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Assessing the effectiveness of innovative city pilots in improving urban carbon emission performance: A spatial difference-in-difference approach

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Existing studies have focused on the impact of innovation on carbon emission performance but ignore the importance of government support for innovation. To overcome this challenge, this paper adopts a spatial difference-in-difference (DID) model to assess the impact of government support for innovation on urban carbon emission performance based on a quasi-natural experiment of innovative city pilots (ICP) in China. Using the high-resolution carbon emission data of 1 km × 1 km for 238 cities from 2008 to 2019 in China, this paper employees an extended stochastic frontier analysis (SFA) model to measure urban carbon emission performance. Our findings indicate that ICP implementation leads to a 1.3% improvement in local carbon emission performance. Meanwhile, there is a significant spatial spillover effect of ICP implementation, with a 3.3% improvement in the carbon performance of the surrounding areas. The results of the mechanism analysis suggest that government innovation support affects carbon emission performance by promoting total factor productivity improvement, green innovation, and industrial upgrading. Further analysis shows that ICP has the strongest impact on carbon performance in the eastern region, and the impact is stronger for large cities and resource-dependent cities. Finally, the paper carries out a series of robustness tests to ensure the reliability of the analytical results, including parallel trend tests, placebo tests and re-estimation of different methods. Based on the findings, this paper proposes feasible policy recommendations in terms of continuous promotion of government innovation support, regional cooperation and differentiated innovation support formulation.

KEYWORDS

carbon emission performance, innovative city pilots, spital difference-in-difference model, stochastic frontier analysis, spatial spillover effect

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1 Introduction

In recent years, the rapid increase in greenhouse gas emissions has exacerbated global warming and extreme climate phenomena, which have seriously threatened the sustainable development of human society (Magazzino, 2017a; Bai et al., 2019; Du and Li, 2019; Chen and Lin, 2020; Statistical Review of World Energy, 2021; He et al., 2021; Li Y et al., 2022, Li Z et al., 2022; Wang K-L et al., 2022; Wu C et al., 2022). As the country with the highest carbon emission in the world, China's total carbon emission has increased from 1.419 billion tons in 1978 to 9.899 billion tons in 2020, an increase of 6.98 times (BP, 2021). This means that China faces enormous pressure to reduce emissions. In 2020, the Chinese government also proposed the dual carbon goals of "2030 carbon peak" and "2060 carbon neutrality", aiming to alleviate the climate problems caused by greenhouse gas emissions. Improving carbon emission performance, i.e., the output per unit of carbon emission, is regarded as the most powerful policy instrument to achieve the dual carbon goals. How to improve carbon emission performance has attracted a large number of scholars to study and discuss.

However, the existing literature has not reached a consistent conclusion on the impact of government support for innovation on carbon emission performance. One view is that government support for innovation can effectively improve carbon emission performance. Pan A et al. (2022) selected enterprise-level panel data from 2010 to 2018 to investigate the effect of the pilot carbon emission trading scheme (CETS). He found a significant positive effect of government support on carbon emission performance and total factor productivity based on the PSM-DID model. Doğan et al. (2022) used data from the G7 countries from 1994 to 2004 to study the effects of environmental taxes on carbon emissions, natural resource rents, and renewable and non-renewable resources. He found environmental tax policies can significantly reduce carbon emissions and improve carbon emission performance in these countries. The opposite view is that government support for innovation has a very limited effect on improving carbon emission performance. Fu et al. (2022) adopted a game-theoretical framework to examine firms' operational strategies under a carbon tax policy. They concluded that carbon taxes do not necessarily lead to the adoption of green technologies and the improvement of carbon emission performance. Yıldırım et al. (2022) empirically investigated the impact of environmental innovation on CO_2 emissions in the energy sector based on a large dataset of 32 OECD countries from 1997 to 2018. Using a panel smooth transition regression (PSTR) model, they found that the impact of government innovation on carbon emission performance is unstable at different stages due to rebound effects.

Improving carbon emission performance through technological innovation is an important measure for countries to mitigate climate problems in the future (Adedoyin et al., 2022; Pan X et al., 2022). The motivation of this paper is to comprehensively assess the impact of government innovation support on carbon emission performance. This paper argues that existing research faces three challenges, ignoring these challenges may lead to conflicting views. The first challenge is to select a more effective model to assess carbon emission performance. The most widely used methods are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (Kumbhakar et al., 2014; Filippini and Hunt, 2015; Kang et al., 2022). DEA based on linear programming ignores unobserved city heterogeneity in carbon emission performance (Filippini and Hunt, 2015). Meanwhile, the traditional SFA method cannot remove individual effects, time effects and unobserved heterogeneity at the same time (Kumbhakar et al., 2014). This can lead to over- or underestimation of city carbon emission performance and interfere with the impact of government support for innovation. The second challenge is to circumvent the endogenous interference of government innovation support. Existing literature generally uses indicators such as government subsidies and tax incentives to measure the government's support for innovative behavior, but such indicators have a strong correlation with urban economic development (Rawte, 2017; Fu et al., 2022; Tang C et al., 2022). Carbon emission performance is also strongly related to economic development, and the resulting endogenous interference will reduce the reliability of the estimated results. The third challenge is to overcome the effect of spatial factors on the results. There are many industrial clusters in China, which makes the economic development of neighboring cities and carbon emissions have obvious spatial correlation (Liu et al., 2022; Zhang Y et al., 2022). In addition, the talents and technologies attracted by the local government through innovation support also accumulate innovation elements for the surrounding areas, thereby affecting the carbon emission performance of the surrounding areas (Peng H et al., 2021; Gao and Yuan, 2022; Zhao and Sun, 2022). Ignoring the potential impact of spatial factors on carbon emission performance in the evaluation model reduces the reliability of the results. To overcome the above challenges, this paper adopts a spatial difference-in-difference (DID) model and uses a quasi-natural experiment in China to assess the impact of government innovation support on urban carbon emission performance.

The contribution of this paper is mainly in the following three points. First, based on the prefecture-level panel data from 2008 to 2019, this paper adopts the extended SFA model proposed by Kumbhakar et al. (2014) to evaluate carbon emission performance. This approach considers all the time-varying, time-invariant, and city characteristics, which help obtain more reliable calculation of carbon emission performance. Second, this paper assesses the impact of government innovation support on carbon emission performance through a quasi-natural experiment. To explore the role of the government in urban innovation, China has implemented the policy of innovative city pilots (ICP), which is committed to improving the agglomeration of urban innovation elements through government participation. ICP identified Shenzhen as the first pilot city for innovation, and in 2009, 14 cities including Dalian and Qingdao were identified as pilot cities for innovation. From 2010 to 2013, more than 40 innovative city pilots were successively approved. In April 2018, another 17 cities were approved to build national innovative cities, and the number of innovative city pilots increased to 78. This policy has strong exogenous nature and can avoid the interference of endogeneity on the evaluation results to a certain extent. The ICP from China is an incremental reform that provides important lessons for other countries and regions committed to improving carbon emission performance through government innovation support policies. Finally, this paper incorporates spatial factors in the traditional DID model. The results estimated through spatial DID model reduce the interference of spatial factors, which can more reliably assess the impact of government innovation support on carbon emission performance.

The reminder of this study is organized as follows: Section 2 provides the literature review. Section 3 provides the policy background and research hypothesis, Section 4 provides the methods and data, Section 5 provides the results, and Section 6 provides the conclusions, recommendations, and limitations.

2 Literature review

The existing literature focuses on two aspects of carbon emission performance, including the measurement of carbon emission performance and the impact of technological innovation on carbon emission performance. First, in the measurement of carbon emission performance, the previous studies used the indicator of economic output per unit of carbon emissions (Lee et al., 2002; Filippini and Hunt, 2015; Chen et al., 2022; Kang et al., 2022). The higher the value of this indicator, the higher the level of carbon emission performance. However, this indicator is limited in that it ignores the potential influence of other factors on carbon emission performance, such as population and industry level (Kang et al., 2022). To overcome this limitation, recent studies widely use DEA and SFA to measure carbon emission performance (Hua et al., 2007; Filippini and Hunt, 2015; Cao and Wu, 2022; Kang et al., 2022). It solves for the optimal combination of input and output factors, and measures carbon emission performance through the gap between actual carbon emissions and expected carbon emissions of optimal combination (Hua et al., 2007; Choi et al., 2012; Molinos-Senante et al., 2014; Liu et al., 2021; Zhang et al., 2021). However, this approach does not consider the unobserved heterogeneity among cities. The bias is acceptable in small samples. However, for large samples, the overestimation or underestimation due to unobserved heterogeneity must be considered (Filippini and Hunt, 2015; Kang et al., 2022). SFA measures carbon emission performance through extracting the residuals from the stochastic frontier function estimates (Aigner et al., 1977). The closer the regression residuals are to zero, the higher the carbon emission performance. However, the traditional SFA model still cannot separate the unobserved heterogeneity in the residuals. Kumbhakar et al. (2014) proposed an extended SFA model that can separate the time-varying characteristics, time-invariant characteristics, and urban heterogeneity in the residuals simultaneously. Therefore, this extended SFA model will be applied in this paper to evaluate urban carbon emission performance more reliably. As an important tool for climate mitigation, how to improve carbon emission performance is a key academic concern. According to previous studies, economic development, industrial structure, government intervention, the level of financial development and the level of foreign investment are the key factors influencing carbon emission performance (Magazzino, 2016; Ashraf et al., 2020; Song et al., 2021; Li L et al., 2022; Pan A et al., 2022; Wang L et al., 2022).

Second, with the rise of emerging technologies such as industrial robots, big data, cloud computing and artificial intelligence, whether technological innovation can provide new impetus for energy conservation and emission reduction has become a hot research topic (Su et al., 2020; Prasath Kumar et al., 2021; Wang K-L et al., 2021; Li N et al., 2022; Saheb et al., 2022). The improvement of cleaner production technology can reduce carbon emissions in the process of production of enterprises and reduce carbon emissions per unit of output (Zhou and Zhao, 2016; Zhou et al., 2021). Zhang and Liu (2022) and studied the impact of digital finance and green technology innovation on carbon emissions in China and found that technology innovation enhances carbon emission performance. Also, Kuang et al. (2022) explored the impact of green technology innovation and renewable energy investments on reducing carbon emissions and found that in the long-term technology innovation can enhance carbon performance. However, studies have also shown that technology innovations increase the risk of enterprises, and the returns to enterprises are particularly limited (Li W et al., 2022; Su and Fan, 2022). Shaikh and Randhawa (2022) found that open technological innovation can also create risks within the organization that can jeopardize the company's operations. Wang S et al. (2022) conducted an in-depth study on the behavioral decisions of executive teams and corporate green technology innovation. He suggested that technological innovation is characterized by long cycles, high investments and high risks for companies.

Previous studies show that energy saving, and emission reduction cannot be achieved solely by enterprises themselves through technological innovation (Qiu, 2022; Zhang R et al., 2022). One important reason is that technological innovations that focus on energy efficiency and emission reduction do not bring higher excess returns to companies (Li W et al., 2021). Companies will devote limited resources to more profitable projects (Salmani and Partovi, 2021; Gabdullina et al., 2022). At this point, the government must subsidize and support the innovative behavior of enterprises to reduce the R&D risks of enterprises (Ma and Li, 2021; Fan et al., 2022). Especially for green production technology, government incentives can stimulate the innovation of enterprises to a certain extent. Therefore, it is necessary to pay attention to the role of government innovation support in the improvement of urban carbon emission performance.

3 Policy background and research hypothesis

3.1 Policy background of innovative city pilots

ICP is an important policy proposed by China based on the increasingly competitive international situation (Yang J et al., 2022). This is to enhance the innovation capacity and realize the national development plan. In the future, China hopes to use independent innovation as a driving force to promote the restructuring of the industrial economy and the construction of a sustainable society. In 2008, Shenzhen became the first innovative pilot city. The country leverages Shenzhen's good innovation capability base to radiate neighboring cities. It is hoped that the leading role of science and technology will be brought into play to achieve an overall improvement in the level of innovation in the region. At the beginning of 2010, 14 more cities, including Dalian and Qingdao, joined the list of pilot innovative cities. With the accelerated expansion of the pilot scale of innovative cities, the number of innovative cities nationwide has reached 78 as of 2018 (see Figure 1). From the lo-cation of the pilot innovative cities, there are a certain number of pilots distributed in the east, middle and west of the country. The relatively economically developed coastal provinces in the east have more pilot innovative cities (Yang Z et al., 2022). In terms of the development of innovative cities, the goal of building innovative cities is gradually evolving from enhancing innovation to restructuring urban industries and building sustainable societies. The country is leveraging the policy advantages of these innovative cities and promoting the synergistic development of innovation levels in the surrounding areas (Gao and Yuan, 2022). Such a trend is important to China's early entry into the forefront of innovative countries.

3.2 Research hypothesis

In this study, we suppose that government innovation support will enhance local carbon emission performance through three main channels. First, government innovation support will improve local carbon performance by enhancing total factor productivity. It has been documented that government innovation support significantly increases total factor productivity (Pan A et al., 2022). This implies that the output from the given total carbon emissions also increases significantly, leading to an increase in carbon emission performance. Second, government innovation support drives the level of local green innovation and thus enhances carbon performance. Government innovation support can effectively reduce the risk of enterprise innovation and greatly stimulate enterprises' innovation behavior in energy saving and emission reduction and other green technologies (Lin and Ma, 2022). Thus, green innovation can significantly reduce carbon emissions per unit of output, i.e., lead to the improvement of carbon emission performance. Finally, government innovation support will also promote industrial upgrading, thus improving the urban carbon emission performance. Government innovation support can accelerate the transformation of local enterprises from production and processing to R&D, i.e., industrial upgrading (Su and Fan, 2022). Industrial upgrading leads to a decrease in the share of energy inputs in enterprise production and an increase in the value added of products (You and Zhang, 2022). Therefore, enterprises can achieve higher output with lower resource inputs, which leads to the improvement of urban carbon emission performance. Based on the above analysis, this paper proposes the first research hypothesis.

H1: Government innovation support can improve local carbon emission performance through promoting total factor productivity, green innovation and industrial upgrading.

In addition to influencing local carbon performance, local government innovation support may also affect the carbon emission performance of neighboring regions through spillover effects. Government innovation can effectively attract various innovation factors to cluster locally, such as R&D personnel and R&D funds (Li X et al., 2021). Has mentioned in his study that government environmental support has a significant innovation agglomeration effect. Similarly, this idea was also supported by the study of (Peng W et al., 2021). Neighboring regions can then share the benefits of local innovation agglomeration through technological cooperation. Thus, they can improve their own carbon emission performance. In addition, neighboring regions can provide a broad market for the output of local innovation factors and match technical talents. The resulting industrial upgrading will improve the overall carbon emission performance of the region (Yang and Liu, 2020; Kuang et al., 2022; Yang Z et al., 2022). Therefore, the second hypothesis is proposed in this paper.

H2: There is a significant positive spillover effect of government innovation on the carbon emission performance of neighboring regions.

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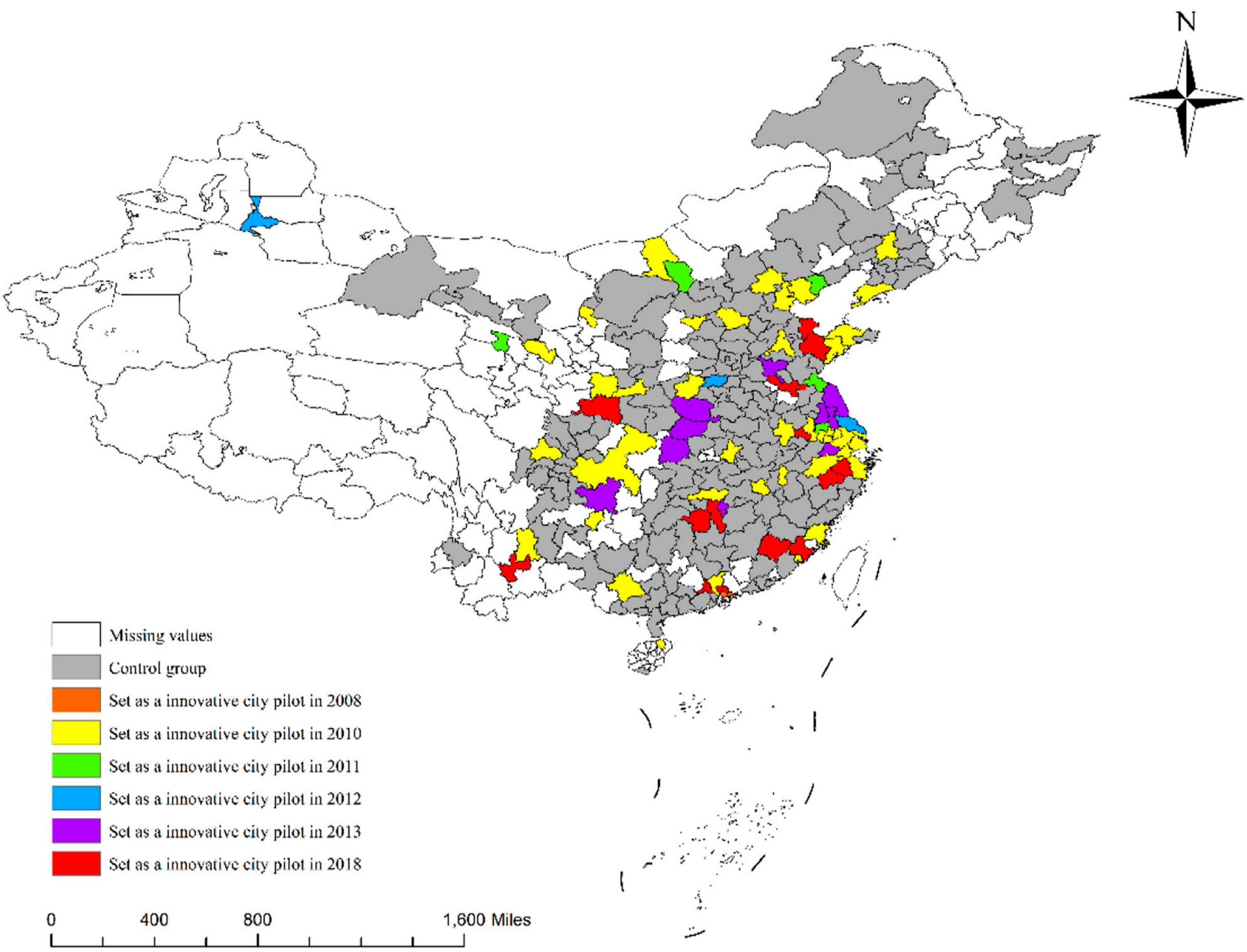

FIGURE 1
Distribution of innovative city pilots in China.

4 Methods and data

4.1 Spatial difference-in-difference model

This paper employees the ICP as a quasi-natural experiment and adopts the DID model to assess the impact of government support for innovation on urban natural carbon emissions. Selecting the implementation of ICP as dependent variables can reduce the potential interference caused by endogenous problems to a certain extent. In addition, considering the spatial spillover effect of urban carbon emissions (Gao and Yuan, 2022; Zhao and Sun, 2022), this paper further incorporates spatial factors into the traditional DID model, and uses the spatial DID to evaluate the impact of the implementation of ICP on urban carbon emission performance.

In the inclusion of spatial factors, the most widely used methods are Spatial Lag Model (SLM), Spatial Error Model (SEM) and spatial Durbin Model (SDM) (Zhao and Sun, 2022). SLM includes the spatial lag term of the dependent variable in the model. SEM incorporates the spatial lag term of the error term into the model. SDM incorporates both the spatial lag terms of the independent variable and the dependent variable into the model. Considering the robustness, this paper will report the estimated results of these three models in the benchmark analysis. First, the spatial DID model based on SLM is constructed as follows:

$$Y_{it} = \alpha + \delta \sum_{j=1}^{n} W_{ij} Y_{it} + \beta ICP_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N\left(0, \sigma^2 I\right) \tag{1}$$

where Y_{it} denotes the urban carbon emission performance of city i in year t, ICP_{it} denotes implementation of the innovative city pilots, $\delta \sum_{j=1}^{n} W_{ij} Y_{it}$ denotes the spatial lag of carbon emission performance. Then, the spatial DID model based on SEM is specified:

$$Y_{it} = \alpha + \beta ICP_{it} + \varepsilon_{it} \tag{2}$$

TABLE 1 Variable definition.

Classification	Symbol	Definition	Measurement
Dependent variable	cep	Carbon emission performance	Calculation based on expanded SFA model
Independent variables	ICP	innovative city pilots	Takes the value of 1 if ICP is implemented, 0 otherwise
Control variables	lnrgdp	Economic development	Logarithm of GDP per capita
	is	Industry structure	Value added of tertiary industry/value added of secondary industry
	gov	Government intervention	Government expenditure/GDP
	fin	Financial development	Deposit and loan balance of financial institutions/GDP
	fdi	Level of foreign investment	Actual amount of foreign capital utilized/GDP
Variables in KLH-SFA	∅lngdp	Economic aggregate	Logarithm of GDP
	∅lnpop	Total population	Logarithm of population
	∅lngov	Government expenditure	Logarithm of government expenditure
	∅lnind	Total industrial output	Logarithm of total industrial output

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	Std	Min	Median	Max	Skewness	Kurtosis
cep	2,856	0.497	0.169	0.071	0.505	0.818	−0.355	2.232
ICP	2,856	0.171	0.377	0.000	0.000	1.000	1.746	4.047
lnrgdp	2,856	0.481	0.099	0.117	0.482	0.851	−0.258	5.283
is	2,856	0.174	0.079	0.044	0.158	1.485	−0.209	3.615
gov	2,856	0.934	0.579	0.112	0.752	6.071	2.979	33.115
fin	2,856	0.003	0.003	0.000	0.002	0.030	2.216	10.399
fdi	2,856	0.481	0.099	0.117	0.482	0.851	2.032	11.309
∅lnco2	2,856	16.887	0.920	13.795	16.860	19.452	−0.153	3.035
∅lngdp	2,856	16.552	0.918	14.067	16.452	19.760	0.464	3.238
∅lnpop	2,856	14.723	0.831	12.387	14.694	18.241	0.579	4.307
∅lngov	2,856	5.965	0.641	3.833	5.986	8.134	−0.358	3.392
∅lnind	2,856	15.796	0.946	12.863	15.754	18.469	0.120	3.008

$$\varepsilon_{it} = \lambda W_{it}\varepsilon + \mu, \quad \mu \sim N\left(0, \sigma^2 I\right) \tag{3}$$

where Y_{it} denotes the carbon emission performance, ICP_{it} denotes implementation of the innovative city pilots, λ denotes the estimated coefficient of the spatial auto-correlation error term; μ denotes the error term. Finally, the spatial DID model based on SDM is specified:

$$\begin{aligned} Y_{it} &= \alpha + \delta\sum\nolimits_{j=1}^{n} W_{ij}Y_{it} + \beta ICP_{it} + +\xi\sum\nolimits_{j=1}^{n} W_{ij}ICP_{it} + \lambda Con_{it} \\ &\quad + \tau\sum\nolimits_{j=1}^{n} W_{ij}Con_{it} + \varepsilon_{it}, \\ \varepsilon_{it} &\sim N\left(0, \sigma^2 I\right) \end{aligned} \tag{4}$$

where Y_{it} denotes the carbon emission performance, ICP_{it} denotes implementation of the innovative city pilots, Con_{it} is the control variables; $\sum_{j=1}^{n} W_{ij}Y_{it}$ denotes the spatial lag term of carbon emission performance, $\sum_{j=1}^{n} W_{ij}Con_{it}$ is the spatial lag term of control variables; $\sum_{j=1}^{n} W_{ij}ICP_{it}$ is the spatial lag term of implementation of the ICP. According to the study of LeSage and Pace (2009), if the spatial panel model has spatial hysteresis, the use of point estimation method to test the spatial spillover effect may lead to bias. Therefore, the total effect can be divided into direct effect and indirect effect by calculus method. The original SDM model can be rewritten into the following form:

$$Y_t = (1 - \delta W)^{-1}(\beta ICP_t + \gamma WICP_t) + (1 - \delta W)^{-1}\varepsilon_t \tag{5}$$

Taking the k-th independent variable as the example, the result can be expressed as a partial differential matrix according to the above formula:

$$\left[\begin{matrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{NK}} \end{matrix}\right]_t = (1 - \delta W)^{-1}\begin{bmatrix} \beta_k & W_{12}\lambda_k & \ldots & W_{1N}\lambda_k \\ W_{21}\lambda_k & \beta_k & \ldots & W_{2N}\lambda_k \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1}\lambda_k & W_{N2}\lambda_k & \cdots & \beta_k \end{bmatrix} \tag{6}$$

The above matrix reflects that the average values of diagonal elements and off-diagonal elements are respectively displayed in the partial differential matrix, and the changes of the independent variables in this region and other regions denote the direct and indirect effects.

4.2 Variable

4.2.1 Dependent variable

Based on the review of existing carbon emission performance assessment approaches, the extended SFA model proposed by Kumbhakar et al. (2014) is adopted in this paper. This model can separate the time-varying inefficiency, time-invariant inefficiency, and urban heterogeneity in the residuals at the same time. The model is specified as follows:

$$CE_{i,t} = \beta_0 + f(X_{i,t}; \beta) + \mu_{it} + \lambda_i - \tau_{it} - \gamma_i \tag{7}$$

$$PCEP_i = exp(-\hat{\gamma}_i) \tag{8}$$

$$RCEP_{i,t} = exp(-\hat{\tau}_{it}) \tag{9}$$

$$CEP_{i,t} = PCEP_i \times RCEP_{i,t} \tag{10}$$

where $CE_{i,t}$ denotes the carbon emission of city i in year t; $f(X_{i,t}; \beta)$ is the random frontier function of the carbon emission. $X_{i,t}$ denotes the output factor related to carbon emissions (Filippini and Hunt, 2015; Mele and Magazzino, 2020); β is the regression coefficient; μ_{it} is the regression error term; λ_i is the urban effect; $\tau_{it} \geq 0$ and $\gamma_i \geq 0$ are the inefficiency of continuous carbon emission and residual carbon emission respectively. Meanwhile, they meet the following mathematical distribution requirements: $\mu_{it} \sim N(0, \sigma_u^2)$, $\lambda_i \sim N(0, \sigma_\lambda^2)$, $\tau_{it} \sim N^+(0, \sigma_\tau^2)$, $\gamma_i \sim N^+(0, \sigma_\gamma^2)$. Furthermore, the total carbon emission performance (CEP) is calculated by multiplying the persistent carbon emission performance (PCEP) and the residual carbon emission performance (RCEP).

4.2.2 Independent variable

ICP is an incremental reform, with six batches of cities implementing ICP. Specifically, 77% of the pilot cities establishment concentrated between 2010 and 2013, including 41, 6, 3 and 10 cities in 2010, 2011, 2012 and 2013, respectively. Only Shenzhen was established in 2008, and the remaining 17 pilot cities were established in 2018. This study adopts the implementation of ICP as the independent variable to assess the effect of government support for innovation on the improvement of urban carbon emission performance. The value is 1 if city i has implemented ICP in year t and 0 if it has not implemented ICP.

4.2.3 Control variable

To assess the impact of ICP on urban carbon emission performance more reliably, this paper incorporates a series of control variables in the model, including the level of economic development (lnrgdp), industrial structure (is), government intervention (gov), the level of financial development (fin) and the level of foreign investment (fdi) (Magazzino, 2017b; Ashraf et al., 2020; Song et al., 2021; Wang B et al., 2021; Pan X et al., 2022; Wang and Huang, 2022; Wang S et al., 2022; Wang W et al., 2022; Wu D et al., 2022). The specific measures of each variable are shown in Table 1. Table 2 further reports the descriptive statistics for each variable.

4.3 Data

This paper is based on the open-source spatial grid monthly dataset of anthropogenic carbon emissions (ODIAC) deduced by the team of Oda et al. (2018). This dataset reports high-resolution carbon emission data of 1 km × 1 km, which is aggregated to form a prefecture-level city panel carbon emission dataset. The period of the sample is from 2008 to 2019. The control variables selected in this paper come from the Chinese City Statistics Database (CCSD) in Chinese Research Data Services (CNRDS) Platform (https://www.cnrds.com/Home/Index#/FinanceDatabase/DB/CCSD) and the China Urban Statistical Yearbook. Since the spatial DID model requires the data structure to be a balanced panel, this paper excludes city samples with missing values in any year. The balanced panel dataset contains 238 cities per year with a total of 2856 samples.

5 Results

5.1 Measurement of carbon emission performance

Figure 2 shows the carbon emission performance maps of cities based on SFA model in 2010, 2015 and 2019. In the same year, the darker color denotes the higher carbon emission performance. In terms of the national carbon emission performance distribution, the average carbon emission performance of northern cities is relatively high in these 3 years. While the carbon emission performance of southern cities is relatively low on average. Meanwhile, the carbon emission performance of coastal cities is on average higher than that of inland cities at similar latitudes. We also found that the pattern of carbon emission performance in China remains roughly the same from 2010 to 2019, but there is an overall increase in carbon emission performance.

5.2 Spatial autocorrelation test

This paper tested the spatial correlation of carbon emission performance of cities. Scatter plots of Moran index can reflect the spatial correlation of carbon emission performance more visually. Figure 3 shows the scatter plots of carbon emission

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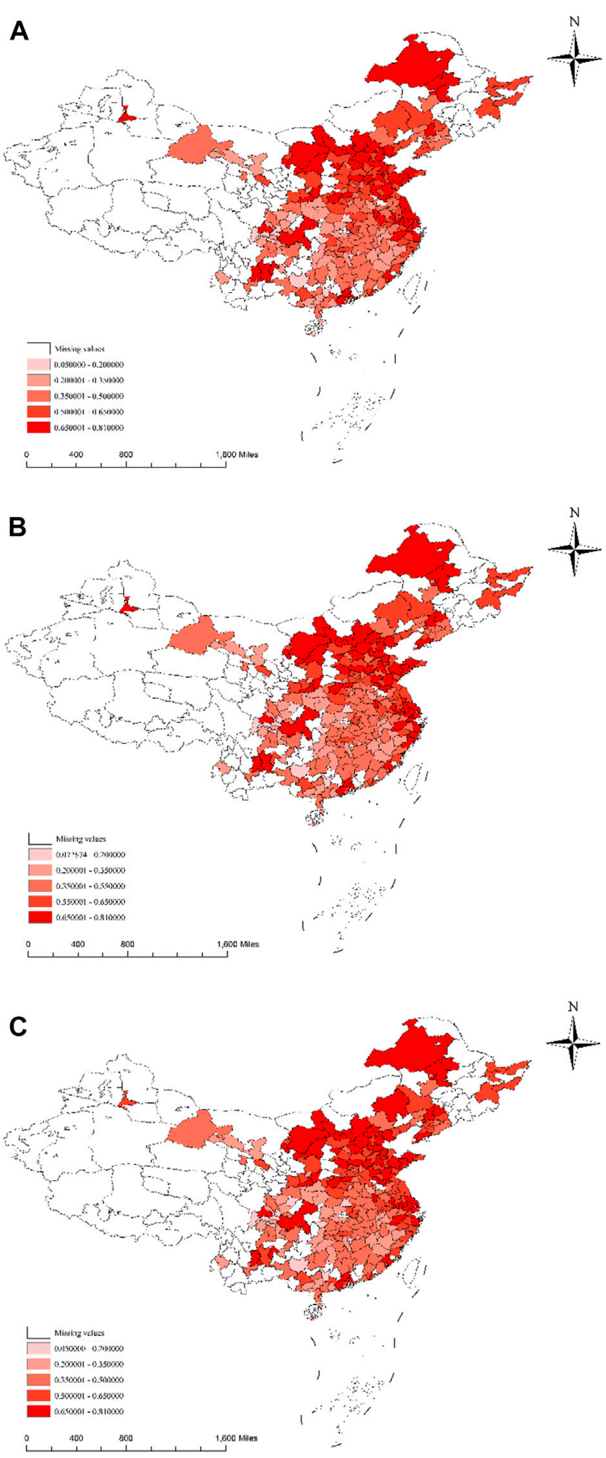

FIGURE 2
Carbon emission performance maps of cities. **(A)** denotes the maps in 2010, **(B)** denotes the maps in 2015, and **(C)** denotes the maps in 2019.

performance of cities in 2010, 2015 and 2019. In these three plots, the horizontal axis represents the standardized carbon emission performance, and the vertical axis represents the spatial lagged values. The coefficients of the primary fit line according to the scatterplot are significantly smaller than zero, which indicates that there is a spatial negative correlation between the urban carbon emission performance. Table 3 shows the specific results of Moran index of carbon emission performance. The Moran index is significantly negative at the 1% level for the period 2008 to 2019. The values of the indexes are between -1 and 0. This shows that the carbon emission performance of cities in China has a strong spatial correlation. Therefore, spatial factors should be considered in the estimation model.

5.3 Impact of innovative city pilots on carbon emission performance

Table 3 reports the baseline regression results. For comparison and to ensure the robustness of the results, here we report the regression results including the fixed effects model, the SLM model, the SEM model, and the SDM model. According to the results, there is a significant positive contribution of ICP policy on carbon emission performance. The coefficients of ICP on carbon emission performance calculated by the four models are 0.9% ($p < 0.01$), 1.7% ($p < 0.01$), 1.2% ($p < 0.01$) and 1.3% ($p < 0.01$), respectively. Since SDM considers both spatial lag effects and spatial error effects, its assessment of ICP effects is more reliable. Thus, the implementation of ICP leads to a final improvement of urban carbon emission performance by 1.3% after excluding the spatial factor interference.

The results indicates that ICP policy can improve carbon emission performance. Meanwhile, the pilot of innovative cities helps to respond to cities for green development and economic improvement. In terms of other control variables, the effect of GDP per capita on carbon emission performance is significantly negative at the 1% level in all four models. The effect of industrial structure on carbon emission performance is also negative at the 1% level. The effect of government expenditure on carbon emission performance is still significantly negative at the 1% level in all four models. On the contrary, the effect of deposit and loan balances of financial institutions on carbon emission performance is significantly positive at the 1% level in all four models. The effect of actual utilization of foreign finance on carbon emission performance is insignificant.

The estimation results of SDM model show that ICP policy has an important enhancement effect on carbon emission performance. Since ICP pilot cities are distributed across the country and carbon emission performance is also spatially correlated, it is necessary to discuss the spatial spillover effects. Table 5 further reports the spatial spillover effects of ICP policies on carbon emission performance. Specifically, the direct, indirect, and total effects of ICP policy on carbon emission performance improvement are significantly positive at the 1% level. This indicates that ICP policies in the region can significantly contribute to the carbon emission performance of

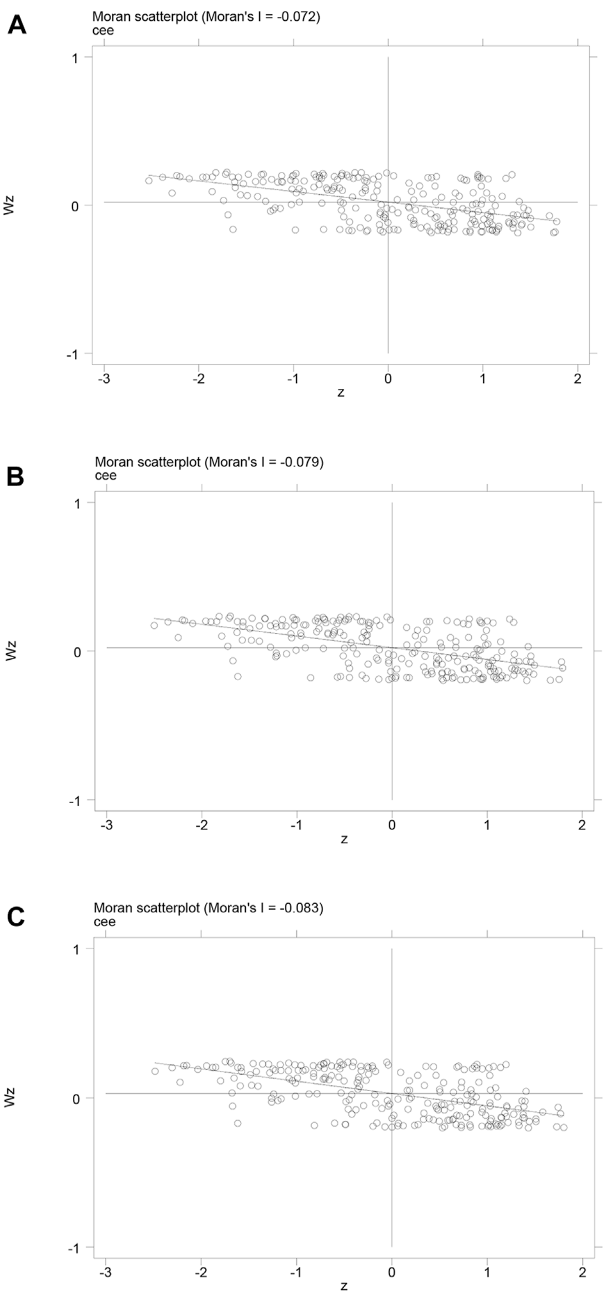

FIGURE 3
Moran scatterplot of urban carbon emission performance. **(A)** denotes the Moran scatterplot in 2010, **(B)** denotes the Moran scatterplot in 2010 in 2015, and **(C)** denotes the Moran scatterplot in 2010 in 2019.

the region firstly, and significantly contribute to the carbon emission performance of other regions. Thus, the average effect of ICP on carbon emission performance is all elevated, which is consistent with the study of Xu et al. (2021). However, the study of Xu et al. (2021) ignored the spatial spillover effect of ICP. This paper holds that the contribution of ICP policy to the

TABLE 3 Calculation of Moran's I index of urban carbon emission performance.

	Moran's I	Z-value
2008	−0.061***	−24.206
2009	−0.061***	−24.247
2010	−0.072***	−28.834
2011	−0.073***	−29.448
2012	−0.073***	−29.432
2013	−0.074***	−29.702
2014	−0.075***	−30.458
2015	−0.079***	−31.884
2016	−0.081***	−32.869
2017	−0.083***	−33.516
2018	−0.082***	−33.201
2019	−0.083***	−33.521

Note: ***, **, and * denote significant at the 1% level, 5% level and 10% level.

carbon emission performance of the region is greater than that for other regions. In addition, some studies use fiscal innovation spending or carbon taxes to measure government innovation support and find that the improvement in carbon performance is not significant (Fu et al., 2022; Yıldırım et al., 2022). This paper argues that the assessment results based on the above indicators may be subject to endogenous interference. In contrast, this paper uses ICP to measure government innovation support, which can reduce the potential interference from endogenous. In conclusion, the government should also pay attention to the demonstration role of pilot cities, which can improve the radiation efficiency by enacting policies such as inter-regional collaboration (De Noni et al., 2017; Tang D et al., 2022). Such policies can promote the overall improvement of carbon emission performance in a larger scale.

5.4 Parallel trend test

Figure 4 reports the results of the parallel trend test. None of the regression coefficients passed the significance test before the implementation of the ICP policy. This shows that there is no significant difference between the control and experimental groups before the implementation of the policy. The hypothesis of parallel trend was satisfied. In addition, after the implementation of ICP policy, the regression coefficients showed a trend of in-creasing and then decreasing. This shows that the innovative city pilot policy has the strongest effect in the first 2 years of implementation. And as time passes, the effect of the policy on carbon emission performance starts to decline. This means that in the short term, the pilot innovative cities can bring about an improvement in carbon emission performance, but the effect will gradually diminish. The

TABLE 4 Impact of innovative city pilots on urban carbon emission performance.

Variables	*FE*	*SLM*	*SEM*	*SDM*
ICP	0.009***	0.017***	0.012***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
lnrgdp	−0.015***	−0.004***	−0.008***	−0.013***
	(0.002)	(0.001)	(0.002)	(0.002)
is	−0.081***	−0.020***	−0.061***	−0.044***
	(0.009)	(0.008)	(0.008)	(0.009)
gov	−0.085***	−0.039***	−0.062***	−0.075***
	(0.009)	(0.010)	(0.010)	(0.010)
fin	0.009***	0.006***	0.010***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
fdi	−0.126	−0.085	−0.062	0.074
	(0.185)	(0.198)	(0.191)	(0.188)
wICP				0.033***
				(0.004)
wlnrgdp				0.023***
				(0.003)
wis				0.127***
				(0.015)
wgov				0.111***
				(0.024)
wfin				−0.023***
				(0.004)
wfdi				−0.736
				(0.453)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	2856	2856	2856	2856
Log-L	98.384	8231.978	8239.058	8265.711
R^2	0.391	0.155	0.036	0.066

Note: 1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. 2) City FE, and Year FE, denote the city fixed effects and year fixed effects. 3) City-level cluster robust standard errors are reported in parentheses.

government should improve the effectiveness of the ICP policy more in the long term while ensuring the short-term performance of the policy.

5.5 Further analysis

5.5.1 Mechanism of innovative city pilots affecting urban carbon emission performance

To test hypothesis 1, this paper constructs the following mediating effect model to explore the mechanism of the innovative city pilots affecting urban carbon emission performance:

$$CEP_{it} = \alpha + \beta ICP_{it} + \lambda Con_{it} + \varepsilon_{it} \tag{11}$$

$$M_{it} = \alpha + \beta ICP_{it} + \varepsilon_{it} \tag{12}$$

$$CEP_{it} = \alpha + \beta ICP_{it} + \gamma M_{it} + \lambda Con_{it} + \varepsilon_{it} \tag{13}$$

where M_{it} denotes the mediating variable, including total factor productivity, green innovation, and industrial upgrading. Total factor productivity is measured through the extended SFA model, where total GDP is the dependent variable and population, government expenditure and foreign investment are the independent variables. Green innovation is measured by the logarithm of the total number of green invention patents and green applicable patents in city i in year t. This paper measures industrial upgrading through the following equation according to the study of Jie and Qian (2016):

$$iu_{it} = \sum_{m=1}^{3} y_{imt} \times m, m = 1, 2, 3 \tag{14}$$

where a denotes the share of industry m of city i in the GDP at time t. This indicator denotes the evolution of the proportional relationship between the three major industries in China from the dominance of the primary industry to the dominance of the secondary and tertiary industries. Higher value of this indicator means the higher level of industrial upgrading. If the coefficients of ***ICP*** in Eqs. 11 and M in Eq. 12 pass the significance test, it indicates that ICP affects urban carbon emission performance through promoting labor productivity, green innovation, and industrial upgrading. Table 6 reports the regression results for this model.

According to the results in Table 6, the impact of ICP on *tfp*, *green_inn* and *iu* are 0.252 ($p < 0.01$), 1.376 ($p < 0.01$) and 0.191 ($p < 0.01$), which all pass the 1% significance test. This shows that government innovation support can significantly improve the urban total factor productivity, green innovation, and industrial upgrading, which are consistent with the study of Xu et al. (2021)

TABLE 5 Direct effect, indirect effect, and total effect of SDM in Table 4.

	ICP	Lnrgdp	is	Gov	Fin	Fdi
Direct effect	0.033***	0.023***	0.127***	0.111***	−0.023***	−0.736
	(0.004)	(0.003)	(0.015)	(0.024)	(0.004)	(0.453)
Indirect effect	0.014***	−0.012***	−0.038***	−0.071***	0.007***	0.056
	(0.002)	(0.002)	(0.009)	(0.009)	(0.002)	(0.191)
Total effect	0.048***	0.026***	0.155***	0.122***	−0.028***	−0.935
	(0.005)	(0.003)	(0.019)	(0.031)	(0.006)	(0.620)

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City-level cluster robust standard errors are reported in parentheses.

TABLE 6 Mechanisms of innovative city pilots affecting urban carbon emission performance.

	tfp	*cep*	*green_inn*	*cep*	*iu*	*cep*
	(1)	(2)	(3)	(4)	(5)	(6)
ICP	0.252***	0.024***	1.376***	0.008***	0.191***	0.011***
	(0.014)	(0.002)	(0.082)	(0.002)	(0.014)	(0.002)
tfp		0.018***				
		(0.006)				
green_inn				0.008***		
				(0.001)		
iu						0.033***
						(0.004)
Control	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observation	2856	2856	2856	2856	2856	2856
F	326.475	31.785	278.610	102.345	184.184	96.233
R^2	0.111	0.079	0.096	0.415	0.066	0.387

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses.

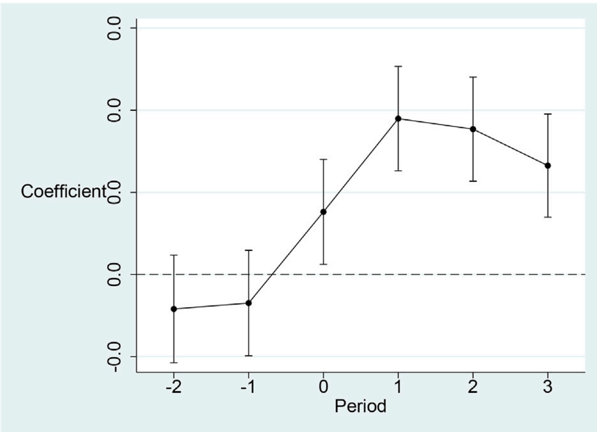

FIGURE 4
Results of Parallel Trend Test. The X-axis denotes the window period for ICP implementation. The Y axis represents the regression coefficient of ICP implementation. The year before ICP is implemented as the base period.

and Zheng and Ge (2022). In addition, the results hold that the coefficients of ***tfp***, *green_inn* and *iu* are 0.018 ($p < 0.01$), 0.008 ($p < 0.01$) and 0.033 ($p < 0.01$). This means that there are significant mechanisms for ICP to improve urban carbon emission performance through the promotion of urban total factor productivity, green innovation, and industrial upgrading, that is, the results support hypothesis 1. Therefore, the government should not only strengthen its support for technological innovation, but also further improve the market allocation of production factors and strengthen the positive impact of the above three mechanisms (Shen et al., 2021; Xi and Mei, 2022).

5.5.2 Heterogeneity analysis

There are huge differences in development between different regions in China. In terms of economic development level, the eastern region is higher than the western region in the central region (Dai and Mischke, 2014). As a government-led financial support policy, there may be differences in the intensity and effectiveness of ICP implementation in different economic development regions. Therefore, it is necessary to analyze the differences in the impact of ICP on different regions. Second, the impact effect of ICP is also related to the size of cities. The larger the city has a more complex and well-developed industrial system, the higher the scale effect of ICP implementation will be (Pan A et al., 2022). Therefore, the differences in the impact of ICP on the carbon emission performance of cities of different sizes should be further explored. Finally, the resource-dependent cities of cities are also factors to be considered. Compared with resource-based cities, non-resource-based cities consume less energy and have lower upside of carbon emission performance from ICP (Sun et al., 2022). Therefore, this paper further evaluates the differences in the impact of ICP on cities of different resource types.

TABLE 7 Heterogeneity analysis.

Variables	Region	Size	Resource Type
ICP	0.019***	0.009***	−0.001
	(0.002)	(0.002)	(0.003)
ICP×Central	−0.018***		
	(0.004)		
ICP×Western	−0.005		
	(0.004)		
ICP×Big		0.008***	
		(0.003)	
ICP×Res			0.020***
			(0.003)
lnrgdp	−0.013***	−0.013***	−0.012***
	(0.002)	(0.002)	(0.002)
is	−0.048***	−0.044***	−0.043***
	(0.009)	(0.009)	(0.009)
gov	−0.078***	−0.073***	−0.076***
	(0.009)	(0.009)	(0.009)
fin	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
fdi	0.159	0.091	0.085
	(0.188)	(0.188)	(0.188)
wICP	0.020***	0.046***	0.030***
	(0.005)	(0.006)	(0.007)
wICP×Central	0.075***		
	(0.011)		
wICP×Western	−0.009		
	(0.010)		
wICP×Big		−0.024***	
		(0.007)	
wICP×Res			0.001
			(0.009)
wlnrgdp	0.023***	0.022***	0.022***
	(0.003)	(0.003)	(0.003)
wis	0.123***	0.127***	0.126***
	(0.015)	(0.015)	(0.015)
wgov	0.112***	0.111***	0.107***
	(0.024)	(0.024)	(0.024)
wfin	−0.026***	−0.023***	−0.023***
	(0.004)	(0.004)	(0.004)
wfdi	−0.924**	−0.762*	−0.576
	(0.454)	(0.451)	(0.451)
City FE	Y	Y	Y
Year FE	Y	Y	Y
Obs	2856	2856	2856
R^2	0.056	0.076	0.105

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses.

Table 7 reports the results of the heterogeneity analysis of ICP policies on carbon emission efficiency. The first row of Table 7 is the baseline row, and the effects of ICP policies on carbon emission performance are reported from left to right for eastern regional cities, small cities, and non-resource cities, respectively. In terms of geographic location, the impact of ICP policy on carbon emission performance for eastern cities is 1.9%. The effect of ICP policy on carbon emission performance in central cities is significantly lower compared to eastern cities, which is only 0.1%. And the improvement effect of ICP policy on carbon emission performance in western cities is not significantly different from that in eastern cities. This indicates that the government should pay attention to the efficiency of the role of ICP policies in central cities, while ensuring the continued improvement of carbon emission performance in the east and west. The synergistic green development of the country's eastern, central, and western cities should be advocated. The size of cities al-so makes a difference in the impact of ICP policies on carbon emission performance. For small cities, ICP policies can significantly improve carbon emission performance by 0.9%. This improvement is more pronounced in large cities. The level of improvement in carbon emission performance for ICP policies in large cities is 1.7%, which is nearly twice as high as in small cities.

The results indicate that the country should pay attention to the radiative effect brought by large cities while paying attention to the development of green innovation in large cities. The large cities should be the center of a more efficient synergy of policy implementation in the surrounding small cities (Li X et al., 2022). Which will promote the synergistic enhancement of technological innovation and green development in a wider range of cities through the extensive layout of ICP policies. The difference between resource-based cities and non-resource-based cities is obvious. The specific setting of resource-based cities is based on the total amount of carbon emissions. Here we set the cities with higher total carbon emissions as resource-based cities using the data of total carbon emissions of different cities. Conversely, the remaining ones are non-resource-based cities. The study of Kang et al. (2022) points out that the focus of energy efficiency and emission reduction is on less efficient regions, but does not further assess the differences in the impact of government innovation support on cities with different resource types. The effect of ICP policy for non-resource-based cities on carbon emission performance is insignificant. In contrast, the ICP policy of resource-based cities has a 2% enhancement effect on carbon emission performance. On the one hand, this indicates that resource-based cities are uniquely positioned to improve their carbon emission performance based on improved technological innovation, which is consistent with the findings of Zheng and Ge (2022). On the other hand, this paper suggests that government

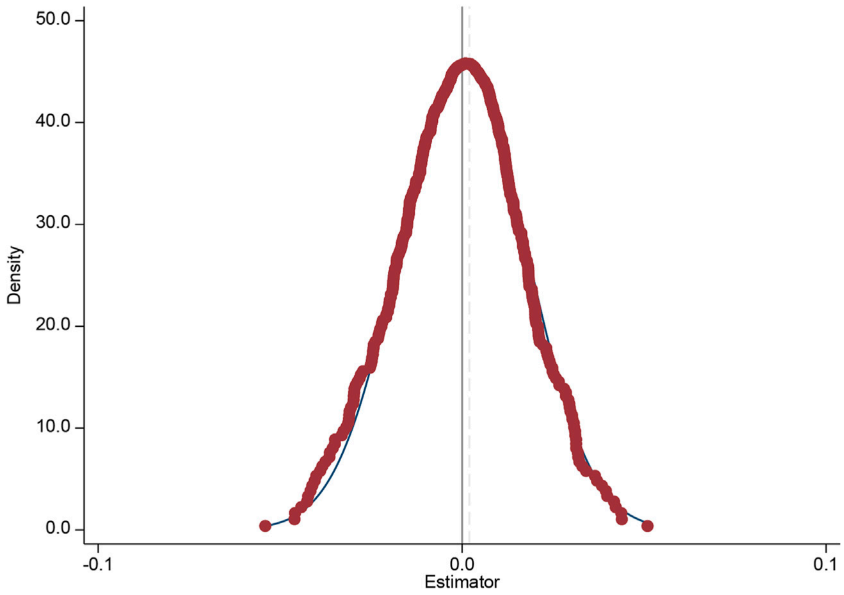

FIGURE 5
Results of placebo test. Treatment groups were randomly drawn 500 times in the control group by Monte Carlo simulation and DID regression was performed. Plot the obtained regression coefficients as a distribution graph. This figure reports the results of carbon emission performance of non-pilot cities as a dependent variable, presenting a normal distribution with an average value of 0.

needs to improve the effectiveness of ICP policies in non-resource-based cities. According to the study of Kang et al. (2022), better policy guidance and implementation are needed to promote the carbon emission performance of all types of cities.

5.6 Robustness test

5.6.1 Placebo test

Considering ICP policies may also affect the carbon emission performance of non-pilot cities, this would lead to unreliable estimation results. In this paper, a placebo test is conducted using Monte Carlo simulation. Firstly, we randomly selected samples from the control group multiple times as the treatment group. Then, based on this we then perform PSM-DID regression analysis and estimate the parameters. If the estimated parameters are normally distributed with a mean value of 0, then the results of the analysis in this paper are reliable. Figure 5 gives the estimated coefficient distributions and kernel density curves after 500 randomly drawn samples. As expected from the placebo test, the estimated coefficients show a normal distribution, and the mean value is around 0. This shows that the change in carbon emission performance of the real treated group originates from the implementation of the ICP policy.

5.6.2 Re-estimation using PSM-DID

In our previous study, we used a spatial panel regression. Based on this paper we obtained a positive result and concluded that the contribution of ICP policy on carbon emission performance is significant. To strengthen the robustness of the study, here we modify the methodology. Instead of using a spatial panel, we use the PSM method for post-matching regressions. In applying the PSM method, we used two conventional matching methods, namely 1:1 nearest neighbor matching and kernel density matching. Table 8 reports the regression results after matching using these two methods. The results show that the ICP policy can significantly improve the carbon emission performance of cities by either using nearest neighbor matching or kernel density matching. This is consistent with the results of the previous study using spatial panels. The results of this paper are robust.

5.6.3 Re-estimation of different dependent variable

To avoid the potential influence of variable settings on the estimation results, this paper also chooses to measure the carbon emission performance of cities by taking the logarithm of GDP per unit of carbon emissions. Table 9 reports the re-estimation results for the replaced dependent variables. Table 9 shows that the effects of ICP policy on urban

TABLE 8 Re-estimation using PSM-DID.

	Neighbor matching (n = 1)	Kernel matching
ICP	0.016**	0.010***
	(0.008)	(0.002)
lnrgdp	−0.053***	−0.014***
	(0.008)	(0.002)
is	−0.070*	−0.077***
	(0.038)	(0.010)
gov	−0.310***	−0.085***
	(0.073)	(0.010)
fin	−0.006	0.010***
	(0.004)	(0.002)
C	1.183***	0.637***
	(0.080)	(0.022)
City FE	Y	Y
Year FE	Y	Y
Obs	469	2302
F-static	23.595	28.098
Adj-R^2	0.371	0.314

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses.

TABLE 9 Re-estimation of different dependent variable.

Variables	FE	SLM	SEM	SDM
ICP	0.049***	0.037***	0.038***	0.034***
	(0.010)	(0.009)	(0.009)	(0.009)
wICP				1.365***
				(0.397)
Control	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	2856	2856	2856	2856
Log-L	1161.54	2932.872	2948.328	3038.752
R^2	0.884	0.064	0.056	0.079

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses.

carbon emission performance under the fixed effects model, SLM model, SEM model and SDM model are 4.9%, 3.7%, 3.8%, and 3.4%, respectively. And all the coefficients passed the 1% significance test. This implies the regression results of replacing individual explanatory variables remain consistent with those of the previous paper. The conclusions of this paper are relatively re-liable.

TABLE 10 Re-estimation excluding contemporaneous policy disturbances.

Variables	(1)	(2)
ICP	0.009***	0.009***
	(0.001)	(0.002)
LCCP	0.001	
	(0.001)	
CETP		0.011***
		(0.002)
Control	Y	Y
City FE	Y	Y
Year FE	Y	Y
Obs	2856	2856
F	92.88	96.43
R^2	0.391	0.403

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses.

5.6.4 Re-estimation excluding contemporaneous policy disturbances

To exclude the interference of other contemporaneous policies on the analysis results of this paper, this paper further controls for low carbon city pilot (LCCP) and carbon emission trading pilot (CETP) policy shocks in the model (Chen et al., 2021; Cui et al., 2021). After adding the above two policy shocks, the results of the impact of ICP on urban carbon emission performance are shown in Table 10. According to the results in Table 10, the coefficients of ICP and LCCP are 0.009 ($p < 0.01$) and 0.001 ($p > 0.1$) in column (1). The coefficients of ICP and CETP are 0.009 ($p < 0.01$) and 0.011 ($p < 0.01$) in column (2). The above results show that controlling for LCCP and CETP separately, ICP still has a significant positive effect on carbon emission performance. This shows that the conclusion that government innovation support enhances carbon emission performance is robust.

5.6.5 Re-estimation based on an expanded SDID approach

Chagas et al. (2016) proposed a spatial DID method that can decompose the treatment effects of the spatial weight matrix. We used this method for re-estimation to ensure the reliability of the analytical results in this paper. The results are shown in the following Table 11.

According to the results in Table 11, the coefficients of ICP and wICP in restricted model are 0.016 ($p < 0.01$) and 0.067 ($p < 0.01$), which both passes the 1% significance test. In addition, the coefficients of $W_{T,T}$ICP and $W_{NT,T}$ICP in restricted model are 0.028 ($p < 0.01$)

TABLE 11 Re-estimation based on an expanded SDID approach.

Variables	Restricted model	Unrestricted model
ICP	0.016***	0.027***
	(0.002)	(0.003)
wICP	0.067***	
	(0.005)	
$W_{T,T}$ICP		0.028***
		(0.009)
$W_{NT,T}$ICP		0.081***
		(0.005)
Control	Y	Y
City FE	Y	Y
Year FE	Y	Y
Obs	2856	2856
Log-L	64.25	60.65
R^2	0.182	0.165

Note: (1) ***, **, and * denote significant at the 1% level, 5% level and 10% level. (2) City FE, and Year FE, denote the city fixed effects and year fixed effects. (3) City-level cluster robust standard errors are reported in parentheses. (4) According to the study of Chagas et al. (2016), the matrix w can be decomposed as $w = w_{T,T} + w_{T,NT} + w_{NT,T} + w_{NT,NT}$., The restricted model reports the results based on matrix w. Since $w_{T,NT}$, and are $w_{NT,NT}$, 0-vectors matrix, the unrestricted model reports the results based on matrix $w_{T,T}$ and are $w_{NT,T}$.

and 0.081 ($p < 0.01$), which also passed the 1% significance test. This means that the implementation of ICP policy not only significantly improves the local carbon emission performance, but also enhance the carbon emission performance of the surrounding areas. Consistent conclusions are obtained based on the extended SDID model estimation proposed by Chagas et al. (2016), indicating the robustness of the analytical results in this paper.

6 Conclusion and recommendations

6.1 Conclusion

This paper uses a spatial DID model to assess the effect of government innovation support on urban carbon emission performance based on a quasi-natural experiment of ICP from China. The main findings of this paper can be summarized in the following three points.

First, this paper measures urban carbon emission performance through the extended SFA model proposed by (Kumbhakar et al., 2014). The measurement results indicate that the average urban carbon emission in China from 2008 to 2019 is 49.7%, and there is still much room for improvement. In addition, our findings indicate that there is a significant spatial correlation in urban carbon emission performance, and that the carbon emission performance in northern and coastal regions is much higher than that in central and western regions.

Second, the estimation results of the spatial DID indicate that the implementation of ICP leads to a 1.3% improvement in the urban carbon emission performance. Meanwhile, the implementation of ICP also leads to a 3.3% improvement in the urban carbon emission performance of the surrounding areas. The total effects of carbon emission performance improvement from ICP implementation are 4.8%. The results shows that government innovation support not only significantly improves local carbon emission performance, but also has a positive spatial spillover effect.

Third, the results of mechanism analysis show that government innovation support enhances urban carbon performance mainly through three mechanisms, namely total factor productivity improvement, green innovation, and industrial upgrading. This paper also conducts a heterogeneity analysis for cities of different regions, sizes, and resource dependencies. The results show that there is no significant difference in the contribution of ICP to carbon performance between eastern and western cities, while the effect of ICP in central cities is relatively low. Meanwhile, the increase of ICP on carbon performance in large cities reaches almost twice that of small cities. In addition, we also observe that ICP in resource-based cities have a significant increase on carbon performance, while ICP in non-resource-based cities have no significant effect on carbon performance.

Finally, a series of robustness tests were conducted to ensure the reliability of the analysis results. The parallel trend test showed that there was no significant difference between the carbon emission performance of the treatment group and the control group before the implementation of ICP, while the carbon emission performance of the treatment group was significantly higher than that of the control group after the implementation of ICP. Therefore, the assessment results of spatial DID are relatively reliable. Meanwhile, the placebo test, re-estimation based on PSM-DID and re-estimation by replacing the dependent variable all yielded more consistent conclusions. This paper further controls for two policies, low-carbon pilot cities and carbon emissions trading pilot, respectively. The results show that after controlling for the above two policies ICP still has a significant positive impact on urban carbon emission performance.

This paper highlights the important role of government innovation support in improving urban carbon performance. Future research can further explore whether the effect of government innovation support differs across firms with different characteristics through micro data of firms. In addition, there is necessary to provide more assessments of the emission reduction effects of different types of government innovation support.

6.2 Recommendations

Based on the findings of the study, this paper puts forward the following recommendations.

First, government innovation support should be increased to improve carbon emission performance. China has become the country with the highest total carbon emissions in the world. The key to achieving peak and neutral carbon targets lies in the control of total emissions from high carbon sectors and the control of overall sectoral emissions performance. The findings of this paper suggest that the implementation of ICP not only significantly improves local carbon emission performance, but also has significant spillover effects on neighboring regions. Therefore, the role of innovation support in pollution control should be better utilized. On the one hand, government innovation support should focus on traditional sectors such as oil, steel and construction. Promote the improvement of carbon emission performance of traditional sectors through financial subsidies and tax incentives. On the other hand, government innovation support also needs to foster frontier industries such as carbon capture and storage. These industries can absorb carbon emissions from traditional sectors, thus effectively improving the overall carbon performance of the region.

Then, for economies with differences in regional development, such as China, differentiated innovation support policies should be developed for different regions. China's economic development is characterized by a more developed eastern coastal region and a more backward central and western region. As a result, the eastern region has been the first to complete industrial upgrading and transformation and has higher carbon performance. While the central and western regions have taken over part of the industrial transfer from the eastern regions, and their carbon emission performance is low. If the similar innovation support policy is adopted nationwide, it will inhibit the willingness of the central and western regions to improve their carbon emission performance through green innovation. Therefore, it is necessary for the government to give stronger incentives to the central and western regions to gather innovation factors to improve their carbon emission performance. The findings of this paper show that ICP has no significant enhancing effect on carbon emission performance in the western region. There are also differences in the effects of ICP with different city sizes and resource dependence. Therefore, the government should consider its own geographic environment, city size and resource dependencies when providing innovation support. For example, for western cities such as Xining and Lanzhou, the implementation of ICP may not be effective in improving carbon emission performance. In contrast, for cities such as Shanghai, Nanjing, or Hangzhou, ICP can significantly improve carbon emission performance. In addition, government can balance such regional differences through the setting of carbon emission trading allowances. For heavy industries in resource-based cities, such as mining and smelting, allow them to obtain higher carbon quotas through green technology innovation. This would further amplify the effect of government innovation support on the carbon performance of such regions.

6.3 Limitations

The study in this paper also has limitations, and further research can be extended in the following ways. First, due to the lack of firm-level carbon emission data, this paper only assesses the impact of government innovation support on carbon emission performance at the city level. Further research can explore the impact of government innovation from a more microscopic perspective by quantifying firm-level carbon emissions. Second, this paper focuses on the impact of government innovation support in a sample of developing countries represented by China. Further research can compare the differences in the impact of government innovation support on carbon performance across countries at different stages of development.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.nies.go.jp/doi/10.17595/20170411.001-e.html.

Author contributions

CY: Conceptualization; Data curation; Methodology; Writing—original draft. CT: Funding acquisition; Supervision; Validation; Project administration. HL: Writing—review and editing; Software; Resources. YT: Writing—review and editing. YZ: Writing—review and editing. CZ: Writing—review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Appendix A

Table A1 reports the regression results for the stochastic frontier function. The regression coefficients of economic aggregate (∅lngdp), total population (∅ln**pop**) and industrialized output (∅ln**ind**) are 0.045, 0.119 and 0.083, respectively. This means that the increase of these factors significantly raises the urban carbon emissions. In addition, the coefficient of government expenditure (∅ln**gov**) on urban carbon emissions is -0.057, which indicates that the increase of government expenditure can reduce urban carbon emissions. Based on the regression results, this paper extracts the residuals and transforms them through the extended SFA model to finally obtain the urban carbon emission performance.

TABLE A1 Results of energy demand stochastic frontier model.

Variable	Coeff	T-value
Basic Regression		
∅ln*gdp*	0.045***	2.250
∅ln*pop*	0.119***	12.910
∅ln*gov*	−0.057***	−2.580
∅ln*ind*	0.083***	6.480
constant	13.432***	99.810
Inefficiency and error term		
$\mathbf{C}_u$	−5.108***	−85.090
$\mathbf{C}_v$	−6.306***	−109.420
Log likelihood	3872.048	

Note: $\mathbf{C}_u$ and $\mathbf{C}_v$ are the unconstrained parameters, where $exp(C_\mu) = \sigma_\mu^2, exp(C_v) = \sigma_v^2$