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The Impact of Exogenous Pollution on Green Innovation

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Abstract

Does environmental quality affect firms' activities that might improve that quality? In this paper, we use China's public heating policy as a quasi-experiment to investigate the impact of exogenous pollution differences on green innovation behavior. We use a regression discontinuity model, and carry out a suite of robustness tests. We consistently find that firms located in cities with an exogenous source of heavy pollution tend to adopt green innovation at a lower rate while we find no difference in the rate at which they adopt non-green innovation. We find a strong causal effect: being north of the boundary, where pollution levels are higher, leads firms to adopt less green innovation. Firms located in the heating areas report roughly 1 less green innovation per billion RMB of assets, a substantial difference given the average number of green innovations per billion RMB of assets of northern firms is 0.641.

Keywords China, Green innovation, Pollution, Quasi-experiment, Regression discontinuity

1. Introduction and Motivation

Pollution problems are severe in developing countries. For example, both China and India have a heavy air pollution problem in many of their large cities (Badami, 2005; Rohde & Muller, 2015). One way to reduce pollution is through green innovation. Green innovation is defined as “the implementation of new, or significantly improved, products (goods and services), processes, marketing methods, organizational structures and institutional arrangements which, with or without intent, lead to environmental improvements compared to relevant alternatives” (Authority & Allé, 2012; OECD, 2010). It is one of the most important choices that firms make to deal with environmental issues and build sustainable development (Eltayeb & Zailani, 2014; Sezen & Cankaya, 2013).

The existing literature shows that when pollution levels are high, consumers and environmental regulations tend to push firms to have more green innovations (Cai & Li, 2018; Horbach, 2008), which in turn leads to less pollution. However, in most situations, pollution is endogenous and regulation is exogenous to firms; firms generate

pollution and the government regulates firms leading to green innovation. In such circumstances, it is difficult to separate the effect of regulations on firm behavior from the effect that pollution itself might have on firms' innovation choices.

It is possible, however, that the causality could be reversed, because firms are in less polluted areas, they might tend to adopt higher levels of green innovation. One way for this to occur is if pollution affects firm green innovation due to its impact on the labor force movement. When workers select a job location, a city's pollution level is an important concern (Lu et al., 2018). Since workers tend to move to a city with less pollution, this affects firms' green innovation capacity (Horbach, 2008). Another possible way that pollution might affect green-innovation choices is if a firm is set in an area in which there is heavy pollution, firms may perceive the marginal benefit of green innovation on air pollution as negligible, disincentivizing adoption of such technology.

In this paper, we take advantage of a unique policy threshold that allows us to study the causal relationship between pollution levels and green innovation. The policy in question, known as the Huai River policy, installs a public heating infrastructure on the northern side of a geographic line. Numerous studies have shown that this policy has significantly increased pollution to the north of the threshold (Almond et al., 2009; Chen et al., 2013; Xiao et al., 2015). Using this policy boundary, we find that firms adopt less green innovation on the north side of this line, where pollution is greater than in comparable areas without the exogenous pollution source. Because the policy was established decades ago and not in response to either pollution or firm innovations, our results provide strong evidence of a causal effect of pollution on green innovation.

2. Policy Background

In the 1950s, the Chinese government implemented its public heating policy across the country. This policy installs a public heating system in a city if it has a daily average temperature less than or equal to 5 degrees Celsius or 41 degrees Fahrenheit for at least 90 days per year. Based on this criterion, cities in northern China have public heating, while the southern cities do not and this roughly coincides with the Huai River. The public heating system burns coal to generate heat and transmits the heat through water

pipes into each household during wintertime. Figure 1 shows the heating boundary.

Studies have found that the policy has a significant effect on air quality. The public heating system worsens air pollution during the winter in cities that use it (Almond et al., 2009; Chen et al., 2013; Xiao et al., 2015). It has also been shown that the public heating system on average reduces 5 years life expectancy of the individuals who live in the cities that have it, compared to individuals who live without public heating (Chen et al., 2013). It would not be surprising if such effects on health and quality of life might affect firm choices, and it is the goal of this paper to look for evidence of such an effect.

Figure 1. The heating boundary in mainland China. The black line shows the heating boundary, the cities in the north of the boundary have public heating, while the cities in the south of the boundary do have public heating. The yellow line indicates longitude 106.1896258 ° E, the heating boundary at the east of the yellow line mostly does not coincide with provincial political boundary, while the heating boundary at the west of the yellow line mostly coincides with provincial political boundary.

3. Data

The International Patent Classification (IPC) system includes the "IPC Green Inventory" category, which includes 7 types of innovations: alternative energy production, transportation, energy conservation, waste management, agriculture/forestry, administrative regulatory or design aspects, nuclear power

generation. Based on IPC green innovation criteria, we use the 2013-2017 green innovation data from Baiten database.¹

Our firm performance data is from the China Stock Market & Accounting Research Database.² To measure the firms at all different scales, we use the number of green innovations per billion RMB of a firm's total assets to measure a firm's green innovation behavior. The location of each firm is identified using the firm address in the Baiten data.

Our geographic data were obtained using as follows. First, the heating boundary was marked in Google Earth based on the historical policy implementation. This boundary was exported as GPS coordinates. Then, using the R geosphere package (Hijmans et al.), we calculate the distance between the city of each firm in our dataset and the closest point on the heating boundary.

4. Identification Strategy

Since the public heating policy has a clear geographic policy boundary, we use a regression discontinuity (RD) design to estimate the policy effect. The RD design has been widely used in literature to investigate the effect of geographically implemented policies (Keele & Titiunik, 2015; Lee & Lemieux, 2010). When a policy treatment has a clear cut-off point, samples around the cut-off point make a good comparison to estimate the treatment effect (Lee & Lemieux, 2010). The Huai River policy is well suited to this type of analysis because it was implemented based on a meteorological feature, and that feature is exogenous to firms. It has been shown that this policy leads to greater pollution in the northern cities, providing an opportunity to study firm behavior under an exogenous pollution source. We make use of this exogenous variation to identify the effect of pollution on firm green innovation.

As the probability of getting public heating treatment is 1 or 0, we apply a sharp RD design (Imbens & Lemieux, 2008). We use the number of green innovations per billion RMB in total assets as the measurement of firm green innovation behavior. Our

¹ Website link: <https://www.baiten.cn>.

² Website link: <http://us.gtadata.com>.

base regression model is as follows:

$$GI_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 heating_i \cdot distance_i + X_{it} \delta + \varepsilon_{it}, \quad (1)$$

where, GI_{it} is the number of green innovations per billion RMB in total assets for firm i at time t ; $heating_i$ is a dummy variable, equal to 1 if the firm i is located in a city with public heating; $distance_i$ is the distance between the city that firm i is located in and the closest point on the heating boundary, $distance_i$ is positive if the city has public heating and negative otherwise; X_{it} is a vector of firm performance control variables: profit margin on net assets (PMoNA), earning per share (EpS), main business increasing rate of income (MBIRoI), number of directors (NoD). Our coefficient of interest is β_1 , which captures the marginal effect on GI_{it} of being in the region with public heating.

As mentioned above, the impact of pollution on the labor force is one possible mechanism through which pollution might affect green innovation. If this holds, then firms in the higher pollution area would have lower innovation capacity, which should affect both green innovation and non-green innovation. On the other hand, if the higher pollution disincentives only green innovation, then non-green innovation would be unaffected. To provide some evidence about the causal mechanism, therefore, we also test the treatment effect on firms' non-green innovation. We calculate the number of non-green innovations by the difference between a firm's total innovations and its number of green innovations.

Figure 2 shows the kernel densities for the green innovation measurement for firms within 100 km of the boundary. Within 100 km of the boundary, the portion of firms that have a small amount of green innovation per assets is higher in the north side of the boundary than the south side. Table 1 shows summary statistics for variables used for firms within different distances both north and south of the policy boundary.³ As seen in the table, within 100 km of the boundary, the total number of green innovations is not different between the two sides at the 5% level. When we normalize by firm assets, however, we see in both Figure 2 and Table 1 that southern firms have

³ In appendix, we show a detailed summary statistics.

significantly more innovations per million RMB in assets than the northern firms. This provides some preliminary evidence that the public heating treatment may affect change the general innovation behavior of the northern firms, so they have fewer innovations overall.

Figure 2. The kernel densities for green innovations for firms within 100 km of the boundary.

Table 1

Summary Statistics

	All Firms within					
	<100 km of the Heating Boundary			<200 km of the Heating Boundary		
	South No Public Heating (N=52)	North Have Public Heating (N=150)	p value	South No Public Heating (N=171)	North Have Public Heating (N=270)	p value
The Number of Total Innovations per Firm						
Mean (SD)	27.592 (38.226)	12.930 (19.716)	< 0.001	19.066 (34.052)	12.833 (19.490)	0.019
The Number of Green Innovations per Firm						
Mean (SD)	6.184 (6.033)	4.359 (7.610)	0.13	6.232 (11.779)	4.081 (6.226)	0.016
The number of Non-Green Innovation						
Mean (SD)	21.408 (33.210)	8.570 (14.861)	< 0.001	12.834 (25.413)	8.752 (16.351)	0.049
Total Assets (unit: billions of RMB)						
Mean (SD)	5.157 (4.455)	15.738 (31.388)	0.02	9.731 (13.718)	13.459 (25.283)	0.095
The Number of Green Innovation per Billion RMB of Assets						
Mean (SD)	1.638 (1.800)	0.641 (1.089)	< 0.001	1.472 (2.808)	0.788 (1.341)	< 0.001
The Number of Non-Green Innovation per Billion RMB of Assets						
Mean (SD)	3.418 (4.237)	1.577 (3.325)	0.002	2.848 (5.395)	2.300 (8.368)	0.471
Profit Margin on Net Assets						
Mean (SD)	0.080 (0.076)	0.035 (0.133)	0.024	0.057 (0.196)	0.025 (0.229)	0.154
Earnings per Share						
Mean (SD)	0.400 (0.427)	0.254 (0.610)	0.123	0.360 (0.797)	0.232 (0.537)	0.052
Distance to the Heating Boundary (unit: kilometers)						
Mean (SD)	37.542 (16.800)	53.187 (23.999)	< 0.001	129.112 (67.519)	93.957 (51.748)	< 0.001
Main Business's Increasing Rate of Income						
Mean (SD)	0.719 (4.598)	0.499 (3.232)	0.714	394.076 (4834.794)	0.329 (2.419)	0.191
Number of Directors						
Mean (SD)	9.020 (1.199)	9.014 (2.186)	0.985	8.735 (1.018)	8.884 (1.880)	0.37

Note: The p-value is for the t-test for the difference of means between the treated (public heating) and control groups.

Table 2

Chi-Square Test on Industrial Structure

	Firms within			
	<100 km of the Heating Boundary	<200 km of the Heating Boundary	<300 km of the Heating Boundary	<400 km of the Heating Boundary
P- value	0.362	0.141	0.344	0.211

Note: The p-value is for the chi-square test for testing the difference in the industrial structure around the heating boundary.

One possible reason for the significant difference in innovation could be different industrial distributions on either side of the boundary. For example, one side might have a large concentration of an industry that tends to innovate a lot more. Our data include 10 industries,⁴ we calculate the number of firms in each industry on both sides. In Table 2, we report the chi-squared test for different industrial structures across the boundary. The results show that there is no significant difference in the industrial structure around the boundary, supporting the conclusion that the differences in innovation behavior are not because of significant differences in the industries on the two sides of the boundary.

5. Results

5.1 Graphical Analysis

In Figure 3 we plot the number of green innovations per billion RMB in total assets against distance from the boundary for firms within 200km of the heating boundary. Our plot uses evenly-spaced bins introduced by Calonico et al. (2015), which separates distance evenly and presents the green innovation measures for all firms within a given bin and includes first, second and third degree polynomial regression lines.

In Figure 3a, the conditional mean function is linear, the left fitting line at the cut-off point is in the 95% confidence interval of the first right data point, which implies there is no strong statistical evidence of discontinuity from left the right, but there is discontinuity from right to left. As we use high-order polynomial to estimate the conditional mean function, the discontinuity from left to right appears in Figure 3c. Overall, we see a very slight break at the policy boundary.

⁴ The 10 industries include: mining, power generation, textile, steel, chemical, petrochemical, cement, metallurgical, pharmaceutical, paper.

a

b

c

Figure 3. Plots of the share of green innovation in total innovation over distance. The data used to create these plots only include the firms located within 200km around the heating boundary. The orders of the polynomial used for regression lines are 1, 2, and 3 respectively.

5.2 Regression results

In Table 2 we report simple OLS regressions using samples in different ranges. When a narrow band is used, there is probably less spatial variation except for the exogenous treatment, but the number of observations is relatively small. As the range increases, there is more room for unexplained variation in the firms, but we also obtain more data points for our estimation. We start using firms located within 100 km on either side of the treatment boundary, then expand the range in 100 km increments to 400 km.

Table 2

The Effect of Public Heating Using OLS

	Firms within			
	<100km	<200km	<300km	<400km
(Intercept)	2.120 *** (0.500)	1.588 ** (0.575)	1.510 *** (0.384)	1.182 *** (0.345)
heating	-1.018 *** (0.220)	-0.660 ** (0.208)	-0.379 ** (0.143)	-0.034 (0.133)
PMoNA	0.011 (1.162)	0.509 (0.520)	0.475 (0.434)	0.120 (0.183)
EpS	-0.110 (0.261)	0.116 (0.175)	0.184 (0.135)	0.351 ** (0.121)
MBIRI	-0.028 (0.030)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
NoD	-0.046 (0.049)	-0.020 (0.062)	-0.039 (0.042)	-0.033 (0.039)
Observations	191	409	843	1101

Note: 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Based on OLS results, the effect on firm green innovation of the public heating threshold is significant within 300 km around the boundary. The results indicate that on average, with everything else held constant, firms in areas with public heating have less green innovation, with an estimated effect of 1.018 innovation per billion RMB total assets for firms located within 100 km of the boundary, falling to 0.379 when looking at firms within 300 km of the boundary. When all firms within 400 km of the boundary are considered, the effect falls to 0.034 and is no longer statistically

significant.

The OLS estimators from Table 2 are unbiased only if unobserved variables are not correlated with heating after controlling for our covariates. One concern is that the city-level infrastructure data that cover all the cities in our sample are not available, and infrastructure is important to firm productivity (Wan & Zhang, 2018). To the extent that infrastructure varies from north to south for reasons unrelated to the provision of public heating, missing infrastructure data could result in a biased OLS estimator of the causal effect of public heating on green innovation. The assumption implicit in RD models is that within a small range of the boundary, cities will tend to have a similar infrastructure. The RD approach controls for this unobserved variation by including the distance from the border, helping to identify the effect of public heating on innovation.

Table 3

The Effect of Public Heating from Regression Discontinuity

	<i>Dependent variable:</i>							
	Green Innovations per Billion RMB of Assets				Non-Green Innovations per Billion RMB of Assets			
	100km	200km	300km	400km	100km	200km	300km	400km
(Intercept)	2.811 *** (0.665)	1.896 ** (0.682)	2.005 *** (0.499)	2.142 *** (0.437)	3.880 * (1.814)	7.142 ** (2.512)	4.550 ** (1.433)	6.169 *** (1.083)
heating	-1.765 ** (0.537)	-1.328 ** (0.440)	-0.964 ** (0.368)	-1.354 *** (0.327)	-1.662 (1.467)	-2.974 (1.619)	-0.549 (1.056)	-1.172 (0.811)
distance	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 *** (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 * (0.000)
heating*distance	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 ** (0.000)
PMoNA	0.015 (1.161)	0.490 (0.519)	0.456 (0.434)	0.090 (0.182)	4.000 (3.169)	1.705 (1.911)	1.052 (1.246)	0.273 (0.452)
EpS	-0.107 (0.261)	0.119 (0.175)	0.186 (0.135)	0.338 ** (0.120)	-0.627 (0.712)	-0.092 (0.643)	0.399 (0.388)	0.537 (0.297)
MBIRI	-0.029 (0.030)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.060 (0.081)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
NoD	-0.050 (0.049)	-0.021 (0.062)	-0.046 (0.043)	-0.041 (0.039)	-0.155 (0.135)	-0.378 (0.230)	-0.213 (0.122)	-0.304 ** (0.096)
Observations	191	409	843	1101	191	409	843	1101

Note: 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Using a local linear regression, we can control the spatial heterogeneity, yielding a preferred identification of the treatment effect. Table 3 presents our base results. We see that within 100 km, firms with public heating have 1.765 fewer green innovations per billion RMB of a firm's total assets than firms to the south of the boundary. This effect is significant at the 5% level. As the distance from the border expands, the magnitude of the effect falls, to 1.328 less for all cities within 200km and 0.964 at 300 km, but remains statistically significant at the 1% level. This finding strengthens the evidence for a causal effect since the group nearest to the cut-off point would tend to have the fewest systematic differences.

Table 3 also shows that the treatment effect on non-green innovation. Here we find no statistically significant effects; the heating boundary appears to affect only green innovation, not all innovation. That is, our results suggest that being north of the public heating boundary leads to lower rates of green innovation without affecting non-green innovation.

6. Robustness Test

6.1 The discontinuity in control variables

The validity of the RD approach requires the covariates are smooth around the cut-off point (Imbens & Lemieux, 2008). As seen in the summary statistics, there are several variables that show significantly different means between the two sides of the boundary. Therefore, we estimate the following regression for each of our control variables to test the discontinuity in our covariates,

$$X_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 heating_i * distance_i + \varepsilon_{it} . \quad (2)$$

where X_{it} is a vector of firm performance control variables.

a

b

Figure 4. The point estimate of β_1 in regression (1) using samples within different ranges. Figure 4a shows the result using the number of green innovations per billion RMB of assets as dependent variables. Figure 4b shows the result using the number of non-green innovations per billion RMB of assets as dependent variables. The whiskers represent the 95% percent confident interval. The results here are the same as reported in Table 3.

In Table 4, we show the point estimate of β_1 in regression (2) for each control variable used in regression (1). Table 4 shows that most of the point estimates of treatment coefficients, β_1 in regression (2), are not significantly different from 0 at the 5% level using data within different ranges for all variables. One exception is earnings per share at 400 km. However, the effect of public heating on green innovation is not significant at 400 km either, so the discontinuity in earnings per share does not change our main results and we believe the covariates are sufficiently smooth across the boundary to support the use of the RD approach to identify a causal treatment effect.

Table 4

Results of Tests on the Discontinuity in Control Variables

Range	Covariates							
	Profit Margin (PmoNA)		Earnings per shar (EpS)		Increasing rate of income (MBIRoI)		Number of directors (NoD)	
	Point estimate	P-value	Point estimate	P-value	Point estimate	P-value	Point estimate	P-value
100km	-0.056	0.255	-0.231	0.318	-0.651	0.661	-0.496	0.542
200km	-0.051	0.287	-0.138	0.331	297.198	0.643	-0.170	0.630
300km	-0.046	0.181	-0.134	0.222	-205.472	0.575	-0.433	0.147
400km	-0.08	0.136	-0.183	0.033	-278.845	0.302	-0.055	0.829

The table reports the point estimate and p-value of β_1 in regression (2) using the samples within different ranges around the boundary.

6.2 Reducing between-province compound effect

Another potential confounding effect in spatial RD design occurs when two or more geographically defined borders occur in the same place (Keele & Titiunik, 2015). As shown in Figure 1, the western part of the heating boundary coincides with some political boundaries. If different provinces have different policies that affect green innovations, then the boundary not only affects the heating policy and air pollution, but it may also coincide with policy differences that affect firm choices. This would lead to a biased estimate of the effect of public heating because the firms on different sides of the boundary are also being treated differently with regard to government policies.

As seen in Figure 1, the heating boundary that is at the west of longitude 106.1896° E coincides with the political boundary with Sichuan, Yunnan, and Tibet areas, the heating boundary to the east of this longitude is mainly inside Shanxi, Hubei, Henan, Anhui, Jiangsu provinces. Hence, using only the sample to the east of this longitude will reduce the potential compound effect. It turns out that our dataset changes little at 100 km and 200 km ranges, but we lose 18.47% and 20% of the observation at 300 km and 400 km accordingly. Table 5 shows the regression results using the subsample data for equation (1). Considering only the portion of the boundary that does not divide provinces, the effect of public heating is largely unchanged for all distance ranges. This suggests that the effect of the heating boundary on green innovation is not an artifact of policy differences between provinces.

Table 5

The Effect of Public Heating Reducing Between-Province Compound Effect

	Firms within			
	100km	200km	300km	400km
(Intercept)	2.811 *** (0.665)	1.972 ** (0.690)	2.128 *** (0.531)	1.959 *** (0.517)
heating	-1.765 ** (0.537)	-1.371 ** (0.445)	-1.155 ** (0.368)	-1.372 *** (0.354)
distance	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 ** (0.000)
heating*distance	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
PMoNA	0.015 (1.161)	0.476 (0.523)	0.510 (0.447)	0.406 (0.481)
EpS	-0.107 (0.261)	0.110 (0.176)	0.093 (0.141)	0.231 (0.150)
MBIRI	-0.029 (0.030)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
NoD	-0.050 (0.049)	-0.025 (0.063)	-0.048 (0.047)	-0.021 (0.046)
Observations	191	400	691	886

Note: 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

6.3 Functional form test

In RD design, using incorrect functional form may generate a biased treatment effect (Lee & Lemieux, 2010). Since the true functional form is unknown, our finding could be a biased result from the misspecification of our regression model. To test this concern, we run the two additional regression models with quadratic and cubic terms:

$$X_{it} = \beta_0 + \beta_1 \text{heating}_i + \beta_2 \text{distance}_i + \beta_3 \text{distance}_i^2 + \beta_4 \text{heating}_i * \text{distance}_i + \varepsilon_{it}, \quad (3)$$

and

$$X_{it} = \beta_0 + \beta_1 \text{heating}_i + \beta_2 \text{distance}_i + \beta_3 \text{distance}_i^2 + \beta_4 \text{distance}_i^3 + \beta_5 \text{heating}_i * \text{distance}_i + \varepsilon_{it}. \quad (4)$$

Table 6 shows the results of these regressions. While the estimated treatment effect is still significantly negative, its magnitude varies dramatically across different functional form specifications. Our base specification in Table 5 is linear; as we use higher-order polynomial as our regression model, the magnitude of the treatment effect at the 100 km range increases from 1.765 to 3.858 in the quadratic specification and 5.415 in the cubic case. The results indicate that our linear model may underestimate the treatment effect, the true effect maybe even larger. With only two exceptions, the estimated treatment effects remain statistically significant at least the 5% level, confirming the conclusion that the heating policy does have an effect on innovation. However, the variation in magnitudes across functional forms does mean that quantitative inferences from our results should be made with a great deal of caution.

Table 6

The Regression Results of RD Using 2ed-order and 3rd-order Polynomial

	Quadratic Specification				Cubic Specification			
	100km	200km	300km	400km	100km	200km	300km	400km
(Intercept)	3.378 *** (0.681)	1.765 * (0.737)	2.343 *** (0.528)	1.967 *** (0.507)	4.322 *** (0.958)	2.638 ** (0.859)	2.166 *** (0.596)	2.100 *** (0.540)
heating	-3.858 *** (0.896)	-1.045 (0.740)	-1.732 ** (0.544)	-1.090 * (0.505)	-5.415 *** (1.428)	-2.891 * (1.198)	-1.334 (0.823)	-1.444 * (0.704)
distance	0.000 ** (0.000)	-0.000 (0.000)	0.000 * (0.000)	0.000 (0.000)	0.000 * (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
distance ²	-0.000 ** (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
distance ³					0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
heating*distance	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
PMoNA	-0.383 (1.147)	0.490 (0.520)	0.447 (0.433)	0.087 (0.182)	-0.248 (1.148)	0.530 (0.518)	0.441 (0.434)	0.083 (0.182)
EpS	-0.005 (0.258)	0.125 (0.175)	0.178 (0.135)	0.338 ** (0.120)	-0.090 (0.265)	0.119 (0.175)	0.181 (0.135)	0.336 ** (0.120)
MBIRI	-0.033 (0.029)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.027 (0.029)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
NoD	-0.035 (0.049)	-0.022 (0.063)	-0.038 (0.043)	-0.040 (0.039)	-0.051 (0.050)	-0.029 (0.062)	-0.038 (0.043)	-0.038 (0.039)
Observations	191	409	843	1101	191	409	843	1101

Note: 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** p < 0.001; ** p < 0.01; * p < 0.05.

6.4 Placebo test

Many unobserved variables could change firm behavior; it is possible, therefore, that our finding is because of some unobserved features that are different across the boundary, and firm behavior is very sensitive to these features. To test this concern, we conduct a placebo test in which we artificially move the heating boundary to the south and north, then regenerate the heating treatment and estimate equation (1). Table 7 shows the point estimate of β_1 in regression (1) under different placebo treatments.

As shown in Table 7, for the most part when the heating boundary treatment artificially moved north or south, the statistical significance of the public heating effect disappears. This lack of significance in the vast majority of the specifications supports our conclusion that the heating boundary does affect green innovations.

Table 7

Results of Placebo Test

		Firms within			
		100km	200km	300km	400km
North 100	Point estimate	0.222	-0.998	0.659	0.179
	p-value	0.367	0.535	0.196	0.579
North 200	Point estimate	0.119	0.444	0.705	0.587
	p-value	0.780	0.112	0.003	0.006
North 300	Point estimate	0.862	0.338	0.299	0.521
	p-value	0.008	0.209	0.143	0.002
South 100	Point estimate	-0.080	0.187	-0.293	0.049
	p-value	0.763	0.417	0.305	0.808
South 200	Point estimate	0.182	0.110	0.174	0.018
	p-value	0.450	0.649	0.361	0.915
South 300	Point estimate	1.830	1.041	0.391	0.247
	p-value	0.011	0.008	0.089	0.251

Table 7 The point estimate and p-value of β_1 in regression (1) under different placebo treatments using the samples within different ranges around the boundary.*6.5 Balanced dataset*

As seen in Table 1, the number of firms within 100km of the boundary and on the north side is almost 3 times that number on the south side, and the average firm size as measured in total assets was significantly larger to the north across all ranges. It is possible, therefore, that the treatment effect is due at least in part to systematic firm differences on the two sides of the boundary. To address this concern, we re-estimate our model using a balanced sample, matching each firm on the south with a similar firm to the north based on the firms' assets and industry codes. The balanced dataset is created via the propensity score matching without replacement; for each southern firm, we pick the northern firm that has the nearest propensity score.⁵

Table 8 shows the results of the model estimated with the balanced dataset. A statistically significant treatment effect of public heating on green innovation is still found for all but the 300 km range. The magnitude of the estimated effect has changed by a small amount with 100 km, from 1.765 to 1.859, an increase of 5.32%.

⁵ We also show the regression result using dataset created using Mahalanobis distance matching in the appendix.

Table 8

The Effect of Public Heating from a Balanced Dataset

	100km	200km	300km	400km
(Intercept)	3.113 *** (0.890)	1.794 * (0.830)	1.776 *** (0.508)	1.937 *** (0.451)
heating	-1.859 ** (0.640)	-1.389 ** (0.535)	-0.921 * (0.368)	-1.329 *** (0.338)
distance_running	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 *** (0.000)
heating_distance	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
PMoNA	-0.438 (1.782)	0.684 (0.967)	0.315 (0.428)	0.092 (0.183)
EpS	0.178 (0.449)	0.074 (0.224)	0.213 (0.134)	0.367 ** (0.131)
MBIRI	-0.062 (0.043)	-0.000 (0.000)	-0.000 (0.000)	-0.002 (0.003)
NoD	-0.086 (0.078)	-0.010 (0.079)	-0.021 (0.045)	-0.022 (0.040)
Observations	98	302	758	1016

Note: 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

7. Conclusion

In this paper, we use China's public heating policy as a quasi-experiment to investigate the impact of exogenous pollution differences on green innovation behavior. We find that firms located in cities with an exogenous source of heavy pollution tend to have less green innovation. After multiple robustness and specification tests, we believe that the data strongly imply a causal effect: being north of the boundary, where pollution levels are higher, leads firms to adopt less green innovation. Firms located in the heating areas report roughly 1 less green innovation per billion RMB of assets. This is a substantial difference given the average number of green innovations per billion RMB of assets of northern firms is 0.641; the estimated effect represents a more than two-fold increase.

One limitation of our analysis is that the Huai River policy also creates exogenous changes in the economic environment in addition to the exogenous difference in pollution. Most directly, there is a difference in the availability and cost of heating. The family heating cost per unit (RMB/h.m²) in the south is 2.2 times that in the north (Wei

et al., 2014). However, on average the total heating cost for each family per year in the north is 3-10 times of the cost in the south due to the longer heating season in the north.⁶ Hence, people in the south pay more for each unit of heating per unit, but may pay less in total, so it seems unlikely that this alone would have a significant effect on firm behavior. Moreover, while households are provided heating through the policy, firms do not receive subsidized heating in the north through the policy. The differences in heating costs and availability could affect firms' green innovation practices, though we believe that is quite unlikely.

While we are unable to test the causal mechanism behind our results with the data that we have available, we can speculate on what might be causing the effect. One explanation of such effect is that air pollution impacts labor force movement in China, especially for highly educated workers, who tend to select cities with lower pollution levels (Weidong Li, 2017). However, if this were the case, it seems that it would affect both green and non-green innovation. Since we do not find evidence that the treatment affects non-green innovation, our evidence does not support this hypothesized mechanism. A second possible explanation is that when pollution is exogenous to firms, green technology for a cleaner production process may be less attractive since it has a minimal discernible effect on the environment or there is little social pressure to innovate in ways that reduce environmental harm. If this is the case, then the exogenous change in pollution would only affect firms' choice with regard to investments in green technology. Our finding is more consistent with this second explanation.

Our findings are novel because in other situations it has been found that lower environmental quality leads to more stringent environmental regulations, and stringent regulations lead to more green innovations (Horbach, 2008). What distinguishes our case is that a major part of pollution in the northern cities does not come from the firms, but a single exogenous source. Thus, we have a situation where northern firms, which are in a more polluted environment through no fault of their own, adopt fewer green innovations. While it is highly speculative to generalize our results from the current

⁶ A comparison between the cost of heating in the south and north: the heating cost in the north is proximately 10 times of the cost in the south.

setting, these findings suggest that there may be virtuous circles in which better environmental conditions lead firms to adopt technology that makes things even better.

Appendix

Table A.1

Detailed Summary Statistics

All Firms within												
<100 km of the Heating Boundary				<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
No Public Heating (N=52)	Have Public Heating (N=150)	p-value		No Public Heating (N=171)	Have Public Heating (N=270)	p-value	No Public Heating (N=424)	Have Public Heating (N=487)	p-value	No Public Heating (N=659)	Have Public Heating (N=531)	p-value
The Number of Total Innovations per Firm												
Mean	27.592	12.930	<0.001	19.066	12.833	0.019	17.702	16.166	0.644	13.432	15.585	0.404
(SD)	(38.226)	(19.716)		(34.052)	(19.490)		(41.853)	(52.378)		(34.570)	(50.441)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	190.000	112.000		190.000	127.000		330.000	719.000		330.000	719.000	
The Number of Green Innovations per Firm												
Mean	6.184	4.359	0.13	6.232	4.081	0.016	5.211	5.705	0.657	4.039	5.817	0.048
(SD)	(6.033)	(7.610)		(11.779)	(6.226)		(12.564)	(18.403)		(10.728)	(18.607)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	25.000	39.000		69.000	39.000		117.000	255.000		117.000	255.000	
The number of Non-Green Innovations												
Mean	21.408	8.570	< 0.001	12.834	8.752	0.049	12.491	10.461	0.396	9.393	9.768	0.839
(SD)	(33.210)	(14.861)		(25.413)	(16.351)		(31.541)	(36.801)		(25.934)	(35.252)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	167.000	96.000		167.000	121.000		235.000	464.000		235.000	464.000	
Total Assets (unit: billions of RMB)												
Mean	5.157	15.738	0.02	9.731	13.459	0.095	9.068	11.909	0.032	7.844	11.938	< 0.001
(SD)	(4.455)	(31.388)		(13.718)	(25.283)		(16.649)	(20.913)		(14.509)	(20.469)	
Min -	1.120 -	0.462 -		0.458 -	0.423 -		0.310 -	0.112 -		0.310 -	0.112 -	
Max	18.039	194.887		74.493	194.887		122.143	194.887		122.143	194.887	

Table A.1-Continued

All Firms within												
	<100 km of the Heating Boundary			<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
	No Public Heating (N=52)	Have Public Heating (N=150)	P-value	No Public Heating (N=171)	Have Public Heating (N=270)	P-value	No Public Heating (N=424)	Have Public Heating (N=487)	P-value	No Public Heating (N=659)	Have Public Heating (N=531)	P-value
The Number of Green Innovations per Billion RMB of Assets												
Mean	1.638	0.641	< 0.001	1.472	0.788	< 0.001	1.265	0.846	0.003	1.025	0.954	0.587
(SD)	(1.800)	(1.089)		(2.808)	(1.341)		(2.542)	(1.553)		(2.197)	(2.183)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	8.776	5.828		25.839	7.902		25.839	11.654		25.839	27.675	
The Number of Non-Green Innovations per Billion RMB of Assets												
Mean	3.418	1.577	0.002	2.848	2.300	0.471	2.811	1.823	0.016	2.330	1.716	0.06
(SD)	(4.237)	(3.325)		(5.395)	(8.368)		(5.126)	(6.456)		(4.634)	(6.187)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	20.718	28.046		33.341	94.763		33.341	94.763		33.341	94.763	
Profit Margin on Net Assets												
Mean	0.080	0.035	0.024	0.057	0.025	0.154	0.061	0.036	0.061	0.042	0.036	0.799
(SD)	(0.076)	(0.133)		(0.196)	(0.229)		(0.162)	(0.211)		(0.472)	(0.208)	
Min -	-0.469	-1.228		-2.312	-3.408		-2.312	-4.545		-11.669	-4.545	
Max												
Earnings per Share												
Mean	0.400	0.254	0.123	0.360	0.232	0.052	0.381	0.265	0.006	0.353	0.266	0.012
(SD)	(0.427)	(0.610)		(0.797)	(0.537)		(0.675)	(0.558)		(0.586)	(0.550)	
Min -	-2.544	-5.868		-8.573	-5.868		-8.573	-6.061		-8.573	-6.061	
Max												

Table A.1-Continued

	All Firms within											
	<100 km of the Heating Boundary			<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
	No Public Heating (N=52)	Have Public Heating (N=150)	p-value	No Public Heating (N=171)	Have Public Heating (N=270)	p-value	No Public Heating (N=424)	Have Public Heating (N=487)	p-value	No Public Heating (N=659)	Have Public Heating (N=531)	p-value
Distance to the Heating Boundary (unit: kilometers)												
Mean	37.542	53.187	<	129.112	93.957	<	198.816	154.824	<	251.963	170.332	<
(SD)	(16.800)	(23.999)	0.001	(67.519)	(51.748)	0.001	(73.799)	(80.559)	0.001	(93.328)	(92.337)	0.001
Min -	13.840 -	11.237 -		13.840 -	11.237 -		13.840 -	11.237 -		13.840 -	11.237 -	
Max	71.229	99.271		194.598	195.823		290.990	298.302		383.885	398.232	
Main Business's Increasing Rate of Income												
Mean	0.719	0.499	0.714	394.076	0.329	0.191	157.258	2.794	0.276	100.576	2.609	0.366
(SD)	(4.598)	(3.232)		(4834.794)	(2.419)		(3051.743)	(39.807)		(2439.726)	(38.056)	
Min -	-32.847	-38.457		-59412.569	-38.457		-59414.275	-745.81		-59414.275	-747.594	
Max												
Number of Directors												
Mean	9.020	9.014	0.985	8.735	8.884	0.37	8.625	8.897	0.019	8.535	8.813	0.007
(SD)	(1.199)	(2.186)		(1.018)	(1.880)		(1.198)	(1.972)		(1.438)	(1.957)	
Min -	5.000 -	5.000 -		5.000 -	5.000 -		5.000 -	5.000 -		5.000 -	5.000 -	
Max	11.000	15.000		11.000	15.000		12.000	17.000		15.000	17.000	

Note: The p-value is for the t-test for the difference of means between the treated (public heating) and control groups.

Table A.2

The Effect of Public Heating from a Balanced Dataset from Mahalanobis Distance Matching

	100km	200km	300km	400km
(Intercept)	3.652***	2.223**	2.078***	1.988***
	-0.928	-0.877	-0.518	-0.459
heating	-1.473*	-0.879	-0.888**	-1.278***
	-0.8	-0.61	-0.373	-0.342
distance_running	0.00002	0	0	0.00000***
	-0.00001	0	0	0
heating_distance	-0.00001	0	0	0
	-0.00002	0	0	0
PMoNA	0.145	0.475	0.434	0.102
	-2.103	-0.609	-0.437	-0.187
EpS	-0.387	0.171	0.193	0.373***
	-0.459	-0.219	-0.138	-0.129
MBIRI	-0.055	-0.00002	-0.00002	-0.002
	-0.051	-0.00004	-0.00003	-0.003
NoD	-0.131*	-0.059	-0.054	-0.033
	-0.075	-0.084	-0.045	-0.04
nobs	98	302	758	1016

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