Applied Energy Symposium 2020: Low carbon cities and urban energy systems
October 10-17, 2020
Paper ID: CUE2020-D-041

How does air pollution affect technological innovation of Chinese cities?

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ABSTRACT

Environmental protection and technological innovation activities are key issues affecting urban sustainable development and value growth. using the data of 272 prefecture-level cities, this paper applying two-stage OLS to investigates how air pollution influences China's technological innovation and its influential channels and, on the basis of the spatial effect of the spread of $PM_{2.5}$ concentrations. The results of research indicate: the rise in air pollution significantly inhibits technological innovation level of regions as a whole. When considering the spatial effect of the spread of $PM_{2.5}$ concentrations, due to the positive spillover effect of innovation activities, the spread of air pollution has negative impacts on the technological innovation activities of the surrounding cities. Human capital and labor cost are important channels through which air pollution influences China's technological innovation. The implementation of carbon trading pilot policy can effectively reduce air pollution, thereby increasing technological innovation in China.

Keywords: Air pollution; Prefectural level $PM_{2.5}$ concentrations; Technological innovation

1. INTRODUCTION

In recent years, environmental problems brought about by China's extensive growth style are rising continuously. According to 2018 statistical bulletin of Ecology and Environment of China, the air quality of 217 in 338 cities at prefecture level or above fail to reach the standard, accounting for 64.2% of all cities. The continuous expansion of the size of industrial production, the rapid development of our infrastructure construction, and tail gas from automobiles led to the increase of air pollutant and inhalable dust, make cities become heavy place polluted by smog [1]. Facing the tremendous pressure to improve environmental quality and achieve innovation-driven development goals, under the guidance of General Secretary Xi Jinping's vision of green development "Lucid waters and lush mountains are invaluable assets", China started pilot carbon emission trading scheme in 2011. At the same time, the "Made in China 2025" initiative aims to transform China from a manufacturing giant into a world manufacturing power, one driven by innovation of science and technology. Therefore, as the economy enters a "new normal", and growth slows, China's economy will rely more on innovation to realize the economic and environmental benefits.

According to the external conditions, there are many factors restricting the improvement of a country's innovation capacity. It cannot be ignored that in the context of China, severe environmental problems, especially poor air quality, may also have an impact on the improvement of innovation capabilities. Of particular concern is that how does air pollution affect technological innovation of Chinese cities? Does environmental quality affect technological innovation through channels such as human capital and business operating costs? Furthermore, as one of the typical environmental policies, can China Carbon Emissions and Trading Pilot (CCETP) policy affect haze and pollution and what impact it will have on technological innovation activities? Throughout current literatures, there are three types of literature that are highly relevant to this paper. The first type of literature is about the impact of environment on technological innovation. Most of the related researches are based on Porter Hypothesis, but have not reached a consensus. In particular, documentaries of scholars related to air pollution and

Selection and peer-review under responsibility of the scientific committee of CUE2020

technological innovation activities, the relevant literature points out that environmental policy plays an intermediary role in environmental pressure and business performance. The second kind of literature mainly perform experiments to validate Tiebout model. Tiebout (1956) pointed out that people vote with their feet to satisfy their preference for public goods [2]. If Tiebout model works, companies need to pay higher wages and benefits in order to compete for liquidity factors, thus cut research and development budgets. Environment belongs to public goods, and population migration will affect technological innovation activities from the perspective of production and living. The last kind of literature highly related to this paper is the negative effects of environmental pollution which have been studied a lot by scholars in recent years. For example, some literatures have found that air pollution affects health, labor supply and work efficiency [3,4]. Human resources are the basic element of innovation, which means that air pollution can affect cities' technological innovation activities by affecting human resources. On that basis, two mechanisms of air pollution affecting technological innovation activities, namely labor cost mechanism and human capital mechanism, are extracted and tested empirically. In light of that, using $PM_{2.5}$ concentration data at China's prefectural level over 2004-2016, by means of the two-stage least square method (2SLS) strategy to alleviate the potential endogeneity problem, we analyze the relationship between $PM_{2.5}$, Carbon Emissions and Trading Pilot, and the level of technological innovation in China.

Under this circumstance, in this paper, we confirm labor cost and human capital mechanisms in the effect of air pollution on technological innovation activities. These findings may help to determine policies direction for government environmental governance and to develop innovative leadership plans for the sustainable development of Chinese economy in the long run.

2. PAPER STRUCTURE

2.1 Model specification and data description

2.1.1 The panel model

We survey the impact of air pollution on China's technological innovation activities. The reduced-form econometric model as follows:

$$InnovationC_{it} = \alpha_0 + \alpha_1 PM_{2.5it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + \xi_{it} \qquad (1)$$

Where $InnovationC_{it}$ and $PM_{2.5_{it}}$ represents technological innovation activities and air pollution level for i -city at period t, respectively. Z_{it} denotes the control variable, ε_{it} and μ_i are the random interferences. According to the hypothesis of this paper, it needs to be verified $\alpha_1 \leq 0$.

The impact of air pollution on technological innovation activities may be interfered by endogeneity, because the level of technical innovation, especially green technological innovation, will also affect environmental quality. Therefore, in this article the air circulation coefficient and the dummy variable of carbon trading policy are taken as the instrumental variables of air pollution. The model as shown in Eq. (2) and Eq. (3).

$$PM_{2.5it} = \gamma_0 + \gamma_1 AF_{it} + \gamma_2 D_{it} + \gamma_3 city_{it} + \nu_t + \varepsilon_{it} \qquad (2)$$

$$InnovationC_{it} = \delta_0 + \delta_1 PM_{2.5it} + \delta_2 D_{it} + \delta_3 Z_{it} + \nu_{it} + \xi_{it} \qquad (3)$$

Where AF_{it} represents the air circulation coefficient of city i in year t; D_{it} indicates the whether this city is the pilot of carbon trading policy or not. If city i is a pilot for CCETP in year t, the value is 1, otherwise, the value is 0. In 2SLS model, the air flow coefficient and dummy variables are taken as the instrumental variables of air pollution. It is not difficult to find that the model can not only evaluate the impact of CCETP pilots on air pollution, but also identify the impact on technological innovation activities.

2.1.2 Spatial econometric model

(Due to the word limit, the exploratory spatial data analysis model is not complete in this manuscript)

Spatial factors are introduced into the impact of air pollution on technological innovation activities in order to examine the spatial effect of the spread of air pollution, and the transmission mechanisms of human capital and labor costs. We found that spatial autoregressive model (SAR) is preferable. Therefore, this paper adopts the spatial dynamic autocorrelation model to test the spatial effect of air pollution on technological innovation activities. Given the model include variables HR and WL, which may lead to multicollinearity. The test results show that the VIF values are below 10, so there is no multiple collinearity in models. The model is given by Eq. (4):

$$InnovationC_{it} = \delta_0 + \delta_1 InnovationC_{i,t\text{-}1} + \rho W_{ij} InnovationC_{it} + \delta_2 PM_{2.5it} + \delta_j \sum_{j=1}^{n} Z_{jit} + \nu_{it} \qquad (4)$$

Where W_{ij} is the element of the spatial weight matrix. We construct three kinds of spatial weight matrices which are based on adjacent distance weight matrix; economic distance and geographic distance, respectively [5,6].

2.1.3 Data description

Dependent variable

Technological innovation activities. We select urban innovation index to represent the level of technological innovation activities. The data are collected from "Report on China's urban and industrial innovation in 2017" released by the Industrial Development Research Center of Fudan University.

Independent variable

Air pollution ($PM_{2.5}$). we use the air pollution grid data joint report by Columbia University and the U.S. air composition group, and extracts the annual PM2.5 average emission concentration of Chinese cities as the core air pollution index by using ARCGIS software. There are two main points to explain the advantages: first, compared with the ground observation data, the air pollution data extracted from satellite images is more objective and covers a wider area, avoiding potential problems such as data manipulation and missing; second, the increasing particulate matter has become the dominant factor of environmental pollution in China.

Control variables

We use the per capita financial expenditure on science and technology to represent the government's R&D investment (GRD). The proportion of foreign direct investment in GDP is used to measure the technology spillover effect of foreign direct investment (FDI). This paper also selected the per capita GDP (PGDP), fiscal autonomy (FD), financial development (FIN), industrial structure (IN) and other control variables to control the influence of economic development, industrial structure change and other factors on technological innovation activities.

2.2 Empirical analysis

2.2.1 Basic regression results

Using OLS estimator as a benchmark, model (1) is first estimated. The column 1 and 2 in Table 1 display the results of the OLS estimations. When instrumental variables are not used, the results show that air pollution has a significant inhibitory effect on urban innovation activities, indicating that the aggravation of environmental pollution has not worked as hoped to promote technological innovation, which implies that it is necessary for the government to interfere in environmental governance and technological innovation. The second stage regression results of 2SLS show that air pollution has a significant negative correlation with technological innovation activities, and all the coefficients are statistically significant at the 1% level. The first-stage regression results in Table 2 show that there is a significant negative correlation between tool variables and air pollution whether the control variables are added or not. The first-stage regression results satisfy the correlation hypothesis of instrumental variables. Among control variables, the proportion of secondary industry has a significant negative impact on urban technological innovation activities, while the per capita GDP, financial development and Government R&D expenditure can significantly improve the urban technological innovation. So, we can conclude that air pollution has a negative impact on technological innovation activities.

Table 1

The impact of air pollution on technological innovation activities.

Variable	(1)	(2)	(3)	(4)
	OLS		2SLS	
$PM_{2.5}$	-0.0159***	-0.0153***	-0.4631***	-0.0298***
	(0.0014)	(0.0015)	(0.0373)	(0.0079)
PGDP		0.9967***		1.0381***
		(0.0400)		(0.0753)
GRD		0.0238***		0.0265***
		(0.0031)		(0.0107)
FIN		0.6980***		0.5975***
		(0.0310)		(0.0636)
IN		-0.0288***		-0.0337***
		(0.0016)		(0.0031)
FD		-0.0126		-0.0049
		(0.0100)		(0.0105)
FDI		-0.0023		-0.0437
		(0.0049)		(0.0953)
DWHChi2			12541.67	131682.74
P-value			(0.0000)	(0.0000)
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
F-first			407.3000	375.6900
R-squared	0.9125	0.9535	0.2044	0.9537

Note: Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, and standard errors are shown in parentheses.

Table 2

The first stage regression results of 2SLS model.

	(1)		(2)	
	coefficient	Z-value	coefficient	Z-value
AF	-3.1803***	0.3493	-3.3320***	0.3473
D	-1.7114***	0.4168	-1.6494***	0.4435
Observations	3536		3536	
Control variables	Not included		Included	

Note: Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, and standard errors are shown in parentheses.

2.2.2 Analysis of the transmission mechanism

Firstly, bases on existing research, we select the average years of schooling as the proxy variables of human capital, to verify the human capital-related effect of air quality changes on technological innovation activities in China. The results are presented in Table 3, and column 2 in Table 3 is used to investigate the impact of 1period lag human capital (L.Human) on technological innovation activities. Similarly, we use the average wage of workers and staff on the job as a proxy variable of labor costs to verify the cost-related effects of air pollution on technological innovation activities in China. The results are presented in Table 4, and column 2 in Table 4 is used to investigate the impact of 1period lag labor cost (L.Wage) on technological innovation activities.

Air pollution in Chinese cities weakens the role of human capital in promoting technological innovation activities by inhibiting human capital accumulation. The coefficients of human capital are significantly positive at the 1% level in Table 3 (1)-(2), indicating that the accelerated accumulation of human capital will help to improve technological innovation activities; the coefficients of variable $PM_{2.5}$ in Table 3 (3)-(7) are significantly negative, indicating that air pollution inhibits human capital accumulation. The conclusion is consistent with the results of research literature [7,8]. In addition, from the angle of heterogeneity, the negative impact of air pollution on human capital are significantly higher in large cities, and become significant over time.

The impact of city air pollution on technological innovation activities will gradually strengthen with the increase of labor cost. As shown in table 4, rising labor cost is not conducive to the improvement of urban technological innovation activities, while air pollution has significantly increased the average wage of workers and staff on the job, that is, there is cost-related effect of labor cost change on technological innovation activities. In addition, from the angle of heterogeneity, the positive impacts of air pollution on labor costs are significantly higher in large cities, and become significant over time.

Table 3

Air pollution and technological innovation activities: human capital mechanism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Full sample	Large cities	Middle-sized and small cities	2004-2008	2009-2016
Human	0.8701^{***}						
	(0.2084)						
L.Human		1.1575^{***}					
		(0.2088)					
$PM_{2.5}$			-0.0218^{**}	-0.0444^{***}	-0.0337^{***}	-0.0152^{*}	-0.0378^{***}
			(0.0116)	(0.0142)	(0.0151)	(0.0207)	(0.0127)
Constant	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
Urban dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Adj.R^2	0.9639	0.9664	0.8181	0.8863	0.8818	0.8335	0.8815

Notes: The dependent variable is InnovationC in regressions (1)–(2); the dependent variable is Human capital in regressions (3)–(7). The figures in parentheses are standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4

Air pollution and technological innovation activities: labor costs mechanism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Full sample	Large cities	Middle-sized and small cities	2004-2008	2009-2016
Wage	-0.2204^{***}						
	(0.0485)						
L.Wage		-0.3453^{***}					
		(0.0552)					
$PM_{2.5}$			0.0121^{**}	0.0199^{***}	0.0187^{***}	0.0012^{*}	0.0288^{***}
			(0.0050)	(0.0070)	(0.0070)	(0.0007)	(0.0027)
Constant	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
Urban dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Adj.R^2	0.9639	0.9665	0.9423	0.8824	0.8782	0.5125	0.8570

Notes: The dependent variable is InnovationC in regressions (1)–(2); the dependent variable is Wage in regressions (3)–(7) . The figures in parentheses are standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.2.3 Spatial econometric regression results

We analyze the direct and indirect effects of air pollution on technology innovation activities based on three different spatial weight matrices: the results of model A1, A2 and A3 are based on the adjacent distance weight matrix; the results of model B1, B2 and B3 are based on the geographic distance weight matrix; and the results of model C1, C2 and C3 are based on the economic distance weight matrix. The results are shown in Table 5. Under three spatial weight matrices, the spatial lag terms of technological innovation activities are positive and passes the 1% significance level. The results of models A1, B1 and C1 do not include the variables PMHR and PMWL; the results of models A2, B2 and C2 include the variable PMHR; the results of models A3, B3 and C3 include the variable PMWL. Moreover, according to the Log Likelihood Function value (LogL) and Akaike Information Criterion (AIC) value, the AIC values of models B1, B2 and B3 are significantly lower than that of other models, that is to say that the spatial autoregressive models of geospatial weight matrix are preferable.

As shown in models A1-C1, the coefficients of $PM_{2.5}$ are -0.0114, -0.0072 and -0.0128, respectively, basing on the positive spatial spillover effect of technological innovation activities. It shows that the spread of air pollution is not only suppresses the city's technological innovation activities but also reduces the spatial spillover of technological innovation activities toward the neighboring cities, and then exerts an inhibitory effect on the improvement of technological innovation activities in surrounding areas. The result reveal that a city's air pollution not only suppresses its technological innovation activities, but also tightens the spillover of innovation, and have a negative impact on the technological innovation activities of neighboring cities. We also confirm that the control variables can affect technological innovation activities. The results demonstrate that industrial structure (IN), financial autonomy (FD), present negative and significant effects on technological innovation activities. The other control variables are positive correlated to technological innovation activities.

There are cost-and human capital-related effects of air quality changes on technological innovation activities at the city level in China. It is found that air pollution can indirectly inhibit technological innovation activities by influencing human capital, as shown in models A1-C1. In models A2-C2, the coefficients of variable PMHR are -0.0113, -0.0048 and -0.0190 respectively, and were statistically significant at the 10% level. However, the signs of variable HR are positive, so we can conclude that the promotion effect of human capital on technological innovation activities has been weakened due to air pollution, and indirectly inhibits the improvement of technological innovation activities. As shown in models A1-C1, it is found that air pollution can indirectly inhibits technological innovation activities by influencing labor cost. In models A3-C3, the coefficients of variable PMWL are -0.2216, -0.2619 and -0.3437 respectively, and were statistically significant at the 5% level. And the signs of variable WL are negative. In other words, the increase of labor remuneration has not stimulated urban's technological innovation activities. It may be because the sharp rise of labor cost aggravates the pressure of innovation, or the rise of labor cost has limited incentive effect on technological innovation activities in the context of prominent environmental problems.

3. CONCLUSION AND POLICY IMPLICATIONS

It is of great value to study the impact of air pollution on urban technological innovation activities for enhance technological innovation and realize sustainable development of Chinese cities in the background of innovative cities and ecological civilization construction. Based on panel data from 272 cities at prefecture level in China, this paper systematically investigates the impact of air pollution on urban technological innovation activities and its transmission mechanism. The following conclusions can be drawn.

(1) Urban air pollution significantly inhibited the technological innovation output of regions as a whole. In addition, the negative impacts of air pollution on technological innovation activities are significantly higher in larger cities and become increasingly significant over time.

(2) When considering the spatial effect of the spread of air pollution, due to the positive spillover effect of innovation activities, the spread of air pollution has negative impacts on the technological innovation activities of the surrounding cities.

(3) Human capital and labor cost are important channels through which air pollution influences China's technological innovation.

(4) China's carbon emissions and trading pilot policies can effectively reduce air pollution, thereby increasing technological innovation in China.

Besides, the results in this paper have some policy implications. Firstly, it is unwise to pursue economic development at the sacrifice of the environment, which will only lead to the economic problems of environmental degradation and a low level of innovation, high-quality economic growth would be prate. Secondly, it is imminent for China to establish a unified national carbon trading market system. Lastly, the spatial correlation effect should be incorporated into the formulation and evaluation of environmental policies, and a scientific, standard and long-term mechanism is needed.

Table 5

The results of spatial panel econometrics model.

variable	Model A1	Model B1	Model C1	Model A2	Model B2	Model C2	Model A3	Model B3	Model C3
L.InnovationC	0.0920***	0.0954***	0.0962***	0.0911***	0.0946***	0.0958***	0.0913***	0.0946***	0.0956***
	(0.0007)	(0.0005)	(0.0004)	(0.0007）	(0.0005)	(0.0004)	(0.0007)	(0.0005)	(0.0004)
W_InnovationC	0.6287***	0.8693***	0.3414***	0.6223***	0.8678***	0.3379***	0.6216***	0.8677***	0.3379***
	(0.0280)	(0.0215)	(0.0212)	(0.0283)	(0.0216)	(0.0212)	(0.0283)	(0.0216)	(0.0212)
$PM_{2.5}$	-0.0114***	-0.0072***	-0.0128***	0.0125	0.0028	0.0174	-0.0110***	-0.0070***	-0.0120***
	(0.0012)	(0.0011)	(0.0012)	(0.0136)	(0.0125)	(0.0137)	(0.0012)	(0.0012)	(0.0012)
HR	1.2609***	1.0085***	1.5053***	1.5463***	1.1354***	1.9392***	1.1595***	0.9782***	1.2876***
	(0.1874)	(0.1708)	(0.1888)	(0.2453)	(0.2321)	(0.2364)	(0.1900)	(0.1724)	(0.1943)
WL	-0.4126***	-0.5722***	-0.3686***	-0.3930***	-0.5622***	-0.3433***	-0.4144	-0.1935	-0.9025***
	(0.0571)	(0.0517)	(0.0595)	(0.0580)	(0.0532)	(0.0599)	(0.3466)	(0.3336)	(0.3431)
PMHR				-0.0113*	-0.0048*	-0.0190***			
				(0.0064)	(0.0056)	(0.0065)			
PMWL							-0.2216**	-0.2619***	-0.3437***
							(0.0917)	(0.0922)	(0.0915)
FDI	0.1559***	0.1110**	0.0649	0.1538***	0.1104**	0.0567	0.1552***	0.1111**	0.0581
	(0.0533)	(0.0491)	(0.0532)	(0.0532)	(0.0491)	(0.0531)	(0.0531)	(0.0491)	(0.0529)
FIN	0.3662***	0.1843***	0.5300***	0.3771***	0.1869***	0.5473***	0.3878***	0.1904***	0.5662***
	(0.0291)	(0.0266)	(0.0265)	(0.0299)	(0.0269)	(0.0272)	(0.0308)	(0.0273)	(0.0284)
PGDP	0.2555***	0.0383	0.5419***	0.2551***	0.0384	0.5300***	0.2464***	0.0413	0.5124***
	(0.0446)	(0.0389)	(0.0418)	(0.0445)	(0.0389)	(0.0419)	(0.0446)	(0.0390)	(0.0424)
FD	-0.0431***	-0.0365***	-0.0272***	-0.0430	-0.0364***	-0.0265***	-0.0432***	-0.0365***	-0.0269***
	(0.0088)	(0.0079)	(0.0091)	(0.0089)	(0.0079)	(0.0091)	(0.0089)	(0.0079)	(0.0091)
IN	-0.0128***	-0.0054***	-0.0172***	-0.0127***	-0.0054***	-0.0169***	-0.0125***	-0.0053***	-0.0165***
	(0.0016)	(0.0014)	(0.0016)	(0.0016)	(0.0014)	(0.0016)	(0.0016)	(0.0014)	(0.0016)
GRD	0.0259***	0.0206***	0.0252***	0.0263***	0.0207***	0.0258***	0.0260***	0.0206***	0.0253***
	(0.0029)	(0.0027)	(0.0030)	(0.0029)	(0.0027)	(0.0030)	(0.0029)	(0.0027)	(0.0030)
VIF	2.3100	2.3100	2.3100	4.3200	4.3200	4.3200	5.0700	5.0700	5.0700
LogL	-1983.7449	-1687.2758	-2120.6740	-1982.1803	-1686.9513	-2116.3774	-1980.8472	-1686.6170	-2113.7041
AIC	4.1124	0.9128	2.3599	4.2331	0.9036	2.2164	4.2237	0.8498	2.9870
W-test	937.8909	8390.0951	2095.5977	940.0932	8433.0156	2104.5020	939.0038	8566.5440	2304.6893
F-test	128.9543	1093.8221	300.4562	130.9054	1105.4504	298.8921	131.0923	1298.0933	294.5912

Notes: standard errors are shown in parentheses, and significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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