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Construction Land Transfer Scale and Carbon Emission Intensity: Empirical Evidence Based on County-Level Land Transactions in Jiangsu Province, China

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Abstract: The expansion of the construction land scale has been vital in supporting rapid economic development and meeting social needs. However, the spatial heterogeneity in the effect of construction land scale on carbon emission intensity at the county level remains underexplored. Therefore, comprehensively investigating the relation between the construction land transfer scale and carbon emission intensity holds substantial research value. Using panel data from 2007 to 2021, this study analyzes the spatiotemporal differentiation characteristics of carbon emission intensity and the effect of construction land scale on carbon emission intensity at the county level in Jiangsu Province, China. The findings reveal that carbon emission intensity at the county level in Jiangsu Province generally exhibits a continuous downward trend over time and a spatial distribution characterized by a gradual decrease from the southern counties to the central and northern counties. Moreover, there is a significant positive relation between the construction land transfer scale and carbon emission intensity, a conclusion supported by robustness tests. Furthermore, mediating analysis indicates that reduction of the construction land transfer scale exhibits a significant promoting effect on green technology innovation and industrial structure upgrading, which, in turn, has a significant inhibitory effect on carbon emission intensity. The impact of the construction land transfer scale from different sources, supply methods, types, and of county economic strength on carbon emission intensity has significant heterogeneity.

Keywords: construction land transfer scale; carbon emission intensity; spatiotemporal characteristics; county scale

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1. Introduction

1.1. Research Background

Global climate anomalies resulting from the greenhouse effect have emerged as a significant challenge facing humanity, garnering widespread attention from the international community. Land use stands out as a notable contributor to the rapid escalation of global greenhouse gas emissions. Research has indicated that carbon emissions stemming from land use and its alterations constitute approximately one-third of the total emissions influenced by human activities over the past 150 years [1]. Particularly, construction land has emerged as a paramount source of carbon emissions due to its intensive material and energy consumption [2]. At the United Nations Climate Conference in Paris in 2015, the

Chinese government committed to achieving a peak in carbon emissions by 2030 and reducing carbon dioxide emissions per unit of GDP by 60–65% compared with the 2005 levels. Rapid urbanization is crucial for achieving these carbon emission reductions [3].

As local governments progressively assume the primary role in implementing energy-saving and emission reduction policies, optimizing land use structure has become a pivotal tool for regulating regional carbon emissions [2,4]. In the context of policy evolution, the transfer of the right to use state-owned construction land through market allocation will help limit carbon emissions. With the implementation of China's in-depth market-oriented reforms, the construction land transfer scale will be further expanded [5]. The increase in the construction land transfer scale brings about an increase in carbon stock per unit of land area and an increase in land use intensity, which in turn leads to an increase in carbon emissions per unit of land area [4,6]. The appropriate construction land transfer scale has become the key to low-carbon urban land use. Hence, deeply exploring the intrinsic relation between construction land transfer scale and carbon emission intensity is not only essential for fulfilling international commitments and establishing China as a responsible major country but also an issue that needs to be addressed urgently by both government and academia.

1.2. Literature Review

There has been a great deal of studies from different perspectives on how land use change effects carbon emissions [7,8]. (a) Exploring the effects of land use on vegetation carbon storage and soil carbon storage at the level of natural ecosystems. For instance, some scholars have assessed carbon emissions for specific land use types, such as croplands [9], wetlands [10,11], and forests [12]. (b) Ecological and economic compensation factors have been incorporated into the study of the spatial and temporal characteristics of carbon emissions [13]. In fact, the process and mechanism of carbon emissions from land use under the economic and social system are far more complex than those under natural ecosystems, which is reflected in the fact that the effect of land use on carbon emissions is often transmitted through other factors, and the determinants of carbon emissions are more varied and related to each other. Scholars have tried to extensively discuss the causal relationship between land use and carbon emissions from the perspectives of urban land expansion [14], urban spatial land use layout [14,15], land use structure change [16], land intensive use [16], land use intensity differences [17], land urbanization, and land finance [18,19]. (c) Previous studies have identified a positive correlation between construction land and carbon emissions [20]. Moreover, research has revealed an inverted "U-shaped" relation between the construction land and carbon emission intensity across different study areas [21], aligning with the EKC hypothesis. Notably, enhancing the intensive utilization level of construction land can contribute to carbon emissions. Some scholars have simulated the effect of land use on carbon emissions under different policy schemes from the perspective of system dynamics [22,23], and discussed the spatiotemporal coupling relationship between land use and carbon emissions from a spatial perspective [13]. With advancements in research, a few scholars have delved into the effect of specific types of construction land on carbon emissions. For instance, studies have examined the effect of residential land [24], industrial land [25], land for public facilities [26], commercial land, and warehouse logistics land [27] on carbon emissions. The function of construction land leads to different carbon emission performance, among which industrial land is the largest source of carbon emissions [28,29]. The research shows that there are also differences in the effect of the scale, supply mode, supply price, and utilization mode of industrial land supply on carbon emissions [28–30]. Construction land, as the most important component of urban land, is the land use type with the largest carbon emissions [28,29], and its total carbon emissions and intensity are dozens or even hundreds of times higher than those of other land use types [15,29].

In general, the effects of construction on carbon emissions have received considerable attention. The mentioned studies have provided a theoretical basis and case support for

the study of land use carbon emissions. Most existing studies have been conducted at the national [3,31] and provincial [26,32] levels, with a few exploring carbon emissions at fine spatial scales and lacking in-depth analysis of land use carbon emissions at the county level. In addition, transferable construction land differs significantly from allocated construction land, leading to variations in their effect on carbon emission intensity. In recent years, many eastern regions have shifted toward stock construction land, resulting in a sharp decline in incremental construction land [33]. In light of these developments, the differential influence of transferable construction land, allocated construction land, stock construction land, and incremental construction land on carbon emissions should be considered comprehensively. Jiangsu Province is the largest carbon emissions region in China [34,35]. In recent years, Jiangsu has placed considerable emphasis on the development of low-carbon cities. Given the context outlined above, this study aims to explore the spatiotemporal evolution characteristics of carbon emission intensity across districts and counties in Jiangsu Province from 2007 to 2021. Then, the study empirically investigates the impact mechanism of the construction land transfer scale on carbon emission intensity. Additionally, a mediating model is developed to investigate the effect of mediating variables in the mechanism of the construction land transfer scale on carbon emission intensity. Finally, this study extends its analysis to examine the heterogeneity of the effect mechanism of the construction land transfer scale on carbon emission intensity based on various factors such as the source of construction land, the method of land supply, construction land types, and county economic strength. Based on the research findings, the study proposes corresponding countermeasures and suggestions for achieving carbon peak and carbon neutrality.

The study makes several notable contributions. First, the most recent studies use total carbon emissions to quantify emission reduction targets [35], while this paper uses carbon emission intensity. Second, this study enriches the existing literature by focusing on county-scale studies, an area that has received limited attention. It achieves this by utilizing panel data from construction land transactions in Jiangsu Province spanning from 2007 to 2021. This integrated approach allows for a comprehensive assessment of the mechanisms of the effect of the construction land transfer scale on carbon emission intensity at the county level. Additionally, from the strands of green technology innovation effects and industrial structure upgrading effects, the internal effect mechanism of the construction land transfer scale on carbon emission intensity is deeply revealed, and the research literature on the impact of land use on carbon emissions is enriched. Meanwhile the study introduces innovative perspectives by investigating the heterogeneity influence of construction land source, supply methods, types, and county economic strength on carbon emission intensity. In this way, it provides more in-depth theoretical support for the implementation of carbon emission reduction policies and the improvement in land use efficiency, and also provides inspiration for relevant government departments to formulate relevant policies in a targeted manner.

The subsequent sections of this paper are organized as follows: Section 2 details Materials and Methods; Section 3 focuses on the empirical process and mechanism analysis. Section 4 explains and discusses the empirical results. Section 5 presents a comprehensive analysis of heterogeneity effects. Finally, conclusions and discussions are presented.

2. Research Hypotheses

2.1. Construction Land Transfer Scale and Carbon Emission Intensity

Construction land is the land use type with the largest carbon emissions, and the human activities it carries, including energy consumption, industrial production processes, and waste emissions, produce a large amount of carbon emissions [36]. On the one hand, the expansion of construction land often takes away from ecological land, a process that leads to changes in surface vegetation cover, which results in the loss of vegetation carbon stocks [37]. The changes in surface vegetation cover also reduce the amount of organic matter that is returned to the soil, which leads to changes in soil carbon stocks [38]. On the other hand, the expansion of construction land not only provides a place for more human

activities, but also is the result of the aggregation of human activities [26]. From the dual perspectives of economic development and energy conservation and emission reduction, the agglomeration effect is likely to reduce carbon emission intensity. Zhou et al. (2019) [39] found that economic agglomeration can effectively reduce regional water pollution discharge intensity. Zhong and Wei (2019) [40] found that industrial agglomeration can reduce pollution emission intensity. As the construction land scale in various counties of Jiangsu Province is gradually approaching the limit of resource and environmental carrying capacity, construction land reduction has been implemented in various places. The construction land transfer scale has gradually decreased, and the agglomeration effect has become more obvious. Based on this, we believe that a reduction in construction land transfer land at this stage can reduce the carbon emission intensity. Therefore, hypothesis H_1 is proposed.

Hypothesis H_1. *There is a positive correlation between construction land transfer scale and carbon emission intensity; namely, the smaller the construction land transfer scale, the lower the carbon emission intensity.*

2.2. Construction Land Transfer Scale, Green Technology Innovation, and Carbon Emission Intensity

Considering the scarcity of land resources, in order to achieve rapid economic growth with limited land resources, the government is more inclined to allocate land elements to industrial enterprises [25], resulting in a large number of highly polluting and highly energy-consuming enterprises, and the introduction of low-end industries brought about by the scaling up of construction land transfer will directly inhibit the progress of green technology. According to the new economic geography theory and endogenous growth theory, it is known that scientific and technological innovation and technological progress is the most important lever of the green development of industry [17]. Green technology innovation has a significant impact on the volume and structure of industrial carbon emissions. Therefore, green technology innovation can help improve energy efficiency, reduce undesired output, and thus, reduce carbon emission intensity, which is one of the important ways to achieve the "dual-carbon" goal [39]. Although enterprises tend to apply technology to improve product revenue in terms of revenue orientation, the increase in pollution costs also plays an important role in inhibiting revenue; and encouraging enterprises as to implement efficient production to achieve carbon emission reduction [40].

Reduction of the construction land transfer scale will force enterprises to upgrade their green innovation and technology, promote the upgrading of enterprise production technology [41], accelerate the replacement of traditional energy-consuming technologies with clean technology, and improve the efficiency of enterprise resource allocation and production efficiency, especially for industries that are the main sources of carbon emissions such as those with high-pollution and high-energy-consumption levels, reduce resource consumption level, and reduce pollutants and carbon dioxide and other greenhouse gas emissions [42,43], thereby reducing carbon emission intensity. Therefore, construction land transfer scale reduction can play an external role through technological innovation to stimulate enterprises to reduce environmental pollution. This paper proposes hypothesis H_2.

Hypothesis H_2. *Construction land transfer scale reduces carbon emission intensity by increasing the green technology innovation level. The smaller the construction land transfer scale, the higher the level of green technology innovation, and the lower the carbon emission intensity.*

2.3. Construction Land Transfer Scale, Industrial Structure Upgrading, and Carbon Emission Intensity

Among the various specific factors affecting carbon intensity, industrial structure emerged as the second most influential factor after energy intensity and population scale [21,41]. Therefore, this paper focuses on mechanism analysis from the perspective of industrial structure optimization. Under the market-oriented allocation mode, the utilization of construction land is oriented to efficiency, and construction land resources

are inclined to regions and industries with higher utilization efficiency, optimizing the industrial structure to a certain extent. The Kuznets fact presented by the optimization of industrial structure shows that the proportion of added value of the tertiary industry gradually increases along with economic development. Compared with secondary industry, the increase in the proportion of tertiary industry can, to a large extent, promote the reduction of carbon emission intensity [36]. With the reduction of construction land transfer scale, high-pollution and high-energy-consuming enterprises have been restricted, the proportion of the tertiary industry has increased, and the industrial structure has been optimized. Since tertiary industry is characterized by low energy consumption and low pollution, the amount of energy consumed per unit of GDP is much lower than that of secondary industry [25], thus reducing the intensity of carbon emissions. With the scarcity of land resources, the degree of industrial structure optimization has increased, and the productivity of various industries has continued to rise, which has greatly improved resource allocation, thereby reducing the consumption of resources and energy per unit of GDP, and ultimately, contributing to a reduction in carbon emission intensity [23,32]. Therefore, the construction land transfer scale is able to reduce carbon emission intensity through industrial structure optimization. This paper proposes hypothesis H_3.

Hypothesis H_3. *Construction land transfer scale reduces carbon emission intensity by influencing industrial structure upgrading. The smaller the construction land scale, the higher the degree of industrial structure upgrading, and the lower the carbon emission intensity.*

3. Materials and Methods

3.1. Study Area

Jiangsu Province, situated along the eastern coast of mainland China, spans between 116°18′ E and 121°57′ E (Figure 1). It comprises 13 cities and 96 districts and counties. With a total area of 1.072×10^6 km^2, construction land occupies 1.832×10^5 km^2, constituting 17.16% of the total area. Endowed with superior natural conditions, Jiangsu Province features low and flat terrain, a vertical and horizontal transportation network, convenient water and land transportation, and a thriving socio-economic landscape. With top-ranking indicators such as population density, per capita GDP, comprehensive competitiveness, and urbanization rate nationwide, the province contributes over 10% to the national economic growth, with the manufacturing industry constituting approximately one-eighth of its economic output. The province has progressed into the late stage of industrialization [35,44]. The output value of high-energy-consuming industries constitutes approximately one-third of the total industrial output value [45]. It is also the region with the largest carbon emissions in China [35]. In recent years, Jiangsu has placed considerable emphasis on the development of low-carbon cities. Notably, Nanjing City, Changzhou City, Huai'an City, and Zhenjiang City have been rated as national low-carbon city pilot cities. Jiangsu Province has set ambitious goals to ensure that carbon emissions peak by 2030, surpassing the national target by the end of the 14th Five-Year Plan. However, the province faces significant challenges due to its substantial energy consumption, leading to continuous increases in carbon emissions. It is crucial to explore the causal relation between construction land and carbon emissions in Jiangsu Province.

3.2. Research Methodology

3.2.1. Static Panel Model

A panel regression model is constructed to characterize the causal relation between construction land transfer scale and carbon emission intensity at the county level:

$$\ln CEI_{it} = \alpha + \beta \ln CLTS_{it} + \chi X_{it} + \mu_i + V_t + \varepsilon_{it} \quad (1)$$

The dependent variable, indicated as $\ln CEI_{it}$, denotes the carbon emission intensity ($\ln CEI$) of county i in the t year. The core independent variable, indicated as $\ln CLTS_{it}$, represents the total area of construction land supply in county i in year t. X_{it} represents the set

of control variables, including urbanization rate, economic development level, population density, environmental regulation intensity, and capital investment. Furthermore, μ_i and V_t represent the fixed effects of the cross-section and the annual fixed effects of the county, respectively. ε_{it} is a random error term. α is a constant term. β and γ are the regression coefficients of the variable, i is the region dimension, and t is the time dimension. When β is >0, it indicates that the promoting effect of the construction land transfer scale on carbon emission intensity is more obvious, and when β is <0, it indicates that the inhibitory effect of the construction land transfer scale on carbon emission intensity is more significant.

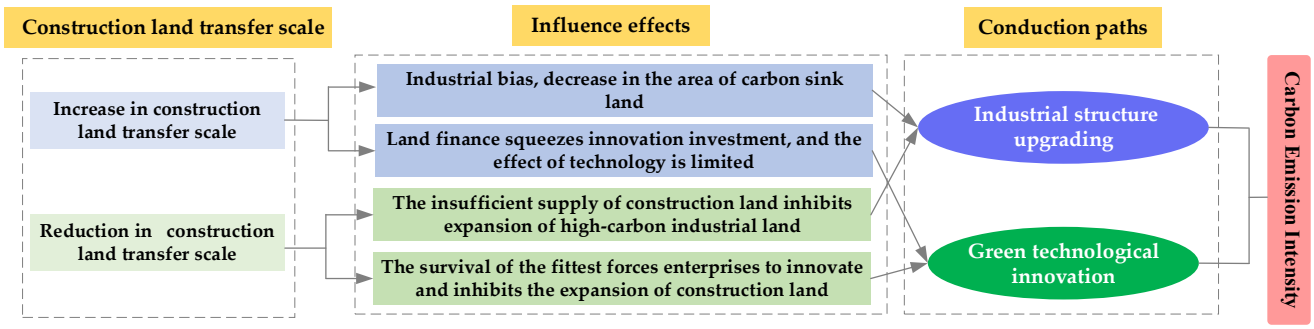


Figure 1. The influencing mechanisms and path of construction land transfer scale on carbon emission intensity.

3.2.2. Mechanism Testing Mode

After testing the effect of the construction land transfer scale on carbon emission intensity, combined with the theoretical logic analysis, this paper constructs the following mechanism-testing model to further identify the conduction path.

The mediating effect of industrial structure optimization is assessed using the method of Weng et al. (2004) [46], and the model is constructed as follows:

$$M_{it} = \alpha + \beta \ln CLTS_{it} + \chi X_{it} + \mu_i + V_t + \varepsilon_{it} \quad (2)$$

M_{it} denotes the mediating variable, including two variables: green technology innovation (lnGTE) and industrial structure upgrading (ISU).

3.3. The Selection and Source of Variables

3.3.1. The Selection and Source of the Dependent Variable

Carbon emissions are highly correlated with socio-economic development, human productivity, and quality of life. In regions with considerable differences in resource endowment and environmental regulation [47], carbon emission intensity may differ, making them appropriate to be considered as the dependent variable. To address potential issues associated with indirect estimation methods, such as those involving the multiplication of various energy quantities and emission coefficients, and to mitigate errors arising from differences in urban energy structure and intensity, the annual carbon emissions of each district and county in this paper are inverted by nighttime light data. The specific processing steps are outlined as follows: first, two types of nighttime light remote sensing data (DMSP/OLS and NPPNVIRS) are selected [48]. These datasets undergo continuity correction and logarithmic transformation. Subsequently, both datasets undergo supersaturation correction and consistency correction to establish a long time-series of nighttime light remote sensing data spanning from 2007 to 2021. The total value of the nighttime light within city boundaries is then extracted. Second, the particle swarm optimization back propagation algorithm is employed to unify the spatial scale, conduct matching and control analysis, and validate the correlation between carbon emissions and nighttime light brightness. This analysis allows for the quantitative construction of a fitting relation between the two and the carbon emission inversion model [49]: $T = a \cdot T_{nli}{}^2 + b \cdot T_{nli} + c$,

$T_c = 0.041 \times T_{nli}$. T is the grayscale correction value of the luminance data. T_{nli} is the original grayscale value of the light data. a, b, and c, are quadratic-fitted model parameters. T_c is the total actual carbon emissions. Then, to assess the accuracy of the data, a comparison is made between the simulated and statistical values. The average relative error between the simulated CO values and the statistical values is determined as 4.72%, indicating a high level of accuracy in simulating the total carbon emissions of the district and county based on the nighttime light data. Furthermore, combined with economic statistics, the total carbon emissions per unit of GDP are used to characterize carbon emission intensity, and the dependent variable is derived after taking the natural logarithm (lnCEI).

The commonly used nighttime light remote sensing data currently include two sets: DMSP-OLS and NPP-VIIRS. The DMSP-OLS nighttime light data from 1992 to 2013 were released by the National Oceanic and Atmospheric Administration (NOAA) of the United States and were generated by the Operational Linescan System (OLS) carried by the Defense Meteorological Satellite Program (DMSP). This dataset has high research value but suffers from problems such as brightness saturation and light spillage in high-brightness areas. To address these issues with the DMSP-OLS light dataset, the Visible Infrared Imaging Radiometer Suite (VIIRS) carried by the National Polar-orbiting Partnership (NPP) satellite, part of the National Polar-orbiting Operational Environmental Satellite System (NPOESS), provided a new generation of high-quality nighttime light data in 2012. Compared to DMSP-OLS data, NPP-VIIRS data have improved spatial and temporal resolution, thereby further expanding the application of nighttime light remote sensing. However, due to differences in sensors, the pixel values of light at the same spatiotemporal location differ greatly between the two types of light data, making direct integration impossible. In this study, the light data used are corrected using a cross-sensor calibration scheme based on an autoencoder model, resulting in a corrected annual composite dataset resembling NPP-VIIRS data from 2006 to 2021 [48].

3.3.2. The Selection and Source of Explanatory Variables

The microdata used to measure land price and construction land transfer scale are sourced from China's land market. The research team trawled 167,654 records of construction land transactions in Jiangsu Province. These records cover all fields available on the detailed page of the land transfer announcement, including location, project name, land area, transaction price, land source, land type, and transaction method. This dataset captures the objective situation of construction land transactions across districts and counties in Jiangsu Province. To address the non-uniformity of the raw data and handle potential issues with abnormal individual values, the code of each district and county is confirmed according to the administrative division code provided by the National Bureau of Statistics of China in 2021. To match the cities, the first four digits of the electronic regulatory number of each construction land transfer transaction, along with the name of the transaction site and the location of the project, are utilized. Subsequently, the date of the contract are employed to ascertain the timing of the land transaction. Finally, the micro land transfer data are aggregated to the district and county levels. Through data cleaning and matching processes, panel data spanning from 2007 to 2021 for the 96 districts and counties in Jiangsu Province are obtained.

The construction land transfer scale is selected as an explanatory variable to assess its impact on carbon emission intensity. In this paper, we measure the construction land transfer scale using the total area of construction land transferred annually within the Chinese land market, and the core explanatory variable is derived after taking the natural logarithm (ln*CLTS*).

3.3.3. Selection and Source of Control Variables

The control variables selected in this study are as follows: (1) Urbanization rate (*UR*). This is measured by the proportion of urban population in the total population of Jiangsu Province. (2) The level of economic development (ln*PGDP*). According to

Maslow's demand theory, the level of economic development influences demand levels, thereby affecting production and consumption patterns, which subsequently impact carbon emission intensity. To gauge the economic development level of different regions and examine the impact on carbon emissions of districts and counties, GDP per capita is selected. (3) Population density (ln*PD*). This variable represents the ratio of the number of permanent residents to the area of the administrative region at the end of the year. Population expansion can have uncertain impacts on carbon emission intensity. The expansion of consumption demand brought about by population growth may stimulate the growth of carbon emission intensity. The demographic dividend can also promote economic development [47,50]. (4) Environmental regulation intensity (ln*ER*). Drawing on the practice of Yan et al. (2023) [51] of measuring environmental regulatory intensity by pollution emissions, this paper uses the entropy weight method to obtain a composite index based on three indicators, namely, industrial wastewater emissions, industrial fume (dust) emissions, and industrial sulfur dioxide emissions, which is used to characterize environmental regulatory intensity. (5) Capital investment (ln*CI*). This variable represents the natural logarithm of the ratio of investment in fixed assets to GDP. According to the "Pollution Paradise Hypothesis", capital investment has a significant negative effect on carbon emission intensity [52]. However, the bias and diverse paths of capital investment may influence carbon emission intensity differently. Hence, the coefficient sign of capital investment cannot be determined.

The control variable data mentioned above are primarily sourced from the China County Statistical Yearbook, the China County (City) Socio-economic Statistical Yearbook spanning from 2007 to 2021. Due to data gaps for specific counties and years, interpolation is employed to supplement missing information. All variables related to monetary accounting are converted to comparable values in the base period using the GDP deflator for Jiangsu provincial administrative regions to eliminate the effects of price changes. The descriptive statistics are summarized in Table 1.

Table 1. Descriptive statistics.

Obs	N	Std. Dev.	Min	Max	Mean	Measurement Units
ln*CEI*	1382	0.566	0.000	2.491	0.580	Tons/RMB 10 thousand
ln*CLTS*	1382	1.472	0.128	19.517	8.360	100 km^2
UR	1306	0.508	36.9	89.6	64.1	%
ln*PGDP*	1382	0.757	1.753	33.311	12.714	RMB 10,000/person
ln*PD*	1382	0.225	0.021	1.783	0.147	100 person/km^2
ln*ER*	1382	0.225	0.016	1.012	0.370	-
ln*CI*	1382	0.256	0.210	1.480	0.794	%

Note: lnER is a composite index between 0~1 calculated using the entropy method.

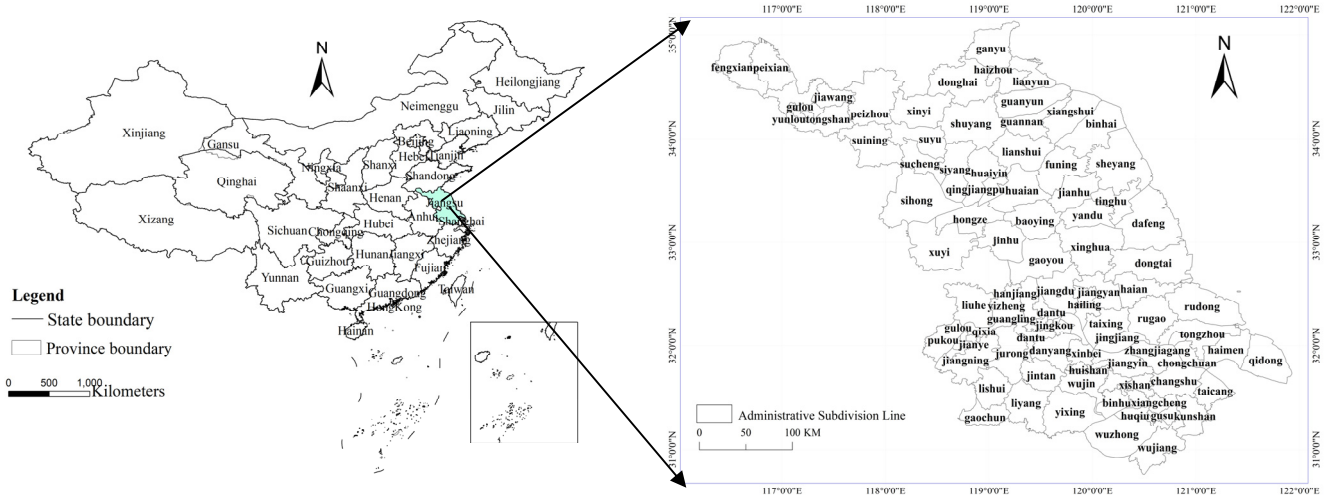
4. Empirical Process and Results Analysis

4.1. Spatiotemporal Characteristics of Carbon Emission Intensity in Jiangsu Province

4.1.1. Time Evolution Trend of Carbon Emission Intensity in Jiangsu Province

Under the double push of economic growth and promotion pressure, local governments in Jiangsu Province have formed a structural tendency to transfer industrial land. At the same time, local governments have taken measures such as industrial restructuring and promotion of green technology development, with a view to promoting economic transformation and the high-quality development process of emission reduction, which has formed the characteristics of the temporal evolution of carbon emission intensity in Jiangsu Province. Before conducting an econometric analysis, we need to understand the trend change in Jiangsu's carbon emission intensity from 2007 to 2021. As shown in Figure 2, Jiangsu's total carbon emissions increased gradually from 33.519 × 100 million tons in 2007 to 33.692 × 100 million tons in 2021, which is an increase of 51.66%. Jiangsu's carbon emission intensity continually decreased from 2.049 tons per RMB 10 thousand in 2007 to 0.429 tons per RMB 10 thousand in 2021, which is a decrease of 82.21%. Overall, the

total carbon emissions in Jiangsu Province from 2007 to 2021 showed a fluctuating upward trend, this was helped by carbon emission intensity showing a continuous downward trend (Figure 3). Peng et al. (2023) [36] showed a decrease in carbon emission intensity in eastern China. Xiao et al. (2023) and Zhang et al. (2024) [3,13] argue that although carbon emissions are increasing, the growth rate is gradually decreasing. This is consistent with the results of this study, and also reflects the persistent low-carbon transition development characteristic at the county scale in Jiangsu Province.



(**a**) Location of Jiangsu Province in China (**b**) Location of 96 districts and counties in Jiangsu Province

Figure 2. Location of 96 districts and counties in Jiangsu Province, China.

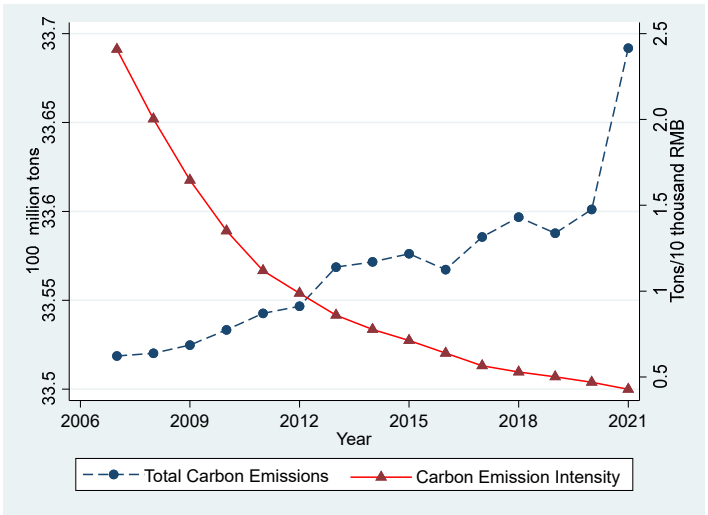


Figure 3. Total carbon emissions and carbon emission intensity of Jiangsu Province from 2007 to 2021.

4.1.2. Spatial Distribution Characteristics of Carbon Emission Intensity in Jiangsu Province

Combined with the inter-regional differences in land resource endowment and economic development base, there are spatial distribution differences in the carbon emission intensity of counties in Jiangsu Province, and this paper shows the spatial pattern and evolution of the carbon emission intensity from 2007 to 2021 (Figure 4). From the spatial distribution of carbon emission intensity in 96 counties, it can be found that carbon emission intensity shows a spatial distribution characteristic of decreasing from the southern region to the central and northern regions, and there is a clustering phenomenon in the "top 100 counties". The spatial heterogeneity of carbon emission intensity at the county

level in Jiangsu Province is obvious. The highest value of carbon emission intensity at the county level in Jiangsu Province increased from 2.032 tons/RMB 10 thousand in 2007 to 1.395 tons/RMB 10 thousand in 2021, while the lowest value remained at 0.000 tons/RMB 10 thousand.

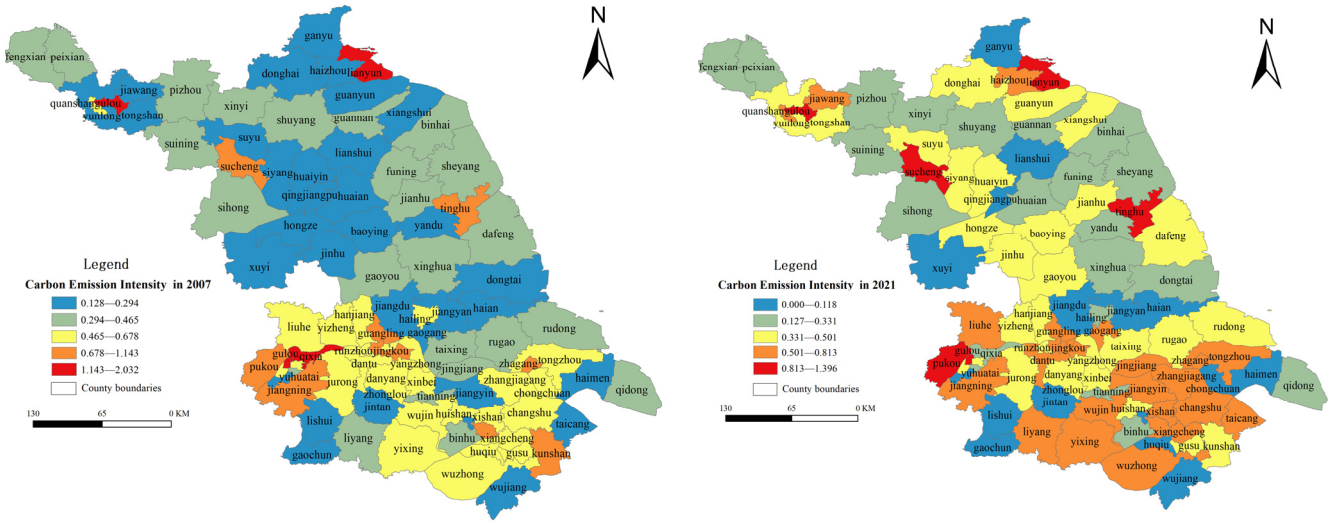


Figure 4. Evolution characteristics of county-scale carbon emission intensity.

From the perspective of the temporal trend of the spatial distribution of carbon emission intensity in different counties, it is found that compared with 2007, the overall carbon emission intensity in 2021 decreased, Huqiu District, Kunshan City, Chongchuan District, Hailing District and other counties decreased significantly, and the carbon emission intensity in the southern region gradually decreased over 15 years (Figure 4). This may be related to the fact that the economic development of the southern district and counties has matched the evolution of technological progress and environmental regulations [35,44,45]. It should be further explained that except for Lianyun District, Gulou District, Tinghu District, and Sucheng District, which have the highest carbon emission intensity in the province, Ganyu County, Lianshui County, Jiangdu District, Jiangyan District, Qingjianpu District, Lianshui County, Xuyi County, Haian County, Lishui County, Jintan District, Liangxi District, Gaochun County, Wujiang District, and so on, have the lowest levels in the province. This may be closely related to Jiangsu Province's focus on exploring low-carbon pathways in recent years [45]. Carbon intensity is a concept that can reflect the efficiency of carbon emissions in the process of economic development [40]. Compared with the counties in the central and northern parts of Jiangsu Province, the carbon emission intensity in the southern part of Jiangsu Province is significantly higher, which verifies that the correlation between economic development level and carbon emission intensity is high [53]. Thus, the carbon emission intensity should be heterogeneous within the area. The spatial pattern of carbon emission intensity in China is characterized by "high in the east and low in the west", with carbon emissions in developed regions in the east being significantly higher than those in less developed regions in the central and western parts of the country [2,13,20]. This may be due to the fact that the number of enterprises in the central and northern districts and counties of Jiangsu has increased the demand for construction land in the districts and counties, which in turn expanded the construction land transfer scale.

4.2. Test of Construction Land Transfer Scale on Carbon Emission Intensity

4.2.1. Regression Results of the Benchmark Model

The basic regression results, according to regression model (1), are presented in Table 2. The estimation results of the benchmark model indicate that for every 1% reduction in the construction land transfer scale, carbon emission intensity decreases by an average of 8.800%. In other words, the reduction of the construction land transfer scale posi-

tively impacts carbon emission intensity. The benchmark model only controlled for the regional and annual fixed effects and did not control for other variables. The coefficient of the construction land transfer scale passed the positive significance test at the 1% level (column 1, Table 2).

Table 2. The estimation results of the benchmark model.

Variable	(1) lnCEI	(2) lnCEI
lnCLTS	0.088 *** (0.002)	0.019 *** (0.004)
UR		−0.157 *** (0.078)
lnPGDP		−0.017 ** (0.007)
lnPD		0.019 *** (0.005)
lnER		−0.028 *** (0.004)
lnCI		3.440 *** (0.487)
Constant	0.220 *** (0.021)	0.825 *** (0.117)
Year FE	Yes	Yes
Individual FE	Yes	Yes
Observations	1382	1381
R^2	0.840	0.962

Note: Corresponding *t*-values under robust standard errors are in parentheses; **, and *** represent a 5%, and 1% significance test, respectively.

Subsequently, a series of control variables were introduced into the benchmark model to further ascertain the relative robustness of the positive relation. Although the coefficient value of the construction land transfer scale decreased, the coefficient of the construction land transfer scale remained positively significant at the 1% level. The regression results indicate that for every 1% reduction in the construction land transfer scale at the county level of Jiangsu Province, carbon emission intensity increases by an average of 1.900% (column 2, Table 2). This implies that the positive effect of construction land transfer scale on carbon emission intensity at the county level in Jiangsu Province cannot be overlooked. Overall, the results of the benchmark regression estimation align with H_1, implying that the larger the construction land transfer scale, the lower carbon emission intensity.

In terms of control variables, as expected, the urbanization level, economic development level, and environmental regulation intensity have a significant negative effect on carbon emission intensity. This suggests that the regional carbon emission intensity is on a downward trend as the regional urbanization level, economic development level, and environmental regulation intensity increase. Population density and capital investment have a significant positive effect on carbon intensity. This indicates that regional carbon emission intensity increases with the increase in population density and investment capital.

4.2.2. Regression Results of Instrumental Variables

The regression estimates in this paper may suffer from endogeneity problems: on the one hand, there is a significant positive correlation between the construction land transfer scale and carbon emission intensity, and the reduction of the construction land transfer scale may lead to a reduction in carbon emission intensity. However, the reduction of carbon emission intensity may also contribute to a further reduction in the construction

land transfer scale, and this two-way causality makes the effect difficult to be precisely identified. On the other hand, the model may have omitted variables. Although a series of control variables have been included in the model, there are still many unobservable factors affecting carbon emission intensity in the actual situation. In order to rule out possible problems of inverted causation and omitted variables, the instrumental variable approach is employed in this paper to further mitigate the influence of endogeneity issues on the study findings.

In line with the principles of the instrumental variable method, adherence of the instrumental variables constructed in this paper to the principle of "exclusivity" was deemed essential. That is, they should be exogenous variables that are only intrinsically related to the construction land transfer scale and not directly related to carbon emission intensity. The construction land transfer scale is influenced by the supply and demand factors. On the supply side, urban topography is employed as an instrumental variable for land transaction scales, drawing from the methodology proposed by Ivus and Boland (2015) [54]. Geographic characteristics variables impact current the construction land transfer scale but do not directly affect current carbon emission intensity, making them suitable instrumental variables. Generally, greater terrain undulation leads to increased costs and difficulties in land construction, thereby reducing the transaction volume of construction land [20,26]. However, in Jiangsu Province, plains constitute over 70% of the total area [35,45], and the topographic differences between counties are minimal. Following the approach of Zhang and Yu (2019) [55], this study uses the interaction term of average slope related to the terrain and per capita GDP of each district and county as instrumental variables (Slope × lnGDP). The DEM data were obtained from the Geospatial Data Cloud of the Computer Network Information Center of the Chinese Academy of Sciences (http://www.gscloud.cn accessed on 17 November 2022) with a spatial resolution of 30 m. Using the ArcGIS10.8 platform, the slope data of the county were extracted from the DEM data. The regression results are shown in model (1) and model (2) of Table 3. Then, from the demand side, existing research has indicated that high land use costs can limit the demand for urban land resources to some extent [53,56], thereby influencing the construction land transfer scale. Therefore, relying on land transfer data, the land price (lnLP) is employed as an instrumental variable for construction land transfer scale estimation. The regression results are shown in model (3) and model (4). Through the instrumental variable test, it is found that the Anderson LM statistic and the Cragg–Donald Wald F statistic of all models significantly reject the assumptions of "insufficient identification of instrumental variables" and "weak instrumental variables", respectively, indicating that the selection of instrumental variables in this paper is reasonable. The construction land transfer scale is significantly positive at the 1% confidence level, indicating that H_1 still holds after considering the endogeneity problem.

4.2.3. Robustness Tests

The study sequentially conducts sensitivity tests on several dimensions to confirm the robustness of the benchmark regression results. These tests include lagging the dependent variable, shortening the sample period, and excluding low-carbon policy shocks.

(1) The lagging effect of construction land transfer scale on carbon emission intensity

On the one hand, the construction land transfer and the carbon emission intensity may be causally related to each other in the same period. On the other hand, the construction period of most industrial projects is not one year in China; that is, the effect of construction land transfer scale on carbon emission intensity may be lagged. Referring to Ramankutty et al. (2007) [57], this study examines the effect of the lagging one period's construction land transfer scale on the current carbon emission intensity to provide a robust supplement to the benchmark regression model. The estimation coefficient of construction land transfer scale is greater than that in the benchmark regression model; it remains positive and statistically significant at the 1% level (column 1, Table 4). Despite the change in the measurement method of carbon emission intensity, the positive impact of construction land transfer scale

on carbon emission intensity persists. This further suggests a lagged effect of construction land transfer scale on carbon emission intensity.

Table 3. Regression estimation results of the instrumental variables method.

Variable	(1) First Stage (lnCLTS)	(2) Second Stage (lnCEI)	(3) First Stage (lnCLTS)	(4) Second Stage (lnCEI)
lnCLTS		0.056 ***		0.399 ***
		(0.021)		(0.067)
lnLP	0.189 ***			
	(0.027)			
Slope × lnGDP			0.272 ***	
			(0.042)	
The first-stage F statistics	50.90 ***		42.19 ***	
Cragg–Donald Wald F statistics	50.04 ***		42.25 ***	
Anderson LM chi-square statistics	50.97 ***		41.62 ***	
Control variables	Yes		Yes	
Year FE	Yes		Yes	
Individual FE	Yes		Yes	
N	1382		1382	
R^2	0.492		0.752	

Note: Corresponding *t*-values under robust standard errors are in parentheses; *** represent a 1% significance test.

Table 4. The results of robustness tests.

Variable	(1) Lagging Effect lnCEI	(2) 2009–2019 lnCEI	(3) Low-Carbon Policies lnCEI
lnCLTS	0.062 ***	0.026 ***	0.003 ***
	(0.025)	(0.005)	(0.001)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1209	981	1306
R^2	0.891	0.204	0.960

Note: Corresponding *t*-values under robust standard errors are in parentheses; *** represent a 1% significance test.

(2) Shortening the sample period

Prior to the 2008 financial crisis, China's economy experienced rapid development, characterized by a high reliance on industrial land and substantial carbon dioxide emissions. During this period, China's real estate market remained relatively stable, and the circulation of urban construction land was relatively sluggish [58]. Since 2009, the adjustment of urban construction land has entered a phase of rapid development [20,26]. While estimating the benchmark model, the sample interval has been maintained up to 2009 to ensure the integrity of the sample. However, the restructuring of urban construction land may underestimate the impact of construction land transfer scale changes on carbon emission intensity. Therefore, this study shortens the sample period to 2009–2021 and retests the hypothesis to alleviate estimation bias. The coefficient of construction land transfer scale significantly positively correlates at the 1% level, but it is larger than that estimated using the benchmark model (column 3, Table 4). This can be attributed to the exclusion of the sample period prior to 2009, reducing the dilution effect of the core explanatory variables in this study. The benchmark regression results in this study remain robust.

(3) Constructing dummy variables for low-carbon policies

This study considers low-carbon pilot cities as the pilot group (experimental group) and other cities as the non-pilot group (control group) to exclude the interference of low-carbon pilot policies on the conclusions of this paper, with reference to existing literature practices. The difference-in-differences model is employed to reperform the regression to weaken the changes in carbon emission intensity caused by environmental protection policies. The coefficient of the construction land transfer scale is 0.003 after accounting for the low-carbon pilot policy effect, which is statistically significant at the 1% level (column 3, Table 4). Although the coefficient of the construction land transfer scale decreases with the inclusion of the low-carbon pilot policy, the conclusion of the benchmark regression remains stable.

4.2.4. Mediating Mechanism Tests

(1) The effect of green technology innovation

This paper uses the number of green patents granted per 10,000 people to measure the green technology innovation (lnGTI). The number of green patents in districts and counties is derived from the patent database of the State Intellectual Property Office of China (SIPO), and is matched according to the IPC classification standards in the "International Patent Green Classification List" published by WIPO. The regression results with green technology innovation as the mediating variable are shown in Table 5. Model (2) in Table 5 shows that a reduction in the construction land transfer scale increases the green technology innovation level. Model (3) reports the regression results of adding green technology innovation to the benchmark regression model. The coefficient of green technology innovation is significantly negative, indicating that the increase in the level of green technology innovation is indeed conducive to the reduction of carbon emission intensity. Thus, it can be concluded that reductions in the construction land transfer scale improve the green technology innovation level, and the increase in the green technology innovation level further reduces the regional carbon emission intensity, so the mediating role of green technology innovation is established. The contribution of this part of the mediating effect to the total effect is calculated to be about 54.20%. This further confirms that the process of reducing carbon emissions will inevitably be accompanied by technological innovation in enterprises, which will upgrade the existing technologies and develop green technologies, thus realizing the "Porter hypothesis" [59]. This confirms the opinions of Huang et al. (2018) and Chen and Li (2023), who proposed that achieving carbon emission reductions requires the support of technology [17,49].

Table 5. Regression results of the effect of green technology innovation.

Variable	(1) lnCEI	(2) lnGTI	(3) lnCEI
lnCLTS	0.019 *** (0.004)	−0.047 ** (0.019)	0.017 *** (0.004)
lnGTI			−0.035 *** (0.006)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1305	1305	1305
R^2	0.204	0.389	0.228
Sobel test Z-value		|Z| = 2.341 ** (0.001)	
Bootstrap mediating effects		54.20%	

Note: Corresponding *t*-values under robust standard errors are in parentheses; **, and *** represent a 5%, and 1% significance test, respectively.

(2) The effect of industrial structure upgrading

This paper uses the ratio of the added value of the tertiary industry to the secondary industry to measure the industrial structure upgrading (ISU). The data are based on the 2007~2021 China County Economic Statistical Yearbook (County and City Volume). The regression results with industrial structure upgrading as the mediating variable are shown in Table 6. Model (2) in Table 6 shows that an increase in the construction land transfer scale will inhibit the industrial structure upgrading. Model (3) reports the regression results of adding industrial structure upgrading to the benchmark regression model. The coefficient of industrial structure upgrading is significantly negative, indicating that industrial structure upgrading is conducive to the reduction of carbon emission intensity. It can be observed that reduction of the construction land transfer scale promotes industrial structure upgrading, and industrial structure upgrading further promotes the reduction of regional carbon emission intensity, which is beneficial to regional carbon emission reduction, so the mediating effect of industrial structure upgrading is established. The contribution of this part of the mediating effect to the total effect is calculated to be about 10.10%. This result proves that promoting industrial restructuring and upgrading will in turn promote a low-carbon transformation of the regional energy structure [23,32].

Table 6. Regression results of the effect of industrial structure upgrading.

Variable	(1) lnCEI	(2) ISU	(3) lnCEI
lnCLTS	0.012 *** (1.690)	−0.885 ** (5.980)	0.008 *** (1.780)
ISU			−0.047 *** (4.342)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1306	1306	1306
R^2	0.414	0.858	0.462
Sobel test		|Z| = 2.430 ** (0.015)	
Bootstrap mediating effects		10.10%	

Note: Corresponding *t*-values under robust standard errors are in parentheses; **, and *** represent a 5%, and 1% significance test, respectively.

5. Heterogeneity Analysis

This section delves into the differential influence through which the construction land transfer scale impacts carbon emission intensity from four strands to verify the validity of the aforementioned findings: construction land transfer scale from different sources, diverse supply methods, different types, and different county economic strength.

5.1. Heterogeneity Test of Construction Land from Different Sources

The sources of construction land include both incremental construction land and stock construction land for secondary renovation. The incremental construction land is mainly used to safeguard public facilities, transportation, municipal facilities and other projects. With the increasing shortage in land resources, the past scale expansion type of development has been unsustainable, the development of Jiangsu Province from the "incremental expansion" to the "stock tapping" transformation, strict control of incremental land [34,35,45]. Combined with the Land Plan, the incremental construction land scale has been gradually reduced, and the approval threshold for incremental construction land has been gradually raised, and the land supply has gradually transitioned from mainly

incremental land to mainly stock land. Therefore, this paper further investigates whether different sources of construction land have different impacts on carbon emission intensity. In this paper, the group regression method is used to test the impact of different sources of construction land on carbon emission intensity; the specific regression results can be seen in Table 7 Pane A's model (1) and model (2). The results show that the coefficients of both incremental construction land and stock construction land on the carbon emission intensity are significantly positive, and the *p*-value of Fisher's coefficient difference test is 0.007; that is, the difference between the coefficients of each group is significant at the level of 1%. Compared with incremental construction land, the impact of stock construction land on carbon emission intensity is more significant. The observed phenomenon can be attributed to the fact that over the past three decades since the 1990s, many industrial land grants in Jiangsu Province have remained valid, resulting in a substantial stock of industrial land primarily owned by small and medium-sized enterprises operating in lower-tier industries. This situation has led to the development of sloppy practices and inefficient use of land resources [21]. The anthropogenic carbon emissions carried by the incremental construction land are generally decreasing, while the stock construction land mainly carries the carbon emissions of the secondary industry. As a result, its total carbon emissions are increasing, but the carbon emission intensity is generally decreasing. Despite existing research on the relation between construction land and carbon emissions, few studies have delved into the connection between incremental construction land and stock construction land with carbon emission intensity. In this regard, this study addresses the research gap and offers policy implications by shedding light on the possible environmental consequences of specific land and macro policies.

5.2. Heterogeneity Test of Construction Land with Different Supply Methods

Currently, there are two supply methods of construction land allocation in China. One is the market-oriented allocation of construction land based on the market mechanism, which mainly sells construction land through "bidding, auction, listing", with a high degree of marketization. The other is the administrative allocation mode of construction land based on government intervention, which mainly transfers construction land through administrative allocation, which has the characteristics of rigid control.

Therefore, this paper further investigates whether construction land with different supply methods will have a different impact on carbon emission intensity. In this paper, the sample of "bidding, auction, listing" is assigned a value of 1 and the allocated sample is assigned a value of 0. The group regression method is used to test the impact of construction land scale with different supply methods on carbon emission intensity, and the specific regression results can be found in Table 7—Pane A's models (3) and (4). The results showed that the coefficients of allocated construction land and transfer construction land are significantly positive at the levels of 1% and 10%, respectively. The *p*-value of Fisher's coefficient difference test was 0.005; that is, the difference between the coefficients between the groups is significant at the level of 1%. Compared with the market-oriented allocated construction land, the transfer construction land has a greater impact on carbon emission intensity. This is consistent with the findings of Li et al. (2023) [60]. This is because from the perspective of efficiency, the economic efficiency of market allocation of construction land is higher, the technological innovation level is higher, the industrial structure tends to be more rational, and the carbon emission intensity tends to decline. However, there is no need to pay the government for land use rights to obtain land use rights through administrative allocation, and most of them are industrial enterprises that use land assets in a low-cost manner, the green technology innovation level is low, the industrial structure is unbalanced, and the carbon emission intensity has increased significantly [60]. On the other hand, since the 1990s, China began to pay land transfer fees, and the amount of allocated land has gradually decreased, and the proportion of allocated land is much lower than the proportion of transfer land, so its effect on carbon emission intensity is relatively small.

Table 7. The results of heterogeneity test. (**Pane A**): Heterogeneity test results of different sources and different supply methods. (**Pane B**): Heterogeneity test results of different types. (**Pane C**): Heterogeneity test results of county economic strength.

Pane A				
Variable	**ICL lnCEI**	**SCL lnCEI**	**ACL lnCEI**	**TCL lnCEI**
lnCLTS	0.009 **	0.014 **	0.009 **	0.012 ***
	(0.006)	(0.004)	(0.006)	(0.005)
Constants	0.200 ***	0.242 ***	0.213 ***	0.268 ***
	(0.029)	(0.032)	(0.023)	(0.047)
Control variables	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	849	533	400	982
R^2	0.372	0.109	0.240	0.877
Between-group coefficient test *p*-value	0.007		0.005	

Pane B					
Variable	**(1) Gland lnCEI**	**(2) Pland lnCEI**	**(3) Rland lnCEI**	**(4) Iland lnCEI**	**(5) Oland lnCEI**
lnCLTS	−0.005	0.014 **	0.013 **	0.078 ***	0.023 *
	(0.007)	(0.006)	(0.082)	(0.004)	(0.059)
Constants	0.721 ***	0.300 ***	0.302 ***	0.215 ***	0.208 ***
	(0.031)	(0.058)	(0.085)	(0.029)	(0.040)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	55	320	254	458	296
R^2	0.994	0.792	0.779	0.869	0.911

Pane C		
Variable	**Top 100 Counties lnCEI**	**Non-Top 100 Counties lnCEI**
lnCLTS	0.015 **	0.007 ***
	(0.004)	(0.003)
Constants	0.182 ***	0.327 ***
	(0.019)	(0.024)
Control variables	Yes	Yes
Individual FE	Yes	Yes
Time FE	Yes	Yes
N	325	1057
R^2	0.275	0.502
Between-group coefficient test *p*-value	0.009	

Between-group coefficient test *p*-value was calculated using Fisher's permutation test (1000 samples). Corresponding *t*-values under robust standard errors are in parentheses; *, **, and *** represent a 10%, 5%, and 1% significance test, respectively.

5.3. Heterogeneity Test of Construction Land Transfer Scale for Different Types

Construction land is categorized into industrial land (iland), residential land (rland), green land (gland), public land (pland), and other land (oland) [6,14] in terms of different use attributes to analyze the causal relation between construction land transfer scale and carbon emission intensity. These five variables have been added to the benchmark regression model as explanatory variables. The coefficient of green land is negative, although it does not pass the significance test, which is consistent with the carbon sink attribute of green land. The reason for the insignificant effect of green land on carbon emission

intensity may be the small scale of green land transfer. The regression results indicate that public land, residential land, industrial land, and other land are statistically significant and positive at the 5%, 5%, 1% and 10% levels, respectively (columns 2 to 5 of Table 7—Pane B). The contribution of different types of construction land to carbon emission intensity is in the order of industrial land > other land > public land > residential land [46]. This can be attributed to the following reasons: first, under a certain construction land transfer scale and a dual-track system of land pricing, local governments may prioritize economic development. They may reduce the supply of residential or public land while increasing the supply scale of industrial land to attract industrial investment [60]. Industrial land is the most important carrier of industrial production and energy consumption, so it has a very strong driving force on carbon emission intensity [28,36,47]. Second, the increase in the industrial land supply scale has brought about a rise in industrial energy carbon emissions due to scale effects [20,32,60]. In addition, green land serves as a vital carbon sink, representing the primary source of the urban carbon sink. Increasing the scale of green land can help mitigate carbon emissions. In the process of county development, the government should increase the proportion of green land to enhance the carbon storage function of land.

5.4. Heterogeneity Test of Construction Land Transfer Scale for County Economic Strength

In addition to the construction land itself, the county economic strength can have a direct impact on carbon intensity [61,62]. Based on the above considerations, a list of the top 25 counties in Jiangsu Province in 2021 is compiled, and the causal relationship between county construction land and carbon emission intensity is captured based on this explicit observable feature.

Model (1) and model (2) of Table 7—Pane C compare the difference in the effect of the construction land transfer scale in the "top 100 counties" on carbon emission intensity between the "top 100 counties" and the "non-top 100 counties", respectively. From the regression results, it can be seen that the coefficients for the top 100 counties and non-top 100 counties are significantly positive at the 5% and 1% levels, respectively. The top 100 counties are 0.80 percentage points higher than the non-top 100 counties. The *p*-value of Fisher's coefficient difference test was 0.009; that is, the difference between the coefficients between the groups is significant at the level of 1%. This means that when the county economy strength is greater, reductions in the construction land transfer scale reduce its carbon emission intensity more significantly. The reason may be that the county government has greater economic strength, and its innovation ability and industrial structure tend to be more optimized, which can help it achieve carbon neutrality faster [61].

6. Conclusions and Discussion

6.1. Conclusions

In China, the construction of low-carbon cities is crucial to achieve carbon neutrality and sustainable development. This study explores the spatial and temporal differentiation characteristics of carbon emission intensity in counties in Jiangsu Province from 2007 to 2021. The construction land transfer data from 2007 to 2021 in counties of Jiangsu Province is integrated to empirically test the effect mechanism of the construction land transfer scale on carbon emission intensity. Our findings reveal that:

(1) The total carbon emissions at the county level in Jiangsu Province from 2007 to 2021 show a fluctuating upward trend, this is helped by the carbon emission intensity showing a continuous downward trend. Carbon emission intensity at the county level in Jiangsu Province generally exhibits a spatial distribution characterized by a gradual decrease from the southern counties to the central and northern counties, and there is a clustering phenomenon in the "top 100 counties".

(2) The results of the benchmark regression indicate a significant positive relation between construction land transfer scale and carbon emission intensity. For every 1% reduction in the construction land transfer scale, the carbon emission intensity decreases by

an average of 1.9%. Furthermore, the green technology innovation and industrial structure upgrading effects play a partially mediating role in the process of the construction land transfer scale affecting carbon emission intensity. The study results remain valid even after a series of robustness tests. Moreover, the urbanization level and the environmental regulation intensity have a significant negative effect on carbon emission intensity. However, an inverse effect exists among population density and capital investment.

(3) Heterogeneity is observed in the impact of different construction land sources, construction land supply methods, and construction land types on carbon emission intensity. From the perspective of different sources of construction land, the impact of stock construction land on carbon emission intensity is more pronounced than that of incremental construction land. In terms of the methods of acquiring construction land, the impact of allocated land on carbon emission intensity is more pronounced than that of transferred land. In terms of different types of construction land, industrial land contributes the most to carbon intensity, while residential land contributes the least. Green land serves as a vital carbon sink, representing the primary source of the urban carbon sink. Finally, from the perspective of the economic strength of counties, the reduction in the construction land transfer scale is more pronounced in the reduction of carbon emission intensity when the county's economic strength is greater.

6.2. Discussion

6.2.1. Characteristics of Spatial and Temporal Distribution of Carbon Emission Intensity

This paper explores the spatiotemporal distribution of carbon emission intensity and examines the relationship between construction land transfer scale and carbon emission intensity. The total carbon emissions at the county level in Jiangsu Province from 2007 to 2021 show a fluctuating upward trend, this is helped by the carbon emission intensity showing a continuous downward trend. Carbon emission intensity at the county level in Jiangsu Province generally exhibits a spatial distribution characterized by a gradual decrease from the southern counties to the central and northern counties. The continuous decline in China's carbon emission intensity is the key to achieving carbon emission reduction. The results align with those obtained in previous studies, indicating that land use significantly influences carbon emissions [8,17], and protecting green land can help mitigate them [63]. However, this paper introduces a novel approach for calculating carbon emissions by inversion of nighttime lighting data. In the previous studies, carbon emission accounting mostly focused on the weight of population and GDP for carbon emission allocation, and there were relatively few studies based on the fitting and estimation of nighttime light data. However, nighttime light data have a high correlation with energy consumption carbon emissions, and the estimation of county-level indirect carbon emissions with the help of nighttime light data can effectively make up for the incomplete statistical data of county-level units [62,64].

In addition, similar to the idea of decomposition of low-carbon goals, China's territorial spatial planning system has also formed a "five-level" target transmission mechanism at the national, provincial, municipal, county, and township levels [65]. It is an important focus of the combination of the national dual-carbon development strategy and territorial spatial planning to optimize the carbon source and sink structure of the land space from top to bottom, so as to achieve carbon control and emission reduction and gradually achieve carbon neutrality [66].

6.2.2. Construction Land Transfer Scale and Carbon Emission Intensity

To sum up, based on the panel data of counties in Jiangsu Province from 2007 to 2021, this paper uses carbon emission intensity to quantify emission reduction targets, and empirically analyzes the effect of the construction land transfer scale on regional carbon emission intensity, as well as its internal mechanism, which provides empirical references

for the land policy regulation of carbon emission reduction. This study reveals that all districts in Jiangsu Province experience a decrease in carbon emission intensity when there is a decrease in the construction land transfer scale. Specifically, for every 1% reduction in the construction land transfer scale, carbon emission intensity is reduced by an average of 1.9%. Furthermore, mediating analysis indicates that the construction land transfer scale reduces carbon emission intensity by enhancing green technology innovation and industrial structure upgrading.

As the most important natural resource input and the most important carrier of carbon emissions in the process of regional urbanization and industrialization, construction land will inevitably lead to a corresponding increase in carbon emissions with the continued expansion of its area [7,26]. This is due to the extensive use of construction land in the early stage of development [7,20]. When the urbanization level and industrialization develop to a certain stage, due to the transformation of the industrial structure carried by the construction land, the improvement of energy technology, and even the strengthening of environmental policies and public awareness of environmental protection, the carbon emission intensity will gradually decrease, which is due to the intensive use of construction land after a certain stage of development. Although the Kuznets curve relationship between construction land expansion and carbon emission intensity shows that the relationship between construction land expansion and carbon emission intensity is an inverted U-shaped Kuznets curve [29], the carbon emission intensity will gradually decrease as the construction land area increases to an inflection point. Therefore, the conclusions of this study are still valid. Therefore, Jiangsu Province, located in the rapidly urbanizing Yangtze River Delta region, must respond positively to land use policy regulation in order to achieve the coordinated development between land use and ecological environment, rather than passively waiting for the inflection point of the Kuznets curve of carbon emissions.

Regardless of whether at the provincial or city level, an increase in industrial land will increase regional economic activity and energy consumption level, thereby significantly increasing carbon emissions [28,34]. In some economically developed regions, such as Beijing City, Guangdong Province, Shanghai City, and Zhejiang Province, the carbon emission intensity of incremental construction land has not decreased significantly [17]. The same goes for New York City and Paris City [6,19]. In this paper, the study area focuses on a finer county scale range, where incremental construction land has a significant impact on carbon emission intensity, and its role is significantly greater than that of the stock construction land. Studies at the smaller county scale are needed.

This paper adds two mediating variables, green technology innovation and industrial structure upgrading, to examine the transmission mechanism of the construction land transfer scale on carbon emission intensity. The previous literature has summarized the conduction paths of environmental pollutants such as carbon emissions into scale effects, technological effects, and structural effects [7,20,49], and reported that the main reasons for economic growth include technological innovation and industrial structure [20,49]. China's manufacturing sector as a whole is at the middle and lower end of the global value chain, and it is much more difficult to reduce carbon intensity by adjusting the industrial structure than in developed countries [60,67]. However, the path to reducing carbon emission intensity is similar, and provinces with similar economic development characteristics can promote and learn from their successful experience in the application of low-carbon technologies and industrial structure adjustment, improve their carbon emission efficiency, and thus, promote the further improvement of their carbon emission intensity.

The construction land data used in the paper have been projected from China land transaction market data. Differences can be observed with the vector data obtained from the land survey. These findings have implications for guiding regional low-carbon development in China. Formulating emission reduction measures is vital to meet the characteristics of individual counties because of the differences in their development in Jiangsu Province. In addition, this study only focuses on the difference in the impact of construction land transfer scale on carbon emissions within regions, without considering the causal relation

between the construction land transfer scale and carbon emissions in different periods. Future research should enhance the precision of construction land data and explore the influence of the construction land transfer scale on carbon emissions and its impact mechanism in different periods.

6.2.3. Policy Recommendations

To encourage Jiangsu and China to develop a low-carbon and regionally balanced model, some policies are proposed.

(1) Considering the heterogeneity among counties and municipal districts in Jiangsu, targeted action plans should be formulated. In light of the conclusions proposed by Liu et al. (2023) and Zhang et al. (2021) [62,65], counties should transform their industrial structure as soon as possible to reduce the cost of carbon emissions of high-emission enterprises, especially secondary industry. At the same time, more enterprises in carbon-emission-intensive industries need to be included in the construction of the carbon market so as to further control counties' high carbon emissions [62,64]. Given that municipal districts always have higher land development, they should focus more on improving green vegetation cover so as to achieve more carbon sequestration by forests, especially the project of "returning farmland to forest" and planting trees in built-up areas [12,16].

(2) Upgrading and optimizing the industrial structure, as well as promoting coordination between industries by adjusting the construction land scale, can help save energy and reduce carbon emissions. Facing unprecedented changes, the transfer of a considerable amount of industrial land presents substantial opportunities for the comprehensive upgrading and transformation of industries in Jiangsu Province. This shift opens up possibilities for enhancing industrial and energy structure optimization. Further refining the industrial structure, fostering low-energy consumption and low-pollution industries, and attracting high-quality labor resources is crucial to achieve carbon neutrality. In particular, government should increase R&D investments and set up R&D platforms for both high-emission and cleaner advanced energy technologies [32,51,59].

(3) Advancing toward a green and low-carbon economy is crucial while carefully monitoring the effects of alterations in construction land on carbon emissions. Accordingly, we should enhance the land use structure by considering stock construction land and incremental construction land, focusing on improving the latter and optimizing the former. This involves reallocating land for industries with varying carbon footprints within construction areas, guiding industrial growth toward green and low-carbon practices, and promoting the decoupling of construction land from carbon emissions [2,14].

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