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Can Urban Green Innovation Promote Collaborative Emission Reduction of CO_2 And Air Pollutants?

-- Based on the Study of Low-carbon Pilot Cities in China

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Abstract

The situation of carbon emission and haze pollution in China is severe. Collaborative emission reduction has become a powerful means to deal with complex pollution problems. To tackle environmental pollution and wean the economy off excessive reliance on carbon, China has launched low-carbon pilot projects in three batches in several places. This paper selects panel data of 66 pilot low-carbon cities in China from 2005 to 2017, uses binary dependent variable index to define urban CO_2 and PM2.5 collaborative emission reduction, and discusses the impact of urban green innovation capability on collaborative emission reduction. The results show that: (1) When multiple factors are excluded, urban green innovation ability significantly promotes the collaborative emission reduction of CO_2 and atmospheric pollutants. (2) Urban green innovation has the best effect on collaborative emission reduction of CO_2 and soot, followed by SO_2, wastewater and $PM_{2.5}$. (3) The research and development cycle is shorter and the low-quality green innovation which is easy to put into actual production is more obvious. Therefore, we should actively promote green technology innovation nationwide, set up more low-carbon pilot areas, give full play to the role of green innovation in haze control and carbon reduction, and promote the realization of the dual carbon goal and haze control.

Keywords

Collaborative emission reduction; Green innovation; Carbon emissions; Low-carbon pilot city.

1. INTRODUCTION

With the continuous progress of industrialization and urbanization in China, the problem of environmental pollution in China is becoming more and more severe, with frequent occurrence of extreme and compound pollution across the country (Dong et al., 2020). Between 1998 and 2015, China's carbon-dioxide emissions rose by 6 billion tones, more than America's total emissions in 2015, and continue to rise every year. In addition, the severe smog problem is also a major problem facing China. According to the "Global Health Data 2016" released by the World Health Organization (WHO), out of every 100,000 deaths in China, at least 163 people died due to severe air pollution.

In order to deal with the serious carbon emissions and smog problem, the Chinese government has made several major attempts. At the 75th session of the United Nations General Assembly in September 2020, China proposed to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060. In July 2018, The State Council issued the Three-year Action Plan for Winning the Blue-Sky Battle, which defines the overall thinking, basic objectives

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and planning process of air pollution prevention and control projects. According to the local application, the Chinese government has successively carried out low-carbon pilot work in three batches in many provinces, cities and regions across the country to find a greener way of economic growth. Energy transformation and green innovation are becoming the main force of energy conservation and emission reduction (Liu and Dong, 2021). It is an important means to solve air pollution, carbon emission and resource constraints in China (Du et al., 2021). Does the green innovation of low-carbon pilot cities promote collaborative emission reduction of greenhouse gases and air pollutants? This is the question that this article tries to answer.

2. LITERATURE REVIEW

Studies on collaborative emission reduction in existing literatures mainly focus on energy conservation and emission reduction policies, a certain industry and measures, and few focus on research cities. What indexes should be used to define collaborative emission reduction? Many scholars have given different solutions. Wei and Song.,(2021) Impact of clean coal technology development on collaborative emission reduction in Jilin Province by using comprehensive pollutant emission indicators and input-output model. Liu et al.,(2022) used the regional cooperation game model to discuss the effect of collaborative governance in the four provinces of the Yangtze River Delta from the perspective of collaborative emission reduction cost. Wang and Zhao.,(2021) used different pollutant emissions as explained variables to measure the impact of collaborative governance on air pollutant emissions in Chinese cities. Yan et al., (2020) also used this method and found that different stages of urbanization have threshold effects on climate change and environmental pollution.

Green innovation refers to the activities to save resource consumption and reduce environmental pollution with the help of new concepts and new technologies in order to achieve coordinated development with resources and environment, and obtain corresponding economic effects at the same time (Zhang et al., 2019). When studying urban green innovation capability, the first problem we face is how to define urban green innovation capability. At present, there is a great dispute on the definition of urban green innovation index at home and abroad. Current scholars' opinions on this issue can be generally divided into two categories: one believes that green innovation output is the most important factor determining urban green innovation, so green innovation output can only be used to represent urban green innovation capability; the other believes that the input of a city should also be taken into account when carrying out green innovation, so it is more reasonable to use a comprehensive index of input and output. Specifically, Du et al.,(2021) measures the number of green patents of listed companies in the city, and Xu et al.,(2021) measures the number of green patents at the overall city level. Peng et al.,(2021) and Qiu et al.,(2021) take the number of green patents authorized as the core and use DEA to comprehensively measure the total green factors in cities. Zeng et al.,(2021) believes that the number of urban green patent applications is used as the core index to construct urban green innovation. They believe that patent research and development process also requires a large amount of investment, which also promotes the development of urban green innovation. Liu et al.,(2021) jointly constructed green innovation indicators from three dimensions: scale, combination and technology effect.

Most of the literatures on green innovation capability and energy conservation and emission reduction focus on the impact of green innovation on carbon emissions or other single factors. Many scholars have pointed out that at the macro national, provincial and city levels, green innovation can play a significant incentive role in energy conservation and emission reduction (Du and Li., 2020; Xu et al., 2021; Fan and Xiao., 2021). Shao et al.,(2021) found that green innovation has a long-term effect on carbon dioxide emission reduction at the national level, but does not play a big role in the short term. Moreover, green innovation will have different

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emission reduction promotion effects due to different regional development levels (Luo et al., 2021). In addition to the single green innovation factor, the other factors combined with green innovation have a certain difference in the promotion effect of reducing carbon dioxide emissions. Liu et al., (2021) discussed the influence of the compound factors of foreign direct investment, trade and green innovation on carbon emissions in China's provinces, and found that all three factors could promote the reduction of carbon emissions at the provincial level, respectively, but the promoting effect of foreign direct investment on provinces with strong green innovation ability was small.

It can be seen from previous literature that most of the current literatures on collaborative emission reduction have not broken through the limitation of taking actual pollutant emission as the evaluation standard, and few scholars have discussed the study of urban green innovation ability on collaborative emission reduction of pollutants from the perspective of city level. In this paper, 66 low-carbon pilot cities in three batches were selected. The study covers the period from 2005 to 2017 to explore the impact of urban green innovation capability on the collaborative emission reduction of CO_2 and $PM_{2.5}$. Compared with previous literatures, the main contributions of this study are as follows:

(1) This paper is the first study to use binary dependent variable index to measure collaborative emission reduction at the city level, which can provide reference for subsequent scholars to study collaborative emission reduction.

(2) Most scholars have not paid much attention to which type of green innovation has the best effect on promoting collaborative emission reduction. By classifying urban green innovation capability and discussing it, this paper seeks for a green innovation model with better effect on promoting collaborative emission reduction, so as to provide help for policy makers.

3. VARIABLE SETTING, EMPIRICAL MODEL AND VARIABLE DESCRIPTION

3.1. Definition of collaborative emission reduction variables

The term "synergistic effect" is extended to "synergistic effect", which was first proposed by the Intergovernmental Panel on Climate Change (IPCC) in 2001. It refers to a specific policy or factor that can reduce the emission of certain pollutants while also controlling the emission of other pollutants, and ultimately reduce the emission of various pollutants together. Based on the definition of collaborative emission reduction and the studies of other scholars, this paper divides collaborative emission reduction into two dimensions, process and result, to explain. From the perspective of process, collaborative emission reduction should control the emission of multiple pollutants at the same time, even if the emission of various pollutants changes cooperatively; As a result, the ultimate goal of collaborative emission reduction is to reduce the emission of various pollutants. From the process dimension, based on the data of CO_2 emission and $PM_{2.5}$ concentration in 66 pilot cities, this paper uses spearman correlation coefficient method to explore whether there is significant synergism in their value changes. From the result dimension, if both CO_2 emission and $PM_{2.5}$ concentration in a certain city decreased in that year, it indicated that the city had achieved collaborative emission reduction in that year, which was defined as 1 and all other cases as 0, and this was taken as the explained variable for empirical study.

3.2. Theoretical basis and empirical model

IPAT model is an environmental determination model proposed by Ehrlich and Holdren. (1972), combining technological determinism and demographic determinism. The specific formula can be expressed as follows: I (Environmental pressure or impact) =P (Population) *A (Affluence) *T (Technology), i.e. environmental impact is a function of regional population,

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affluence and technology level. Environmental pressure or influence factors that usually guide environmental degradation, such as emissions of atmospheric pollutants such as CO_2, NO_x and SO_2; The larger the population, the more resources will be consumed and the greater the environmental pressure (Velez et al., 2019); Many scholars have pointed out that regional affluency and pollutant emission present an inverted U-shaped relationship, that is, pollutant emission first increases and then decreases with the increase of regional affluency (Liu and Lai., 2021). However, some scholars have estimated that in many developing countries (such as China), pollutant emissions have not reached the peak, which is not in line with the rule of EKC (Wang et al., 2021). Skill level usually appears as a residual term in IPAT models.

However, a huge limitation of IPAT model is that the relationship between all independent variables and dependent variables in IPAT model is completely proportional and linear. Many scholars believe that this model is far from the actual situation (Da et al., 2021). In order to reflect the nonlinear effects of various factors on environmental pressure, Dietz and Rose. (1994) modified IPAT model into STIRPAT model, whose expression is: $I = aP_i^{\alpha} A_i^{\beta} T_i^{\gamma} e_i$, a is the constant term, α, β and γ are the coefficients of different factors, e is the residual term, and T is a separable variable. It can be expressed as different influencing factors such as technology. However, all explanatory variables in STIRPAT model are logarithmic, which still has some limitations. Therefore, after synthesizing the above models, subsequent scholars concluded that environmental pressure would be jointly affected by population, affluence and technology level. Based on this, the benchmark model of this paper was set as follows:

$$coem_{it} = c + \alpha lnpatent_{i,t-1} + \beta rpgdp_{it} + \gamma lnemploy_{it} + \delta pro2_{it} + \varepsilon lnindgdp_{it} + e$$

Where i represents the individual low-carbon city, c is the constant term, e is the residual term, α, β, γ and are the coefficients of each variable, and the remaining variables are:

(1) $coem$ is the collaborative emission reduction index of low-carbon cities, which is a binary dependent variable and is set according to the standard mentioned above.

(2) $lnpatent$ is the logarithmic form of the number of green patents granted in low-carbon cities lagging one period, where the number of green patents granted is the sum of green invention patents and utility model patents.

(3) $rpgdp$ is the real per capita GDP of the city, the unit is ten thousand yuan.

(4) $lnemploy$ is the natural logarithm of the number of employed people in the city.

(5) $pro2$ is the proportion of the added value of the secondary industry in the gross regional product of the city, representing the level of the industrial structure of the city.

(6) $lnindgdp$ is the logarithmic form of the proportion of the total industrial output value above the quota in the gross regional product, which is used to measure the level of the industrial structure of the city. The difference between gross industrial output value and GDP is that GDP measures the added value, while gross industrial output value measures the total value including raw materials and other costs, so gross industrial output value is usually higher than GDP. The higher the value, the stronger the wealth creation ability of the city's secondary industry, so the industrial structure is more reasonable.

Among them, CO_2 data came from China Carbon Accounting Database (CEADs), $PM_{2.5}$ data came from Dalhousie Atmospheric Composition Analysis Group, green patent issuance data were retrieved from the State Intellectual Property Office according to the Green Patent List released by the World Intellectual Property Office (WIPO) in 2010, and the remaining variables were all from the Statistical Yearbook of China Cities.

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Table 1. Descriptive statistics of main variables

Variables	Mean	Standard deviation	Minimum	Maximum
coem	0.1166	0.3211	0	1
lnpatent	4.4912	2.0635	0	9.5273
rpgdp	0.8843	0.5318	0.1098	2.8874
lnemploy	4.7300	1.0406	2.2376	7.4553
pro2	48.0678	9.4962	12.1500	84.6100
lnindgdp	0.4842	0.4680	-1.7226	1.3181

4. EMPIRICAL RESULTS AND ROBUSTNESS TEST

4.1. Main model regression results and analysis

First, Spearman correlation coefficient method was used to explore the synergy between CO_2 emission and $PM_{2.5}$ concentration in low-carbon pilot cities. The results showed that the correlation coefficient was 0.3606, which was significant at the significance level of 99%, indicating that the changes had strong synergy.

Secondly, this paper uses probit model and logit model respectively to explore the impact of green innovation level in low-carbon pilot cities on the collaborative emission reduction of urban CO_2 and $PM_{2.5}$. In addition, in this part, the environmental Kuznets (EKC) curve was verified, that is, the relationship between affluence and pollutant emission was investigated. Table 2 shows the regression results of the benchmark model, where (1) - (3) and (4) - (6) are listed as the results of the quadratic and cubic terms of real per capita GDP added in the probit and logit models respectively.

Table 2. Regression results of the benchmark model

	probit			*logit*		
	(1)	(2)	(3)	(4)	(5)	(6)
lnpatent	0.0464***	0.0462***	0.0416**	0.0471***	0.0473***	0.0429**
	(0.0165)	(0.0170)	(0.0171)	(0.0177)	(0.0183)	(0.0186)
rpgdp	0.0810**	0.0903	0.8150***	0.0736*	0.0691	0.8397***
	(0.0339)	(0.0931)	(0.2682)	(0.0377)	(0.1027)	(0.3082)
rpgdp2		-0.0035	-0.6298***		0.0016	-0.6471***
		(0.0310)	(0.2208)		(0.0315)	(0.2501)
rpgdp3			0.1556***			0.1582**
			(0.0554)			(0.0624)
lnemploy	-0.0882***	-0.0882***	-0.0815***	-0.0886***	-0.0887***	-0.0812***
	(0.0263)	(0.0263)	(0.0258)	(0.0269)	(0.0269)	(0.0264)
pro2	-0.0040**	-0.0040**	-0.0044**	-0.0043**	-0.0042**	-0.0044**
	(0.0019)	(0.0019)	(0.0019)	(0.0021)	(0.0021)	(0.0020)
lnindgdp	0.0952**	0.0952**	0.0966**	0.1090**	0.1092**	0.1042**
	(0.0467)	(0.0466)	(0.0442)	(0.0529)	(0.0535)	(0.0505)
cons	0.2834	0.2676	-1.001	0.7589	0.7728	-1.9274*
	(0.6822)	(0.6827)	(0.8328)	(1.3425)	(1.3361)	(1.6868)
N	842	842	842	842	842	842
pseudo R^2	0.1257	0.1257	0.1436	0.1244	0.1244	0.1420

Note: (1) Values in brackets are robust standard error. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. (2) The result reported is the average marginal effect of each variable. The rest of the tables are consistent.

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As can be seen from the regression results, the core explanatory variable lnpatent in the probit model and logit model is significant at a high significance level, and there is a positive correlation between urban green innovation and collaborative emission reduction. Usually, enterprises, especially industrial enterprises, apply for and authorize green patents. After these enterprises apply for green patents and obtain authorization, they will apply new green technologies to reduce pollutant emissions. As the main source of urban pollutant discharge, enterprises can effectively reduce pollution at the city level with the improvement of their technological level (Zhao et al., 2021).

In addition, the results in Table 2 also reflect the relationship between the overall wealth of low-carbon cities and collaborative emission reduction. It can be seen from columns (1) - (3) and (4) - (6) that the average marginal effect of the variable per capita GDP is significantly positive when the second and third terms of per capita GDP are not included, that is, the overall urban wealth can promote collaborative emission reduction. After the inclusion of the secondary item, the mean marginal effect of both the primary and secondary items was not significant, which indicates that there is no obvious inverted U-shaped relationship between the prosperity of the low carbon pilot cities and the emission of pollutants in the sample period; After adding the third term, the first term, the second term and the third term are all significant, and the coefficient of the third term is also positive, indicating that the relationship between urban affluence and collaborative emission reduction is not completely linear, but S-shaped. This seems to be contradictory with the single significant conclusion of the first item in column (1) and (4). However, after calculating the two inflection points in the third column, it is found that the two inflection points are very close, and only in a small area in the middle of the two inflection points, there is a negative correlation between the overall urban wealth and the collaborative emission reduction of greenhouse gases and air pollutants. The other parts show a positive correlation between affluence and collaborative emission reduction. The reason may be that one of the main purposes of low-carbon pilot cities is to promote urban economic development away from excessive dependence on carbon, which is also consistent with the conclusion of Zhang et al., (2019).

According to the results, the average marginal utility of the variable natural logarithm of the number of urban employed population is significantly negative, which indicates that the more urban employed population, the greater the pressure of collaborative emission reduction, which is also consistent with the "population explosion theory" (Harper and Snowden., 2017). The higher the proportion of the added value of the secondary industry, the more dominant the position of the industry in the city. In most cases, the pollution generated by the industry is far greater than that of the service industry and agriculture. Therefore, in the results of this paper, the average marginal effect of the variable of the proportion of the added value of the secondary industry is significantly negative. That is, the more the city's industry occupies a dominant position, the more difficult it is to achieve coordinated emission reduction of CO_2 and $PM_{2.5}$. The industrial advanced degree measures the ability of a city's industrial industry to create wealth. The larger the value is, the more reasonable the industrial structure of a city is compared with other cities. Therefore, it can be found from the results that a reasonable industrial structure can promote the city's haze control and carbon reduction.

4.2. Robustness test

4.2.1 Replace explained variables

The first step is to replace the explained variables and find new indicators to define collaborative emission reduction, so as to judge whether urban green innovation ability can still promote collaborative emission reduction under other indicators. In the benchmark model, the explained variable used in this paper is set according to the emission of CO_2 and $PM_{2.5}$, and the concept of collaborative emission reduction is not limited to this, but also includes the

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synchronous emission reduction of pollutants such as SO_2, soot and wastewater with CO_2. Therefore, this part of this paper is based on the above explained variable setting method. CO_2 and urban soot emissions, wastewater and SO_2 emissions were respectively used to set explained variables. Table 3 shows the test results of this part.

According to the robustness test results in Table 3, it can be seen that urban green innovation ability has a very robust and significant promoting effect on the collaborative emission reduction of different types of pollutants, indicating that green innovation plays a comprehensive and effective role in energy conservation and emission reduction. Moreover, it can be seen that urban green innovation ability has the best effect on the collaborative emission reduction of CO_2 and soot, followed by SO_2 and wastewater. In addition, only the first term of real per capita GDP is added in this part of this paper, resulting in some regression results of this variable are not significant. However, if the second and third terms of real per capita GDP are added in the actual regression process, all relevant variables were significant, and the coefficients were similar to the benchmark regression results, which were not shown due to space limitations. The results for the remaining variables were also significant.

Table 3. Robustness test - Replace explained variables

	probit			*logit*		
	dust	Waste water	SO_2	dust	Waste water	SO2
lnpatent	0.0870*** (0.0174)	0.0534*** (0.0168)	0.0769*** (0.0186)	0.0887*** (0.0186)	0.0538*** (0.0188)	0.0794*** (0.0201)
rpgdp	0.0228 (0.0347)	0.0944*** (0.0345)	0.0809** (0.0385)	0.0161 (0.0377)	0.0829** (0.0412)	0.0680 (0.0435)
lnemploy	-0.1393*** (0.0264)	-0.1205*** (0.0240)	-0.1244*** (0.0282)	-0.1386*** (0.0273)	-0.1165*** (0.0244)	-0.1250*** (0.0290)
pro2	-0.0069*** (0.0017)	-0.0046** (0.0019)	-0.0044** (0.0020)	-0.0070*** (0.0017)	-0.0046** (0.0021)	-0.0048** (0.0021)
lnindgdp	0.0957** (0.0442)	0.0913** (0.0429)	0.0902** (0.0437)	0.0997** (0.0486)	0.0977** (0.0472)	0.0990** (0.0471)
cons	1.6507*** (0.0017)	1.094* (0.6281)	0.4985 (0.6271)	3.0352*** (1.1101)	2.0158* (1.2084)	1.1404 (1.1787)
N	842	842	842	842	842	842
pseudo R^2	0.1653	0.1317	0.1548	0.1628	0.1269	0.1524

4.2.2 Replace the regression model

In addition to changing the explained variables, different model choices may also affect the regression results, resulting in the phenomenon of pseudo-regression. Therefore, in addition to using the probit model and logit model, this paper uses the linear probability model to regression the benchmark model (1). Table 4 shows the robustness test results of this part. As can be seen from the results in Table 4, when the linear probability model is used to regression the original benchmark model, the coefficient of urban green innovation capability is still significantly positive, and the coefficients and symbols of other variables do not change much. And there is still no inverted U-shaped relationship between real per capita GDP and pollutant emissions.

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Table 4. Robustness test: linear probability model

	linear probability model		
	(1)	(2)	(3)
lnpatent	0.0230** (0.0138)	0.0365** (0.0143)	0.0282* (0.0146)
rpgdp	0.1177*** (0.0372)	-0.0293 (0.0955)	0.5269*** (0.1910)
rpgdp2		0.0607 (0.0421)	-0.4688*** (0.1808)
rpgdp3			0.1410*** (0.0500)
lnemploy	-0.0735*** (0.0248)	-0.0787*** (0.0251)	-0.0670*** (0.0253)
pro2	-0.0050** (0.0020)	-0.0044** (0.0020)	-0.0051** (0.0021)
lnindgdp	0.0979** (0.0440)	0.0967** (0.0442)	0.1004** (0.0439)
cons	0.4184*** (0.1228)	0.4527*** (0.1223)	0.3189*** (0.1212)
N	842	842	842
R-squared	0.0878	0.0915	0.1018

Note: The results reported in this section are coefficients rather than average marginal effects.

4.3. Alternative interpretation

4.3.1 Government expenditure on energy conservation and environmental protection

A possible alternative explanation for the regression results obtained in this paper is that the efforts of local governments to control environmental pollution will affect both urban green innovation and pollutant emission (Fan et al., 2020), which makes the results obtained in this paper unable to prove that urban green innovation promotes collaborative emission reduction. Therefore, this paper collected the data of energy conservation and environmental protection expenditure in the fiscal expenditure items in the statistical yearbook of each city, and finally collected 522 sample data, a small part of which was obtained by interpolation method. In order to eliminate the influence of this alternative explanation, logarithm of energy conservation and environmental protection expenditure is put into the benchmark model (1) to discuss whether urban green innovation ability can promote collaborative emission reduction of greenhouse gases and air pollutants under the condition that this variable is controlled.

4.3.2 Total energy consumption

Currently, coal-fired power generation is the main means of power generation in China (Chen et al., 2021), and in the process of coal-fired power generation, CO_2, SO_2, soot and other pollutants will be emitted at the same time, and the sources of all kinds of pollutants are largely the same root and origin (Du et al., 2020). Therefore, a possible alternative explanation is that it is not the city's green innovation capability that promotes collaborative emission reduction, but the city itself reduces energy consumption, thus simultaneously reducing the emission of various pollutants. In this paper, energy consumption per unit of GDP of each city was collected from the annual government work report of each city, the local Bureau of Energy Statistics and other channels, and the energy consumption per unit of GDP was multiplied by the corresponding base annual constant price GDP to calculate the total amount of energy consumption in the corresponding years. A small part of missing data was filled by interpolation method. According to the data obtained, logarithm of total energy consumption is added into

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model (1) in this paper to discuss whether urban green innovation ability can promote the collaborative emission reduction of CO_2 and $PM_{2.5}$ under the condition that total energy consumption is controlled. Table 5 shows the regression results of robustness test of this part, where lnexpend and lnenergy are logarithms of energy conservation and environmental protection expenditure and total energy consumption, respectively.

The regression results in Table 5 show that under the premise of controlling the expenditure on energy conservation and environmental protection and the total amount of energy consumption, the average marginal effect of the variable of urban green innovation is still significantly positive at a high significance level, and the average marginal effect of the variable of energy conservation and environmental protection input is also significantly positive, indicating that the increase of expenditure on energy conservation and environmental protection can effectively control the collaborative emission of pollutants. According to the robustness test results of this part, the alternative explanation of energy conservation and environmental protection expenditure and total energy consumption is not valid.

Table 5. Alternative explanations

	probit		*logit*	
	(1)	(2)	(3)	(4)
lnpatent	0.0442***	0.0565**	0.0441**	0.0586**
	(0.0170)	(0.0266)	(0.0185)	(0.0277)
rpgdp	0.8583***	1.4396***	0.9061***	1.5021***
	(0.2742)	(0.4874)	(0.3160)	(0.5664)
rpgdp2	-0.6292***	-1.1384***	-0.6659***	-1.1836**
	(0.2201)	(0.3949)	(0.2510)	(0.4644)
rpgdp3	0.1513***	0.2714***	0.1584***	0.2813**
	(0.0542)	(0.0967)	(0.0617)	(0.1146)
lnemploy	-0.0884***	-0.1309***	-0.0830***	-0.1296***
	(0.0267)	(0.0378)	(0.0277)	(0.0405)
pro2	-0.0043**	-0.0040*	-0.0044**	-0.0040*
	(0.0020)	(0.0023)	(0.0021)	(0.0024)
lnindgdp	0.0886**	0.1286**	0.0933*	0.1308*
	(0.0431)	(0.0630)	(0.0484)	(0.0686)
lnexpend		0.0567***		0.0531***
		(0.0183)		(0.0184)
lnenergy	-0.0187		-0.0199	
	(0.0175)		(0.0186)	
cons	-0.2669	-4.9213***	-0.7292	-8.7223***
	(0.8515)	(1.5410)	(1.1724)	(2.9905)
N	790	522	790	522
pseudo R^2	0.1547	0.1563	0.1521	0.1523

5. HETEROGENEITY ANALYSIS

Patent is divided into invention patent, utility model patent and design patent three types, green patent is the same. Design patents do not need to go through complex application and authorization links, and contain the lowest quality, so this paper does not include them in the

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scope of research. The application and authorization of invention patent need a long period. In China, it usually takes more than one year or even two years for an invention patent to be applied for and authorized. Therefore, the number of application and authorization of invention patent is generally far less than that of utility model. In this paper, the number of green patents is divided into the number of green invention patents granted and the number of green utility model patents granted, and the promoting effect of two different green innovations on urban collaborative emission reduction is discussed. Table 6 shows the results of heterogeneity analysis in this paper.

Table 6. Heterogeneity analysis

	probit		*logit*	
	(1)	(2)	(3)	(4)
lninvent	0.0144 (0.0150)		0.0140 (0.0150)	
lnut		0.0504*** (0.0167)		0.0518*** (0.0181)
rpgdp	0.1058*** (0.0390)	0.0812** (0.0338)	0.1025** (0.0409)	0.0728* (0.0377)
lnemploy	-0.0572** (0.0273)	-0.0915*** (0.0255)	-0.0584** (0.0283)	-0.0921*** (0.0260)
pro2	-0.0053** (0.0022)	-0.0040** (0.0019)	-0.0058** (0.0024)	-0.0042** (0.0021)
lnindgdp	0.1528*** (0.0509)	0.0897* (0.0465)	0.1627*** (0.0558)	0.1016* (0.0528)
cons	0.3387 (0.7260)	0.3456 (0.6767)	1.0322 (1.3873)	0.8692 (1.3214)
N	747	841	747	841
pseudo R^2	0.0947	0.1284	0.0950	0.1217

In Table 5, (1) - (2) and (3) - (4) are listed as the results of the logit model and probit model, respectively, of the number of green invention patents granted with a delay of one phase (lninvent) and the number of green utility model patents granted with a delay of one phase (lnut). It can be seen from the results that although the average marginal effect of invention patent is positive, the result is not significant, while the average marginal effect of utility model is significantly positive. The reason may be that, in the context of China's innovation-driven strategy and energy conservation and emission reduction, many local governments in order to reduce local pollutant emissions, will give enterprises certain innovation subsidies, the form of which can be generally divided into two categories, one is based on the amount of enterprise R&D investment, based on financial subsidies or tax relief (Gao and Yuan., 2021), The other type is based on the R&D achievements of enterprises in a certain period of time (mainly the amount of patent authorization) based on subsidies, and the authorization cycle of invention patents is much larger than that of utility model patents. Therefore, in order to obtain more subsidies and tax breaks, enterprises are more inclined to develop utility model patents rather than innovate invention patents of higher quality, especially for small and medium-sized enterprises. As a result, utility model patents outnumber invention patents in cities. Therefore, in the link of heterogeneity analysis in this paper, the large number of utility model patents are more significant than invention patents.

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6. CONCLUSION

In this paper, a new binary dependent variable is used to define collaborative emission reduction. 66 pilot low-carbon cities in China from 2005 to 2017 are taken as research samples to explore the impact of urban green innovation capability on collaborative emission reduction of greenhouse gases and air pollutants. The main conclusions are as follows:

(1) After replacing the explained variables and the empirical model, and excluding the influence of the increase of urban environmental protection input and the decrease of total energy consumption, the study found that the urban green innovation ability significantly promoted the collaborative emission reduction of CO_2 and air pollutants.

(2) The relationship between the degree of affluence and pollutant emission in China's pilot low-carbon cities does not show a significant inverted U-shaped relationship, but an S-shaped relationship. When the degree of affluence is low and high, the degree of affluence and collaborative emission reduction show a positive correlation, while in the middle, the degree of affluence shows a negative correlation.

(3) Urban green innovation has the best effect on collaborative emission reduction of greenhouse gases and soot, followed by SO_2 and wastewater.

(4) Compared with high-quality innovation which has a longer R&D and authorization period and is more difficult to put into practice, low-quality innovation which is easier to put into practice has a more significant effect on collaborative emission reduction.

In the context of innovation-driven strategy and energy conservation and emission reduction, green innovation has become an effective means to control pollutant emission. As enterprises are the main body of pollutant emission and green innovation, promoting enterprises to carry out green innovation research and development will not excessively discourage enterprises' production enthusiasm, but also enable enterprises to reduce pollutant emission while improving their own energy utilization efficiency, encourage enterprises to grasp core technological advantages, and form a mutually beneficial friendly relationship between local governments and enterprises on environmental issues. The government should adopt more efficient incentive policies for green innovation based on local conditions, and actively promote the establishment of an industrial system with low energy consumption and low pollution. This will not only help reduce the energy consumption per unit of GDP, but also strengthen the spillover effect of green technology innovation. Enterprises with strong innovation ability can provide technical support and guidance to a large number of smaller enterprises, thus improving the overall regional green technology innovation strength.

REFERENCES

[1] Dong Z, He Y, Wang H, et al. Is there a ripple effect in environmental regulation in China? – Evidence from the local-neighborhood green technology innovation perspective[J]. Ecological Indicators, 2020, 118: 106773.

[2] Liu Y, Dong F. How technological innovation impacts urban green economy efficiency in emerging economies: A case study of 278 Chinese cities[J]. Resources, Conservation and Recycling, 2021, 169: 105534.

[3] Du G, Yu M, Sun C, et al. Green innovation effect of emission trading policy on pilot areas and neighboring areas: An analysis based on the spatial econometric model[J]. Energy Policy, 2021, 156: 112431.

[4] Yang W, Song J. Simulating optimal development of clean coal-fired power generation for collaborative reduction of air pollutant and CO_2 emissions[J]. Sustainable Production and Consumption, 2021, 28: 811-823.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202302_9(2).0006

[5] Liu X, Wang W, Wu W, et al. Using cooperative game model of air pollution governance to study the cost sharing in Yangtze River Delta region[J]. Journal of Environmental Management, 2022, 301: 113896.

[6] Wang Y, Zhao Y. Is collaborative governance effective for air pollution prevention? A case study on the Yangtze river delta region of China[J]. Journal of Environmental Management, 2021, 292: 112709.

[7] Yan Y, Zhang X, Zhang J, et al. Emissions trading system (ETS) implementation and its collaborative governance effects on air pollution: the China story[J]. Energy Policy, 2020, 138: 111282.

[8] Zhang J, Liang G, Feng T, et al. Green innovation to respond to environmental regulation: How external knowledge adoption and green absorptive capacity matter?[J]. Business Strategy and the Environment, 2020, 29(1): 39-53.

[9] Du G, Yu M, Sun C, et al. Green innovation effect of emission trading policy on pilot areas and neighboring areas: An analysis based on the spatial econometric model[J]. Energy Policy, 2021, 156: 112431.

[10] Xu L, Fan M, Yang L, et al. Heterogeneous green innovations and carbon emission performance: Evidence at China's city level[J]. Energy Economics, 2021, 99: 105269.

[11] Peng W, Yin Y, Kuang C, et al. Spatial spillover effect of green innovation on economic development quality in China: Evidence from a panel data of 270 prefecture-level and above cities[J]. Sustainable Cities and Society, 2021, 69: 102863.

[12] Qiu S, Wang Z, Liu S. The policy outcomes of low-carbon city construction on urban green development: Evidence from a quasi-natural experiment conducted in China[J]. Sustainable Cities and Society, 2021, 66: 102699.

[13] Zeng J, Škare M, Lafont J. The co-integration identification of green innovation efficiency in Yangtze River Delta region[J]. Journal of Business Research, 2021, 134: 252-262.

[14] Liu L, Zhao Z, Su B, et al. Structural breakpoints in the relationship between outward foreign direct investment and green innovation: An empirical study in China[J]. Energy Economics, 2021, 103: 105578.

[15] Du W, Li M. Assessing the impact of environmental regulation on pollution abatement and collaborative emissions reduction: Micro-evidence from Chinese industrial enterprises[J]. Environmental Impact Assessment Review, 2020, 82: 106382.

[16] Xu L, Fan M, Yang L, et al. Heterogeneous green innovations and carbon emission performance: Evidence at China's city level[J]. Energy Economics, 2021, 99: 105269.

[17] Fan J, Xiao Z. Analysis of spatial correlation network of China's green innovation[J]. Journal of Cleaner Production, 2021, 299: 126815.

[18] Shao X, Zhong Y, Liu W, et al. Modeling the effect of green technology innovation and renewable energy on carbon neutrality in N-11 countries? Evidence from advance panel estimations[J]. Journal of Environmental Management, 2021, 296: 113189.

[19] Luo Y, Salman M, Lu Z. Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China[J]. Science of the Total Environment, 2021, 759: 143744.

[20] Liu X, Wahab S, Hussain M, et al. China carbon neutrality target: Revisiting FDI-trade-innovation nexus with carbon emissions[J]. Journal of Environmental Management, 2021, 294: 113043.

[21] Ehrlich P R, Holdren J P. Impact of population growth in population, resources and the environment[J]. Washington, DC: US Government Printing Office, 1972: 365-377.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202302_9(2).0006

[22] Vélez-Henao J A, Vivanco D F, Hernández-Riveros J A. Technological change and the rebound effect in the STIRPAT model: A critical view[J]. Energy Policy, 2019, 129: 1372-1381.

[23] Liu Y, Lai X. EKC and carbon footprint of cross-border waste transfer: Evidence from 134 countries[J]. Ecological Indicators, 2021, 129: 107961.

[24] Wang K, Zhu Y, Zhang J. Decoupling economic development from municipal solid waste generation in China's cities: Assessment and prediction based on Tapio method and EKC models[J]. Waste Management, 2021, 133: 37-48.

[25] da Silva B A, Constantino M, de Moraes P M, et al. Econometric analysis of IPAT-e: A new tool for the environmental impact assessment of publicly traded companies[J]. Environmental Impact Assessment Review, 2021, 89: 106586.

[26] Dietz T, Rosa E A. Rethinking the environmental impacts of population, affluence and technology[J]. Human ecology review, 1994, 1(2): 277-300.

[27] Zhao Y, Peng B, Elahi E, et al. Does the extended producer responsibility system promote the green technological innovation of enterprises? An empirical study based on the difference-in-differences model[J]. Journal of Cleaner Production, 2021, 319: 128631.

[28] Zhang Q, Yu Z, Kong D. The real effect of legal institutions: Environmental courts and firm environmental protection expenditure[J]. Journal of Environmental Economics and Management, 2019, 98: 102254.

[29] Harper C L, Snowden M. Environment and society: Human perspectives on environmental issues[M]. Routledge, 2017.

[30] Fan W, Li L, Wang F, et al. Driving factors of CO_2 emission inequality in China: the role of government expenditure[J]. China Economic Review, 2020, 64: 101545.

[31] Chen D, Han Z, Guo D, et al. Exergoeconomic perspective to evaluate and optimize supercritical carbon dioxide coal-fired power generation system[J]. Energy Conversion and Management, 2021, 244: 114482.

[32] Du X, Jin X, Zucker N, et al. Transboundary air pollution from coal-fired power generation[J]. Journal of Environmental Management, 2020, 270: 110862.

[33] Gao K, Yuan Y. The effect of innovation-driven development on pollution reduction: Empirical evidence from a quasi-natural experiment in China[J]. Technological Forecasting and Social Change, 2021, 172: 121047.