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Carbon Reduction Effect of Green Technology Innovation from the Perspective of Energy Consumption and Efficiency

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Abstract: Consumption-oriented or efficiency-oriented, it is a hard choice for the green technology innovation pathway. This paper uses the intermediary model to empirically analyze the panel data from 250 prefecture-level cities in China from 2010 to 2019. The conclusions show that: 1. At present, energy consumption-oriented green technology innovation at the national level in China shows a completely intermediary effect, which has a more obvious emission reduction effect; compared with energy consumption, energy efficiency-oriented green technology innovation only has a very weak intermediary effect of 6.58%. 2. Only the Eastern non-resource cities and the Midwest resource cities' green technology innovation have the effect of energy efficiency-oriented emission reduction, accounting for 8.11% and 9.02%, respectively. 3. Both the Eastern resource cities and the Midwest non-resource cities have no intermediary effect on energy efficiency, so carbon emission reduction is more difficult than in other cities.

Keywords: green technology innovation; carbon emission reduction; energy efficiency; energy consumption

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1. Introduction

China is a large energy consumer, with a large amount of energy consumption and carbon emissions rising yearly. With the continuous promotion of the "double carbon" policy, China urgently needs to vigorously promote green technology innovation to achieve its "double carbon" goal [1]. As a special case of environmentally biased technological progress [2], green technological innovation is considered to be able to achieve the transformation of the low-carbon development model [3].

Existing research mostly discusses the emission reduction effect of green technology innovation from the perspectives of energy consumption and energy efficiency. From the perspective of energy consumption, it has been confirmed that green technology innovation can significantly improve energy consumption. Whether it can truly form the emission reduction effect is also affected by energy consumption [4–6], the scale of energy consumption [7] and residents' awareness [8]. For example, Khazoom et al. have confirmed the nonlinear relationship between green technology innovation and energy consumption. He argues that green technology innovation can reduce energy consumption at the initial stage, but when it exceeds a certain critical value, it will increase energy consumption and finally increase carbon emissions [9]; Huang, on the other hand, has empirically concluded that the increase in renewable energy consumption brought about by green technology innovation can significantly reduce carbon emissions [10]. From the perspective of energy efficiency, most scholars focus on the relationship between energy efficiency, energy consumption, and green technology innovation [11,12]: Fisher et al. believe that in different forms of technological development, capital-saving technological innovation is the most critical factor to improving energy efficiency in China [13]; Weina et al. found that although green technology can improve overall environmental productivity, it does not contribute to reducing carbon emissions. It is not difficult to find that although energy efficiency is considered an important means to ensure stable economic growth, steadily reduce energy consumption, and thus reduce carbon emissions [14], there is little literature that can confirm this opinion.

From the above research results, the close relationship between energy consumption and carbon emissions has been confirmed, and green technology innovation also plays an important role in it; that is, green technology innovation helps reduce traditional energy consumption, increase green energy consumption, and then reduce carbon emissions. However, most of the studies focus on the provincial level, and there is a lack of more targeted research for countries or regions with greater regional heterogeneity [15]. In terms of energy efficiency, most studies focus on the relationship between energy efficiency, energy consumption, and green technology innovation. At the same time, due to the existence of the energy rebound effect, it is unclear whether energy efficiency can really reduce emissions. In order to make up for the shortcomings of these two types of research results, this paper simultaneously brings energy efficiency and energy consumption into the intermediary model and discusses the emission reduction mechanism of energy efficiency and energy consumption with the help of the data from Chinese prefecture-level cities. On the one hand, the energy consumption end can be refined to the prefecture-level cities, while on the other hand, it can also confirm the existence of green technology innovation and emission reduction in energy efficiency. Finally, it compares the effects of green technology innovation on emission reduction between these two parts, serving as a reference for the policy guidance of China's energy planners, which has certain practical significance.

2. Materials and Methods

2.1. Index Selection and Data Collection

2.1.1. Explained Variable: Carbon Emissions

Based on the county-level carbon emission data published in the China Carbon Emission Accounting Database (CEADS) [16], this article sums up the carbon emission data of the counties and cities under the jurisdiction of each prefecture-level city to obtain the urban carbon emission data in this article, denoted as ce.

2.1.2. Core Explanatory Variable: Green Technology Innovation

According to the green patent standards published by the World Intellectual Property Organization (WIPO) [17]: green patents include seven categories of waste management, nuclear power, transportation, energy conservation, agriculture and forestry, alternative energy production, administrative supervision, and design. The China Research Data Service Platform (CNRDS) collects and summarizes the green patents of various prefecture-level cities in China [18]. The green patent data in this article comes from this database and is recorded as gp.

2.1.3. Mediating Variable

This article includes two intermediate variables: energy efficiency and energy consumption. The energy efficiency measurement is more complicated. Following the research of Li [19] and Yu [20], this article uses the SBM-GML index method to measure the energy efficiency of cities. The green total factor energy efficiency is accumulated and multiplied into a cumulative productivity index with 2004 as the base period, and perform the logarithmic transformations; then, the value obtained is used as the variable data in the empirical study.

In order to measure energy efficiency, labor, capital, and energy are selected as input indicators. Labor input: this article selects the number of employees in each city at the end of the year (10,000 people) to measure the labor input. Capital input: this article selects the perpetual inventory method to calculate capital input, and the formula is: $k_{t+1} = i_t + (1 - \delta_t)k_t$, among which, δ_t refers to the depreciation rate of physical capital in period t, which is set at 10.96%, the total fixed assets form i_t, and the current capital stock k_t. Drawing from Shan's [21] research, this paper chooses the total fixed capital formation to characterize i_t, and uses the fixed asset investment price index of each province instead of the investment price index to deflate the investment data to obtain the actual fixed asset formation. Energy input: as data on total energy consumption is only provided by a few cities at the prefecture level, there is a serious lack of data. Therefore, this paper selects the electricity consumption (10,000 kW·h) of the city's municipal districts to measure the regional energy input.

The selected output indicators include expected output and undesired output. Expected output: select the actual regional GDP (GDP, ten thousand yuan) of each city based on the year 2000 as the expected output. Unexpected output: select the industrial wastewater discharge (effluents, ten thousand tons), industrial sulfur dioxide emissions (SO2, ten thousand tons), and industrial smoke and dust emissions (smoke, ten thousand tons) of each city to measure the undesired output. On this basis, this article uses Maxdea to measure the SBM's GML index of the selected 257 prefecture-level cities, and this index is used as an index to measure the green total factor energy efficiency, denoted as *ee*, which will be used for the empirical analysis later.

For the characterization of energy consumption, this paper draws on the research of Lin [22], selecting the annual electricity consumption of residents to characterize the energy consumption of urban residents, which is recorded as es.

2.1.4. Other Control Variables

This paper draws on previous research on energy efficiency and carbon emissions [23,24], and combines the variables involved in the green technology innovation and emission reduction mechanism. The selected control variables include: (1) Fiscal strength (fin), selecting the proportion of regional fiscal revenue to fiscal expenditure as a measure of regional fiscal autonomy. (2) Population size (pop), this article uses the total population of each city at the end of the year as a measure of population size. (3) Infrastructure construction (inf), selecting the per capita road area as a measure of the level of regional infrastructure construction. (4) Industrial structure (ind), selecting the proportion of the tertiary industry's GDP in the region as a measure of the regional industrial structure. (5) Education Level (edu), selecting the number of primary school teachers per 10,000 people in the region as an indicator to measure the regional education level.

2.1.5. Data Sources and Descriptive Statistical Analysis

The sample for this article is 257 prefecture-level cities in China, and the time interval is 2004–2016. The data mainly comes from the "China City Statistical Yearbook"; the green patent innovation data comes from the China Research Data Service Platform (CNRDS); the carbon dioxide emission data comes from the China Carbon Emission Accounting Database (CEADS), and the missing values of some data have been created by the linearly interpolated method. The statistical software used is stata16.0. The definition of each variable and the descriptive analysis of the data are shown in Table 1:

Table 1. Variable definitions and data descriptive analysis.

Variable	The Meaning of Variable	The Way of Calculating	Average	Standard Deviation	Minimum	Maximum
ce	Carbon dioxide emissions	Total carbon emissions of various industries in cities	6.306	1.153	3.438	9.172
GP	Green technology innovation	Number of green invention applications	3.312	8.626	0.010	58.280
fin	Financial strength	Regional fiscal revenue/financial expenditure	0.463	0.222	0.090	1.015
pop	Population size	Total population at the end of the year	0.650	0.700	0.081	5.122
inf	infrastructure	Road area/population	0.032	0.021	0.004	0.115
ind	Industrial structure	Tertiary industry output value/Gross regional product value	0.404	0.097	0.204	0.699
edu	Education level	Number of primary school teachers per 10,000 people	0.457	0.399	0.049	14.900

Table 1. *Cont.*

Variable	The Meaning of Variable	The Way of Calculating	Average	Standard Deviation	Minimum	Maximum
GDP	Gross domestic product	Regional per capita GDP	5.028	3.115	1.142	16.412
ee	Energy efficiency	SBM-GML model measured	4.611	0.122	4.104	5.025
es	Energy consumption	Annual electricity consumption of urban residents	4.194	1.165	1.254	6.851

2.2. Model Construction

2.2.1. SBM Model and GML Index

In this paper, the SBM (slack-based measure) model and GML (global Malmquist Luenberger) index are used to measure the green total factor energy efficiency of prefecture-level cities. This measurement can overcome two previous problems in measuring total factor productivity: (1). In the radial model, the distance between invalid DMU and strong effective target value includes not only the component of equal proportion improvement but also the part of relaxation variable improvement SBM model can effectively avoid the influence of relaxation variables on energy efficiency measurement. (2). The maximum efficiency value measured by the traditional DEA method is 1. At this time, the efficiency value cannot be compared between regions. The efficiency value measured by SBM-GML can effectively avoid this problem.

As for the setting of the SBM model, this paper first assumes that each prefecture-level city is set as a decision-making unit, which is set as DMU_n, where n represents 257 prefecture-level cities. Each DMU has j inputs, $k1$ expected outputs, and $k2$ unexpected outputs, which are expressed as $x = (x_1, \cdots, x_i) \in R_j^+$, $y = (y_1, \cdots, y_i) \in R_{k1}^+$, and $b = (b_1, \cdots, b_i) \in R_{k2}^+$, respectively, and (x^{nt}, y^{nt}, b^{nt}) is used to represent the inputs and outputs of the current period. Let the production possibility $P^t(x, y, b)$ of the current period be as shown in Formula (1):

$$P^t(x,y,b) = \left\{ \left(x^t, y^t, b^t\right) \middle| x^t \geq \sum_{i=1}^{n} x^t\lambda, y^t \leq \sum_{i=1}^{n} y^t\lambda, b^t = \sum_{i=1}^{n} b^t\lambda, \sum_{i=1}^{n} \lambda = 1, \lambda \geq 0 \right\} \tag{1}$$

In Formula (1), λ is the weight of phase t cross-sectional data, and if $\sum_{i=1}^{n} \lambda = 1, \lambda \geq 0$, it means that the return to scale is variable. If there is only $\lambda \geq 0$, it means that the return to scale remains unchanged. Secondly, build the SBM model. In this paper, the non-oriented SBM model with unexpected output is defined as:

$$\min\rho = \frac{1 - \frac{1}{m}\sum_{r=1}^{s} s_r^- / x_{ik}}{1 + \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{r=1}^{q_2} s_t^{b-} / b_{rk}\right)} \tag{2}$$

$$\begin{gathered} s.t. X\lambda + s^- = x_k Y\lambda - s^+ = y_k \, \mathrm{B}\lambda + s^{b-} = \mathrm{b}_k \\ \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \end{gathered} \tag{3}$$

where, s^-, s^+ and s^{b-} represent relaxation variables: input, expected output, and unexpected output. The objective function ρ represents the efficiency value of DMU, with a value of 0–1. If and only if $\rho = 1$, the evaluated DMU_n is strongly efficient, that is, there is no weak efficiency problem with the radial model. When $\rho < 1$, the evaluated DMU_n is weakly efficient, and there is room for improvement in both input and output variables. In this case, the global production possibility function can be defined as:

$$pps^t = \left\{x^t \to (y^t, b^t), t = 1, 2, \cdots, T\right\} \tag{4}$$

Model construction of the global Malmquist–Luenberger (GML) index. This paper constructs the GML index based on the SBM model, which effectively solves the lack of transitivity and the lack of feasible solutions of the ML index. At the same time, the GML index can be decomposed into technical efficiency change index (GEC) and the technological progress change index (GTC). The specific model is constructed as follows:

$$GML_g(t, t+1) = \frac{1 + E^g(x_k^t, y_k^t, b_k^t)}{1 + E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})} \tag{5}$$

$$GEC_g(t, t+1) = \frac{1 + E^t(x_k^t, y_k^t, b_k^t)}{1 + E^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})} \tag{6}$$

$$GTC_g(t, t+1) = \frac{(1 + E^g(x_k^t, y_k^t, b_k^t))/(1 + E^t(x_k^t, y_k^t, b_k^t))}{(1 + E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}))/(1 + E^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}))} \tag{7}$$

where, $E^g(x_k^t, y_k^t, b_k^t)$ and $E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ represent the distance function of DMU_n evaluated in t period and t + 1 period when the production possibility set composed of all input and output values in the study sample period is used as the common reference value in different periods. If GML > 1, green total factor energy efficiency shows an increasing trend. If GML $\leq$ 1, the green total factor energy efficiency shows a downward or unchanged trend. Since the evaluated "DMU" must be included in the global reference set, there is no problem of no feasible solution for the VRS model in the global reference Malmquist index. At the same time, since each period refers to the common global frontier, the global reference Malmquist index is also transitive and can be multiplied.

2.2.2. Benchmark Model Construction

Based on theoretical analysis and a relevant literature review, through the primary term fitting and secondary term fitting of the scatter diagram of green technology innovation and carbon dioxide emission, it is found that there is a positive linear relationship between green technology innovation and carbon dioxide emission (Figure 1). Based on this, this paper launches the subsequent construction of a measurement model. Based on the theoretical analysis and Figure 2, this paper studies the effect of green technology innovation on carbon dioxide emissions by constructing an econometric model. In the selection of fixed effect and random effect, this paper uses the Hausman test method to test whether the fixed effect model is better than the random effect model, and the benchmark model is shown in Formula (8).

$$ce_{it} = \alpha_0 + \beta_0 gp_{it} + \alpha_1 fin_{it} + \alpha_2 pop_{it} + \alpha_3 \mathrm{inf}_{it} + \alpha_4 ind_{it} + \alpha_5 edu_{it} + \delta_i + \gamma_t + \varepsilon_{it} \tag{8}$$

where, i represents region, t represents time, α_0 represents constant term, δ_i represents individual fixed effect, and γ_t represents time fixed effect. ε_{it} represents the error term in the model and other factors affecting carbon dioxide emissions. The meaning of other relevant variables has been described in the descriptive data analysis (Table 1).

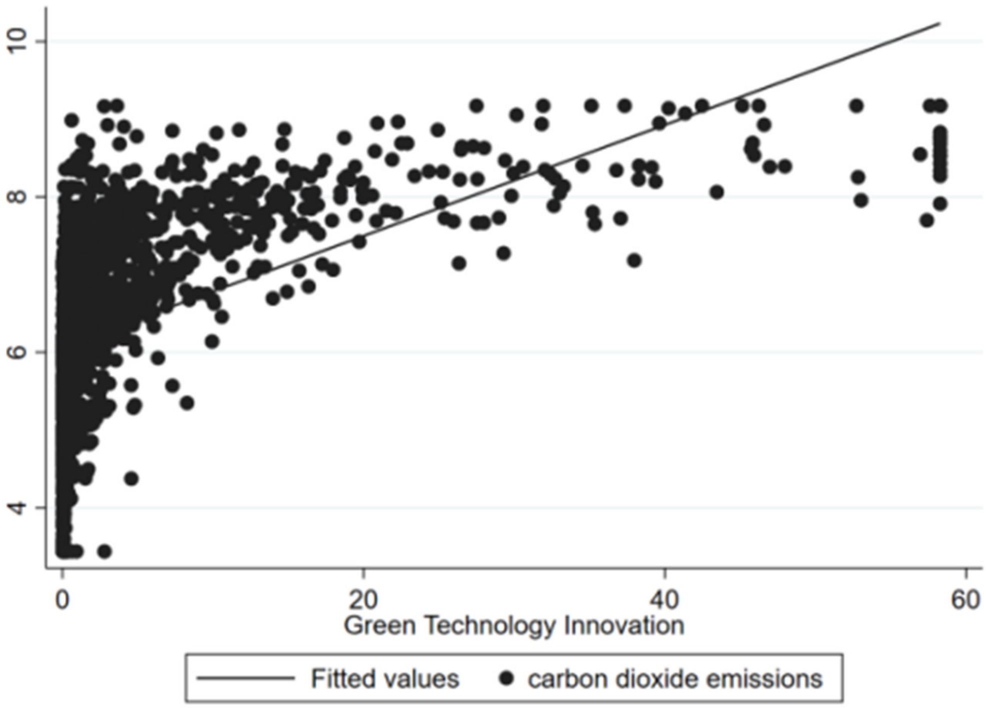

Figure 1. Fitting diagram of scatter and primary term.

Figure 2. Regional distribution map of different types of cities.

2.2.3. Mediating Effect Model

According to the fitting diagram of scatter points and primary terms (Figure 1), there is a positive correlation between green technology innovation and carbon dioxide emissions, which is contrary to reality. In order to explore the reasons for this phenomenon, this paper takes energy efficiency and energy consumption as intermediary variables to study the mechanism of green technology innovation that affects carbon emissions by acting on energy efficiency and energy consumption. Drawing lessons from the practice of Baron R et al. [25], this article builds a mediation effect model on the basis of the benchmark model (8). The model is shown in Formulas (9)–(12):

$$ee_{it} = \beta_1 gp_{it} + \alpha_0 + \alpha_1 fin_{it} + \alpha_2 pop_{it} + \alpha_3 \inf_{it} + \alpha_4 ind_{it} + \alpha_5 edu_{it} + \varepsilon_{it} \tag{9}$$

$$ce_{it} = \beta_2 gp_{it} + \lambda ee_{it} + \alpha_0 + \alpha_1 fin_{it} + \alpha_2 pop_{it} + \alpha_3 \inf_{it} + \alpha_4 ind_{it} + \alpha_5 edu_{it} + \varepsilon_{it} \tag{10}$$

$$es_{it} = \beta_1 gp_{it} + \alpha_0 + \alpha_1 fin_{it} + \alpha_2 pop_{it} + \alpha_3 \inf_{it} + \alpha_4 ind_{it} + \alpha_5 edu_{it} + \varepsilon_{it} \tag{11}$$

$$ce_{it} = \beta_2 gp_{it} + \lambda es_{it} + \alpha_0 + \alpha_1 fin_{it} + \alpha_2 pop_{it} + \alpha_3 \inf_{it} + \alpha_4 ind_{it} + \alpha_5 edu_{it} + \varepsilon_{it} \tag{12}$$

Among them, i represents the area, t represents the time, and ε_{it} represents the random disturbance term. According to the test method of the mediation effect by Wen et al. [26], in order to test the existence of the mediation effect, the first step is to test the significance of the coefficient β_0 in the model (8). If it is significant, then perform the mediation effect test, otherwise stop the mediation effect test. The second step is to test the coefficients λ and β_1. If both are significant, the third step is to be tested. If one of the two is not significant, then the fourth step is to be performed. The third step is to test the coefficient β_2. If it is significant, there may be a partial mediation effect. If it is not significant, it is a complete mediation effect. In the fourth step, on the basis of the second step, perform the SOBEL test. If the test passes, the mediation effect is established; otherwise the mediation effect does not exist. According to the research of Wen et al. [27], the Bootstrap method has higher testing power than other methods, so this paper selects the Bootstrap method when testing the mediation effect.

3. Results

3.1. Analysis of the Emission Reduction Effect of Green Technology Innovation

This paper analyzes the emission reduction effect of green technology innovation through the panel fixed effect model. The regression results are shown in Table 2:

It can be seen from Table 2 that only under the individual fixed effect without control variables, the coefficient of green technology innovation is positive, and the rest are negative and significant at the significance level of 1%. Considering that when the coefficient of green technology innovation (GP) is positive, it will promote carbon dioxide emissions, which is contrary to the policy orientation, this paper tests the multicollinearity in the model. The average Vif value is 2.75, far less than 10, and it is considered that there is no multicollinearity problem in the model. The only positive coefficient of green technology innovation may be that it does not consider the emission reduction effect and time effect of control variables, which leads to insufficient model optimization, and most cities in the sample period have not achieved effective emission reduction but are still increasing emissions. However, after adding the control variables and time effect, the green technology innovation coefficient immediately changes to a negative value, which means that with the passage of time, the improvement in the level of green technology innovation can reduce carbon dioxide emissions, forming the emission reduction effect proposed in this paper.

Table 2. Empirical regression results of the benchmark model.

	Carbon Dioxide Emissions			
GP	**0.034 *****	**−0.032 *****	**−0.013 *****	**−0.023 *****
	(11.28)	**(−9.89)**	**(−6.59)**	**(−8.45)**
fin		**−0.761 *****		**0.505 *****
		(−4.72)		**(3.67)**
inf		**0.002**		**−0.245**
		(0.00)		**(−0.67)**
pop		**0.418 *****		**0.304 *****
		(6.13)		**(5.11)**
edu		**0.007**		**0.003**
		(0.23)		**(0.10)**
ind		**4.548 *****		**−0.446**
		(21.05)		**(−1.62)**
GDP		**0.136 *****		**0.009**
		(14.62)		**(1.00)**
Constant	**6.195 *****	**3.966 *****	**5.874 *****	**5.679 *****
	(394.56)	**(30.89)**	**(254.91)**	**(43.54)**
Individual fixed effect	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effect	**No**	**No**	**Yes**	**Yes**

Note: The numbers in parentheses are t values; *** indicate that they have passed the 1% significance tests. In addition, in order to make green technology innovation more observable, this data is reduced by 100 times, as shown in the table below.

From the results of the control variables, the impact coefficient of infrastructure construction (inf) and education level (edu) on carbon dioxide is not significant, indicating that the relevant infrastructure construction has not made an effective contribution to carbon emission reduction nationwide, and there is a decoupling between education and practice in carbon emission reduction in China, so that there is no significant emission reduction effect in both the short and long term. The relationship between the coefficient of financial strength (fin) and carbon dioxide emissions has changed from negative to positive after adding the time effect, and it is significant at the level of 1%, indicating that although the financial support of urban governments can promote the development of green technology innovation enterprises and achieve a certain degree of emission reduction, over-investment in green technology innovation enterprises has occurred in some cities over time, resulting in green overcapacity and eventually increased carbon emissions. The influence coefficient of population size (pop) on carbon dioxide is significantly positive, reflecting the general law of carbon emission growth after the expansion of the social scale. The influence coefficient of industrial structure (ind) and economic development level (GDP) on carbon dioxide is only significantly positive under the individual fixed effect, which can be understood as: a large amount of traditional energy consumption will be consumed in the early stage of industrial structure transformation, thus significantly increasing carbon emissions. At the same time, at present, China's economic development level largely depends on traditional energy consumption, so it is reasonable that these two kinds of control variables will increase carbon emissions. When the time effect is added, the significance of both disappears, which means that with the passage of time, the energy consumption of industrial structure transformation has stabilized, and some green technology innovation enterprises have gradually become the main force of China's economic development, which may significantly promote carbon emission reduction in the future.

3.2. Intermediary Effect between Energy Efficiency and Energy Consumption

In order to investigate the emission reduction mechanism of green technology innovation, this paper takes energy efficiency and energy consumption as intermediary variables at the same time and constructs an intermediary effect model to analyze whether they play an intermediary role in green technology innovation on carbon emissions. First of all, this paper examines the existence of intermediary effects at the national level. The regression results of the effect model are shown in Table 3.

Table 3. Regression results from intermediary effects of energy efficiency and energy consumption at the national level.

	ce	ee	ce	es	ce
GP	−0.023 ***	0.002 ***	−0.022 ***	−0.025 ***	−0.002
	(−8.45)	(2.62)	(−8.04)	(−8.40)	(−1.62)
ee			−0.757 ***		
			(−11.49)		
es					0.884 ***
					(128.31)
fin	0.505 ***	−0.075 *	0.448 ***	0.451 ***	0.107 **
	(3.67)	(−1.75)	(3.35)	(3.08)	(2.24)
inf	−0.245	−0.171	−0.375	−0.371	0.083
	(−0.67)	(−1.50)	(−1.06)	(−0.96)	(0.65)
pop	0.304 ***	−0.042 **	0.273 ***	0.289 ***	0.049 **
	(5.11)	(−2.24)	(4.70)	(4.57)	(2.35)
edu	0.003	−0.006	−0.002	−0.002	0.005
	(0.10)	(−0.73)	(−0.08)	(−0.08)	(0.52)
ind	−0.446	0.003	−0.443 *	−0.612 **	0.095
	(−1.62)	(0.04)	(−1.65)	(−2.09)	(0.99)
gdp	0.009	0.006 **	0.014	0.001	0.008 **
	(1.00)	(2.18)	(1.55)	(0.12)	(2.57)
cons	5.679 ***	4.667 ***	9.213 ***	3.568 ***	2.526 ***
	(43.54)	(114.68)	(27.69)	(25.76)	(49.18)
N	2500	2500	2500	2500	2500
R2	0.674	0.193	0.693	0.700	0.961

Note: The numbers in parentheses are t values; ***, **, * indicate that they have passed the 1%, 5%, and 10% significance tests, respectively.

According to the results shown in Table 3, referring to the stepwise regression intermediary effect test steps, the core test coefficients of energy efficiency all passed the significance test of 1%, indicating that there are some intermediary effects mediated by energy efficiency at the national level. At the same time, in order to quantify the proportion of the intermediary effect of energy efficiency in the impact of green technology innovation on carbon emissions, according to the algorithm by Wen [27], this paper calculates that the proportion of the intermediary effect of energy efficiency is weak, only 6.58% ($0.002 \times 0.757/0.023$, see Table 4 for the data), which may have other mediation variables. From the perspective of the intermediate variable of energy consumption, the impact of green technology innovation on carbon dioxide emissions under the influence of this intermediate variable is not significant, while the other core coefficients have passed the significance test of 1%, which indicates that there is a complete intermediary effect mediated by energy consumption in the emission reduction of green technology innovation at the national level (when only the regression coefficient is not significant, it indicates that the model has a complete intermediary effect). That is, the intermediate variable of energy consumption is of great significance as to whether green technology innovation can reduce emissions. Therefore, this paper infers that the emission reduction effect of green technology innovation led by energy consumption is more obvious in the emission reduction mechanism of green technology innovation at the national level.

Table 4. Regression results of Eastern resource cities.

Eastern Resource Cities						
	ce	**ee**	**ce**		**es**	**ce**
gp	**−0.037 *****	**0.002**	**−0.036 *****	**gp**	**−0.041 *****	**0.001**
	(−3.58)	**(0.30)**	**(−3.60)**		**(−3.76)**	**(0.49)**
ee			**−0.478 *****	**es**		**0.921 *****
			(−3.28)			**(67.26)**
fin	**−0.109**	**−0.091**	**−0.153**	**fin**	**−0.374**	**0.236 *****
	(−0.25)	**(−0.44)**	**(−0.37)**		**(−0.82)**	**(2.73)**
inf	**0.630**	**−0.135**	**0.565**	**inf**	**0.762**	**−0.073**
	(0.71)	**(−0.31)**	**(0.65)**		**(0.81)**	**(−0.41)**
pop	**0.117**	**−0.063**	**0.087**	**pop**	**0.062**	**0.060**
	(0.57)	**(−0.64)**	**(0.44)**		**(0.29)**	**(1.46)**
edu	**−0.011**	**−0.002**	**−0.012**	**edu**	**−0.014**	**0.003**
	(−0.53)	**(−0.22)**	**(−0.60)**		**(−0.67)**	**(0.61)**
ind	**2.336 *****	**−0.833 ****	**1.938 ****	**ind**	**2.971 *****	**−0.402 ****
	(2.92)	**(−2.15)**	**(2.46)**		**(3.49)**	**(−2.42)**
gdp	**0.071 *****	**−0.006**	**0.068 *****	**gdp**	**0.067 *****	**0.009 ****
	(3.62)	**(−0.60)**	**(3.57)**		**(3.22)**	**(2.29)**
cons	**4.794 *****	**5.047 *****	**7.205 *****	**cons**	**2.493 *****	**2.497 *****
	(10.43)	**(22.66)**	**(8.36)**		**(5.10)**	**(25.31)**
N	**230**	**230**	**230**	**N**	**230**	**230**
R2	**0.797**	**0.169**	**0.808**	**R2**	**0.814**	**0.992**

Note: The numbers in parentheses are t values; ***, ** indicate that they have passed the 1%, 5%, significance tests, respectively.

Due to the wide area of the country and the difference in resource endowment, the intermediary effect characteristics of energy consumption and energy efficiency are different in cities in different regions. In order to further explore the role of energy efficiency and energy consumption in reducing emissions, this paper divides Chinese cities into Eastern and Midwest cities according to the "Heihe–Tengchong" demographic, geographical boundary, and cities are divided into resource and non-resource cities according to the national resource city sustainable development plan (2013–2020) issued by the State Council in 2013. The two classification methods are combined into two and finally divided into four categories: "Eastern resource cities" (23), "Eastern non-resource cities" (77), "Midwest resource cities" (64), and "Midwest non-resource cities" (86), as shown in Figure 2.

From Table 4, the regression results of Eastern resource cities show that green technology innovation does not have a partial intermediary effect on energy efficiency, while energy consumption shows a complete intermediary effect. From the significance of energy consumption and energy efficiency, although green technology innovation has not significantly improved the energy efficiency of the region, it has effectively reduced energy consumption and has an indirect emission reduction effect based on energy consumption. From the results of the control variables, the industrial structure (and) will not only consume a lot of energy in the initial stage of transformation but also reduce energy efficiency. Increasing energy consumption in the region can significantly reduce emissions. Therefore, on the whole, the Eastern resource cities have a high awareness of green technology innovation, but the green industry they develop needs such cities to have sufficient consumption capacity; otherwise, it will lead to the dilemma of excessive energy consumption pressure in the cities, and it will be difficult for green technology innovation enterprises to play an effective role.

From Table 5, the regression results of Eastern non-resource cities show that energy efficiency and energy consumption have some intermediary effects. From a numerical point of view, although the proportion of energy efficiency intermediation in the Eastern non-resource cities is 8.11% ($0.003 \times 0.676/0.025$), which is higher than the national average level of 6.58%, it is far lower than the proportion of energy consumption end of 83.9% ($0.024 \times 0.874/0.025$). Further, looking at the control variables, the financial strength (fin) has a negative effect on increasing emissions, which indicates that the financial revenue of such cities rises only under the influence of the income effect, which is not conducive to carbon emission reduction. At the same time, population (pop) aggregation has also hindered the improvement of local energy efficiency and expanded the traditional energy consumption demand. In order to solve these problems, such cities can give full play to the double intermediary effect of emission reduction, further improve the policy orientation of energy consumption, and promote green energy consumption.

Table 5. Regression results of Eastern non-resource cities.

	Eastern Non-Resource Cities					
	ce	**ee**	**ce**		**es**	**ce**
gp	**−0.025 *****	**0.003 ****	**−0.023 *****	**gp**	**−0.024 *****	**−0.004 ****
	(−5.98)	**(2.24)**	**(−5.59)**		**(−5.62)**	**(−2.08)**
ee		**.**	**−0.676 *****	**es**	**.**	**0.874 *****
		(.)	**(−5.58)**		**(.)**	**(46.54)**
fin	**0.485 ****	**−0.132**	**0.396 ***	**fin**	**0.362**	**0.169**
	(2.05)	**(−1.64)**	**(1.71)**		**(1.50)**	**(1.57)**
inf	**0.147**	**−0.025**	**0.130**	**inf**	**0.091**	**0.068**
	(0.21)	**(−0.10)**	**(0.19)**		**(0.13)**	**(0.21)**
pop	**0.415 *****	**−0.072 ****	**0.366 *****	**pop**	**0.419 *****	**0.049**
	(4.90)	**(−2.51)**	**(4.42)**		**(4.86)**	**(1.24)**
edu	**−0.649**	**0.032**	**−0.628**	**edu**	**−0.942**	**0.173**
	(−0.78)	**(0.11)**	**(−0.78)**		**(−1.11)**	**(0.46)**
ind	**−1.245 ****	**0.134**	**−1.155 ****	**ind**	**−0.999 ***	**−0.373**
	(−2.29)	**(0.73)**	**(−2.18)**		**(−1.80)**	**(−1.51)**
gdp	**−0.009**	**0.007**	**−0.004**	**gdp**	**−0.015**	**0.004**
	(−0.63)	**(1.40)**	**(−0.31)**		**(−1.02)**	**(0.63)**
cons	**6.659 *****	**4.636 *****	**9.793 *****	**cons**	**4.585 *****	**2.654 *****
	(13.44)	**(27.52)**	**(13.23)**		**(9.07)**	**(11.03)**
N	**640**	**640**	**640**	**N**	**640**	**640**
R2	**0.679**	**0.150**	**0.696**	**R2**	**0.713**	**0.934**

Note: The numbers in parentheses are t values; ***, **, * indicate that they have passed the 1%, 5%, and 10% significance tests, respectively.

From Table 6, in the Midwest resource cities, the intermediary effect characteristics are basically consistent with the overall characteristics of the whole country: there is a partial intermediary effect of green technology innovation in energy efficiency, while energy consumption shows a complete intermediary effect. Among them, the intermediary effect of energy efficiency accounted for 9.02% ($0.005 \times 0.794/0.044$), which was also higher than the national average. Although such cities do not have location advantages, their resource endowment conditions are good, even surpassing some Eastern resource cities. In addition, the state's policy support for the Midwest regions has enabled the green technology innovation enterprises in such cities to flourish and be effectively utilized in recent years. In terms of energy consumption, they have also successfully achieved a green transformation. Therefore, they show a full intermediary effect on energy consumption. It is worth noting that population (pop) and economic development (GDP) will still significantly increase carbon emissions, so many cities still have a certain distance from the goal of low-carbon transformation.

From Table 7, Midwest non-resource cities have no intermediary effect on their energy efficiency, and the energy consumption is reflected as a complete intermediary effect. The phenomenon of light and power abandonment in this area is serious, which makes green technology innovation enterprises abandon it, which is reflected in the current inability to significantly improve energy efficiency. It is worth noting that the indirect impact coefficient of green technology innovation on carbon emissions on the energy consumption side is very small. This is because there are no advantages in location and resources, resulting in high maintenance costs for the development of green technology innovation, and the emission reduction effect of energy consumption variables that can achieve emission reduction is not obvious. From the perspective of control variables, infrastructure construction (inf) has a significant effect on carbon emission reduction and will also reduce local energy consumption. This shows that the urgent task of such economically backward cities should be to optimize and improve the local public infrastructure rather than excessively pursue green technology innovation.

Table 6. Regression results of Midwest resource cities.

	Midwest Resource Cities					
	ce	ee	ce		es	ce
gp	−0.044 ***	0.005 **	−0.040 ***	gp	−0.048 ***	−0.002
	(−5.68)	(2.13)	(−5.32)		(−5.74)	(−0.87)
ee			−0.794 ***	es		0.863 ***
			(−6.00)			(68.36)
fin	0.228	−0.078	0.167	fin	0.134	0.113
	(0.78)	(−0.93)	(0.58)		(0.42)	(1.08)
inf	0.640	−0.410 **	0.315	inf	0.338	0.348
	(0.95)	(−2.14)	(0.47)		(0.46)	(1.45)
pop	0.359 ***	−0.052	0.317 **	pop	0.369 ***	0.041
	(2.76)	(−1.42)	(2.50)		(2.62)	(0.87)
edu	1.101	−0.034	1.074	edu	0.642	0.547
	(1.09)	(−0.12)	(1.09)		(0.59)	(1.53)
ind	0.425	0.211	0.593	ind	−0.406	0.776 ***
	(0.79)	(1.39)	(1.13)		(−0.70)	(4.06)
gdp	0.082 ***	0.000	0.082 ***	gdp	0.075 ***	0.018 **
	(4.12)	(0.04)	(4.23)		(3.46)	(2.46)
cons	4.601 ***	4.638 ***	8.285 ***	cons	2.889 ***	2.107 ***
	(9.75)	(34.72)	(10.80)		(5.65)	(12.27)
N	770	770	770	N	770	770
R2	0.662	0.241	0.679	R2	0.687	0.957

Note: The numbers in parentheses are t values; ***, ** indicate that they have passed the 1%, 5% significance tests, respectively.

Table 7. Regression results of Midwest non-resource cities.

	Midwest Non-Resource Cities					
	ce	ee	ce		es	ce
gp	−0.010 *	−0.000	−0.010 **	gp	−0.011 **	0.000
	(−1.96)	(−0.12)	(−2.05)		(−2.08)	(0.16)
ee		.	−0.813 ***	es	.	0.907 ***
		(.)	(−6.82)		(.)	(99.53)
fin	0.804 ***	−0.026	0.783 ***	fin	0.812 ***	0.067
	(3.36)	(−0.36)	(3.37)		(3.20)	(1.04)
inf	−1.587 **	−0.089	−1.660 ***	inf	−1.654 **	−0.087
	(−2.41)	(−0.45)	(−2.59)		(−2.36)	(−0.49)
pop	0.239 *	−0.011	0.230 *	pop	0.212	0.047
	(1.71)	(−0.26)	(1.69)		(1.42)	(1.26)
edu	0.235	0.028	0.258	edu	−0.476	0.666 ***
	(0.28)	(0.12)	(0.32)		(−0.54)	(3.02)
ind	−1.246 ***	−0.095	−1.323 ***	ind	−1.340 ***	−0.030
	(−2.67)	(−0.69)	(−2.92)		(−2.70)	(−0.24)
gdp	−0.049 **	0.015 **	−0.037 *	gdp	−0.053 **	−0.001
	(−2.44)	(2.43)	(−1.90)		(−2.46)	(−0.25)
cons	5.888 ***	4.628 ***	9.648 ***	cons	4.009 ***	2.250 ***
	(14.05)	(37.29)	(14.08)		(9.00)	(19.14)
N	860	860	860	N	860	860
R2	0.688	0.240	0.706	R2	0.712	0.978

Note: The numbers in parentheses are t values; ***, **, * indicate that they have passed the 1%, 5%, and 10% significance tests, respectively.

3.3. Robustness Test

In order to test the robustness of the results of this paper, the robustness test is carried out for all the above empirical results, including the robustness test of the direct linear and nonlinear effects of green technology innovation on carbon emissions and the bootstrap test of mediating effect. The specific inspection method is shown below.

3.3.1. Robustness Test of the Linear and Nonlinear Direct Impact of Green Technology Innovation on Carbon Emissions

1. Replace the core explanatory variable. Green technology innovation is replaced by the data with a lag period. The results of linear regression are consistent with those in Table 2. At the same time, this also alleviates the possible endogenous problems among the data in the same period to a certain extent.
2. Replace the control variable. Replace the measurement method of education level in the control variable with regional education fiscal expenditure/regional GDP, and the empirical results are the same as those in Table 2.

3.3.2. Existence Test of the Intermediary Effect

Although Wen and Ye (2014) [27] proposed that stepwise regression is also an effective way to test the existence of a mediating effect, this paper uses a bootstrap method to test the existence of a mediating effect in the robustness test. The test results show that in all stepwise regression with partial mediating effect and masking effect when using the bootstrap method to test it, the 95% confidence interval of the total indirect effect does not contain 0, which proves that the intermediary effect is significant and there is no spurious regression. At the same time, the signs of direct effect and indirect effect reported by the bootstrap method are the same as those of the stepwise regression coefficient reported in Tables 3–7, which proves that the existence of the intermediary effect is robust.

4. Discussion

Energy consumption-oriented green technology innovation refers to demand-side innovation, such as green transportation and new energy. This innovation can reduce traditional energy consumption and let consumers enjoy the same quality of life but with reduced emissions. Energy efficiency-oriented green technology innovation refers to supplier innovation such as ultra-supercritical power generation. This innovation can enable manufacturers to produce the same products with fewer emissions by promoting green productivity. This paper first discusses the emission reduction effect of green technology innovation in energy consumption and energy efficiency. It is found that the emission reduction effect of energy efficiency is uncertain due to the low fitting value. Therefore, based on the existing relevant research results, this paper focuses on analyzing the emission reduction effects of green technology innovation in different cities from the perspective of energy consumption intermediaries and divides Chinese cities into four categories by using two dimensions of regional distribution and resource endowment: Eastern non-resource cities, Eastern resource cities, Midwest resource cities, and Midwest non-resource cities. In this way, different green technology innovation policy recommendations can be formulated for different types of cities.

This paper mainly discusses the emission reduction effect of green technology innovation with the help of two intermediary variables: energy efficiency and energy consumption. The emphasis on variable selection and empirical method is different from other studies: most scholars study innovation emission reduction from the perspective of industrial structure [28,29], economic growth [30], income level [31], environmental supervision [32], and so on. Few works in the literature have compared the green technology innovation and emission reduction effects of energy efficiency and energy consumption. From the empirical results, this paper confirms that the emission reduction effect of energy consumption-oriented green technology innovation is stronger than energy efficiency, and the intermediary difference between different types of cities is large, but it fails to reasonably explain the reason for the low fitting value of the energy efficiency-oriented emission reduction effect, and whether it can really achieve emission reduction is still unclear, which is also the limitation of this paper.

Our research results show that the energy consumption-oriented emission reduction strategy of the Eastern resource cities is the main development direction in the future. As most of them are first-line cities located in the coastal areas of China, the green industry system is relatively perfect, and the strong resource agglomeration effect makes the economy develop rapidly, but there is also a certain amount of resource surplus. The Eastern non-resource cities have two intermediary effects at the same time. The better location advantages enable them to properly undertake the remaining green industries of the Eastern resource cities and form a good technology transfer effect. The energy consumption of Midwest resource cities has a complete intermediary effect, and energy efficiency is only a part of the intermediary effect, so the emission reduction effect of energy consumption is better than that of energy efficiency. At the same time, Midwest resource cities are generally highly industrialized, and their traditional energy consumption is high. However, as most of the energy consumption serves Eastern cities, it is difficult to achieve a balance between low-carbon transformation and energy supply. Due to the limitations of the development scale, Midwest non-resource cities cannot achieve indirect emission reduction of energy efficiency, and the indirect emission reduction coefficient of energy consumption is also very small. As such, cities can only achieve emission reduction through energy consumption, and the premise of improving green energy consumption cannot be separated from economic development; it is urgent to increase the economic aggregate of local cities.

5. Conclusions

Taking 250 prefecture-level cities in China from 2010 to 2019 as data samples, this paper first analyzes the emission reduction mechanism of green technology innovation and examines the linear impact of green technology innovation on carbon emissions. Then, from the two dimensions of regional distribution and resource endowment, the city classification is gradually refined to explore the emission reduction effect of green technology innovation when energy efficiency and energy consumption are intermediary variables. The conclusions are as follows: (1). At present, the energy consumption-oriented green technology innovation in most cities in China has a more obvious emission reduction effect, while the energy efficiency-oriented green technology innovation is weaker. (2). Only the Eastern non-resource cities and the Midwest resource cities can achieve indirect emission reduction through energy efficiency. (3). Both the Eastern resource cities and the Midwest non-resource cities have no intermediary effect of energy efficiency, and carbon emission reduction is more difficult than in other cities.

Based on the above conclusions, this paper draws the following three insights and puts forward corresponding policy suggestions for different cities in the sub-region and resource endowment:

For the Eastern resource cities, green industries need to be promoted to more consumption areas, such as new energy vehicles and green finance, to prevent green industries from going into surplus. At the same time, the participation of local green technology innovation enterprises should be appropriately limited, R&D investment should be increased, and scientific and technological resources in the dual carbon field should be provided for other types of cities.

For the Eastern non-resource cities, a parallel reduction policy of energy efficiency and energy consumption can be adopted. Accelerate the improvement of the energy price mechanism conducive to sustainable development and intensive use of resources; increase the research and development of clean energy and promote the transformation of the entire industrial chain in the direction of clean and high-added value; increase the proportion of renewable energy and clean energy in the industry, so as to increase green energy consumption.

For the Midwest resource cities, the priority should be given to energy consumption-side emission reduction policies, supplemented by energy efficiency-side emission reduction policies. Strengthen the connection between green industry and eastern cities, absorb green technology spillovers from eastern cities through better regional cooperation, promote the transformation of traditional industries to green, develop green steel, green chemicals, and other industries, and jointly promote China's carbon emission reduction as practitioners of the industrial chain.

For the Midwest non-resource cities, we can learn from the development path of Eastern resource cities, formulate long-term sustainable development policies, improve the price mechanism of environmental resources, and appropriately develop low-carbon and low-threshold industries such as tourism services and modern agriculture. Then focus on improving the scale of local public infrastructure construction to lay a solid foundation for future low-carbon transformation.

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