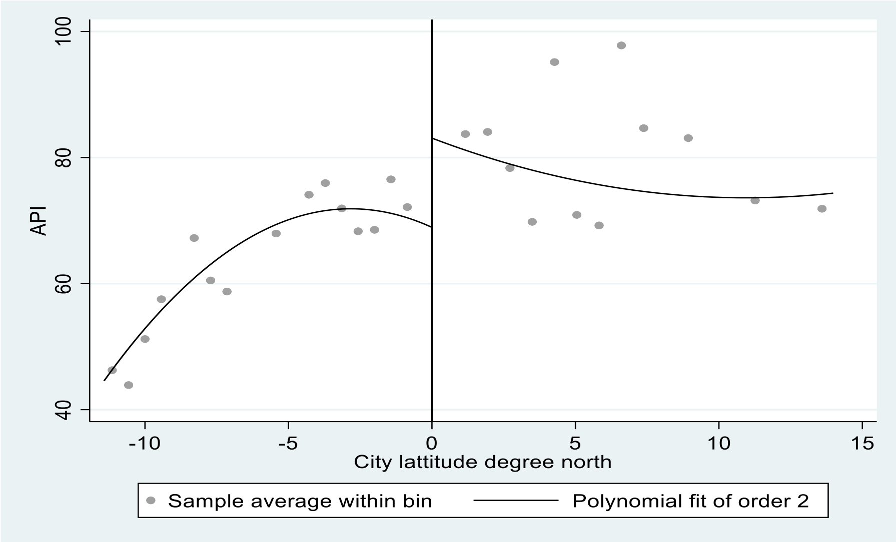

Figure 3. Regression Discontinuity Plot of Air Pollution Index

Notes: This figure plots the API against degrees north of the Huai River. The x-axis represents the latitude degree, with 0 indicating the latitude of the Huai River and positive (negative) degrees indicating the degrees north (south) with respect to the Huai River. Each dot represents the average within each bin. The line presents the fitted values of API obtained from a quadratic specification.

Table 1. Differences of Innovation and Air Pollution Between South and North Sides of Huai River

Variables	South	North	Difference (South-North)	T-value
Ln(1+number of patents)	0.413	0.319	0.094	2.689***
	(0.727)	(0.616)		
API	66.124	77.409	-11.285	-10.610***
	(15.105)	(15.949)		

Notes: This table reports means and differences of the innovation and Air Pollution Index (API) between south and north of the Huai River. Number of patents is the number of patents filed to United States Patent and Trademark Office (USPTO) by individuals and institutes of a city in a given year. API is the air quality index, which measures the concentration and duration of several major air pollutants (e.g., sulfur dioxide (SO2), nitrogen oxides (NO2) and inhalable particle matter (PM10) or total suspended particulates) near to the ground. Numbers in the parentheses are standard deviations. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 2. Differences of City Characteristics and Expected Innovation Between South and North around the Huai River by A Small Margin ([-1°, 1°])

Variables	Mean (South)	Mean (North)	Difference in Means (South-North)	*t*-value
Temperature	15.121	14.737	0.384	1.011
	(3.049)	(0.716)		
GDP growth	0.182	0.24	-0.059	-1.146
	(0.157)	(0.427)		
GDP per capita	9.654	9.691	-0.038	-0.321
	(0.851)	(0.616)		
Expected innovation	0.357	0.351	0.006	0.182
	(0.243)	(0.116)		

Notes: This table reports the differences of city characteristics and expected innovation between south and north around the Huai River within a small margin (one degree). Temperature is an annual value of average temperature of a city. GDP growth is the annual change in Gross Domestic Product (GDP). GDP per capita is the natural logarithm of GDP divided by population of a city. The expected innovation is the fitted values by regressing the natural logarithm of one plus number of patents on the city characteristics (i.e. temperature, GDP growth and GDP per capita). The *t*-value is the *t*-test statistics of testing the difference in mean. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3. Regression Analysis of Innovation on Air Quality Index

Indep. Var.	Model 1	Model 2
API	0.005***	0.014***
	(0.002)	(0.002)
Temperature		0.027***
		(0.006)
GDP per capita		0.674***
		(0.048)
GDP growth		0.140
		(0.115)
Constant	0.182	-7.656***
	(0.144)	(0.513)
Year fixed effect	Yes	Yes
N	880	788
R-squared	0.075	0.303

Notes: This table reports OLS regression analysis for innovation. Dependent variable is innovation, which is the natural logarithm of one plus the number of patents of a city in a given year. Air Pollution Index (API) is the air quality index, which measures the concentration and duration of several major air pollutants (e.g., sulfur dioxide (SO2), nitrogen oxides (NO2) and inhalable particle matter (PM10) or total suspended particulates) near to the ground. Other variables are described in Table 2. Year fixed effect is incorporated, and N indicates the number of city-year observations. Robust standard errors clustered at the city level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Regression Discontinuity Estimation for Impact of Huai River Policy on Innovation

Indep. Var.	Model 1	Model 2
North	-0.410***	-0.344***
	(0.078)	(0.084)
Temperature		0.052***
		(0.010)
GDP per capita		0.348***
		(0.026)
GDP growth		0.085
		(0.103)
Constant	0.402***	-3.640***
	(0.080)	(0.286)
Year fixed effect	Yes	Yes
Polynomial in latitude	Yes	Yes
N	1,661	1,465
R-squared	0.071	0.206

Notes: This table presents the regression discontinuity estimation the effects of Huai River policy on innovation. Dependent variable is the natural logarithm of one plus the number of patents of a city in a given year. North is an indicator variable that is equal to one if a city is located in the north of the Huai River/Qinling Mountain Range; zero otherwise. Other variables are described in Table 2. Year fixed effect and a quadratic polynomial in the degrees north of the Huai River are incorporated, and N indicates the number of city-year observations. Robust standard errors clustered at the city level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Two-Stage Least Squares Estimation of Innovation Based on Huai River Policy

	Model 1		Model 2	
	1st stage	2nd stage	1st stage	2nd stage
Indep. Var. \ Dep. Var.	API	Innovation	API	Innovation
North	14.158 ***		8.565 ***	
	(2.673)		(2.742)	
API_hat		-0.049 ***		-0.069 **
		(0.016)		(0.032)
Temperature			0.452	0.084 **
			(0.324)	(0.040)
GDP per capita			-2.680 ***	0.379 ***
			(0.860)	(0.129)
GDP growth			-3.008 **	-0.114
			(1.396)	(0.211)
Constant	71.085 ***	4.038 ***	90.648 ***	-0.599
	(2.793)	(1.250)	(9.666)	(3.108)
Year fixed effect	Yes	Yes	Yes	Yes
Polynomial in latitude	Yes	Yes	Yes	Yes
N	869	869	778	778

Notes: This table presents the two-stage least squares estimation of innovation based on Huai River policy. In the first stage, we perform RDD analysis, where API is regressed on a north indicator variable (equal to one if a city is located in the north of the Huai River/Qinling Mountain Range; zero otherwise) in Model 1. Model 2 further controls for temperature, GDP per capita and GDP growth in the regression. In the second stage, the fitted API (*API_hat*) from the first stage is regressed with natural logarithm of one plus the number of patents. Other variables are described in Table 2. Year fixed effect and a quadratic polynomial in the degrees north of the Huai River are incorporated, and N indicates the number of city-year observations. Robust standard errors clustered at the city level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Two-Stage Least Squares Estimation of Innovation Based on Huai River Policy ([-10°, 10°])

	Model 1		Model 2	
	1st stage	2nd stage	1st stage	2nd stage
Indep. Var. \ Dep. Var.	API	innovation	API	innovation
North	23.505 *** (3.158)		16.606 *** (3.211)	
API_hat		-0.035 *** (0.009)		-0.038 *** (0.014)
Temperature			0.532 (0.331)	0.077 *** (0.027)
GDP per capita			-1.966 ** (0.966)	0.426 *** (0.082)
GDP growth			-3.453 *** (1.335)	-0.090 (0.149)
Constant	71.785 *** (2.974)	3.310 *** (0.830)	83.347 *** (10.915)	-2.779 * (1.504)
Year fixed effect	Yes	Yes	Yes	Yes
Polynomial in latitude	Yes	Yes	Yes	Yes
N	759	759	678	678

Notes: This table presents the two-stage least squares estimation of innovation based on Huai River policy using a subsample including cities located within 10 degree of latitude to the north and the south of the Huai River/Qinling Mountain Range. In the first stage, we perform RDD analysis, where API is regressed on a north indicator variable (equal to one if a city is located in the north of the Huai River/Qinling Mountain Range; zero otherwise) in Model 1. Model 2 further controls for temperature, GDP per capita and GDP growth in the regression. In the second stage, the fitted API (*API_hat*) from the first stage is regressed with natural logarithm of one plus the number of patents. Other variables are described in Table 2. Year fixed effect and a quadratic polynomial in the degrees north of the Huai River are incorporated, and N indicates the number of city-year observations. Robust standard errors clustered at the city level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Two-Stage Least Squares Estimation of Innovation Based on Huai River Policy- Using the Number of Patents Scaled by Population as Innovation Measure

	Model 1		Model 2	
	1st stage	2nd stage	1st stage	2nd stage
Indep. Var. \ Dep. Var.	API	innovation	API	innovation
North	27.410***		20.247	
	(5.057)		(4.788)	
API_hat		-0.0140**		-0.024**
		(0.007)		(0.011)
Temperature			0.083	0.027
			(0.445)	(0.017)
GDP growth			-3.700**	-0.042
			(1.762)	(0.092)
Constant	71.806***	1.697***	66.302***	1.611**
	(5.086)	(0.641)	(6.215)	(0.781)
Polynomial in latitude	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	759	759	678	678

Notes: This table presents the two-stage least squares estimation of innovation based on Huai River policy. In the first stage, we perform RDD analysis, where API is regressed on a north indicator variable (equal to one if a city is located in the north of the Huai River/Qinling Mountain Range; zero otherwise) in Model 1. Model 2 further controls for temperature and GDP growth in the regression. In the second stage, the fitted API (*API_hat*) from the first stage is regressed with the natural logarithm of one plus the number of patents scaled by city population. Other variables are described in Table 2. Year fixed effect and a cubic polynomial in the degrees north of the Huai River are incorporated, and N indicates the number of city-year observations. Robust standard errors clustered at the city level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.