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Impact of Green Infrastructure Investment on Urban Carbon Emissions in China

Jinhui Sang and Lingying Pan *

Business School, University of Shanghai for Science and Technology, Jungong Road 516, Yangpu District, Shanghai 200093, China; 212010887@st.usst.edu.cn
* Correspondence: panly@usst.edu.cn; Tel.: +86-18221483268

Abstract: Given the increasingly severe global climate change, the reduction in urban greenhouse gas emissions has become the common goal of all nations. As a widely concerned sustainable development strategy, green infrastructure investment (GII) aims to reduce urban carbon emissions, improve the efficiency of resource utilization, and improve environmental quality. However, the construction cycle of green infrastructure is long, and the construction process itself may produce carbon emissions; so, the final effect of GII on urban carbon emissions is unclear, which deserves our in-depth study. Further, is this effect having a time-lag effect? Is there only a simple linear relationship between GII and urban carbon emissions? Based on panel data from 235 Chinese cities from 2006 to 2019, this study conducted an econometric regression analysis using time-lag-effect and threshold-effect models. The results showed the following: (1) GII had a negative inhibitory effect on urban CO_2 emissions. Adding one unit to the GII could reduce urban CO_2 emissions by 0.032 units. (2) GII exhibited a time-lag effect on urban CO_2 emissions, and the greatest reduction in CO_2 emissions occurred in the third lag period. (3) GII had a threshold effect on urban CO_2 emissions based on technological progress (TP). This paper used the static and dynamic panel threshold models to research separately, and obtained the corresponding regression results. In the static panel, the double threshold values for TP were 3.9120 and 6.8035. At different TP levels, GII had an inhibitory effect on CO_2 emissions, but the coefficients were different. However, in the dynamic panel, the threshold value was 3.666. The threshold changed over time and the effect of GII on CO_2 emissions shifted from facilitation to inhibition.

Keywords: green infrastructure investment; CO_2 emissions; time-lag effect; threshold effect

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1. Introduction

With global climate warming and the increasingly deteriorating state of resources and the environment, the development idea of a low-carbon, sustainable, and green economy has been implemented. In the process of low-carbon and sustainable development, the international community has successively signed international agreements to address climate change. The local governments of various countries have also formulated policies and measures to reduce emissions, put forward targets for the reduction in greenhouse gas emissions at all stages, and formulated strategic plans and specific arrangements at the national, industrial, and enterprise levels. The Proposal of the CPC Central Committee on formulating the 14th Five-Year Plan for National Economic and Social Development and the Long-term goals for 2035 clearly indicates that we should hasten the promotion of green and low-carbon development. The total carbon emissions should peak by 2030 and then show a downward trend, and the ecological environment should manifest fundamental improvements. Chinese President Xi Jinping, in his speech at the 75th session of the United Nations General Assembly, pledged that China would increase its autonomous contribution and adopt more effective policies and measures, and emphasized that China will strive to reach its peak carbon dioxide (CO_2) emissions before 2030 and achieve carbon neutrality before 2060.

China is the largest developing country in the world and has the highest primary energy consumption [1]. In a global rigid carbon constraint environment, the reduction in CO_2 emissions has become the core focus for China to achieve its set goals in a timely manner and achieve sustainable economic development. China's CO_2 emission reduction policy can be traced back to the 11th Five-Year Plan proposed in 2006, which states that energy consumption per unit of gross domestic product (GDP) and total emissions of major pollutants will be reduced by approximately 20% and 10%, respectively, during the 11th Five-Year Plan period. As shown in Figure 1, China's total CO_2 emissions from 2006 to 2019 fluctuated; that is, these initially increased, decreased, and then increased again. From the source of CO_2 production, the proportion of raw coal in the total CO_2 emissions has decreased but still accounts for a large proportion. Therefore, China's dependence on traditional high-carbon energy remains very high, and the task of CO_2 emission reduction is still arduous.

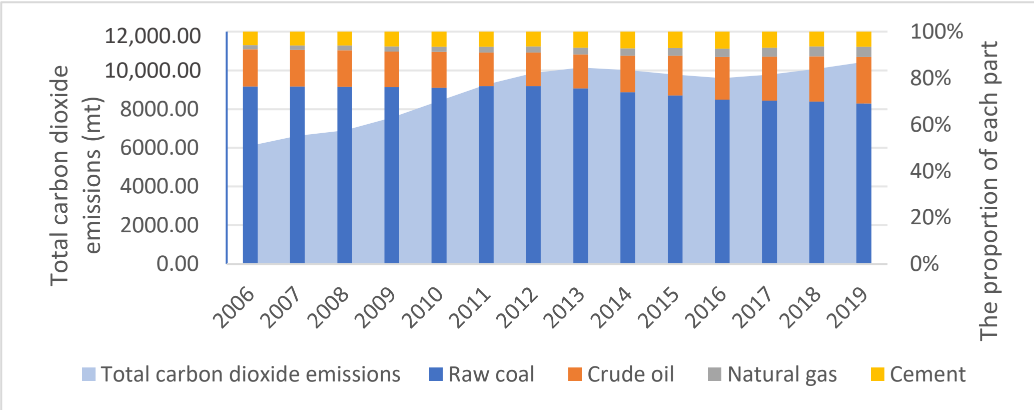

Figure 1. Changes in China's CO_2 emissions from 2006 to 2019.

Urban carbon emissions refer to the emissions of greenhouse gases, such as CO_2, produced by urban activities. As the core of climate change mitigation and the sustainability of human development [2], cities represent two-thirds of global energy consumption and account for more than 70% of greenhouse gas emissions [3]. The green industry is a key means to achieve green, low-carbon, and sustainable development. In the urban development process, the green upgrading of infrastructure plays an important role. Green infrastructure investment (GII) refers to a category of investment in sustainable and environmentally friendly infrastructure projects. It aims to address the shortcomings of existing infrastructure and promote economic growth and social wellbeing while reducing the negative impact on the environment. From 2006 to 2020, China's GII total showed an overall upward trend, with an average annual growth rate of 13.71% (Figure 2).

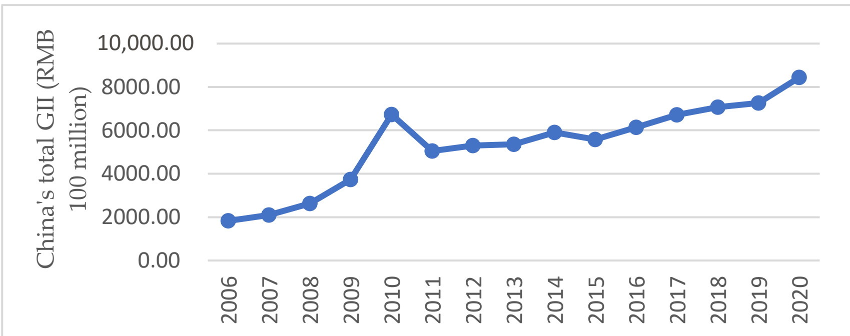

Figure 2. The time change in GII in China.

In this section, the total GII in Chinese cities in 2006–2019 was grouped into more than RMB 50 billion, RMB 10–50 billion, RMB 5–10 billion, and less than RMB 5 billion, and its geographical distribution characteristics were observed. The results showed the unbalanced distribution of GII in Chinese cities. Cities with the highest investment levels are mainly concentrated in municipalities such as Beijing, Tianjin, and Chongqing. Cities with relatively high investment levels are mainly located in eastern coastal regions. Meanwhile, cities with lower investment levels are primarily distributed in central, western, and northeastern regions (Figure 3). Such an imbalance may be influenced by a combination of factors, including the level of economic development, urban size and population, government policies, geographical and climatic conditions, and urban sustainable development needs.

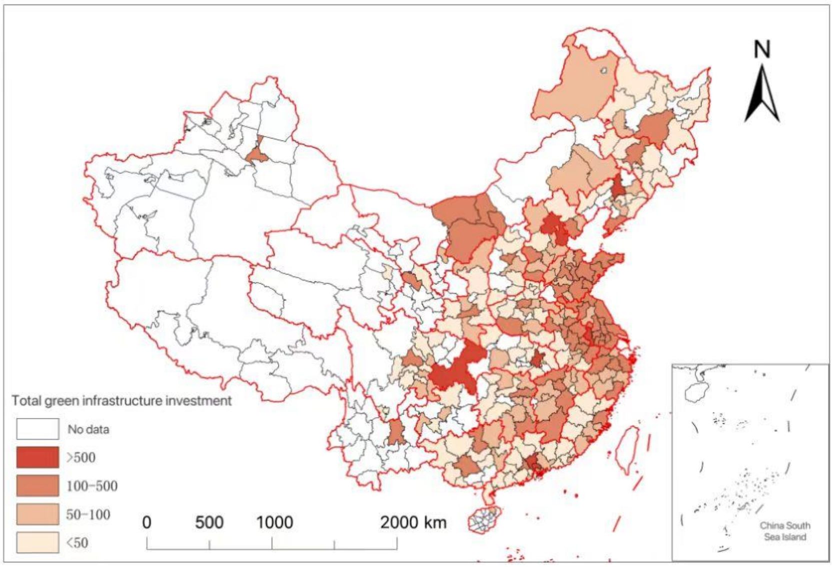

Figure 3. Distribution map of GII in China.

To sum up, GII and urban carbon emissions are complex systems. It is important to deeply explore the relationship between GII and urban carbon emission for sustainable urban development and the timely achievement of carbon emission reduction targets in China. This paper is organized into five sections. The first part of this article is the introduction. This section presents the background and significance of this study. The second part explores the research status of the domestic and foreign literature and presents a brief literature review. The third section begins with a detailed description of how GII affects urban carbon emissions and presents the research hypotheses of this paper. In addition, the study model is introduced, including data and variables. The fourth part conducts a scientific empirical analysis and explains the results. The fifth part first summarizes the main conclusions, and then puts forward the corresponding suggestions according to the actual situation.

The main goal of this paper was, first, to explore the complex influence mechanism of GII on urban carbon emissions, because the role of GII on urban carbon emissions may have two sides. Green infrastructure was aimed at carbon reduction, but the green infrastructure construction process may lead to increased energy consumption and increased carbon emissions. On this basis, another main goal of the study was to verify whether there is a time-lag effect and a threshold effect for the impact of GII on carbon emissions.

The unique contributions of this paper are as follows: (1) Lots of studies have empirically analyzed the influencing factors of carbon emissions, such as economic level, population size, and fiscal expenditure. However, these explanatory variables are relatively macro. This paper refines the research perspective to a certain type of infrastructure investment and deeply explores the impact of GII on urban carbon emissions to better fill the gap of previous studies. (2) Most of the existing literature focused on the accounting methods, influencing factors, industry differences and potentials of carbon emissions, but few studies have gone deeper into the mechanisms that affect carbon emissions. This paper provides a comprehensive analysis of the mechanism of GII on urban carbon emissions. According to the scale, technological, and structural effect, this paper gives a general analysis of the relationship between GII and urban carbon emissions, and combines a specific impact of GII on urban carbon emissions. (3) This paper considers the time-lag effect and the threshold effect, and sets up the corresponding models for empirical studies. Compared with the existing linear studies which can only reflect the overall trend and relationship, the threshold-effect study in this paper can find the neglected turning points, identify the key thresholds for technological progress affecting carbon emissions, and deepen the understanding of the relationship between variables.

The conclusions drawn from this study are useful for all parties in society to make more reasonable investment decisions. This study can be applied to carbon emission reduction initiatives, providing lessons for reducing greenhouse gas emissions and helping global climate governance.

2. Literature Review

2.1. Research on Green Infrastructure

Rosenstein defined infrastructure as social prior capital, and it mainly includes economic infrastructure, such as electricity, transportation, communication, and energy [4]. Later, some scholars expanded the definition of infrastructure and assumed that it includes not only economic but also social infrastructures, such as medical care, education, and public health [5]. Compared with the traditional infrastructure, which produces more pollution in the construction process, the construction of green infrastructure has more ecofriendly attributes in terms of subject, object, and construction concepts that are aimed at a greener and more ecological development direction [6].

At present, the definitions of the green infrastructure concept lack unity. Huang et al. defined green infrastructure from the macro-, meso-, and microscales [7]. Sun et al. referred to green infrastructure as ecological infrastructure, including, but not limited to, renewable energy, wastewater treatment, and other projects; this definition is notably different from traditional infrastructure projects [8]. Other scholars believe that the components of green infrastructure include a green space and park system and an open space system [9,10]. Zhang et al. defined “green infrastructure” as the range of measures that use plant or soil systems, permeable pavement or other permeable surfaces or substrates, stormwater harvest and reuse, or landscaping to store, infiltrate, or evapotranspirate stormwater and reduce flows to sewer systems or surface waters [11]. The pattern of green infrastructure and its changes are influenced by a variety of factors, among which natural endowment conditions, regional development level, social and cultural atmospheres, and decision-making management orientation act as the main driving factors [12]. Song and Feng explored the internal relationship between green infrastructure and urban renewal [13]. Zhou et al. observed that an urban environment and green infrastructure have multiple impacts on urban economic development and vary across regions [14].

The GII studied in this paper originated from three parts of fixed asset investment in urban municipal utility construction. The first part is drainage investment, which includes investment in sludge disposal, sewage treatment, and recycled water utilization. The second part is landscaping investment. Finally, the third part is urban environmental sanitation investment, including garbage disposal investment.

2.2. Research on Urban Carbon Emissions

2.2.1. Accounting Methods of Carbon Emissions

The first type of carbon accounting method supports the carbon-trading market, and it is mainly based on the methodology and guidance system issued by the IPCC (Intergovernmental Panel on Climate Change) and other institutions. The emission factor, mass balance, and field measurement methods are widely recognized carbon accounting methods. Singh et al. used the basic mass balance method of energy consumption to calculate in detail the energy and carbon footprint accounting situation of sewage treatment plants based on different technology selections and sizes [15]. Tang et al. installed a CO_2 continuous-emission monitoring system in gas-fired power plants using the emission factor and field measurement methods and further compared and analyzed the differences in carbon emissions from gas-fired power plants and the surplus and shortage of the trial quota under the two calculation methods [16]. The emission factor method is the most widely used carbon emission accounting method. Abdul-Wahab et al. used the emission factor method to study gas- and oil-related activities in the Sultanate of Oman from 1972 to 2013 and observed that local consumption, crude oil, and natural gas production increased sharply, and CO_2 emissions also increased [17]. Huang and Qu used the carbon emission coefficient method (IPCC) to calculate the carbon emission data of 30 provinces and cities in China from 1997 to 2019 and analyzed the spatial and temporal changes in carbon emissions in the textile and garment industry [18]. Alam et al. calculated the relationship between economic growth, energy consumption, and carbon emissions in various regions of Bangladesh using the IPCC method [19]. Kurokawa et al. calculated the carbon emissions generated by China, India, and other Asian countries between 2000 and 2008 using the IPCC inventory method [20]. Jorgenson computed CO_2 emissions in 50 USA states and the District of Columbia using the IPCC inventory method [21]. Köne and Büke applied the IPCC inventory method to measure Turkey's CO_2 emissions between 1971 and 2014 [22].

The second type of carbon emission estimation method is based on the input–output and life cycle evaluation methods, and it is used to measure the greenhouse gas emissions at each production step of the product and the whole life cycle. For example, a multi-regional input–output (MRIO) model was constructed to measure and compare the trade-induced carbon emissions within the forest industry among the BRICS countries: Brazil, Russia, India, China, and South Africa [23]. The third category is based on the factor decomposition method and is mainly conducted via modeling to analyze the interaction between relevant factors and carbon emissions. The most common methods belonging to this category include index and structural decomposition analyses.

2.2.2. Factors Influencing Carbon Emissions

Regarding the research on factors influencing carbon emissions, to date, most scholars start from the basis of three factors, namely, population, affluence, and technology, and extend their research using the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model. Wei et al. investigated five indicators, namely, population size, economic development level, urbanization rate, industrial structure (IS), and energy intensity [24]. Di et al. selected six indicators, including economic scale, population scale, IS, public income, public expenditure, and living standard, as the influencing factors of carbon emissions [25]. From the perspective of supply-side reform, Wang et al. studied six indicators, such as human, capital, technical, industrial, and institutional factors, and economic growth [26]. According to Lenzen et al., the main reasons for the increased carbon emissions are the improvement in the living standards of residents, the increase in exports, and the expansion of population size; they conducted an empirical analysis using data sets from various regions in Brazil [27]. Glaeser and Kahn attempted to quantify the CO_2 emissions associated with new constructions in different locations across the country and observed a strong negative association between emissions and land use regulations [28].

2.2.3. Industry Carbon Emissions

An increasing number of studies have focused on the carbon emissions of different industries. For example, Chen et al. analyzed the influencing factors of industrial carbon emissions at the provincial scale [29]. Muryani et al. identified the main agents, problems and strategies for lowering industrial CO_2 emissions in the cement industry in East Java, Indonesia, by applying an analytical network process [30]. Gao et al. established an extended STIRPAT model, with the rural population, crop sown area, number of large-scale animal husbandry, per capita agricultural GDP, rural per capita disposable income, agricultural mechanization level, and urbanization rate as the influencing factors of agricultural carbon emission [31]. Lin et al. examined the linear and non-linear relationships between green finance and carbon emissions using spatial measurement methods [32]. Lee et al. explored the direct correlation between tourism and carbon emissions in European countries, and their results showed that tourism development can reduce carbon emissions to a certain extent [33]. Nadezhda studied pollution abatement and environmental equity in a dynamic panel model using data from 234 plants in the USA's pulp and paper industry [34].

2.2.4. Carbon Emission Potential

On the basis of revealing the evolution mechanism and action law of provincial carbon emissions, Wu delineated four types of emission reduction zones based on agglomeration characteristics and discovered that different provinces in China have differentiated emission reduction characteristics and potentials [35]. Zhang et al. divided 31 provinces into five categories based on economic development, energy consumption, IS, and emission characteristics and proposed differentiated peaking action paths based on their respective peaking action schedules and peaking situations [36]. Considering the importance of equity and efficiency principles in China's carbon emission reduction potential, Zhou et al. re-estimated the carbon emission reduction potential of 29 provinces in Mainland China from 1997 to 2016; they observed that regional differences in carbon emission reduction potential and the dynamic evolution of distribution are influenced by many factors, such as population size, economic development, IS, lifestyle, energy intensity, and research and experimental development (R&D) funding [37]. Tian and Chen comprehensively evaluated the carbon emission reduction effectiveness of 30 provinces and regions in Mainland China from 2005 to 2016, and their results showed that most regions have achieved or can potentially achieve the set carbon emission reduction targets; however, nine regions, including Shanxi, Inner Mongolia, and Hainan, lagged in emission reduction [38].

2.3. Research on the Correlation between Infrastructure Investment and Carbon Emissions

Research on the correlation between infrastructure investment and carbon emissions is often put into the broad framework of economy and environment. Using a global panel comprising 140 countries from 1980 to 2021, Acheampong and Opoku observed inverted U-shaped and U-shaped relationships between emissions and economic growth and between ecological footprint indicators of environmental degradation and economic growth, respectively [39]. With the 11 categories of major infrastructure in Shanghai as an example, Guo studied the socioeconomic and natural geographical driving factors behind the material metabolism of infrastructure and quantified the impact of urban infrastructure development on the cross-regional ecological environment [40]. Li and Huang observed that the government's investment in environmental protection had direct and indirect impacts on carbon emission reduction [41]. On the one hand, the fiscal environmental protection expenditure has a considerable inhibitory effect on local carbon emissions, which can effectively promote local carbon emission reduction. On the other hand, the increase in the local financial environmental protection expenditure remarkably reduces the carbon emission of the surrounding areas, which causes the spatial spillover effect of carbon emission reduction management. Zhang studied the impact of environmental policy, environmental protection expenditure, and government execution on carbon emissions and revealed that improvements in the three can inhibit carbon emissions [42]. Zhong and Sun argued that the impact of infrastructure on carbon emissions shows temporal differences, and an infrastructure with remarkable sustainability needs to act in the long term to promote carbon reduction [43].

The limited research on GII and the environment indicates that scholars failed to arrive at a unified conclusion. Some scholars believe that GII can substantially reduce CO_2 emissions. Green infrastructure implementation in urban areas can alleviate the impacts of urban stormwater on aquatic ecosystems and human health, improve the quality of surface and ground water [44–48], considerably reduce surface air temperature [49,50], and therefore reduce energy consumption in air conditioning [51,52]. Jayaraman et al. observed that GII benefits Arab countries in reducing CO_2 emissions [53]. Mwanzu et al. also found that urban green spaces are essential for reducing the negative environmental and health impacts of rapid urbanization in Kenya [54]. According to other scholars, although GII can improve energy efficiency and bring additional benefits, it does not considerably reduce carbon emissions and improve air quality [55]. Lin and Yang found that in China as a whole, an inverted U-shaped relationship exists between GII and carbon emissions [6].

The existing literature has certain reference significance, but there is still room for expansion. First, although a large number of studies pay close attention to carbon emissions, most of the research focuses on the accounting and influencing factors of carbon emissions. Most of these studies were based on the STIRPAT model and gave a comprehensive and perfect consideration of the influencing factor system of carbon emissions. However, the research still adopts relatively macro and well-defined indicators such as population, economy and industry, and few studies focus on the impact of GII on carbon emissions. Second, in the existing literature on the correlation of GII and carbon emissions, the research conclusions were not uniform. The impact of GII on urban carbon emissions is complex, and it cannot be simply assumed that GII can certainly reduce carbon emissions. However, the previous literature has mostly focused on the low energy consumption of green infrastructure benefits, ignoring the possible increase in carbon emissions in the construction process, and did not fully consider the various effects brought by the increase in GII.

3. Materials and Methods

3.1. Mechanism Analysis of GII on Urban Carbon Emissions

This part mainly analyzes the mechanism of GII on urban carbon emissions and puts forward research hypotheses accordingly. Why does GII contribute to urban carbon emissions? GII is essentially an economic phenomenon, and the intuitive level of urban carbon emissions belongs to the environment. The relationship of economy and environment can be largely explained by the scale, structural, and technological effects proposed by Grossman and Krueger [56] in 1991. Therefore, this paper extends its research ideas to the specific research of GII and urban carbon emissions. The above three effects were applied to the general analysis of the relationship between GII and urban carbon emissions, and three corresponding hypotheses were proposed combined on the specific effects of GII on urban carbon emissions.

3.1.1. Scale Effect of GII

The scale effect of GII on urban carbon emissions was divided into economies and diseconomies of scale. Economies of scale are manifested as follows. As the scale of GII increases, the cost of related technologies and equipment usually decreases, and the benefits generated per unit of investment gradually increase, attracting more investment and adoption, driving market penetration and diffusion, and further promoting green development. Diseconomies of scale are mainly reflected in the fact that although GIIs aim to reduce reliance on fossil fuels, they still require energy and material consumption during construction and operation. Large-scale increases in GII may lead to a higher demand for energy and materials, which results in a certain level of environmental impact and increased carbon emissions.

In addition, GII can increase the carbon sink capacity of cities to some extent. GII often involves urban green space construction and urban forest planning. Green space helps in reducing CO_2 concentrations in the atmosphere by absorbing carbon dioxide and fixing carbon elements. Urban forests and vegetation can provide shade and evaporation, slow down the urban heat island effect [57], reduce the demand for air conditioners, and further reduce carbon emissions. Therefore, the following hypothesis was proposed.

H1: *GII plays a negative role in urban carbon emissions.*

3.1.2. Structural Effect of GII

The structural effect of GII mainly includes the transformation of the energy structure and industrial structure. From the perspective of energy, GII encourages cities to implement energy transformation and innovation and to adopt cleaner and more renewable forms of energy, such as solar, wind, and geothermal energy. The use of renewable energy will gradually replace traditional high-carbon energy sources, such as coal burning and oil, and reduce the dependence on fossil fuels, thus reducing urban carbon emissions [58].

From the perspective of industries, on the one hand, GII contributes to the formation of a comprehensive and efficient green industrial ecosystem, which has a positive impact on the upgrading of IS and low-carbon transformation. Investing in and supporting green infrastructure construction will drive the development of the entire industrial chain and stimulate the demand of related industries, which will promote the expansion and optimization of the supply chain. For example, increased investment in landscaping will drive the development of industrial chains, such as garden design and construction, garden maintenance and management, and tourism and leisure, leading to a more desirable industrial ecosystem. On the other hand, increasing GII may change market demand and consumer behavior patterns. Through the promotion of green technologies and products, consumers' demand for green products and services may increase, which will lead to a shift in IS towards green and sustainable development direction.

To sum up, as the transformation of energy structure and industrial structure brought by GII needs time to realize, the impact of GII as an input on urban carbon emissions may not be fully observed in the current period. In economics, the response of the dependent variable to the independent variable often exhibits a temporal delay, which is called a lag. In addition, the green infrastructure projects are large and complex, and they will still take a long time to build after the investment. In this process, the transfer and distribution of human capital and other production factors need time to adjust, and people's psychology, lifestyle and consumption habits also need to be gradually changed. These adaptation and transition processes lead to a lag in carbon reduction effects. Therefore, the following hypothesis is proposed.

H2: *A time-lag effect exists in the impact of GII on urban carbon emissions.*

3.1.3. Technological Effect of GII

Uncertainty exists regarding the technological effect of GII. On the one hand, GII will promote the research and adoption of new environmentally friendly technologies and solutions, which will drive innovation and progress in related technologies. In addition, through the introduction and adoption of green technologies and equipment, experience and best practices can be shared between regions to accelerate the application and diffusion of green technologies in various regions and further promote the green transformation of cities. On the other hand, technical innovation caused by GII may raise a country's carbon emissions [59]. In the early stage of GII, the spillover effect of technology is low because the innovators focus on their own economic benefits. Moreover, a certain run-in period may be observed when innovative technologies are used; that is, the expected effects can be gradually manifested as scientific and technological innovation matures.

Thus, the impact of GII on urban carbon emissions is extremely complex and may not be a simple linear relationship. Technological progress (TP) is an important factor that cannot be ignored in the topic of economic and environmental pollution. A low level of scientific and technological innovation is inadequate to produce positive externalities; therefore, it is difficult to attract resources and enterprises to invest in green infrastructure with a long investment cycle and slow return. However, with the improvement in the level of scientific and technological innovation, innovation subjects will gradually improve the ecosystem of scientific and technological innovation and become more mature in their application. At this point, the positive spillover effect of scientific and technological innovation will attract more green investment and show an inhibitory effect on carbon emissions. Therefore, the following hypothesis is proposed.

H3: *The impact of GII on urban carbon emissions has a threshold effect based on TP.*

3.2. Benchmark Model Construction and Related Tests

3.2.1. Model Design

This paper refers to the research of Huo and Zhang [60] and considers carbon emission intensity (CEI) as the explained variable. GII is the core explanatory variable of this paper, and it is the sum of drainage investment, landscaping investment, and environmental sanitation investment. As for the control variables, this paper selects the indicators of energy consumption structure (ECS), openness (O), population density (PD), TP, urbanization level (UL), and government environmental governance (GEG) with reference to previous studies [61–65]. The indicators corresponding to the variables covered in this paper are shown in Table 1 and can be explained as follows.

Table 1. Relevant variables.

Variable		Explanation	Indicators
Explained variable	CEI	Carbon emission intensity	Ratio of carbon emissions to the gross economic product
Core explanatory variable	GII	Green infrastructure investment	Sum of drainage investment, landscaping investment, and environmental sanitation investment
Control variables	ECS	Energy consumption structure	Ratio of coal consumption to total energy consumption
	O	Openness	Actual amount of international investment used in the current year
	PD	Population density	Size of population per unit area
	TP	Technical progress	Number of green utility model patent applications
	UL	Urbanization level	Ratio of the urban built-up area to the urban area
	GEG	Government environmental governance	Proportion of words related to environmental protection (such as emission reduction, low carbon, and air) in the local government work report

The consumption of fossil energy, such as coal, is highly related to urban carbon emissions. A reasonable and green ECS will effectively improve energy utilization efficiency. The impact of O on urban carbon emissions requires further investigation. On the one hand, an improved level of O is conducive to the introduction of advanced production technology to improve the pollution status. On the other hand, according to the hypothesis of pollution paradise, an improved level of O will be accompanied by the transfer of highly polluting industries to relatively backward countries and regions. Cities with high PD have highly intensive economic activities, which promotes energy consumption leading to increased carbon emissions. Therefore, PD is predicted to promote urban CEI. The improvement of technology is conducive to improving energy efficiency and changing production methods, which reduces the CEI. Therefore, the coefficient of TP is theoretically negative. Urbanization, to a certain extent, can promote the use of clean energy and the reduction in carbon intensity. In addition, the relocation of economic activity due to agglomeration is likely to operate at especially short distances [66], which reduces the transport demand and carbon emissions. GEG can better reflect the whole image of the GEG policy, unlike indicators such as the number of environmental protection personnel, R&D investment in environmental pollution control, and pollution tax rate or pollution control cost, which only focus on one aspect of the GEG.

In conclusion, the following model was constructed to verify the impact of *GII* on urban carbon emissions.

$$lnCEI_{it} = \alpha_0 + \alpha_1 lnGII_{it} + \alpha_k \sum_{k=2}^{7} X_{control} + \varepsilon_{it} \quad (1)$$

where *CEI* corresponds to the explained variable, *GII* refers to the core explanatory variable, $X_{control}$ represents the above series of control variables, α_0 is the intercept term, α_1 stands for the regression coefficient for the core explanatory variable, and α_k (k = 2, 3, ..., 7) is the regression coefficient of the control variable. i and t indicate the region and time, respectively. ε_{it} is a random error term.

3.2.2. Data Processing

Given the serious lack and unavailability of some data, the sample in this paper included 235 cities at the prefecture level and above in China from 2006 to 2019. The original data were mainly obtained from China Carbon Emission Accounting and Database, the China Statistical Yearbook, China Provincial and Municipal Economic Development Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, China City Statistical Yearbook, the local statistics bureau, and the municipal statistical bulletin of national economic and social development. Some of the missing data were complemented by the linear interpolation method. To solve the problem of excessive disparity in data magnitudes, the data corresponding to urban CEI, GII, O, PD, TP, and GEG were processed logarithmically (the base of logarithms is natural logarithms) before the empirical analysis. Table 2 shows the descriptive statistics for each variable.

Table 2. Descriptive statistics of relevant variables from 2006 to 2019.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
lnCEI	3290	5.219	0.821	0.814	8.354
lnGII	3290	10.420	1.420	0.000	16.070
ECS	3290	0.805	0.152	0.040	1.000
lnO	3290	10.080	1.767	0.000	14.700
lnPD	3290	7.945	0.742	5.513	9.908
lnTP	3290	4.173	1.813	0.000	9.433
UL	3290	0.410	0.274	0.021	1.000
lnGEG	3290	−5.357	0.477	−9.210	−4.012

3.2.3. Related Tests

(1) Multicollinearity test

Variance inflation factor (VIF) is an indicator of multicollinearity. It measures how much the variance of an estimated regression coefficient is inflated due to collinearity with other independent variables in the model. A VIF value greater than 10 indicates high correlation between the independent variable and other variables, suggesting serious multicollinearity. A VIF between 5 and 10 indicates moderate correlation. A VIF between 1 and 5 is acceptable. A VIF of 1 means the independent variable is completely uncorrelated with others.

As shown in Table 3, the VIF of each variable was less than 10, which indicates that no multicollinearity existed among the explanatory variables considered in this paper.

Table 3. VIF of each variable.

Variable	VIF	1/VIF
lnGII	1.80	0.56
ECS	1.04	0.96
lnO	2.01	0.50
lnPD	5.15	0.19
lnTP	2.49	0.40
UL	5.03	0.20
lnGEG	1.19	0.84
Mean VIF	2.67	

(2) Unit root and stationarity test

Regression analysis requires the variables to be stationary. If there is a unit root in the variables, it means the variables are non-stationary. If regression is directly conducted on non-stationary variables, it will lead to spurious regression and thus unreliable regression results. Therefore, a unit root test needs to be conducted to examine whether the variables are stationary or not. Each variable series is investigated with panel unit root tests, including that of Levin, Lee and Chu (LLC), Im, Pesaran and Shin (IPS), Fisher's ADF test, and the Hadri test. If the null hypothesis of the existence of the unit root is rejected in the test, then this sequence is stationary, and vice versa. The results are given in Table 4. The results suggest that all variables are stationary and the next regression analysis can be performed using the original series.

Table 4. Unit root results.

Variable	LLC	IPS	Fisher (ADF)	Hadri
lnCEI	−15.0201 [0.0000]	−4.2707 [0.0000]	4.3075 [0.0000]	92.7700 [0.0000]
lnGII	−22.7601 [0.0000]	−13.7239 [0.0000]	8.5672 [0.0000]	44.1441 [0.0000]
ECS	−29.8575 [0.0000]	−10.4491 [0.0000]	1.6631 [0.0481]	48.8136 [0.0000]
lnO	−19.7984 [0.0000]	−7.5213 [0.0000]	7.1764 [0.0000]	46.0506 [0.0000]
lnPD	−49.1060 [0.0000]	−11.0072 [0.0000]	16.3269 [0.0000]	63.6515 [0.0000]
lnTP	−29.9960 [0.0000]	−18.1917 [0.0000]	12.0455 [0.0000]	105.1208 [0.0000]
UL	−73.2781 [0.0000]	−9.5385 [0.0000]	14.9808 [0.0000]	59.3164 [0.0000]
lnGEG	−41.9037 [0.0000]	−21.1444 [0.0000]	15.2618 [0.0000]	46.8086 [0.0000]

Note: LLC, IPS, Fisher and Hadri represent Levin, Lee and Chu t; lm, Pesaran and Shin Z; Fisher ADF Ki-square; Hadri Z, respectively. Probabilities are given in parentheses.

(3) Model selection

For the selection of the regression models, the individual effect was first examined with a p-value of 0.0000, which indicates that the fixed-effects model is superior to the mixed ordinary least squares (ols) model. The time effect was then examined with a p-value of 0.0000, which indicates that the random-effects model outperformed the mixed ols model. The Hausman test is often used to choose between fixed-effects model and random-effects model in panel data analysis. The null hypothesis is that the preferred model is random-effects, while the alternative hypothesis is that the preferred model is fixed-effects. If the p-value is small (typically less than 0.05), then we reject the null hypothesis and conclude that the fixed effects model is appropriate. For the panel data presented in this paper, the Hausman test was performed at a p-value of 0.0000, and the results showed that a fixed-effects model should be used for this study.

4. Results and Discussion

4.1. Benchmark Regression Results Based on the Fixed-Effects Model

Table 5 presents the regression results based on the fixed-effects model. The influence coefficient of the core explanatory variable GII on the urban CEI was −0.032, and it passed the significance test of 1% level. This finding suggests that GII can inhibit the CEI in local cities.

Next, this paper divided the samples into four groups for regression (the same grouping method in Section 1). As shown in Table 6, heterogeneity was observed in the effects of cities with different GII levels on their CEI. In the group with the highest level of GII, that is, the cities with a total investment of more than RMB 50 billion from 2006 to 2019, the impact of the core explanatory variable on the explained variable changed into a significant positive effect. This change may be due to the diseconomies of scale of GII, which led to a short-term increase in carbon emissions. For example, in municipalities like Beijing, Tianjin and Chongqing, land use was relatively saturated. However, green infrastructure projects require large areas of land for construction, which may lead to the destruction of or reduction in existing vegetation, thus reducing the carbon absorption capacity. And in the process, activities such as excavation or landfill will also produce certain carbon emissions.

Table 5. Regression results of the whole sample based on the fixed-effects model.

Explanatory Variable	Explained Variable lnCEI Coefficient	t-Value
lnGII	−0.032 ***	−4.69
ECS	0.287 ***	4.08
lnO	−0.070 ***	−10.10
lnPD	0.074 **	2.39
lnTP	−0.204 ***	−31.65
UL	−0.105	−1.18
lnGEG	−0.094 ***	−6.21
Constant	5.827 ***	22.73

Note: **, and *** represent the 5%, and 1% significance levels, respectively.

Table 6. Sample grouping regression results.

Explanatory Variable	Benchmark Situation	GII More than RMB 50 Billion	Explained Variable GII between RMB 10 and 50 Billion	GII between RMB 5 and 10 Billion	GII Less than RMB 5 Billion
lnGII	−0.032 ***	0.050 ***	−0.021 **	−0.070 ***	−0.021 *
	(0.007)	(0.018)	(0.010)	(0.013)	(0.012)
ECS	0.287 ***	0.546 ***	0.386 ***	0.195	0.250 **
	(0.070)	(0.123)	(0.126)	(0.133)	(0.119)
lnO	−0.070 ***	−0.157 ***	−0.039 ***	−0.065 ***	−0.077 ***
	(0.007)	(0.032)	(0.015)	(0.014)	(0.010)
lnPD	0.074 **	0.299 ***	0.261 ***	0.118 *	−0.022
	(0.031)	(0.093)	(0.052)	(0.062)	(0.050)
lnTP	−0.204 ***	−0.374 ***	−0.225 ***	−0.162 ***	−0.212 ***
	(0.006)	(0.021)	(0.010)	(0.012)	(0.011)
UL	−0.105	−0.503 *	−0.271 *	−0.226	0.035
	(0.089)	(0.301)	(0.143)	(0.168)	(0.148)
lnGEG	−0.094 ***	−0.105 **	−0.001	−0.111 ***	−0.133 ***
	(0.015)	(0.044)	(0.023)	(0.026)	(0.027)
_cons	5.827 ***	5.665 ***	4.622 ***	5.752 ***	6.140 ***
	(0.256)	(0.802)	(0.441)	(0.504)	(0.416)

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Standard deviations are given in parentheses.

In the second, third, and fourth group cities with lower levels of GII, the influence of the core explanatory variable on the explained variable remained negative. Among these groups, in the cities with a total GII between RMB 5 billion and 10 billion, GII had the largest and most significant inhibitory effect on CEI, and its inhibitory effect was higher than that of the whole sample. Such cities include Qinhuangdao, Chifeng, Guilin and Haikou. They are often known for their rich natural landscapes and ecological environment, and are at a critical stage of urban scale and development. In order to achieve sustainable development, they need to increase GII, improve environmental quality, and improve the quality of life of residents while reducing carbon emissions. Moreover, these cities may have suitable climate conditions, such as being sunny, warm and humid, which provides better conditions for the use of renewable energy (such as solar and wind energy). In addition, these cities may have received the attention and support of the government and society.

4.2. Robustness Discussion

The results of the panel metrology model may be influenced by the data-processing and estimation methods. For example, the choice of a fixed-effects model or a random-effects model may change the outcome. As shown in Table 7, the choice of fixed-effects and random-effects models did not significantly differ on the regression results, and it can be tentatively considered that the selected models are robust. This means that individual or group effects have less influence on the results, and choosing either of the model yields reliable estimates of the results.

Table 7. Comparison of fixed-effects model and random-effects model.

Explanatory Variable	Explained Variable	
	Fixed-Effects Model	**Random-Effects Model**
lnGII	−0.032 ***	−0.030 ***
	(0.007)	(0.007)
ECS	0.287 ***	0.260 ***
	(0.070)	(0.069)
lnO	−0.070 ***	−0.067 ***
	(0.007)	(0.007)
lnPD	0.074 **	0.084 ***
	(0.031)	(0.030)
lnTP	−0.204 ***	−0.201 ***
	(0.006)	(0.006)
UL	−0.105	−0.147 *
	(0.089)	(0.086)
lnGEG	−0.094 ***	−0.099 ***
	(0.015)	(0.015)
Constant	5.827 ***	5.692 ***
	(0.256)	(0.254)

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses.

The explained variable was replaced with carbon emissions per unit of industrial production to further verify the robustness of the model. Table 8 shows the whole-sample regression results, which showed good robustness. The role of GII in urban carbon emissions remained significantly negative, but the impact coefficient changed. Among the other control variables, only the individual effects changed.

Table 8. Full-sample robustness regression results.

Explanatory Variable	Explained Variable	
	Coefficient	**t-Value**
lnGII	−0.052 ***	−7.37
ECS	0.426 ***	5.74
lnO	−0.100 ***	−13.76
lnPD	0.066 **	2.01
lnTP	−0.151 ***	−22.17
UL	−0.086	−0.92
lnGEG	−0.095 ***	−5.94
Constant	6.823 ***	25.22

Note: **, and *** represent the 5%, and 1% significance levels, respectively.

Thus far, it has been demonstrated that the model estimates are reliably robust and that H1 holds true.

4.3. Analysis of the Empirical Results Based on the Time-Lag Effect

Referring to the study by Zhong and Sun [43], temporal differences exist in the impact of infrastructure investment on carbon emissions. Considering the long construction cycle of green infrastructure, this paper set the sample data to a lag of five periods to further verify the lag in the impact of GII on urban CEI. Each period step mentioned in this article is one year. According to the construction of Equation (1), the time-lag model of GII lagging by 1, 2, 3, 4 and 5 years can be expressed as follows:

$$lnCEI_{it} = \alpha_0 + \alpha_1 lnGII_{it-\tau} + \alpha_k \sum_{k=2}^{7} X_{control} + \varepsilon_{it} \ (\tau = 1,2,3,4,5) \tag{2}$$

where α_1 is the coefficient of the independent variable lagging behind τ period, reflecting the effect of the independent variable value of the past period on the value of the dependent variable in the current period. ε_{it} is the error term, representing the random error term, the total influence term of the explanatory variable not included in the model and some other random factors on the explained variable. The rest of the letters mean the same as in Equation (1).

By regression, the coefficients of the core explanatory variable at one lags, two lags, three lags, four lags and five lags were −0.046, −0.054, −0.058, −0.053 and −0.049, respectively, and all were significant at the 1% level (Table 9). It can be seen that the inhibitory effect of GII on CEI is significantly present in all the five lag periods, among which the inhibition of three lags is the strongest, and then shows a decreasing trend. Thus, the impact of GII on urban carbon emissions has a time-lag effect, which proves that H2 holds true.

Table 9. Results of the time-lag effect regression.

Variable	No Lag	Lag One Year	Lag Two Years	Lag Three Years	Lag Four Years	Lag Five Years
lnGII	−0.032 ***	−0.046 ***	−0.054 ***	−0.058 ***	−0.053 ***	−0.049 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
ECS	0.287 ***	0.276 ***	0.205 ***	0.143 *	0.029	−0.010
	(0.070)	(0.072)	(0.074)	(0.078)	(0.082)	(0.089)
lnO	−0.070 ***	−0.066 ***	−0.065 ***	−0.064 ***	−0.060 ***	−0.054 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
lnPD	0.074 **	0.069 **	0.074 **	0.060	0.041	0.033
	(0.031)	(0.033)	(0.035)	(0.038)	(0.041)	(0.047)
lnTP	−0.204 ***	−0.198 ***	−0.189 ***	−0.178 ***	−0.165 ***	−0.154 ***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
UL	−0.105	−0.034	−0.058	−0.014	0.052	0.090
	(0.089)	(0.094)	(0.100)	(0.107)	(0.115)	(0.128)
lnGEG	−0.094 ***	−0.082 ***	−0.080 ***	−0.082 ***	−0.065 ***	−0.046 **
	(0.015)	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)
_cons	5.827 ***	5.986 ***	6.039 ***	6.149 ***	6.273 ***	6.286 ***
	(0.256)	(0.271)	(0.286)	(0.305)	(0.332)	(0.368)

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Standard deviations are given in parentheses.

The time lag in GII on urban CEI was mainly caused by three factors. The first factor is the building cycle. The construction of green infrastructure usually requires a long time and includes multiple stages, such as planning, design, bidding, construction, and checking. These stages require some time to complete, especially for large infrastructure projects. During the construction period, some carbon emissions may occur. Thus, the emission reduction benefits of green infrastructure cannot be reflected immediately before it has been fully built and put into use. The second factor is the accumulation of technology and experience. In the field of green infrastructure, the related TP and accumulation of experience are improved and optimized gradually to enhance the effect of emission reduction. The third reason is the change in civic behavior patterns. The successful application of green infrastructure requires the active participation and adaptation of citizens. For example, if a city invests in intelligent recycling bins for garbage classification, but citizens refuse to cooperate with the active classification, then the effect of emission reduction may not be immediately evident.

However, the inhibitory effect of GII on CEI being strongest at three lags and then starting to weaken could also be explained. The marginal inhibition of carbon emissions in green infrastructure projects will decline over time. Without a new round of GII, the use of completed projects and the aging of the equipment will reduce the suppression effect.

4.4. Analysis of the Empirical Results Based on the Threshold Effect

4.4.1. Static Panel Threshold Model

Based on the analysis of the impact mechanism in Section 3.1, this paper assumed that a nonlinear relationship possibly exists between GII and urban carbon emissions, and TP has a threshold effect. To test this hypothesis, we first employed the non-dynamic panel regression model proposed by Hansen [67]. The threshold regression model can be expressed as follows:

$$\begin{aligned} y_i &= x_{i\prime}\beta_1 + \mu_i,\ q_i \le \gamma \\ y_i &= x_{i\prime}\beta_2 + \mu_i,\ q_i > \gamma \end{aligned} \tag{3}$$

where y_i is the explanatory variable; $x_{i\prime}$ is the explanatory variable vector of order $P \times 1$; q_i is the threshold variable, which may or may not be part of the $x_{i\prime}$; and γ is the threshold value.

Using Hansen's ideas, this paper constructs the following static panel threshold model with TP as the threshold variable:

$$\begin{aligned} lnCEI_{it} = \beta_0 + \beta_1 lnGII_{it} \cdot I(lnTP_{it} \le \omega_1) + \beta_2 lnGII_{it} \cdot I(\omega_1 < lnTP_{it} \le \omega_2) + \ldots + \\ \beta_{n+1} lnGII_{it} \cdot I(lnTP_{it} > \omega_n) + \gamma_1 ECS_{it} + \gamma_2 lnO_{it} + \gamma_3 lnPD_{it} + \gamma_4 UL_{it} + \gamma_5 lnGEG_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

Here, β_0 is a constant term, and β_1 to β_{n+1} are the elasticity coefficients of the core explanatory variable *lnGII* at different threshold values. *TP* was selected for the threshold variables. $I(\cdot)$ is an indicator function with a value of 0 or 1. ω_1 to ω_n are the threshold values to be estimated.

The threshold existence test was conducted using Stata16, and the test results under different thresholds are shown in Table 10. The single- and double-threshold models had *p*-values of less than 0.05 and passed the significance test, but the triple-threshold model failed. Therefore, this paper can consider that GII had a double-threshold effect on urban carbon emission based on TP, which verifies H3.

Table 10. Test results of the threshold number.

Model	Bootstrap Times	F-Value	*p*-Value	Critical Value		
				Crit10	Crit5	Crit1
single	300	287.05	0.0000	131.5298	140.8715	158.4264
Double	300	264.16	0.0000	70.4831	86.2701	127.7891
Triple	300	114.05	0.9467	227.4568	252.8525	288.2599

In the double-threshold model regression, the first threshold value for TP was 3.9120 with a 95% confidence interval of [3.8286, 3.9703]. The second threshold value for TP was 6.8035, with a 95% confidence interval of [6.5624, 6.9791]. Figure 4 shows the corresponding threshold map. The red dashed line indicates the critical value at the 5% significance level. The part of the LR image below the dashed line is the confidence interval of the threshold value. At different levels of TP, GII had a significant negative impact on urban carbon emissions, but the degrees of impact varied (Table 11). The inhibitory effect of GII on urban CEI was strengthened with the level of TP. Specifically, when the level of TP did not exceed the first threshold value, the effect coefficient of GII on urban CEI was −0.057. When the level of TP was between the first and second threshold values, the effect coefficient of GII on urban CEI was −0.088. In addition, when the level of TP was greater than the second threshold, the effect coefficient of GII on urban CEI was −0.126. This result indicates that when lnTP exceeds the second threshold value 6.8035 (number of green utility model patent applications greater than 901), the inhibitory effect of TP on CEI increases by 121.0526% relative to lnTP, which is less than the first threshold. At this time, the technical content of green infrastructure has greatly increased, which improves investment efficiency and significantly reduces urban carbon emissions.

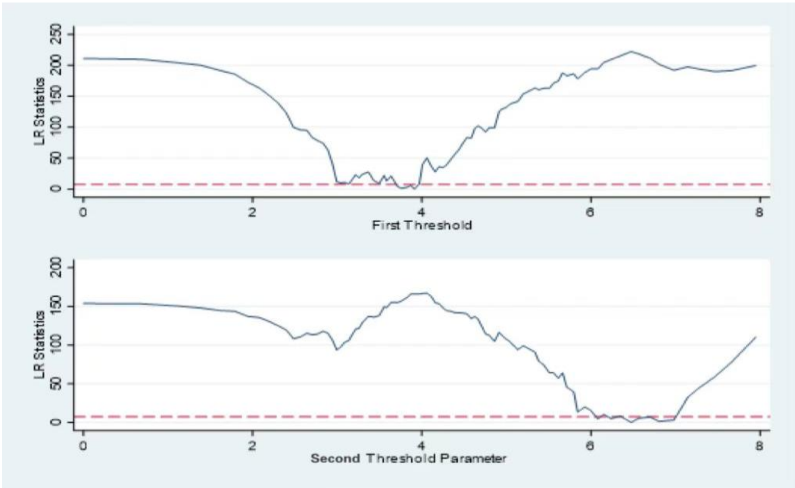

Figure 4. Double-threshold map.

Table 11. Regression results of the threshold model.

Variable	Coefficient
ECS	0.140
lnO	−0.083 ***
lnPD	0.081
UL	−0.240
lnGEG	−0.208 ***
lnGII (lnTP ≤ 3.9120)	−0.057 ***
lnGII (3.9120 < lnTP ≤ 6.4754)	−0.088 ***
lnGII (lnTP > 6.4754)	−0.126 ***
Constant	5.104 ***

Note: *** represent the 1% significance level.

4.4.2. Re-Examination of the Dynamic Panel Threshold Model

Considering that the current urban carbon emissions may have an impact on the next phase through greenhouse gas accumulation, carbon cycle and climate feedback, and the continuity of infrastructure investment, we introduced the lag phase of the dependent variable CEI to build a dynamic panel model in this section. Caner and Hansen [68] proposed two-stage least squares (2SLS) estimation and Generalized Method of Moments (GMM) estimation for threshold parameters for cross-section data containing endogenous explanatory variables and exogenous threshold variables. Kremer et al. [69] further applied the above methods to dynamic panel data to solve the inherent endogenous problems of dynamic panel data. In this paper, using the method of Kremer et al., $lnCEI_{it-1}$ was added to Equation (4) to obtain the following dynamic panel threshold model:

$$\begin{aligned} lnCEI_{it} = \beta_0 + \beta_1 lnGII_{it} \cdot I(lnTP_{it} \leq \omega_1) + \beta_2 lnGII_{it} \cdot I(\omega_1 < lnTP_{it} \leq \omega_2) + \ldots + \\ \beta_{n+1} lnGII_{it} \cdot I(lnTP_{it} > \omega_n) + \varphi lnCEI_{it-1} + \gamma_1 ECS_{it} + \gamma_2 lnO_{it} + \\ \gamma_3 lnPD_{it} + \gamma_4 UL_{it} + \gamma_5 lnGEG_{it} + \varepsilon_{it} \end{aligned} \quad (5)$$

where φ is the influence coefficient of the current CEI on the next CEI. The rest of the letters mean the same as in Equation (4).

For the dynamic panel data model, to exclude the model setting error, the autocorrelation of the residual terms and the validity of the instrumental variables must be statistically tested after the GMM estimation. The results of systematic GMM regression are shown in Table 12.

Table 12. Dynamic panel systematic GMM regression results.

	lnCEI
L.lnCEI	1.029 ***
lnGII	−0.038 ***
ECS	−0.156 ***
lnO	−0.005 *
lnPD	−0.111 ***
lnTP	0.010 **
UL	0.333 ***
lnGEG	0.076 ***
_cons	0.000
Year	Yes
AR(1)	0.000
AR(2)	0.258
Hansen	0.387

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. AR (1) and AR (2) report the p-values of the first- and second-order sequence correlation tests, respectively; Hansen reports the p-value of the over-identification test.

The p-value corresponding to AR (1) was of less than 0.1 and that corresponding to AR (2) was greater than 0.1, indicating that the residual terms had first-order but not second-order autocorrelation, which meets the requirements of the autocorrelation test. The p-value of the Hansen test was 0.387, greater than 0.1, indicating that the instrumental variable was jointly valid and there was no over-identification. The above tests showed that the model setting in this paper was appropriate. In addition, the current CEI was indeed positively affected by the previous period and the coefficient was 1.029. The regression coefficient for the core explanatory variable GII was −0.038, which was significantly negative at the 1% level.

Referring to the research of Wang and Peng [70], the effect of GII on CEI was further analyzed by the dynamic panel threshold regression model using TP as the threshold variable. According to the dynamic panel threshold regression model test, GII and CEI had a nonlinear relationship under the TP threshold (Table 13). The threshold was 3.666 and was significant at the 95% confidence interval [3.575, 3.756]. Next, the samples were divided into two groups for dynamic panel regression based on the threshold value 3.666 (Table 14). It can be seen that when lnTP is below 3.666, GII cannot yet inhibit CEI. However, when lnTP is greater than 3.666, GII can significantly inhibit CEI.

We log-converted the threshold value (3.666) mentioned above and found that the corresponding TP was 39.095. Two examples of real cities were considered for further verification, as shown in Figures 5 and 6. The TP, represented by the number of green utility model patent applications, in Qinhuangdao City gradually exceeded the threshold value after 2008. During the period when Qinhuangdao City's TP had not reached the threshold value, its CEI exhibited significant fluctuations, indicating that the carbon reduction effect had not yet been realized. However, from 2009 onwards, its CEI started to decline. In addition, in the case of Haikou City, its TP exceeded the threshold value after 2010, and the turning point of CEI was also in 2010: the CEI of Haikou remained relatively stable between 2006 and 2010, and began to decline significantly from 2010. Such a reality is consistent with the conclusion drawn by the above threshold regression, indicating that TP has a threshold effect on the process of carbon emission reduction.

Table 13. The threshold regression model test of the dynamic panel.

lnCEI	Coefficient	Standard Error	Z Statistics	p Value	The 95% Confidence Interval Superior Limit	Lower Limit
Lag_lnCEI_b	0.916	0.002	484.22	0.000	0.912	0.920
lnGII_b	−0.003	0.001	−5.61	0.000	−0.004	−0.002
lnTP_b	0.025	0.001	29.84	0.000	0.023	0.026
kink_slope	−0.053	0.001	−53.57	0.000	−0.055	−0.051
r	3.666	0.046	79.05	0.000	3.575	3.756

Table 14. Results of the dynamic panel group regression.

	lnCEI	
	Lower Regime	Upper Regime
L.lnCEI	1.003 ***	0.912 ***
	(203.855)	(73.340)
lnGII	0.006 ***	−0.024 ***
	(2.812)	(−4.473)
ECS	0.022	0.104 ***
	(0.776)	(2.767)
lnO	−0.007 ***	0.003
	(−6.138)	(0.702)
lnPD	−0.050 ***	0.090 ***
	(−6.593)	(6.497)
lnTP	−0.006 ***	−0.009 **
	(−3.000)	(−2.017)
UL	0.155 ***	−0.335 ***
	(7.616)	(−8.282)
lnGEG	−0.060 ***	0.076 ***
	(−14.548)	(8.190)
_cons	0.000	0.402 ***
	(0.000)	(3.367)
Year	Yes	Yes
AR(1)	0.000	0.000
AR(2)	0.261	0.140
Hansen	0.987	0.182

Note: **, and *** represent the 5%, and 1% significance levels, respectively.

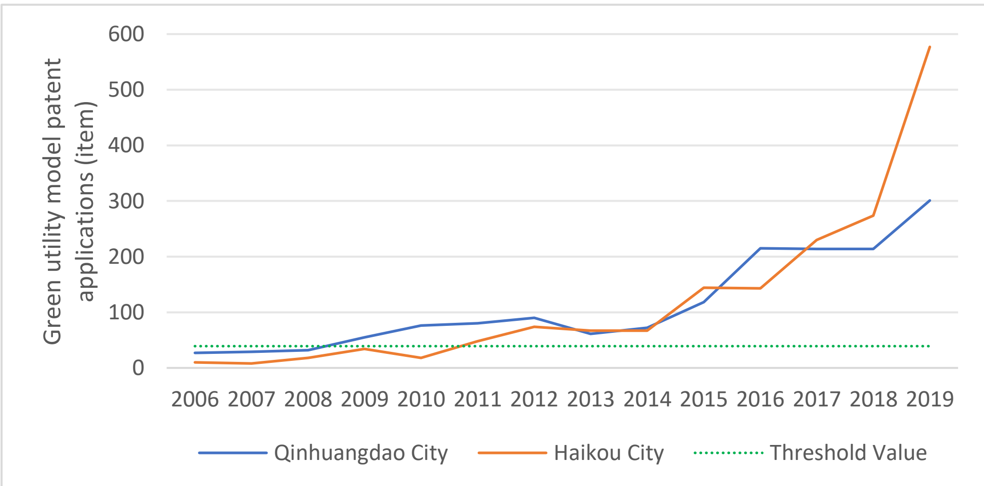

Figure 5. TP of the case cities.

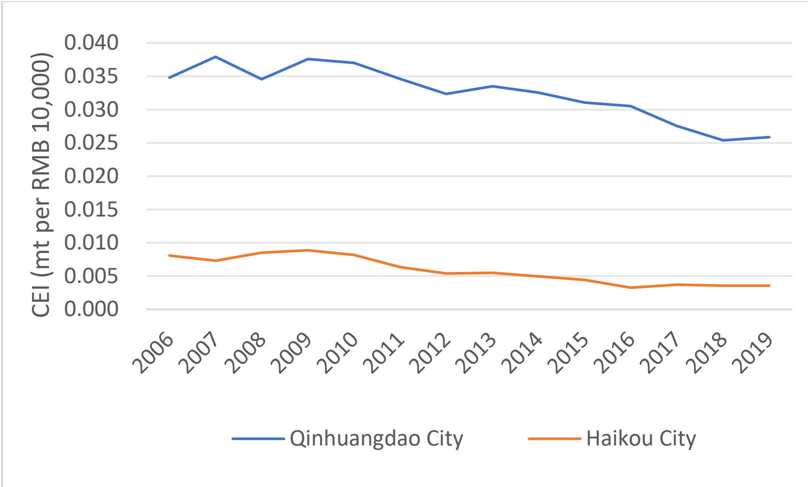

Figure 6. CEI of the case cities.

In conclusion, the static panel exhibited double thresholds. At different TP levels, GII had an inhibitory effect on CEI, but the coefficients were different. The higher the level of TP, the more significant the inhibitory effect of GII on CEI. In the dynamic panel, however, the threshold changed over time and the effect of GII on CEI shifted from facilitation to inhibition. This means that GII suppressed CEI only after the TP reached a specific threshold. The change in the threshold number of the static and dynamic panels may be due to the different treatment of the time dimension between the two panel data models. In the static panel data model, the cross-sectional data at a specific time point were considered. In this case, multiple thresholds may be present as different thresholds may have effects on the relationship between the explanatory variable and the explained variable at different time points. However, the dynamic panel data model considered the changing time series. In this case, the evolution of TP, the market uptake process, or other external factors may lead to threshold changes over time.

4.5. Conclusions and Policy Suggestions

Using the panel data from 235 cities in China from 2006 to 2019, this paper studied the impact of GII on urban carbon emissions from the perspective of time lag and threshold effects. The main conclusions are as follows: (1) GII has a negative inhibitory effect on urban carbon emission; that is, increasing GII can reduce urban carbon emissions. (2) A time-lag effect exists on the impact of GII on urban carbon emissions, and the greatest reduction in carbon emissions occurs in the third lag period. (3) The impact of GII on urban carbon emissions has a non-linear relationship based on the threshold variable TP.

However, when we try to reduce CEI by increasing GII, the trade-offs, limitations, or potential negative impacts of increasing GII should be critically considered. First, green infrastructure projects usually require a high capital investment. This could lead to a higher cost of capital, which reduces the return on investment. Second, some green infrastructure projects may have adverse effects on local communities in the early stage of construction, such as land acquisition, relocation, and social conflicts. Therefore, a comprehensive assessment of the economic benefits and social impact of the GII is needed to ensure its feasibility and sustainability.

Based on the above conclusions and considerations, we can draw the following policy suggestions: (1) The increase in GII plays an important role in promoting sustainable development and reducing carbon emissions. Governments should formulate relevant incentive policies and regulations, including incentive tax policies, preferential financing, and loan conditions, to attract various forces and funds as well as to encourage and support GII. (2) From the perspective of energy structure, we should reduce the dependence on high-carbon energy and develop and promote renewable energy. In the process, the environmental preferences of urban residents are more important than the content of their climate plans [71]. Individual and family awareness and actions play an important role in carbon reduction in cities. We should advocate for a low-carbon lifestyle and encourage environmental behaviors such as green traffic and garbage sorting to aid in the low-carbon transformation of urban energy consumption. For example, measures to incentivize include using electric cars, electric buses or shared bikes instead of traditional cars to reduce carbon emissions and traffic congestion. (3) TP is an important internal driving force for the reduction in urban carbon emissions. We should encourage cooperation between scientific research institutions, universities, and enterprises to realize the sharing of research results and technical resources for the continuous improvement of the overall green technology innovation capability. Meanwhile, we should strengthen international exchanges and actively participate in international green technology innovation projects. (4) Based on the resource endowments and geographical conditions of different regions, we must formulate appropriate carbon emission reduction targets and paths. In addition, we should fortify exchanges and cooperation between cities and rationally allocate capital, labor force, information, and other resources. For example, we can establish an intercity information disclosure platform to provide comprehensive and accurate data on GII opportunities and project information to help investors further gain insights into investment opportunities, reduce the risk of information asymmetry, and promote the market to achieve a healthy flow of factors.

4.6. Study Limitations and Recommendations for Future

There are still some shortcomings in this study. First, this paper uses panel data from 235 cities at the prefecture level and above in China from 2006 to 2019 to study the impact of GII on urban carbon emissions. However, due to the limitation of data access channels, this paper fails to include all prefecture-level cities in China. Secondly, due to the different calculation caliber of CO_2 emissions, this paper chooses to use China Carbon Emission Accounting and Database for research and analysis, but it was only updated up to 2019 during the writing period, which limits the time span of this study and does not rule out the possibility that different conclusions will be drawn after extending the length of the study period. Third, one of the control variables in this study failed to show the expected results in the model regression. Specifically, the variable of UL was not significant, which may be because of the error or incompleteness of the measurement and representative indicator for UL. Future studies could focus on these issues. We will also use the updated database as much as possible to improve data collection and measurement to make the results more reliable and valid.

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