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Low-carbon city pilot policy, fiscal pressure, and carbon productivity: Evidence from china

Yun Yang[1]* and Chunli Peng[2]*

[1]School of Economics, Tianjin University of Commerce, Tianjin, China, [2]School of Management, National Defense University, Beijing, China

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EDITED BY
Ayman Elshkaki,
Key Laboratory of Resource Utilization and Environmental Restoration, Institute of Geographic Sciences and Natural Resources Research (CAS), China

REVIEWED BY
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University of Salerno, Italy
Elchin Suleymanov,
Baku Enginering University, Azerbaijan

*CORRESPONDENCE
Chunli Peng,
pcl-1990@163.com
Yun Yang,
yangyunpaper@126.com

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The implementation of the low-carbon city pilot policy is an important measure to reduce carbon emissions and promote low-carbon economic development in China. However, the resulting fiscal pressure may be counterproductive. The aim of this paper is to investigate the impacts of the low-carbon city pilot policy and fiscal pressure on carbon productivity. Based on the data of 282 cities in China over the period 2005 to 2017, this paper uses the staggered difference-in-differences (DID) model to identify the causal relationship among the low-carbon city pilot policy, fiscal pressure, and carbon productivity. The results show that this pilot policy can significantly improve carbon productivity and that the improvement effect presents a dynamic and persistent feature. However, the fiscal pressure resulting from this pilot policy can reduce carbon productivity, and the degree of reduction depends on the status of fiscal pressure. Increased fiscal pressure has a negative impact on carbon productivity, which is heterogeneous with different levels of economic development. Moreover, the mediation effect analysis finds that this pilot policy affects carbon productivity by adjusting the energy production and consumption structure, enhancing green technology innovation capabilities, and increasing the number of low-carbon-type enterprises entering the market. This paper provides new ideas for improving carbon productivity without increasing fiscal pressure. It also recommends that fiscal pressure cannot be ignored in the implementation of the low-carbon city pilot policy.

KEYWORDS

low-carbon city pilot, fiscal pressure, carbon productivity, staggered DID, mediation effect

1 Introduction

In recent years, extreme weather conditions related to global warming have frequently occurred, highlighting the challenges to high-quality economic development. Therefore, effective strategies to improve carbon productivity and reduce carbon emissions have elicited increasing attention. The goal of the low-carbon policy is to promote carbon productivity and enhance the development of a low-carbon economy. However, Tao and Li (2021) found that China's low-carbon city pilot policy had a negatively impact on economic growth and fiscal revenue, thus aggravating the fiscal pressure on local governments. To alleviate fiscal pressure, local governments may relax environmental regulations to induce more pollution-intensive enterprises, thereby increasing the degree of industrial pollution (Wang and Zhang, 2017; Bai et al., 2019; Huang and Zhou, 2020). This raises the question of whether the fiscal pressure brought about by the low-carbon city pilot policy reduces carbon productivity. Under the condition of controlling for the impact of fiscal pressure brought about by this pilot policy, can the low-carbon city pilot policy still improve carbon productivity?Clarifying the above problems will not only unveil the internal relationship between the low-carbon city pilot policy and carbon productivity but also provide policy implications for further improving the latter.

The low-carbon city pilot policy is an important way to significantly reduce carbon emissions (Huo et al., 2022; Liu et al., 2022; Ren et al., 2022), and it has positive spillover effects (Liu, 2022). Most of the literatures have focused on the ways in which the low-carbon policy affects carbon emissions. First, the low-carbon city pilot policy can promote urban green total factor productivity (Cheng et al., 2019; Qiu et al., 2021). Second, the low-carbon city pilot policy can promote the green technology innovations of enterprises, and its green innovation effect is reflected in patent applications for energy conservation and alternative energy production (Chen et al., 2022; Pan et al., 2022). An increase in the use of clean energy has been shown to reduce coal-fired power generation and carbon emissions (Fell and Kaffine, 2018; Huo et al., 2022; Zhou et al., 2022). Third, carbon tax increases the cost of carbon consumption and significantly reduces carbon emissions (Nordhaus, 2006; Andersson, 2019). Moreover, carbon tax and research and development (R&D) subsidies can encourage companies to innovate clean technologies, thereby reducing pollutant emissions and promoting output growth (Acemoglu et al., 2016; Aghion et al., 2016). Fourth, the carbon emission trading system is also conducive to low-carbon technology innovation and carbon emission reduction (Calel and Dechezleprêtre, 2016; Li et al., 2022).

However, in the implementation of the low-carbon city pilot policy, local governments may directly shutdown high-energy-consuming enterprises, which can lead to reductions in the tax base and tax revenue. In turn, this can increase the fiscal pressure on local governments. On the one hand, to alleviate fiscal pressure, local governments can increase the number of industrial enterprises and relax environmental regulations to promote the proliferation of more pollution-intensive enterprises, thus increasing the degree of industrial pollution (Wang and Zhang, 2017; Huang and Zhou, 2020). On the other hand, local governments can increase fiscal revenues through non-tax methods, which will increase the actual non-tax burden of enterprises (Peng et al., 2020; Zhao and Fan, 2020). In both cases, regardless of which way is chosen to alleviate fiscal pressure, it may have a negative impact on enhancing carbon productivity.

In general, the above literature contribute to the impacts and mechanisms of the low-carbon city pilot policy on carbon emissions, as well as the rise in fiscal pressure, leading to the relaxation of low-carbon environmental regulations by local governments. However, there are still some shortcomings. First, the relationship among the low-carbon city pilot policy, fiscal pressure, and carbon productivity has not been established. In fact, the low-carbon city pilot policy may lead to increased fiscal pressure that will prompt the local government loosening its environmental regulations, which may increase carbon emissions and reduce carbon productivity. Second, the existing literature does not consider the impact of fiscal pressure brought about by the low-carbon city pilot policy. This not only not only has the problem of biased estimation results caused by the omission of variables, but also fails to fully understand the role of the low-carbon city pilot policy. Only perceiving the positive aspects of the pilot policy will not be conducive to providing effective strategies for solving fiscal pressure problems. It will have a perverse effect on reducing carbon emissions and improving carbon productivity.

The aims of this paper are twofold. First, it investigates whether the low-carbon city pilot policy and fiscal pressure brought about by the low-carbon city pilot policy affect carbon productivity. This will not only establish a full understanding of the impact of the low-carbon city pilot policy but also resloves the problem of estimation bias caused by the omission of variables to avoid only seeing the positive impacts of the pilot policy. Second, this study deconstructs the mediation mechanism of the low-carbon city pilot policy on carbon productivity and discusses the heterogeneity of the impact of the pilot policy between different regions and economic development levels, which will enhance the understanding of the impacts of the low-carbon city pilot policy.

Based on the background of the low-carbon city pilot policy and the proposed hypothesis, this paper obtains data from 282 cities in China over the period 2005–2017 and then uses the staggered difference-in-differences (DID) model to identify the relationships among the low-carbon city pilot policy, fiscal pressure, and carbon productivity. The results are as follows:1) the low-carbon city pilot policy can significantly improve carbon productivity, and the impact is persistent; 2) the fiscal pressure resulting from the low-carbon city pilot policy will reduce carbon productivity, and the degree of decline depends on the status of fiscal pressure; (3) increased fiscal pressure will reduce carbon productivity, and the degree of reduction is heterogeneous with different levels of economic development; and 4) the mediation effect analysis shows that the low-carbon city pilot policy affects carbon productivity by adjusting the structure of energy production and consumption, enhancing the ability for green technology innovation and increasing the number of low-carbon-type enterprises entering the market. In this sense, this paper delivers new ideas and supplements the existing literature on the impacts of such a pilot policy.

Compared to the existing literature, the marginal contributions of this paper are as follows. *First*, most existing studies focus on whether the low-carbon city pilot policy can reduce carbon emission and the negative relationship between this pilot policy and economic growth. This paper incorporates fiscal pressure into the analysis of the impacts of such a pilot policy on carbon productivity, which not only provides an explanation for the negative relationship between the pilot policy and economic growth (Tao and Li, 2021) but also solves the estimation bias problem caused by the omission of variables. In addition, without controlling for the impact of fiscal pressure brought about by this pilot policy, the size of the impact of the low-carbon city pilot policy is similar to that reported by Huo et al. (2022) and Liu (2022). However, after controlling for the impact of the fiscal pressure brought about by the pilot policy, the impact of the low-carbon city pilot policy is greater, which is significantly different from that of Huo et al. (2022) and Liu (2022). Meanwhile, the impact of the fiscal pressure brought about by this pilot policy is the opposite; the ultimate impact of the low-carbon city pilot policy also depends on the status of fiscal pressure. *Second*, studies on the effects of the low-carbon city pilot policy usually use technological innovation and energy structure as mediation variables to analyze the mediation effect (Huo et al., 2022; Liu et al., 2022). Apart from these, this paper adds the registration number of low-carbon-type enterprises and fiscal pressure brought about by this pilot policy as additional mediation variables, thus expanding the literature on the impact path of the low-carbon city pilot policy on carbon productivity. *Third*, in terms of policy implications, this paper evidences that the fiscal pressure brought about by the implementation of the low-carbon city pilot policy will reduce carbon productivity. However, if the implementation of this policy can raise the low-carbon access standards for new enterprises, optimize the low-carbon technology level of existing enterprises, and adjust the energy structure, this policy will not increase the fiscal pressure. On the contrary, it will help improve carbon productivity and resolve fiscal pressure.

The remainder of this paper is organized as follows. Section 2 presents the background of the low-carbon city pilot policy and proposes the theoretical hypotheses. Section 3 describes the empirical model and data. Section 4 delivers the results of the estimation and robustness tests. Section 5 discusses the impacts of heterogeneity and the mediation effects. Finally, Section 6 provides the conclusions and policy implications.

2 Background of the low-carbon city pilot policy and theoretical hypothesis

2.1 Background of the low-carbon city pilot policy

China is the largest manufacturing country globally; hence, it is considered "the world's factory." However, the rapid development of the manufacturing industry has been inevitably accompanied by massive energy consumption, and many industries that use traditional fossil fuel energy have emitted large amounts of carbon dioxide (CO_2). To reduce carbon emissions, the Chinese government has actively adopted measures and committed to the realization of global carbon emission reduction. At the 15th Session of the Conference of the Parties to the United Nations Framework Convention on Climate Change held in Copenhagen, Denmark in 2009, the Chinese government pledged that by 2020, the country's carbon dioxide emissions per unit of gross domestic product (GDP) would be reduced by 40–45% compared to 2005 figures, Such an effort represents a huge contribution to emission reduction efforts. In particular, Chairman Xi Jinping proposed that China would strive to achieve a carbon peak by 2030 and carbon neutrality by 2060 during the general debate held at the 75th United Nations General Assembly in September 2020, thus representing China's action plan for achieving its carbon emission reduction targets.

After the Chinese State Council proposed the goal of controlling greenhouse gas (GHG) emissions in November 2009, the National Development and Reform Commission (NDRC) announced its plan to reduce carbon emissions by issuing the "Notice on the Implementation of thePilot Policy for Low-Carbon Provinces, Regions, and Low-carbon Cities" (Development and Reform Climate [2010] No. 1587) in July 2010. This policy requires low-carbon pilot cities to formulate their own action goals, key tasks, and response measures to control GHG emissions, advocate low-carbon production and consumption, and formulate supporting policies conducive to achieving low-carbon and green development. This policy also aimed to establish an industrial system characterized by low carbon emissions to reduce the intensity of carbon emissions and promote carbon productivity. The first batch of selected low-carbon cities consisted of eight cities, including Tianjin and Chongqing, which were further expanded in 2012. In april 2012, the Climate Department of the NDRC issued the "Notice on Organizing the Recommendation and Declaring the Second Batch of low-carbon Pilot Provinces and Cities" (Development and Reform Climate [2012] No. 3760). This batch comprised 28 cities, including Beijing and Shanghai. After that, the NDRC issued the "Notice on Carrying Out the Third Batch of National Low-carbon City Pilot Policy Work" (Development and Reform Climate [2017] No. 66) in January

2017, this time including 45 cities (e.g., Wuhai City) in the third batch of selected areas.

Thus far, a total of 81 cities have been selected as low-carbon city pilot policy areas. In terms of geographical distribution, these areas include cities in the Eastern, Central, and Western regions, such as cities in the south and north of the Qinling Mountains and the Huai River. From the perspective of location, the selected areas include provincial capital cities, municipalities directly under the Central Government, and general prefecture-level cities. With respect to economic development level, the list comprises cities in both economically developed and underdeveloped areas in the Central and Western regions. Generally, the selected areas for the low-carbon city pilot thoroughly represent a broad spectrum of Chinese cities with varying characteristics.

2.2 Theoretical hypothesis

The low-carbon city pilot policy affects carbon productivity in several ways. *First*, traditional fossil energy sources, such as raw coal and coke, have high CO_2 emissions. Low-carbon cities reduce the proportion of traditional fossil energy use, increase the use of clean energy (e.g., hydropower, wind power, and solar energy), and reduce carbon emission by adjusting their respective energy structures (Liu et al., 2022). *Second*, the low-carbon city pilot policy requires the acceleration of low-carbon technology demonstration, promotion, and application. In terms of policy, carbon tax and R&D subsidies can encourage companies to invest in cleaner production and technological innovations, reduce carbon emissions, increase carbon productivity, and promote low-carbon economy growth (Acemoglu et al., 2016; Aghion et al., 2016). In other words, such a policy can promote the progress of low-carbon technology and increase the number of green patent applications, thus improving carbon productivity. *Third*, different from Acemoglu et al.(2016), Huo et al.(2022) and Liu et al. (2022) argued that to reduce carbon emissions by adjusting the energy structure and promoting low-carbon technology innovation, if the local government improves the low-carbon technology access standards of enterprises and expands the number of low-carbon-type enterprises entering the market, it can reduce the overall carbon emission intensity and improve carbon productivity. Accordingly, the first hypothesis is proposed:

Hypothesis 1. The low-carbon city pilot policy can improve carbon productivity, and the mediation effect of this pilot policy operates by adjusting the energy structure, increasing the number of low-carbon-type enterprises entering the market, and enhancing green technology innovation.

To alleviate fiscal pressure, local governments may adopt two measures. *First*, they could increase the number of high-energy-consuming industrial enterprises and relax environmental regulations, thus increasing the number of pollution-intensive enterprises (Wang and Zhang, 2017; Huang and Zhou, 2020). Although this will increase fiscal revenue and alleviate fiscal pressure, it will also increase carbon emissions and lead to a decline in carbon productivity. *Second*, they could alleviate fiscal pressure by increasing the actual non-tax burden of enterprises (Peng et al., 2020; Zhao and Fan, 2020). Such an increase leads to a concomitant increase in policy uncertainty and operating costs for enterprises. Excessive non-tax burdens lead to insufficient funds for low-carbon technological innovation. At the same time, enterprises may cease operations due to excessive non-tax burdens, which is seriously detrimental to carbon emission reduction and carbon productivity improvement. In addition, strengthening tax collection and management and increasing the non-tax burden will have a distorting effect on investment in capital factors and reduce the efficiency of capital allocation (Huang and Deng, 2020), which are also not conducive to improving carbon productivity. Unlike Huang and Zhou (2020), Zhao and Fan (2021), and other studies, we link fiscal pressure to carbon productivity, recognizing the role of fiscal pressure. Accordingly, the second hypothesis is proposed:

Hypothesis 2. An increase in fiscal pressure leads to the decline of carbon productivity.

During the implementation of the low-carbon city pilot policy, some enterprises with high energy and resource consumption may be shut down, thereby reducing government revenues and increasing fiscal pressure. To alleviate the fiscal pressure, local governments either increase the intensity of tax collection and management(Huang and Zhou, 2020) or increase non-tax collection efforts(Peng et al., 2020; Zhao and Fan, 2020), or both, which will increase the actual burden on enterprises. As a result, enterprises do not have enough funds for the research and development and use of low-carbon clean technologies, which will not help reduce carbon emissions and improve carbon productivity. When the tax and non-tax burdens of enterprises have reached high levels, and there is no way to further increase the intensity of tax and non-tax collection, local governments have to relax environmental regulations again and increase the entry of high-energy-consuming enterprises, resulting in increased carbon emissions and lower carbon productivity.

By contrast, during the implementation of the low-carbon city pilot policy, if the local government provides policy support for the low-carbon clean technology transformation of stock enterprises (note: high-polluting enterprises must be closed), such action can stabilize the tax base and improve carbon productivity. In addition, the low-carbon technology access standards for new enterprises should be improved to enable them to meet the requirements of low-carbon development, thereby expanding the tax base and reducing the intensity of carbon emissions. The above measures will not increase fiscal pressure but will alleviate fiscal pressure and improve carbon productivity. Accordingly, the third hypothesis is proposed:

Hypothesis 3. The fiscal pressure brought about by the low-carbon city pilot policy will hinder the improvement of carbon productivity. However, if the local government increases the policy support for the optimization of low-carbon technologies of existing enterprises and raises the low-carbon access standards for new enterprises, such a pilot policy will not lead to increased fiscal pressure. Moreover, carbon productivity will be reduced.

3 Methodology

3.1 Empirical model

This paper examines the impacts of the low-carbon city pilot policy in 2010 and 2012. Referring to the methods of Angrist and Pischke (2008), Callaway and Sant'Anna (2021), and Baker et al. (2022), the staggered DID model is used for estimation. The benchmark model is set as follows:

$$CP_{it} = \beta_0 + \beta_1 Treat_i * Post_{it} + \beta_2 Treat_i * Post_{it} * FP_{it} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \theta_t + \varepsilon_{it}, \quad (1)$$

where i stands for city, t stands for year, CP_{it} denotes carbon productivity, $Treat_i$ stands for whether city i is a low-carbon pilot city, $Post_{it}$ is a time dummy variable of the low-carbon city pilot policy, $Treat_i{*}Post_{it}{*}FP_{it}$ is the interaction term of the dummy variable of the low-carbon city pilot policy and its fiscal pressure, μ_i is the city-specific fixed effect, θ_t is the year-specific fixed effect, ε_{it} is the random disturbance term, and X_{jit} is a set of control variables, including investment growth rate (IGR_{it}), population growth rate (PGR_{it}), trade competitiveness (TC_{it}), human capital level (HC_{it}), and fiscal pressure (FP_{it}). Moreover, to investigate whether there is a time-lag effect in the impact of the low-carbon city pilot policy on carbon productivity, the model is set as follows:

$$CP_{it} = \beta_0 + \beta_1 Treat_i * Post_{it-1} + \beta_2 Treat_i * Post_{it-1} * FP_{it} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

where $Post_{it-1}$ is one period lag of the low-carbon city pilot policy. The other variables are the same as those in Eq. 1.

To test whether the staggered DID model satisfies the assumption of parallel trends and to examine the dynamic effects of the low-carbon city pilot policy over time, this paper draws on the methods of Jacobson et al. (1993), Freyaldenhoven et al. (2019), and Sun and Abraham (2021) and adopts the event analysis method for estimation. The model is set as follows:

$$CP_{it} = \beta_0 + \sum_{k=2005}^{t} \beta_k Treat_i * D_{it}^k + \beta_2 Treat_i * Post_{it} * FP_{it} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \theta_t + \varepsilon_{it}, \quad (3)$$

where i stands for city, t stands for year, $Treat_i$ is a dummy variable representing whether city i is a low-carbon city, and D_{it}^k is the time dummy variable, D_{it}^k is assigned a value of one in k year and 0 for other years. The coefficient of β^k is the interaction term ($Treat_i{*}D_{it}^k$) that measures the difference between the treatment group and the control group during the period of the low-carbon city pilot policy. The other variables are the same as those in Eq. 1.

3.2 Variables

3.2.1 Dependent variable

This paper refers to the method of Shao et al. (2014) and Hu and Liu (2016) to measure carbon productivity as follows:

$$CP_{it} = \frac{GDP_{it}}{(CO_2)_{it}}, \quad (4)$$

where i stands for city, t stands for year, CP_{it} denotes carbon productivity, GDP_{it} is the city's gross domestic product(unit: yuan, ¥), and $(CO_2)_{it}$ is the city's total CO_2 emissions (unit: kilograms).

3.2.2 Independent variables

According to the basic steps of the staggered DID model, two dummy variables related to the low-carbon city pilot policy are constructed. The first one consists of the group dummy variable of the low-carbon city pilot policy ($Treat_i$), namely, the control group and the treatment group, in which the low-carbon city is defined as the treatment group and is assigned a value of 1, while the non-low-carbon city is defined as the control group and is assigned a value of 0. The second consists of the time dummy variable of the low-carbon city pilot policy($Post_{it}$). If the city i is selected as a low-carbon pilot area in year t, the time dummy variable of the low-carbon city pilot policy($Post_{it}$) is assigned a value of one in year t and subsequent years, while the others are assigned a value of 0.

The low-carbon city pilot policy($Treat_i \times Post_{it}$), which is a dummy variable, is measured by the interaction term of the group dummy variable of the low-carbon city pilot policy($Treat_i$) and the time dummy variable of the low-carbon city pilot policy($Post_{it}$).

Fiscal pressure (FP_{it}) is obtained as follows: calculate the difference between the general budget expenditure and tax revenue, and then divide it by the general budget expenditure.

The fiscal pressure brought about by the low-carbon city pilot policy($Treat_i \times Post_{it} \times FP_{it}$) is measured by the interaction

TABLE 1 Variable definitions and descriptive statistics.

Variables	Definitions	Observations	Mean	Standard deviation	Minimum	Maximum
CP	Carbon Productivity	3,666	5.871	2.967	1.990	12.592
Treat*Post	Low-carbon City Pilot Policy	3,666	0.060	0.238	0.000	1.000
Treat*Post*FP	FP brought about by the Treat*Post	3,666	0.029	0.127	0.000	0.892
FP	Fiscal Pressure	3,666	0.641	0.194	0.228	0.892
IGR	Investment Growth Rate	3,666	0.683	0.248	0.304	1.176
PGR	Population Growth Rate	3,666	0.057	0.043	−0.016	0.149
TC	Trade Competitiveness	3,666	0.314	0.441	−0.657	0.944
HC	Human Capital Level	3,666	1.197	0.375	0.735	2.278

term of the low-carbon city pilot policy($Treat_i \times Post_{it}$) and fiscal pressure (FP_{it}).

3.2.3 Control variables

With reference to the research of Liu (2022), Huo et al. (2022), and Ren et al. (2022). The selected control variables are as follows: investment growth rate (IGR_{it}), population growth rate (PGR_{it}), trade competitiveness (TC_{it}), and human capital level (HC_{it}). Investment growth rate (IGR_{it}) is measured by the annual growth rate of fixed asset investments, while population growth rate (PGR_{it}) is measured by the annual natural growth rate of the population. Trade competitiveness (TC_{it}) is obtained as follows: calculate the difference between the trade imports and exports, get the sum of the total imports and exports, and then calculate the ratio of that difference to the total. In addition, human capital level (HC_{it}) is measured as follows: get the sum of the number of students in colleges and universities*16 + the number of ordinary middle schools*9 + the number of ordinary primary schools*6, and then divide by the total population.

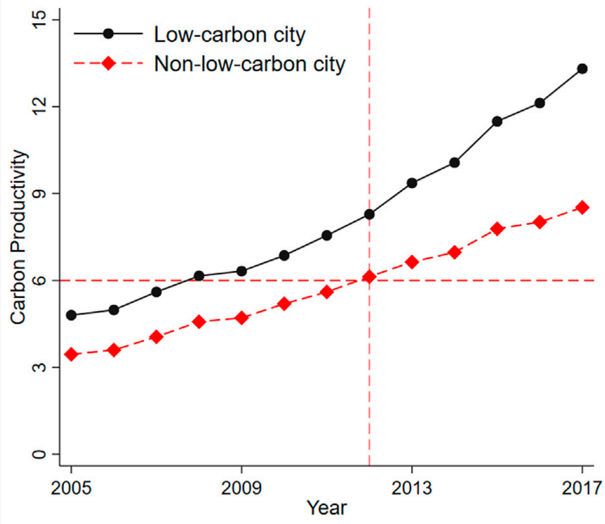

FIGURE 1
Carbon productivities of low-carbon and non-low-carbon cities.

3.3 Data

Fixed asset investment, population growth rate, GDP, general budget expenditure, human capital, and trade import and export data were sourced from the China Statistics for Regional Economy Database and China City Statistics Database of the EPS DATA platform. CO_2 emission data came from the China Carbon Accounting Database (CEADS), while the tax revenue data were sourced from the China Statistics for Regional Economy Database of the EPS DATA platform and China Economic Database of the CEIC data platform. For these different sources of data, we matched by city and year to obtain the required data.

After obtaining the data, we further processed them according to the following principles: 1) For any city with missing GDP data for 5 years or more, we deleted the sample data of the city. 2) Next, we deleted city samples whose numbers of corresponding years in the city code were less than 14 (i.e., the data whose statistical year was less than 14 years). 3) We used the three-period moving average method to make up for missing data. 4) After filling in the missing data, if the sample number of all indicators in any city was less than 13, the sample data of that city was deleted. 5) Except for the dummy variables of the low-carbon city pilot policy, other variables were winsorized at the level of 5%. 6) Given that Jiyuan City is a county-level city and the Daxing'an Mountains region has missing data, the samples from these two regions were deleted, leaving a total of 34 low-carbon pilot cities. In this way, we obtained the sample data for 282 cities in China over the period 2005–2017. The variables and their descriptive statistical characteristics are shown in Table 1.

Subsequently, we divided the whole sample of carbon productivity into two sample groups: the low-carbon city group and the non-low-carbon city group. Then, we

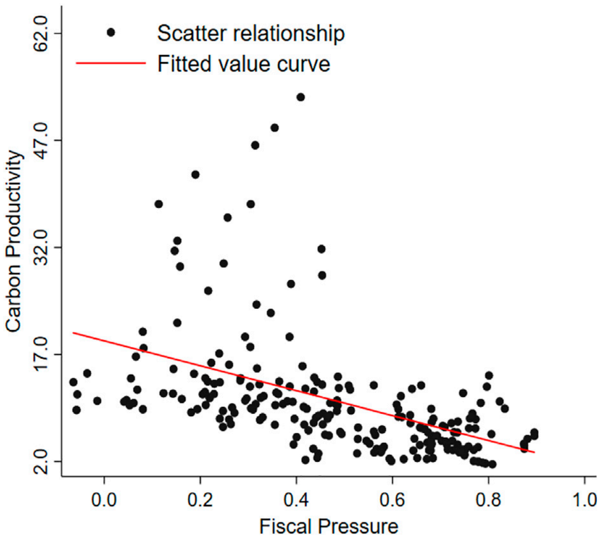

FIGURE 2
Scattered relationship between fiscal pressure and carbon productivity.

calculated the average value of the carbon productivity in each group every year. Finally, we plotted them. The trend chart of carbon productivity is displayed in Figure 1. In addition, we plotted a scatter diagram to present the relationship between fiscal pressure and carbon productivity, as shown in Figure 2.

Figure 1 indicates that before 2012, carbon productivity met the parallel assumption in both low-carbon and non-low-carbon cities. However, since 2012, the changes in the carbon productivity of the low-carbon cities have become significantly higher than those of non-low-carbon cities. These results initially reflect that the low-carbon city pilot policy strongly promotes carbon productivity. The results in Figure 2 demonstrate that a negative relationship between fiscal pressure and carbon productivity, that is, the greater the fiscal pressure, the lower the carbon productivity.

4 Empirical result analysis and robustness test

4.1 Parallel trend and heterogeneous treatment effect test

When using the staggered DID model to estimate the impacts of the low-carbon city pilot policy and fiscal pressure on carbon productivity, one necessary condition is that the control and treatment groups must meet the parallel trend assumption. If there is a difference in the time trend of carbon productivity between low-carbon and non-low-carbon cities before the launch of the low-carbon city pilot policy, it can be inferred that the difference is not caused by this pilot policy. In addition, although the staggered DID model estimates the average treatment effect of the low-carbon city pilot policy, the impacts of this policy in different years are not shown. Therefore, to test whether the staggered DID model is a suitable method, we used the event analysis method to test the parallel trends and dynamic effects of the low-carbon city pilot policy. This specific method involves the following procedure: first, generate the interaction term of a low-carbon city pilot policy group dummy variable and the year dummy variable, then estimate the coefficient of the interaction term to obtain the dynamic effect of the low-carbon city pilot policy. The results are shown in Figure 3.

Figure 3 plots the estimated results of the coefficients of the interaction term between the low-carbon city pilot policy group dummy variable and the year dummy variable under a 95% confidence interval (CI). Evidently, the coefficients of the interaction term are all around 0 in the years before the start of the low-carbon city pilot policy, suggesting that before the pilot policy was started, there was no significant difference between the treatment and control groups. Hence, the conditions for the assumption of parallel trends are established. After the launch of the pilot policy, the coefficient is positive and increases significantly, showing a stable trend. At this point, the estimated coefficients of the control and treatment groups are significantly different, which indicates that the implementation of the low-carbon city pilot policy significantly improves the carbon productivity of low-carbon cities.

The two-way fixed effects (FE) regression of the staggered DID model is a popular method to evaluate treatment effects. However, if the error term is not mean zero conditional on group and period, this can lead to the problem of heterogenous treatment effects (Gardner, 2021). de Chaisemartin and D'Haultfoeuille (2020) demonstrated that in several DID models, the two-way FE estimator is a weighted sum of the treatment effect in each group and period. If the average treatment effects (ATEs) are heterogeneous across groups or periods, it will result in the question of negative weights. The two-way FE estimators of the staggered DID model do not identify the typical effect of the treatment. To test whether heterogeneous treatment effects exist, de Chaisemartin and D'Haultfoeuille (2020) recommended computing the weights attached to the two-way FE regression of the staggered DID model and calculating the ratio of the coefficient of variable and the standard deviation of the weights. If many weights are negative and if the ratio is small, we should use the new method to estimate the staggered DID model. Thus, referring to the method of de Chaisemartin and D'Haultfoeuille (2020), we computed the weight of the treated group and periods. The results are shown in Table 2.

In Table 2, the results indicate that under the condition of the estimation of the two-way FE of the staggered DID model, there are 220 positive weights and 0 negative weights. Moreover, the standard deviation of the treatment effect across the low-carbon cities and years is 0.879, which is

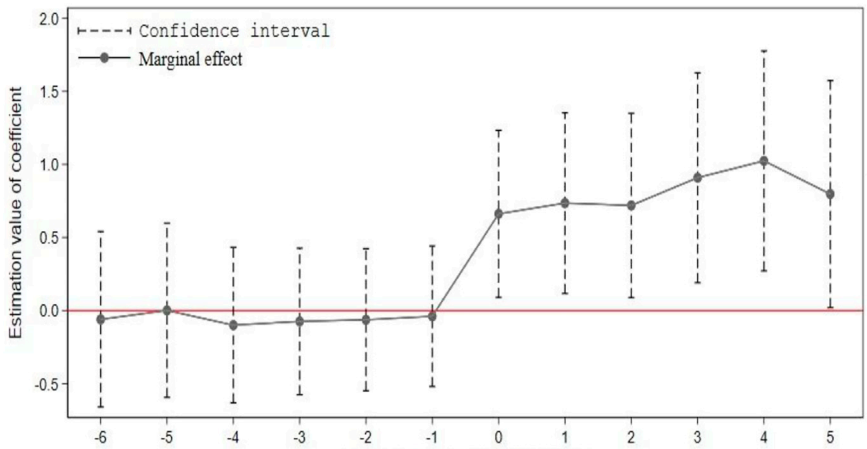

FIGURE 3
Dynamic effect of low-carbon city pilot policy.

TABLE 2 Estimation of weights.

	Positive Weights	Negative Weights
Number of weights	220	0
Sum of weights	1	-
Standard deviation of the treatment effect	0.879	-

greater than 0. Thus, we can use the two-way FE regression of the staggered DID model to estimate the treatment effect of the low-carbon city pilot policy.

4.2 Baseline DID model estimation

As a major policy measure to promote carbon productivity, the low-carbon city pilot policy advocates low-carbon production and consumption, which can undoubtedly reduce CO_2 emissions and improve the quality of economic development. Therefore, the implementation of this pilot policy provides a quasi-natural experiment for this study. We used a staggered DID model to estimate the impacts of the policy and fiscal pressure on carbon productivity. The results are provided in Table 3.

In Table 3, Columns (1)–3) show the results of the staggered DID estimation under the conditions of controlling for only the year FE, only the city FE, and both types of FE, respectively. Columns (4)–6) present the effects of one period lag of the low-carbon city pilot policy. The results indicate that the coefficients pass the significance test after controlling for both the city and year FE, regardless of whether it is the current period or one lag period.

Specifically, Column 3) shows that when the city and year FE are controlled simultaneously, the coefficient of $Treat*Post$ is significant for 1.318 at the 1% level, which indicates that the low-carbon city pilot policy can significantly promote carbon productivity. The coefficient of $Treat*Post*FP$ is significant for–2.722, which means that the fiscal pressure brought about by the low-carbon city pilot policy will reduce carbon productivity, and the degree of reduction depends on the status of fiscal pressure. The coefficient of fiscal pressure (FP) is significant for –0.931, which suggests that an increase in fiscal pressure will decrease carbon productivity. Peng et al. (2020) and Zhao and Fan (2021) explained that the government might relax environmental regulations to relieve fiscal pressure, which can result in an increase in high-energy-consuming enterprises that reduces carbon productivity. As seen in Column (6), after controlling for the city FE and the year FE, the coefficients of $Treat*Post_{-1}$, $Treat*Post*FP$ and fiscal pressure (FP) are 0.609, –1.309, and –1.157, respectively, all of which are significant at the 1% level. These results demonstrate that the effects of the low-carbon city pilot policy are persistent. Hence, Hypotheses one to three are verified. In other words, we cannot ignore the negative effects of fiscal pressure on carbon productivity when implementing the low-carbon city pilot policy.

TABLE 3 Benchmark estimation results.

Variables	Carbon Productivity (*CP*)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ∗ *Post*	4.451***	3.155***	1.318***			
	(0.331)	(0.377)	(0.242)			
Treat ∗ $Post_{-1}$				2.244***	1.740***	0.609***
				(0.217)	(0.317)	(0.138)
Treat ∗ *Post* ∗ *FP*	−5.352***	−5.793***	−2.722***	−0.956**	−2.969***	−1.309***
	(0.635)	(0.789)	(0.463)	(0.409)	(0.583)	(0.259)
FP	2.376***	−3.869***	−0.931***	2.138***	−4.106***	−1.157***
	(0.470)	(0.231)	(0.340)	(0.492)	(0.249)	(0.350)
IGR	5.016***	−1.320***	0.386**	4.800***	−1.351***	0.417**
	(0.151)	(0.226)	(0.156)	(0.160)	(0.233)	(0.163)
PGR	3.304***	2.746***	3.443***	3.143***	2.796***	3.847***
	(0.873)	(0.967)	(0.613)	(0.867)	(0.998)	(0.610)
HC	−1.512***	0.846***	1.308***	−1.704***	0.920***	1.267***
	(0.219)	(0.133)	(0.164)	(0.228)	(0.140)	(0.175)
TC	0.105	0.273***	0.291***	0.071	0.304***	0.260***
	(0.085)	(0.093)	(0.066)	(0.089)	(0.099)	(0.069)
Constant	2.401***	7.977***	4.350***	3.042***	8.282***	4.699***
	(0.464)	(0.275)	(0.330)	(0.478)	(0.288)	(0.342)
Year fixed effect	NO	YES	YES	NO	YES	YES
City fixed effect	YES	NO	YES	YES	NO	YES
Observations	3,666	3,666	3,666	3,384	3,384	3,384
Number of cities	282	282	282	282	282	282
R_squared	0.782	0.412	0.904	0.792	0.383	0.908
Fvalue	343.823	160.546	22.838	256.637	133.955	20.006

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

4.3 Robustness test

To verify whether the relationship among the low-carbon city pilot policy, fiscal pressure, and carbon productivity is robust, we test the robustness of the conclusions by taking a series of measures, including index substitution, the Tobit-DID model of data merging processing, and counterfactual testing methods.

4.3.1 Robustness analysis after carbon productivity Is substituted by $\ln CO_2$

A similar indicator to carbon productivity is carbon emissions. We use the logarithm of the total carbon emissions ($\ln CO_2$) as an alternative indicator of carbon productivity and then estimate the model. In doing so, it is also helpful to compare the connections and differences between this paper and the study by Huo et al. (2022) and Liu et al. (2022) and explore whether the fiscal pressure brought about by the low-carbon city pilot policy is a factor that cannot be ignored. The estimated results are provided in Table 4.

Columns (3)–4) in Table 4 indicate that, without controlling for the effects of the interaction term of the low-carbon city pilot policy and fiscal pressure(*Treat*∗*Post*∗*FP*), the coefficient of *Treat*∗*Post* is significant for -0.040. This estimated coefficient size is similar to the results obtained by Huo et al. (2022) and Liu et al. (2022). When controlling for the influence of the interaction term of the low-carbon city pilot policy and fiscal pressure(*Treat*∗*Post*∗*FP*), the coefficient of *Treat*∗*Post* is -0.165, while the coefficient of *Treat*∗*Post*∗*FP* is 0.252. Both are significant at the 1% level. These results reveal that the low-carbon city pilot policy can reduce carbon emissions and improve carbon productivity; however, the fiscal pressure brought about by this pilot policy will increase carbon emissions and reduce carbon productivity.

At the same time, compared to those that do not control for the influence of the interaction term of the low-carbon city pilot policy and fiscal pressure(*Treat*∗*Post*∗*FP*), under the condition of controlling the influence of *Treat*∗*Post*∗*FP*, the results indicate that not only is the coefficient of *Treat*∗*Post* larger, but the coefficient of *Treat*∗*Post*∗*FP* is also significantly positive,

TABLE 4 Estimations after using $\ln CO_2$.

Variables	Carbon Emission ($\ln CO_2$)			
	Without $Treat*Post*FP$ (Huo et al., 2022)	With $Treat*Post*FP$ (The way of this paper)	Without $Treat*Post*FP$ (Huo et al., 2022)	With $Treat*Post*FP$ (The way of this paper)
	(1)	(2)	(3)	(4)
$Treat*Post$	−0.039***	−0.175***	−0.040***	−0.165***
	(0.009)	(0.024)	(0.009)	(0.023)
$Treat*Post*FP$		0.276***		0.252***
		(0.040)		(0.039)
FP			-0.050*	-0.064**
			(0.027)	(0.027)
Constant	23.704***	23.704***	23.622***	23.627***
	(0.001)	(0.001)	(0.030)	(0.030)
Control variables	NO	NO	YES	YES
Year fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Observations	3,666	3,666	3,666	3,666
Number of cities	282	282	282	282
R_squared	0.989	0.989	0.989	0.990
Fvalue	19.444	27.244	15.018	16.971

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

which implies that the ultimate impact of the low-carbon city pilot policy also depends on the status of fiscal pressure, that is, the marginal impact is $\beta_1 + \beta_2{}^*FP$.This is significantly different from the study of Huo et al. (2022) and Liu et al. (2022), where they obtained the impact as β_1.Therefore, ignoring the impact of the fiscal pressure brought about by the low-carbon city pilot policy will lead to not only a biased evaluation of the effect of the pilot policy but also a failure to recognize the negative side of this pilot policy, which will be detrimental to reducing carbon emissions and improving carbon productivity.

4.3.2 Robustness analysis after substituted by secondary industry and industrial carbon productivity

The low-carbon city pilot policy advocates low-carbon production and consumption. Secondary industry, especially the industrial sector, is the main source of CO_2 emissions. This means that if the secondary industry and the industrial sector carbon productivity in a low-carbon city are significantly improved, then the pilot policy will be able to promote carbon productivity; otherwise, the pilot policy is invalid. We used the ratio of secondary industry output value (unit: yuan) and industrial output value (unit: yuan) to CO_2 emissions(unit: kilogram) to measure the secondary industry and industrial sector carbon productivity. Subsequently, the GDP carbon productivity in the staggered DID model in Eq. 2 was substituted by the secondary industry carbon productivity and industrial sector carbon productivity. After controlling for the city FE and the year FE, we estimated the impacts of the low-carbon city pilot policy and fiscal pressure on carbon productivity. To examine the continuous effects of the low-carbon city pilot policy, we estimated the impact of the one period lag of interaction term($Treat*Post_{-1}$). The results are shown in Table 5.

Table 5 presents the estimated results after replacements with secondary industry carbon productivity. In Columns 1) and (2), the coefficient of $Treat*Post$ is 1.093 and the coefficient of $Treat*Post*FP$ is −1.847, both pass the significance test. In Column (2), the coefficient of $Treat*Post_{-1}$ is significant for 0.659, while the coefficient of $Treat*Post*FP$ is significant for −0.900. These results suggest that the low-carbon city pilot policy strongly promotes carbon productivity in secondary industry, and this promotion has a persistent character. The fiscal pressure brought about by the policy hinders the improvement of carbon productivity in the same industry.

In Column (3), after substituting carbon productivity with industrial sector, the coefficient of $Treat*Post$ is significant for 0.761, while the coefficient of $Treat*Post*FP$ is significant for −1.511. In Column(4), the coefficients of $Treat*Post_{-1}$ and $Treat*Post*FS$ are significant for 0.422 and −0.789 at the 1%

TABLE 5 Estimations after using the secondary industry and industrial carbon productivity.

Variables	Secondary Industry Carbon Productivity		Industrial Carbon Productivity	
	(1)	(2)	(3)	(4)
$Treat*Post$	1.093***		0.761***	
	(0.222)		(0.203)	
$Treat*Post_{-1}$		0.659***		0.422***
		(0.126)		(0.113)
$Treat*Post*FP$	−1.847***	−0.900***	−1.511***	−0.789***
	(0.387)	(0.201)	(0.352)	(0.178)
FP	−0.262	−0.305	−0.341	−0.268
	(0.270)	(0.288)	(0.249)	(0.263)
Constant	2.252***	2.407***	2.689***	2.762***
	(0.246)	(0.260)	(0.228)	(0.239)
Control variables	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Observations	3,666	3,384	3,666	3,384
Number of cities	282	282	282	282
R_squared	0.863	0.870	0.856	0.864
Fvalue	13.056	12.715	7.579	6.871

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

level, respectively. These results indicate that the low-carbon city pilot policy promotes carbon productivity in the industrial sector, but the fiscal pressure brought about by the low-carbon city pilot policy reduces carbon productivity in industrial sector. Therefore, the conclusion that the low-carbon city pilot policy can promote carbon productivity is robust. At the same time, the conclusion that the fiscal pressure brought about by the policy can decrease carbon productivity is also robust, and the extent of such decline depends on the magnitude of the fiscal pressure.

4.3.3 Censored data and tobit-DID estimation

To deal with the possible adverse effects of variable singular values, we used the winsorize method to deal with all variables at the 5% level, which resulted in the problem of censored data. Although we observed the data for all samples, data with variable values below the 5% level were censored to the 5% level, and those with values above the 95% level were censored to the 95% level. However, the potential issue with censored data is that the estimates of the staggered DID model with two-way FE are inconsistent. To solve this problem, the method of censored regression (i.e., Tobit model estimation) was adopted. Therefore, we used the panel Tobit-DID model to estimate the impacts of the low-carbon city pilot policy and fiscal pressure on carbon productivity. The estimation results are provided in Table 6.

In Table 6, Columns 1) and 2) indicate that, without controlling for the influence of other variables, the coefficients of both current period $Treat*Post$ and one period lag of $Treat*Post_{-1}$ are significantly greater than 0, suggesting that the impact of the low-carbon city pilot policy on carbon productivity is robust. At the same time, the coefficients of $Treat*Post*FP$ and FP are negative, which confirms that the negative effect of fiscal pressure brought about by the policy on carbon productivity is also robust. Under the condition of controlling for the influence of other variables, Columns 3) and 4) show that the impacts of the policy and fiscal pressure on carbon productivity remain unchanged. Therefore, the effects of the low-carbon city pilot policy are robust.

4.3.4 Counterfactual testing

We tested the relationship among the low-carbon city pilot policy, fiscal pressure, and carbon productivity through indicator substitution and Tobit-DID methods, all of results reveal that the conclusions are robust. However, a further placebo test is needed to determine whether counterfactual experiments in different cities and in different periods can yield consistent conclusions. The basic idea involved the selection of a total of 34 cities as low-carbon cities in 2010 and 2012, with 248 unselected cities. Initially, there were 36 low-carbon pilot cities, but Jiyuan City is a county-level city and the Daxinganling area has missing data. Thus, the samples from these two pilot areas were deleted. Next, we randomly selected 34 cities from 282 cities as "pseudo-low-carbon cities." Assuming that these 34 cities were selected as low-carbon cities, namely, the treatment group, and the other cities

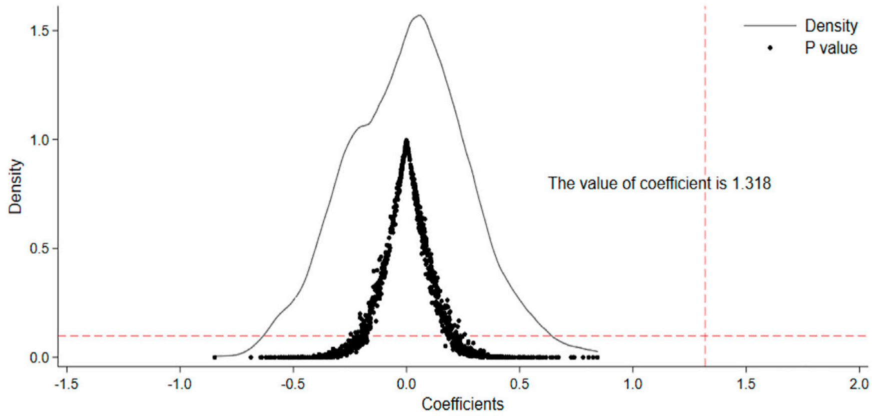

FIGURE 4
The placebo effects of thelow-carbon city pilot policy. Note: The figures show the distribution of estimated coefficients and corresponding p-values of the pseudo-low-carbon city pilot dummy variables sampled 1,000 times. The vertical dashed line represents the estimated value of the true coefficient, while the horizontal dashed line represents a value of 0.1.

TABLE 6 Tobit-DID estimation results.

Variables	Carbon Productivity (*CP*)			
	(1)	(2)	(3)	(4)
*Treat*Post*	1.457***		0.943***	
	(0.424)		(0.222)	
$Treat{*}Post_{-1}$		1.527***		1.078***
		(0.421)		(0.250)
*Treat*Post*FP*	−2.141	−2.722	−2.513	−2.846*
	(2.218)	(2.486)	(1.550)	(1.670)
FP	3.485	3.529	2.332	2.389
	(2.358)	(2.433)	(1.536)	(1.643)
Constant	−0.087	0.098	−0.056	0.015
	(0.426)	(0.417)	(0.213)	(0.220)
Control variables	NO	NO	YES	YES
Year fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Observations	3,666	3,384	3,666	3,384
Number of cities	282	282	282	282
R_squared	0.013	0.014	0.131	0.126
LLvalue	−7197.071	−6475.852	−6331.831	−5744.990

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

comprised the control group, then more than 500 random samples were taken to complete the placebo test.

However, the pilot policy times of the two batches of selected low-carbon cities vary, and this factor cannot be ignored in counterfactual experiments. Therefore, in the quasi-natural experiment using the staggered DID model to evaluate the effects of the low-carbon city pilot policy, it is necessary to use the placebo test method to conduct the counterfactual experiments. The specific methods are as follows. First, we used the "sample"command to randomly select a year as a pseudo-low-carbon city pilot policy year, after which we randomly selected 34 cities as pseudo-low-carbon cities and kept the city code and year from which the sample was drawn. Then, the sample was matched with the original data, and the cities that were successfully matched were classified as the pseudo-low-carbon cities (i.e., the samples of the treatment group); the cities that were not matched became the samples of the control group. Then, the dummy variable of the pseudo-low-carbon city pilot policy was generated by comparing the sequential relationship between each period and the pseudo-low-carbon city pilot policy year. Based on this estimation, the estimated coefficient, standard error, and p-value of the pseudo-low-carbon city pilot policy dummy variable were obtained. We repeated this process 1,000 times to obtain the results of the placebo effect test of the low-carbon city pilot policy. The detailed results are shown in Figure 4.

The results in Figure 4 reveal that the estimated coefficients of the pseudo-low-carbon city pilot policy are basically around 0, and the corresponding p-values are all greater than 0.1. Hence, the estimated value of the low-carbon city pilot policy in the real staggered DID model is not obtained by chance or coincidence, so the influence of random factors or other similar policies can almost be ignored. This finding further illustrates that the estimated coefficient of the low-carbon city pilot policy is robust, which evidences that the pilot policy effectively promotes carbon productivity.

5 Discussion of the heterogeneity and mediation effects

In this section, we carry out two aspects of research. First, we conduct a heterogeneous analysis of the effects of the low-carbon

TABLE 7 Estimations under different regional conditions.

Variables	Carbon Productivity (*CP*)			
	Eastern, Central and Western Regions		North and South Regions	
	Central and Western Regions	Eastern Regions	North Regions	South Regions
	(1)	(2)	(3)	(4)
*Treat*Post*	1.450***	1.182***	1.580***	0.497*
	(0.341)	(0.356)	(0.510)	(0.257)
*Treat*Post*FP*	−3.038***	−2.743***	−3.206***	−1.462***
	(0.558)	(0.884)	(0.773)	(0.531)
FP	−3.684***	2.633***	−1.731***	0.064
	(0.466)	(0.447)	(0.431)	(0.403)
Constant	5.940***	3.524***	3.236***	6.816***
	(0.449)	(0.444)	(0.428)	(0.399)
Control variables	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Observations	2,366	1,300	1911	1755
Number of cities	182	100	147	135
R_squared	0.891	0.922	0.885	0.932
Fvalue	27.992	13.290	23.771	3.705

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

city pilot policy and fiscal pressure on carbon productivity and test whether this effect is the same under different conditions of geographic location and economic development levels. Second, we perform a test of the effect of the mediation mechanism, explore the mechanism by which the pilot policy and fiscal pressure affect carbon productivity, and provide multiple mediation mechanisms for the impact of the low-carbon city pilot policy on carbon productivity.

5.1 Analysis of heterogeneity

There may be differences in the effects of the low-carbon city pilot policy under different geographic locations and economic development levels. Thus, we conducted heterogeneity analyses based on these aspects and discussed the reasons for any potential differences.

5.1.1 Heterogeneity test in different geographical locations

To distinguish the impact of geographic location on the effect of the low-carbon city pilot policy, we divided the sample based on two geographic locations. First, we divided the entire sample into cities from the Eastern region and those from the Central and Western regions. The Eastern region included 11 Eastern provinces and cities, such as Beijing and Tianjin. The corresponding city samples were the samples of the Eastern region. The corresponding city samples of other provinces, municipalities, and districts comprised the samples of the Central and Western regions. Second, we divided the entire sample into groups consisting of samples from the southern and northern cities. China was divided into Northern and Southern regions along the Qinling–Huai River line. Most of the cities in Jiangsu, most of the cities in Anhui, and a small part of the cities in Shaanxi, Chongqing, Sichuan, and 17 other provinces, cities, and districts comprised the group of southern cities. Other provinces, municipalities, and districts made up the northern region. The cities corresponding to other provinces, municipalities, and districts were comprised northern cities. After dividing the sample groups, we adopted the staggered DID model for estimation. The results are provided in Table 7.

Table 7 presents the estimation results of the staggered DID model under different regional conditions. In Columns 1) and (2), it is apparent that the coefficients of $Treat*Post$ are significantly greater than 0, whilethe coefficients of $Treat*Post*FP$ are significantly less than 0 in the Eastern, Central, and Western regions. In Columns 3) and (4), the coefficients of $Treat*Post$ are significantly greater than 0, and the coefficients of $Treat*Post*FP$ are significantly less than 0 in

TABLE 8 Estimations under different economic development levels.

Variables	Carbon Productivity (CP)			
	Size of GDP		Per Capita GDP	
	small	large	low	high
	(1)	(2)	(3)	(4)
$Treat*Post$	−0.946	1.258***	0.792	1.338***
	(0.839)	(0.258)	(0.524)	(0.295)
$Treat*Post*FP$	0.789	−3.028***	−1.342*	−3.583***
	(1.400)	(0.517)	(0.723)	(0.688)
FP	−3.103***	0.950**	−2.673***	−0.020
	(0.475)	(0.462)	(0.474)	(0.470)
Constant	4.564***	6.034***	6.222***	4.625***
	(0.541)	(0.401)	(0.468)	(0.462)
Control variables	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Observations	1833	1833	1833	1833
Number of cities	141	141	141	141
R_squared	0.890	0.916	0.902	0.901
Fvalue	20.192	6.813	10.382	12.516

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

both the Southern and Northern regions. These results indicate that whether in the Eastern, Central and Western regions or the Southern and Northern regions, the low-carbon city pilot policy significantly promotes carbon productivity, but the fiscal pressure resulting from this pilot policy have an adverse impact on carbon productivity.

At the same time, the results show that the coefficients of FP in the Eastern and Southern regions are both positive, while the coefficients of FP in the Northern, Central, and Western regions are negative. Compared with the Northern, Central, and Western regions, an increase in fiscal pressure can promote carbon productivity in the Southern and Eastern regions. The likely reason is that the region turned fiscal pressure into a driving force to create conditions and environments that are conducive to economic development, which would increases carbon productivity and provides a possible explanation for the North–South and East–West regional differences in economic development.

5.1.2 Heterogeneity of the difference in the level of economic development

One fact that cannot be ignored is that the level of economic development itself may also have an influence on carbon productivity, which may affect the effective of the low-carbon city pilot policy. To characterize such an impact, we adopted the following methods. First, we examined whether there are differences in the effects of the low-carbon city pilot policy under different conditions of GDP size. To this end, we calculated the average GDP of each city in the sample period, sorted the averaged GDP according to size and divided the sorted data into two groups: the cities with small GDPs and those with large GDPs. Then, we used the staggered DID model to perform the estimation. Second, we also investigated whether there are differences in the effects of the low-carbon city pilot policy under different per capita GDP levels. For this, we calculated the average per capita GDP of each city in the sample period, sorted the average per capita GDP, and divided the sorted per capita GDP into city groups with low and high per capita GDP. Finally, we performed the estimation after grouping. The results are displayed in Table 8.

Table 8 presents the estimated results of the low-carbon city pilot policy effects under different sizes of GDP and levels of per capita GDP. Columns 1) and 2) show that in the city group with small GDPs, the coefficients of $Treat*Post$ and $Treat*Post*FP$ are not significant, while the coefficients of FP are significantly negative. In the city group with large GDPs, the coefficients of $Treat*Post$ and FP are significantly greater than 0, and the coefficient of $Treat*Post*FP$ is significantly less than 0. A possible reason is that most of the low-carbon pilot projects are located in provincial capital cities, and most cities with small GDPs are located in non-provincial capital cities, where such a pilot policy has not yet been implemented. Therefore, the impacts of the low-carbon city pilot policy on their carbon productivity are not obvious. However, relative to cities with large GDPs, increased fiscal pressure can reduce the carbon productivity levels in cities with small GDPs.

The results in Columns 3) and 4) in Table 8 indicate that under the condition of cities with low levels of per capita GDP, the coefficient of $Treat*Post$ is positive but not significant; the coefficient of $Treat*Post*FP$ is significantly negative at the 10% level, and the coefficient of FP is significantly less than 0. Under the condition of cities with high levels of per capita GDP, the coefficients of $Treat*Post$ and $Treat*Post*FP$ both pass the significance test, and the coefficients of FP are positive. Therefore, compared to cities with high levels of per capita GDP, in cities with low levels of per capita GDP do not display an obvious effect of the low-carbon city pilot policy. A possible reason is that most of the cities selected for the low-carbon pilot areas are located in provincial capitals and economically developed cities with high per capita GDP levels. Meanwhile, most cities with low per capita GDP levels are not within the scope of such a policy pilot region, as reflected in the small impact of the low-carbon city pilot policy on them. However, compared to cities with high levels of per capita GDP, cities with low levels of per capita GDP suffer from increased fiscal pressure, which will be detrimental to carbon productivity.

5.2 Test of the mediation effect.

The impacts of the low-carbon city pilot policy and fiscal pressure on carbon productivity are mainly achieved through technological innovation and progress, closing or restricting the production of high-energy-consuming enterprises, restricting new high-energy-consuming enterprises, and increasing the use of clean energy. At the same time, closing down enterprises will increase fiscal pressure. To resolve this problem, some local governments will partially relax restrictions on the development of high-energy-consuming industries. In view of this, we introduced four mediation variables: "energy structure,""the number of green patent applications,""the number of registrations of low-carbon-type enterprises," and "fiscal pressure brought about by the low-carbon city pilot policy." We constructed the mediation effect model of the low-carbon city pilot policy and fiscal pressure on carbon productivity and tested the mediation effect of the policy.

Among them, the number of green patent applications ($\ln(NP)$) is measured by using the natural logarithm of the number of green patent applications. The relevant data came from the State Intellectual Property Office. The registration number of low-carbon-type enterprises ($NLCE$) is measured by the ratio of registration of non-high energy-consuming companies to the total population. The original data sourced from Liu (2019) were shared on GitHub. The fiscal pressure brought about by the low-carbon city pilot policy ($Treat \times Post \times FP$) is measured by the interaction term between the dummy variables of the low-carbon city pilot policy and fiscal pressure. The original fiscal expenditure and tax data used to measure fiscal pressure were derived from the CEIC Database and the China Statistics for Regional Economy Database of the EPS DATA platform. The energy structure includes two measurement indicators: the ratio of electricity consumption to total energy consumption (PSE_{it}) and non-thermal power generation (NTP_{it}). The specific measurement methods are as follows:

$$PSE_{it} = PSE_{jit} = \frac{\left(NL_{jit} \Big/ \sum_{s=1}^{S} NL_{jst} \right) * PC_{jt}}{\left((CO_2)_{jit} \Big/ \sum_{s=1}^{S} (CO_2)_{jst} \right) * TEC_{jt}}, \quad (5)$$

$$NTP_{it} = NTP_{jit} = \frac{NL_{jit}}{\sum_{s=1}^{S} NL_{jst}} * \left(TEG_{jt} - TPG_{jt} \right), \quad (6)$$

where j stands for province, i stands for city, t stands for year, S stands for the total number of cities, CO_2 denotes carbon dioxide emissions, TEC_{jt} is total energy consumption, PC_{jt} is total power consumption, TEG_{jt} is total power generation, TPG_{jt} is thermal power generation, and NL_{jit} is night light brightness. When calculating the ratio of electricity consumption to total energy consumption, we converted the electricity consumption into standard coal usingthe method of 0.1229 kg/kWh and then calculated its ratio. The raw data of night light brightness was collected by the Operational Linescan System (OLS) carried by the US Defense Meteorological Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIIRS) of the Suomi National Polar Orbiting Partnership Satellite(Suomi-NPP) (Li and Gong, 2019). The light data in this paper were sourced from the Mark Community Database, and such data were processed by saturation correction and continuous correction. We still used the staggered DID model to estimate the mediation effect model.

We refer to the methods of Baron and Kenny (1986), Imai et al. (2010), and Hicks and Tingley (2011) to construct a model of the mediation effect of the low-carbon city pilot policy on carbon productivity:

$$CP_{it} = \beta_0 + \beta_1 Treat_i * Post_{it} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \varepsilon_{it}, \quad (7)$$

$$M_{it} = \beta_0 + \beta_1 Treat_i * Post_{it} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \varepsilon_{it}, \quad (8)$$

$$CP_{it} = \beta_0 + \beta_1 Treat_i * Post_{it} + \beta_2 M_{\mathrm{it}} + \sum_{k=1}^{n} \phi_j X_{jit} + \mu_i + \varepsilon_{it}, \quad (9)$$

where i stands for city, t stands for year, CP_{it} denotes carbon productivity, $\mathrm{Treat}_i{*}\mathrm{Post}_{it}$ is a dummy variable of the low-carbon city pilot policy, and M_{it} is a mediation variable, including energy structure (PSE_{it} and NTP_{it}), the number of green patent applications($\ln(NP_{\mathrm{it}})$), the number of registrations of low-carbon-type enterprises ($NLCE_{\mathrm{it}}$), and the fiscal pressure brought about by the low-carbon city pilot policy ($\mathrm{Treat}_i \times Post_{it} \times FP_{it}$). μ_{i} is the city FE, θ_{t} is the year FE, ε_{it} is a random disturbance item, and X_{jit} is a set of control variables, including investment growth rate (IGR_{it}), population growth rate (PGR_{it}), trade competitiveness (TC_{it}), human capital levels (HC_{it}), and fiscal pressure (FP_{it}). The measurement method is the same as that in Eq. 1. The data source is specified in Section 3.3 of this paper.

5.2.1 Mediation effect based on energy structure

In the process of implementing the low-carbon city pilot policy, there is a need to involve the change of energy structure. This is because raw coal, coking coal, and other traditional fossil energy sources not only contain high sulfur elements but also cause high CO_2 carbon emissions. However, the use of electrical energy, especially hydropower, wind, and solar power, can effectively reduce carbon dioxide emissions. As for the change of energy structure, it is assumed that for energy consumption, the proportion of electric energy in total energy consumption will increase. For energy production, there will be a big push to develop clean energy sources, such as hydro, wind, and solar, which means that non-thermal power generation will increase. This development

TABLE 9 Estimation results based on energy structure.

Variables	Channels for the Proportion of Electricity Consumption			Channels for Non-Thermal Power Generation		
	(1)	(2)	(3)	(4)	(5)	(6)
	CP	*PSE*	*CP*	*CP*	*NTP*	*CP*
Treat∗Post	1.819***	0.037***	1.512***	1.819***	41.269***	1.173***
	(0.144)	(0.004)	(0.142)	(0.144)	(4.806)	(0.143)
PSE or NTP			8.226***			0.016***
			(0.849)			(0.001)
Constant	2.489***	0.133***	1.395***	2.489***	−48.101***	3.242***
	(0.466)	(0.013)	(0.461)	(0.466)	(11.828)	(0.453)
Control variables	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
Mediation effect			0.034***			0.660***
Observations	3,666	3,666	3,666	3,666	3,666	3,666
Number of cities	282	282	282	282	282	282
R_squared	0.777	0.872	0.796	0.777	0.779	0.803
F value	359.097	74.912	338.400	359.097	83.690	370.776

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

will effectively boost carbon productivity. Based on the mediation variables of electricity consumption ratio and non-thermal power generation, the stepwise regression coefficient method was used to estimate the mediation effect model based on the energy structure, after which we calculated the size of the mediation effect. The results are shown in Table 9.

In Table 9, when examining the mediation channels for the proportion of electricity consumption, Column 1) indicates that the coefficient of $Treat{*}Post$ is significant for 1.819. The coefficient of $Treat{*}Post$ is significant for 0.037, as shown in Column (2), which implies that the low-carbon city pilot policy can promote the proportion of electricity consumption. In Column (3), the coefficient of $Treat{*}Post$ is significant for 1.512, the coefficient of *PSE* is also significant for 8.226, and the mediation effect is 0.037, which indicates that the low-carbon city pilot policy promotes carbon productivity by affecting the energy consumption structure. Furthermore, after considering the mediation channels for non-thermal power generation, Column 5) shows that the coefficient of $Treat{*}Post$ is 41.269, which suggests that the low-carbon city pilot policy has a significant impact on clean energy production. Meanwhile, in Column (6), the coefficient of $Treat{*}Post$ is significant for 1.173, and the coefficient of NTP is significant for 0.016. Hence, the estimated mediation effect value is 0.660, which indicates the establishment of the mediation mechanism by which the low-carbon city pilot policy affects carbon productivity through the change in the energy production structure and consumption structure.

5.2.2 Mediation effect based on the number of green patent applications

The low-carbon city pilot policy advocates low-carbon production and consumption. In the production field, this effort will inevitably lead to greener and cleaner production technological progress, which is reflected in the expansion of green patent applications. At the same time, the expansion of the number of green patents will produce corresponding rewards, such as improved clean production capacity, lower carbon emissions, and higher carbon productivity. Therefore, based on the number of green patent applications, we used the stepwise regression coefficient method to estimate the mediation effect model and then calculated the size of the mediation effect. The results are provided in Table 10.

In Table 10, without controlling for the influence of other variables, Column 1) shows that the coefficient of $Treat{*}Post$ is significantly positive. Column 2) specifies that the coefficient of $Treat{*}Post$ is significantly greater than 0, which means that the low-carbon city pilot policy promotes the application of green patents. Column 3) reveals that the coefficients of $Treat{*}Post$ and $\ln(NP)$ are significantly greater than 0, which indicates that the establishment of the mediation mechanism of the impact of the low-carbon city pilot policy on carbon productivity. Furthermore, after controlling for the influence of other variables, Column 5) shows that the coefficient of $Treat{*}Post$ is 0.789, which indicates that the low-carbon city pilot policy significantly boosts the number of green patent applications. In Column (6), the coefficient of $Treat{*}Post$ is significant for 0.913,

TABLE 10 Estimation results based on the number of green patent applications.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CP	$\ln(NP)$	CP	CP	$\ln(NP)$	CP
$Treat*Post$	2.784***	1.324***	0.994***	1.819***	0.789***	0.913***
	(0.129)	(0.059)	(0.128)	(0.144)	(0.059)	(0.131)
$\ln(NP)$			1.352***			1.149***
			(0.022)			(0.028)
Constant	5.704***	3.464***	1.021***	2.489***	2.597***	-0.494
	(0.030)	(0.017)	(0.078)	(0.466)	(0.269)	(0.372)
Control variables	NO	NO	NO	YES	YES	YES
Cityfixed effect	YES	YES	YES	YES	YES	YES
Mediation effect			1.790***			0.907***
Observations	3,666	3,666	3,666	3,384	3,384	3,384
Number of cities	282	282	282	282	282	282
R_squared	0.644	0.648	0.850	0.777	0.807	0.859
Fvalue	465.774	499.404	2040.464	359.097	515.374	643.504

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

and the coefficient of $\ln(NP)$ is 1.149. The mediation effect value obtained from 0.789×1.149 is 0.907, which means that the mediation mechanism for the impact of the low-carbon city pilot policy on carbon productivity through green and low-carbon technological progress is established.

5.2.3 Mediation effect based on the number of registrations of low-carbon-type enterprises

One of the most direct ways for the government to implement the low-carbon city pilot policy is to restrict the development of high-energy-consuming industries. Specifically, local governments can reduce their approval for high-carbon-type enterprises and expand access for low-carbon-type enterprises. Thus, the number of registrations of high-carbon-type enterprises will be declined, and those of low-carbon-type enterprises will be increased. If the low-carbon city pilot policy increases the number of registrations of low-carbon-type enterprises, then the pilot policy supports the development of low-carbon enterprises, in turn, improves carbon productivity. In view of this, we estimated the mediation mechanism effect model based on the number of registrations of low-carbon-type enterprises under the conditions of not controlling and controlling for the influences of other variables. The results are shown in Table 11.

In Table 11, without controlling the influence of other variables, Column 2) shows that the coefficient of $Treat*Post$ is significantly greater than 0. This result suggests that the low-carbon city pilot policy has increased the number of registrations of low-carbon-type enterprises. In Column (3), the coefficient of $Treat*Post$ is positive, and the coefficient of $NLCE$ is also significantly positive. Furthermore, under the condition of controlling for the influence of other variables, Column 5) shows that the coefficient of $Treat*Post$ is significant for 0.074. In Column (6), the coefficient of $NLCE$ is significant for 0.078 at the 1% level; thus, the mediation effect value can be calculated as 0.001. This result supports the validity of the hypothesis that the low-carbon city pilot policy can improve carbon productivity by affecting the number of low-carbon-type enterprises entering the market.

5.2.4 Mediation effect based on fiscal pressure brought about by the low-carbon city pilot policy

In the actual implementation of the low-carbon city pilot policy, some high-energy-consuming enterprises will inevitably be shut down, which will eliminate some tax sources. In the case of rigid growth of government expenditure, the fiscal expenditure gap will increase, as will fiscal pressure on the local government. Especially in the case of economic downturns and fiscal difficulties, local governments are likely to respond to fiscal pressure by loosening restrictions on the development of high-energy-consuming enterprises, which will adversely affect carbon productivity. In this regard, it is necessary to minimize the adverse effects. This paper used the interaction term between the dummy variable of the low-carbon city pilot policy and the fiscal pressure to describe the fiscal pressure brought about by such a pilot policy, after which we estimated the mediation effects based on this mediation variable. The results are provided in Table 12.

In Table 12, under the condition of controlling for the influence of other variables, Column 2) reports that the

TABLE 11 Estimation results based on the number of registrations of low-carbon-type enterprises.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CP	*NLCF*	*CP*	*CP*	*NLCF*	*CP*
Treat*Post*	2.784***	0.572***	2.654***	1.819***	0.074	1.813***
	(0.129)	(0.192)	(0.133)	(0.144)	(0.192)	(0.143)
NLCE			0.227***			0.078***
			(0.016)			(0.014)
Constant	5.704***	2.531***	5.129***	2.489***	−1.189*	2.582***
	(0.030)	(0.030)	(0.048)	(0.466)	(0.712)	(0.466)
Control variables	NO	NO	NO	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
Mediation effect			0.130***			0.001
Observations	3,666	3,666	3,666	3,384	3,384	3,384
Number of cities	282	282	282	282	282	282
R_squared	0.644	0.753	0.663	0.777	0.776	0.779
Fvalue	465.774	8.936	331.318	359.097	59.348	307.866

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

TABLE 12 Estimation results based on the fiscal pressure brought about by the low-carbon city pilot policy.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CP	*T***reat***Post*FP*	*CP*	*CP*	*T***reat***Post*FP*	*CP*
Treat*Post*	2.784***	0.494***	4.101***	1.819***	0.492***	4.451***
	(0.129)	(0.011)	(0.323)	(0.144)	(0.011)	(0.331)
Treat*Post*FP*			−2.664***			−5.352***
			(0.593)			(0.635)
Constant	5.704***	-0.000	5.703***	2.489***	-0.016	2.401***
	(0.030)	(0.001)	(0.030)	(0.466)	(0.012)	(0.464)
Control variables	NO	NO	NO	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
Mediation effect			−1.316***			−2.633***
Observations	3,666	3,666	3,666	3,384	3,384	3,384
Number of cities	282	282	282	282	282	282
R_squared	0.644	0.911	0.645	0.777	0.913	0.782
Fvalues	465.774	2,126.140	251.095	359.097	395.914	343.823

Note: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors are reported in parentheses.

coefficient of Treat*Post* is significantly greater than 0. In Column (3), the coefficient of Treat*Post* is greater than 0, and the coefficient of *Treat**Post*FP* is less than 0. These results indicate that the mediation effect exists. Furthermore, under the condition of controlling for the influence of other variables, In Column 6) shows that the coefficient of Treat*Post* is significant for 0.492, which implies that the direct effects of the low-carbon city pilot policy are significant. At the same time, in Column(5) the coefficient of Treat*Post* is significant for 0.492. In Column (6), the coefficient of *Treat**Post*FP* is significant for–5.352 at the 1% level, and the value of the mediation effect is–2.633. These results illustrate that the hypothesis that the low-carbon city pilot policy influences carbon productivity through the mediation mechanism of fiscal pressure is valid. Thus, Hypothesis three is confirmed.

6 Conclusion and policy implications

The low-carbon city pilot policy is an important measure for China to promote carbon productivity, as it provides a certain degree of experience and demonstrations for China to achieve a carbon peak in 2030. At the same time, the low-carbon city pilot policy will affect the development of high-energy-consuming enterprises and the tax base to some extent, which may lead to an increase in fiscal pressure. Several results were obtained in this paper. First, the low-carbon city pilot policy can significantly improve carbon productivity, and the improvement effect presents a dynamic and persistent feature. Second, the fiscal pressure resulting from the low-carbon city pilot policy will reduce carbon productivity, and the degree of reduction depends on the status of fiscal pressure. Third, an increase in fiscal pressure will significantly decrease carbon productivity, which is heterogeneous with different levels of economic development. Finally, the examination of the mediation effect found that the low-carbon city pilot policy improves carbon productivity by affecting the energy structure, green and low-carbon technological progress, and the entry of low-carbon-type enterprises. However, the fiscal pressure brought about by the low-carbon city pilot policy has a negative impact on the improvement of carbon productivity, whose influence we cannot ignore. Therefore, the issue of how to improve carbon productivity without affecting fiscal pressure is a scientific problem. In relation to this, optimizing the low-carbon clean technology of existing enterprises and raising the low-carbon technology access standards of new enterprises may be a feasible strategy.

The conclusions drawn from the above research can offer inspiration to developing countries for improving carbon productivity in several ways. First, these countries can expand the scope of their low-carbon city pilot policy and provide policy support for improving carbon productivity. In the process of expanding the scope of such policies, the central government must strictly select the criteria, clarify the conditions and requirements for selection, and plan the strategic tasks for the development of low-carbon cities. Second, the low-carbon technology level of existing enterprises must be optimized, and the low-carbon technology access standards of new enterprises must be raised. A fact that cannot be ignored is that in the process of promoting a low-carbon economy, some local governments still need to bridge the gap between their policy approaches and local economic development conditions and resource endowments. Solving one problem can lead to the emergence of another problem. Therefore, in the process of improving carbon productivity, attention should be allocated to resolving fiscal pressure and preventing fiscal risks. Third and finally, there is a need to adjust the energy structure and improve energy efficiency. The use of traditional energy sources, such as thermal power, raw coal, crude oil, and gasoline, will lead to the emission ofmassive amounts of CO_2. However, emerging energy sources, such as hydropower, wind power, and solar energy, do not generate carbon emissions. This means that if the structure of energy production and consumption can be improved to produce and use cleaner energy, which can directly reduce carbon emissions and promote carbon productivity. At the same time, even if the energy structure remains unchanged, improving energy efficiency can also promote carbon productivity.

Although our research has given rise to valuable conclusions, it still has certain limitations. First, in view of the limitations involving carbon emission data, the latest annual data were not obtained for analysis. Second, an analysis based on micro-level (enterprise) data has not been performed. In the future, we will expand and analyze these two aspects to provide strong evidence for the relationship among the low-carbon city pilot policy, fiscal pressure, and carbon productivity.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material further inquiries can be directed to the corresponding author.

Author contributions

YY contributed to methodology, funding acquisition, writing—original draft preparation; CP contributed to conceptualization, writing—review, editing. All authors contributed to the article and approved the submitted version.

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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.

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