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Mechanism and Spatial Spillover Effect of New-Type Urbanization on Urban CO_2 Emissions: Evidence from 250 Cities in China

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Abstract: Exploring the effect of new-type urbanization (NTU) on urban carbon abatement is of great practical significance for promoting urban green construction and coping with the challenge of global climate change. This study used data from 250 cities in China from 2008 to 2020 and constructed the NTU evaluation indicator system from five dimensions. We used classical panel regression models to examine the effects of NTU on urban CO_2 emissions, and further used spatial econometric models of SEM, SAR, and SDM to identify the spatial spillover effects of NTU on urban CO_2 emissions. The main results are that China's NTU and CO_2 emissions are generally rising, and NTU has a significantly negative effect on urban CO_2 emissions, with an impact coefficient of -0.9339; the conclusions still hold after subsequent robustness tests. Heterogeneity analysis reveals that NTU's carbon abatement effect is more pronounced in resource-based cities, old industrial areas, and cities with lower urbanization levels and higher innovation levels. Mechanism analysis shows that improving urban technological innovation and optimizing resource allocation are important paths for realizing urban CO_2 emission reduction. NTU's effect on urban CO_2 emissions has a noticeable spatial spillover. Our findings provide policy makers with solid support for driving high-quality urban development and dual-carbon targets.

Keywords: CO_2 emissions; mechanism analysis; new-type urbanization; spatial spillover effect

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1. Introduction

Nowadays, global warming is becoming a key issue in international sustainable development research [1,2]. The Emissions Gap Report 2020 by the UNEP pointed out that the global temperature could rise by more than 3 °C this century, well above the Paris Agreement's control temperature goals of limiting global warming to well below 2 °C and pursuing 1.5 °C, which would trigger catastrophic climate change [3]. The IPCC also states that climate-related risks to natural and human systems are higher for global warming above 1.5 °C than at present but lower than at 2 °C [4]. Humans' extensive use of fossil fuels, which has caused a sharp increase in CO_2 emissions, may be the primary cause of climate change [5]. Cities, where there is a concentration of human economic activity, are the primary contributors to CO_2 emissions. According to studies, up to 70% of CO_2 emissions are produced in urban areas [6]. Currently, cities occupy less than 3% of the global land area but more than 50% of the worldwide population [7]. With large-scale population clustering in cities, global urbanization will continue to accelerate. Cities are the most important carriers and governance units for green and low-carbon development. However, whether new-type urbanization (NTU) can promote urban CO_2 reduction still needs to be determined. Hence, a thorough investigation of the connection between NTU and CO_2 emissions is essential.

China is undergoing significant changes as the second-largest economy and the largest emitter of carbon dioxide in the world. Over the past 30 years, there has been a rise in CO_2 emissions in China. To combat climate change, China has announced plans to boost its National Independent Contribution, with CO_2 emissions expected to peak in 2030 and an endeavor to achieve carbon neutrality by 2060 [8]. The above facts indicate that China still faces a considerable challenge in reducing CO_2 emissions. Based on the latest data, China's urbanization rate reached 65.2% in 2022, an increase of 47.3% compared to 17.9% in 1978 (data source: China National Bureau of Statistics). In 2021, the urbanization rates in the U.S. and U.K. reached 82% and 84.2%, respectively, which indicates that China will reach an urbanization pace comparable to that of developed countries in the future. According to the United Nations, the global urbanization process will continue to accelerate, and the world's urban population is expected to exceed 6.6 billion by about 2050, with an urbanization rate of 68% [9].

China's urbanization development path has made an essential contribution to humans. Rapid urbanization improves external agglomeration effects, significantly promotes economic development, and raises the quality of life of residents. Despite this progress, problems and challenges have remained. For example, urbanization has introduced problems such as the irrational spatial layout of cities and towns, imbalance of market structure, and the disproportionate layout of industrial structure, leading to the emergence of "urban diseases" [10]. Low-carbon urbanization has become a new trend in future urban construction to achieve the "double carbon" target [11]. Thus, debating the driving mechanisms and paths to realizing "CO_2 emission reduction" is critical to ensure the coordination of NTU and urban green development. It may be an imperative strategy to develop a comprehensive vision of a "beautiful China" and deal with the problems posed by global climate change.

Clarifying how NTU affects urban CO_2 emissions is theoretically and practically important to successfully fulfill a "win-win" aim of ecological civilizations as well as economic growth. Consequently, four major questions are posed in this study: (i) How can we build a scientific evaluation indicator system of NTU? (ii) How does NTU affect urban CO_2 emissions? (iii) What is the inner mechanism? (iv) Does the spatial spillover effect exist? These questions are in urgent need of scientific evaluation. A more accurate analysis of the above questions can help coordinate the goals of NTU and a green, low-carbon economy.

Consequently, the possible contributions of this research are as follows. First, this study is based on an essential connotation of NTU: emphasizing people as the core, four modernizations synchronization, optimal layout, ecological civilization, and cultural heritage, and constructing an NTU evaluation indicator system with five dimensions of population, economy, society, space, and ecology to expand and enrich the research scope and content of NTU. Second, numerous existing studies directly discuss the impact of the urbanization process on CO_2 emissions. However, this study in-depth examines the internal mechanism of NTU that reduces urban CO_2 emissions and uses empirical methods to verify mechanisms including technological innovation and resource allocation optimization. Third, in terms of policy inspiration, this research conducts an array of heterogeneity analyses, and also explore NTU's spatial spillover effects on CO_2 emissions, and the findings provide policy inspiration for promoting green and low-carbon urban development in a sub-regional, focused, and cross-regional collaboration.

This study's remaining sections are arranged as follows. Section 2 is a literature review, followed by a research hypothesis presented in Section 3. Section 4 details the materials and methods. The results and discussion are given in Sections 5 and 6, respectively, and the conclusions and policy recommendations are presented in Section 7. The primary research framework of this study is depicted in Figure 1.

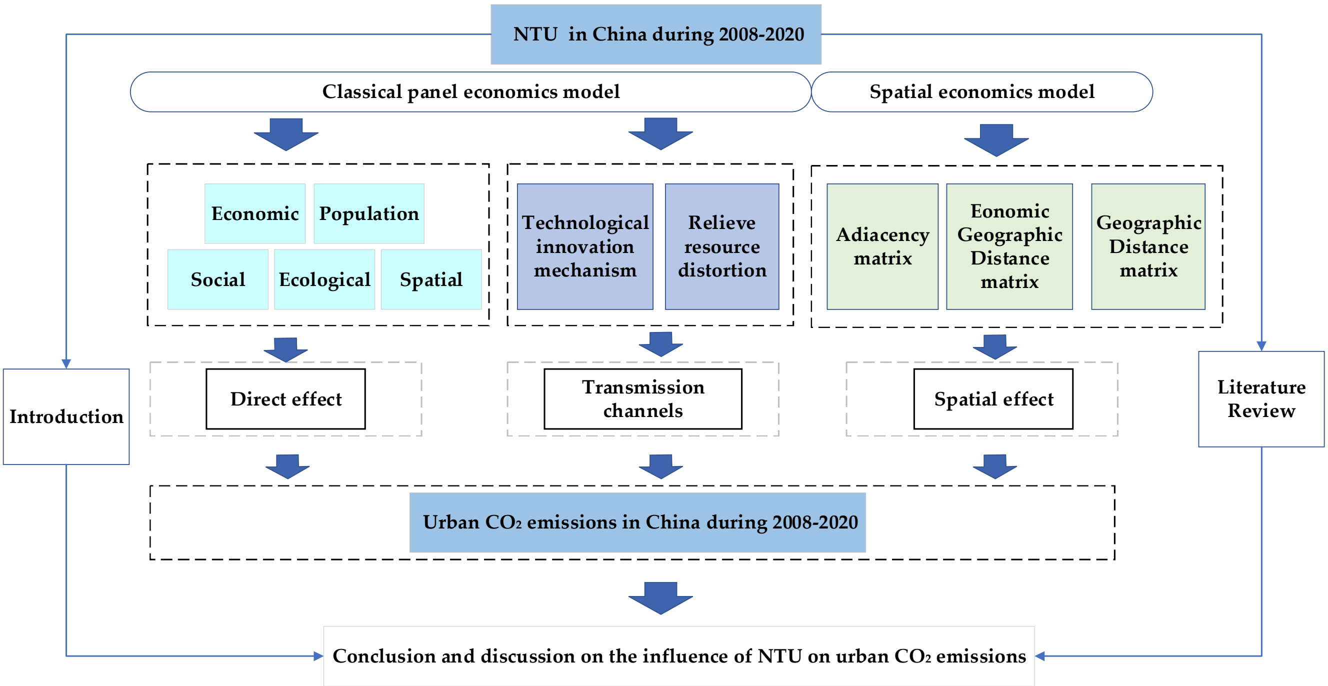

Figure 1. Research framework.

2. Literature Review

2.1. Construction of Urbanization Evaluation Index System

The study of NTU has enriched the scientific connotation of urbanization construction, and a growing number of findings have verified the close links between the evolutionary process of urbanization and economic development [12,13], demographic factors [14,15], industrial structure [16], spatial structure layout [17], and the ecological environment [18,19]. However, there is a big difference between traditional urbanization and NTU. Traditional urbanization has many areas for improvement in the development process, such as uncoordinated human–land development [20] and prominent deep-seated contradictions in the urban–rural dual structure [21]. Additionally, existing research on NTU has made great progress, focusing on the essential connotation and development characteristics of NTU [22] and the construction of an indicator system [23]. The scientific construction of the evaluation indicator system of NTU is conducive to exploring the speed and path of its sustainable and healthy development. In the past, most studies focused on constructing urbanization indicator systems using a single dimension. For example, using population size to measure population urbanization is common [24]; some scholars also use the level of GDP or disposable income per capita to measure economic urbanization [25]. As research advances toward a deeper perspective, scholars have gradually proposed a more scientific and comprehensive indicator system to measure urbanization. Several researchers have tried constructing a multidimensional urbanization indicator system with four aspects: economic, demographic, spatial, and social [6].

2.2. The Driving Factors Affecting CO_2 Emissions

The drivers of carbon emissions have been an essential aspect of studies at home and abroad, and exploring the internal driving factors of CO_2 emissions helps formulate CO_2 emission reduction policies and realize sustainable economic and social development. Several existing studies have analyzed the effects of many factors on CO_2 emissions, such as economic scale, the structure of industry and energy, population size, household size, low-carbon technology, investment, export, and income level [26,27]. Studies show that the economic development level is the primary driver that may affect CO_2 emissions [28]; furthermore, technological progress contributes significantly to reducing CO_2 emissions [29], and the energy consumption structure is the leading factor affecting the difference in CO_2 emissions [30]. Additionally, environmental policies play an important part in CO_2 emissions, such as environmental regulations being a fundamental reason for curbing CO_2 emissions [31,32]. Furthermore, the STIRPAT model, IPAT model, EKC curve, Kaya constant equation, and LMDI model were used to evaluate the impact of CO_2 emissions [24,33–35].

2.3. How Urbanization Affects CO_2 Emissions

Throughout the existing studies, scholars mainly focus on the following areas. The first is the impact of single-dimensional urbanization on urban carbon emissions. Most empirically explicate the effect of urbanization on CO_2 emissions from the population urbanization dimensional [36]. Some scholars also use the proportion of urban land to characterize spatial urbanization and further study its impact on CO_2 emissions [37]. Secondly, the connotation of NTU has diverse characteristics, urgently reevaluating the effects of urbanization on carbon emissions [38]. For example, at present, several studies have discussed NTU into low-carbon development [39]. Scholars have fully explored the model, policy logic, and action direction for the transition to low-carbon development transition of NTU [40,41]. Thirdly, to explore the relationship between urbanization and environmental pollution. Numerous studies have examined the link between them at the theoretical or empirical level, verifying that an accelerated NTU process leads to worsening environmental pollution, although the government's environmental regulations can effectively improve the situation in the short term [42]. Another part of researchers concentrated on how urbanization affects pollutants such as AQI and PM2.5 [43,44]. In addition, the spatial threshold effect of urbanization on energy efficiency has also been explored [45].

In conclusion, the current literature has produced a relatively comprehensive discussion on the link between urbanization development and CO_2 emissions. However, there may still be some areas for improvement in three aspects. First, the majority of the existing research is based on single-dimensional urbanization, such as population, economy, or land, but ignores a critical dimension of NTU: ecological urbanization. Second, few literature have examined in depth the internal mechanisms underlying the impact of NTU on CO_2 emissions. Therefore, it is difficult to provide more targeted countermeasure suggestions based on the research results. Third, most existing studies overlook the spatial characteristics of NTU's effects on CO_2 emissions, except for a few papers that mention that urban CO_2 emissions are not purely local pollution [46,47].

3. Research Hypothesis

3.1. The Effect of NTU on Urban CO_2 Emissions

NTU directly affects CO_2 emissions in four ways. First, population urbanization is favorable for improving resource efficiency and lowering industrial carbon emissions. The aggregation of human capital and information brought by NTU is beneficial to improve the intensive use of resources and cut industrial emissions [48]. Second, spatial urbanization can contribute to building a low-carbon-oriented territorial spatial organization system. NTU constructs green space urban planning with a low-carbon orientation, accelerating the formation of green, low-carbon cycle cities [49]. Third, green development is the essence of the construction of ecological urbanization. NTU incorporates the ecological dimension, and "green, intensive, intelligent, and low-carbon" are the essential characteristics. Finally, promoting "double carbon" is urgent to resolve the significant problems of urban resources and environmental constraints and force urban infrastructure's low carbonization. Therefore, the following research hypothesis is proposed.

H1: *NTU can reduce urban CO_2 emissions.*

3.2. The Mechanism Analysis of NTU on Urban CO_2 Emissions

At present, green technology innovation is an essential path to realizing sustainability for cities around the world [50]. First, NTU can promote the clustering of innovation factors. NTU is conducive to improving accessibility within and between cities, significantly reducing urban transaction costs, and promoting the flow of inter-regional innovation factors. Secondly, NTU can deepen urban digitalization. NTU takes advantage of the massive information, data sharing, and high efficiency of computing brought by digitalization to promote innovation in various fields, especially the use of renewable energy, and then boost energy efficiency to decarbonize production processes [51]. Accordingly, the following hypothesis is proposed.

H2: *NTU can facilitate urban CO_2 emission reduction through the improvement of urban technology innovation.*

Under the premise of following the law of urbanization development, NTU fully coordinates the organic unity of land, labor, capital, and technology. First, NTU promotes urban capital renewal. NTU reduces transportation and inventory costs through agglomeration, achieves more efficient resource allocation, and improves the overall synergistic factor allocation efficiency to reduce carbon emissions [52]. Second, NTU can enhance the allocation efficiency of labor resources. Specifically, NTU changes the spatial distribution of labor, optimizing the efficiency of labor market allocation. Third, NTU accelerates the construction of an open and modernized industrial system. NTU is conducive to forming the industry chain and supply chain of "resources–products–waste material–new resources–new products" and has the advantage of intensive and sustainable use. Accordingly, the following hypothesis is proposed.

H3: *NTU can reduce urban CO_2 emissions by improving the factor allocation effect.*

3.3. The Spatial Spillover Impact of NTU on Urban CO_2 Emissions

Then, what is the theoretical logic of the spatial spillover effect of NTU on urban CO_2 emissions? It is mainly through the following three processes: the first is the agglomeration effect. The clustering of urban elements is beneficial for the emergence of an exemplary zone that is a green, low-carbon, and inclusive modern city [53], which has a sound demonstrative impact on nearby cities. The second is the diffusion effect. According to the "center-periphery" theory, the demonstration effect can drive the imitation and learning of "neighboring areas", further forming the diffusion effect [54]. Further, the areas that take the lead in green and low-carbon urban development due to their first-mover advantage are more likely to be the targets of imitation and learning [55]. The third is the mutual feedback effect. The degree of openness among cities is expanding through the socio-spatial interaction mode in which regions, industrial sectors, and residents are linked to production networks, accelerating the flow of various factors and strengthening the spatial linkage of commodity markets among different cities. The research framework of the theoretical hypotheses is given in Figure 2.

H4: *NTU has a spatial spillover effect on urban CO_2 emissions.*

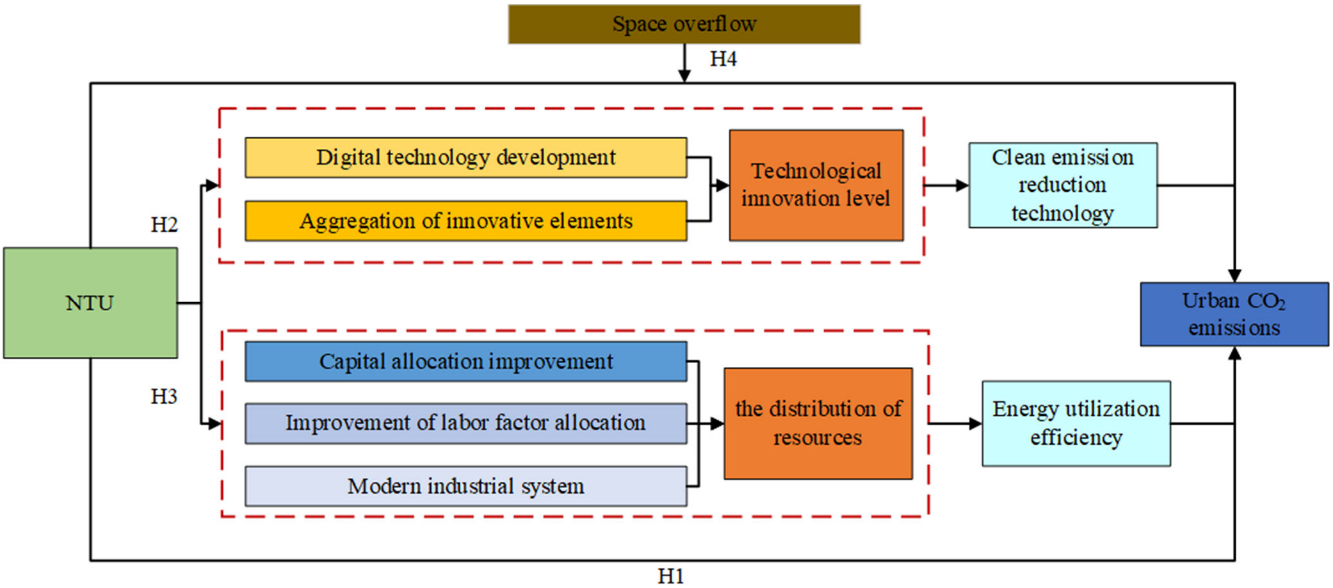

Figure 2. The impact mechanism between NTU and CO_2 emissions.

4. Materials and Methods

This study used the entropy value method to measure the dependent variable's NTU level. The OLS was applied to reveal NTU's mechanism of action and heterogeneity on CO_2 emissions. Additionally, a spatial econometric model was used to examine the spatial spillover effect brought by NTU on CO_2 emissions.

4.1. Model

4.1.1. Model Setting

Referring to Clark and Cummins [56] and Ren et al. [57], this study empirically tested the relationship between NTU and urban CO_2 emissions. The following econometric model was constructed as listed below in which NTU is set as the core independent variable.

$$lnCO_{2it} = \alpha_i + \beta_1 URB_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where subscripts i and t denote city and time, respectively; $lnCO_2$ represents urban CO_2 emissions as a logarithm; URB represents NTU; X represents each control variable, and the following control variables are planned: energy intensity (ENE), financial development (FIN), economic development (GDP), government intervention (GOV), average temperature (TEM), precipitation (PRE), average relative humidity (HUM). μ_i and δ_t denote individual and year fixed effects, respectively, and ε_{it} represents random disturbance terms.

4.1.2. Spatial Autocorrelation Analysis

Based on the above mechanism analysis, there is a certain degree of spatial correlation between NTU and CO_2 emissions. This study uses spatial autocorrelation methods and spatial econometric models to explore the spatial effect of NTU between cities and its impact on CO_2 emissions.

First, there is a need to verify if there is spatial autocorrelation between NTU and urban CO_2 emissions. Learning from Cole et al. [58], this study uses the Global Moran's I index to examine this spatial autocorrelation of NTU and CO_2 emissions. The formula of the index is as follows:

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} * \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \quad (2)$$

where x_i is the observed value, $\bar{x}$ is the mean value, and w_{ij} denotes the element corresponding to the spatial weight matrix W_i. Given existing investigations, such as Yuan et al. [59], the spatial spillover effect is not only linked to the geographical distance of cities and whether they are adjacent, but also may be associated with the economic development level in different cities. Hence, to assure the reliability of the results, we employ three spatial weight matrix in this study, namely geographical distance (W_1), neighborhood (W_2), and economic distance (W_3). They are calculated as shown below.

$$W_1 = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{3}$$

$$W_2 = \begin{cases} 1,\ City\ i\ and\ city\ j\ are\ adjacent \\ 0,\ City\ i\ and\ city\ j\ are\ not\ adjacent \end{cases} \tag{4}$$

$$W_3 = \begin{cases} \frac{1}{|GDP_i - GDP_j|}, i \neq j \\ 0, i = j \end{cases} \tag{5}$$

In Equations (3)–(5), d_{ij} stands for the distance from city i to city j; GDP_i and GDP_j represent the average level of the real GDP of each city during the investigation year. The range of Moran's I index is $[-1, 1]$. When the index < 0, it denotes negative spatial correlation; when it is equal to 0, it stands for no correlation; otherwise, it denotes positive spatial correlation.

4.1.3. Spatial Econometric Model

Regarding passing the spatial autocorrelation test, an appropriate spatial econometric model was selected by referring to the studies [60,61]. The models used in this study are as follows:

$$lnCO_{2it} = \alpha_i + \rho WlnCO_{2it} + \beta_1 URB_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \qquad \varepsilon_{it} \sim N\left(0, \sigma_{it}^2, I_n\right) \tag{6}$$

$$lnCO_{2it} = \alpha_i + \beta_1 URB_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it},\ \varepsilon_{it} = \lambda W \varepsilon_{it} + \varphi_{it}, \varphi_{it} \sim N\left(0, \sigma_{it}^2, I_n\right) \tag{7}$$

$$lnCO_{2it} = \alpha_i + \rho WlnCO_{2it} + \beta_1 URB_{it} + \beta_2 X_{it} + \beta_3 WURB_{it} + \beta_4 WX_{it} + \mu_i + \delta_t + \varepsilon_{it}, \varepsilon_{it} \sim N\left(0, \sigma_{it}^2, I_n\right) \tag{8}$$

Equations (6)–(8) represent the SAR (Spatial Autoregressive Model), SEM (Spatial Error Model), and SDM (Spatial Durbin Model). i and t denote city and time, respectively; $lnCO_2$ represents urban CO_2 emissions taken as a logarithm; W is the spatial weight matrix and ρ measures the effect of the spatial lag $WlnCO_2$ on $lnCO_2$; URB represents NTU; X represents each control variable, the same as above; μ_i and δ_t denote individual fixed effects of individual and year, respectively; ε_{it} represents random disturbance terms. In Equation (8), coefficient β_3 of $WURB$ stands for the impact from neighboring cities' URB; coefficient β_4 of WX stands for the impact from neighboring cities' control variables.

4.2. Variables

4.2.1. Dependent Variable

The level of CO_2 emissions is chosen as the dependent variable in the paper. Moreover, the data obtained from the CO_2 Emissions Accounts and Datasets (CEADs) team are regarded as China's CO_2 emissions [62] and the total CO_2 emissions of 250 cities in China, except Xinjiang, Tibet, Hong Kong, Macao, and Taiwan, from 2008 to 2020. The research shows that the use of electricity is up to 40% of the total energy consumption [63], and the carbon emissions of the power sector also take up a large proportion of the carbon emissions of fossil energy [64]. Accordingly, to compensate for the missing data on CO_2

emissions in 2020, this paper calculates the proportional coefficient of urban electricity consumption and CO_2 emissions in 2019. The study simulates urban CO_2 emissions with the data on urban electricity consumption in 2020.

4.2.2. Independent Variables

NTU is the independent variable in this paper. With reference to Refs. [6,11,23], according to the National New Urbanization Plan (2021–2035) promulgated by China in 2022, the essential characteristics of urbanization are proposed: people-oriented, four modernizations synchronization, optimal layout, ecological civilization, and cultural heritage. Following the principles of objectivity, rationality, systematicness, and comprehensiveness in the selection of indicators and the availability of data, the study constructs the evaluation index system of NTU containing five dimensions—population, economic, spatial, social, and ecological urbanization—to reflect the characteristics of the new urbanization more objectively and comprehensively. Population urbanization mainly reflects the population size and population density; economic urbanization mainly covers per capita GDP, economy, and investment scale; social urbanization considers the factors of education, medical care, Internet, and transportation; spatial urbanization considers construction land and spatial structure; ecological urbanization comprehensively considers urban environment and production pollution. Table 1 lists the individual indexes for each dimension. The weight of each indicator is calculated by the entropy value method to further measure the level of NTU [65].

Table 1. Indicator system for measuring NTU in China.

Target	Dimension	Index	Direction
New-Type Urbanization (NTU)	Population urbanization	Registered unemployment rate in urban areas	-
		Population density	+
	Economic urbanization	Per capita GDP	+
		Total investment in fixed assets	+
		Per capita local general public budget revenue	+
		Per capita disposable income of urban households	+
	Social urbanization	Number of students enrolled in higher education per 10,000 persons	+
		Number of doctors per 1000 persons	+
		Number of beds of hospitals per 10,000 persons	+
		Number of Internet users per 100 persons	+
		Per capita local general public budget expenditure for education	+
		Number of civil vehicles owned	+
		Number of employees joining urban basic pension insurance	+
		Number of employees joining urban basic medical care system	+
	Spatial urbanization	Green coverage rate of built district	+
		Area of built district	+
	Ecological urbanization	Rate of domestic garbage harmless treatment	+
		Ratio of industrial solid wastes comprehensively utilized	+

4.2.3. Mechanism Variables

(1) Technological innovation (GIN_1/GIN_2). We adopted the city green innovation output to measure the innovation level, which mainly includes the quantity of new products and patents. Following Li and Lu [66], two indicators are used in this study: the quantity of urban green invention patent applications (GIN_1) and urban green patent applications

(GIN_2), adding one and taking the logarithm to characterize them. The green patents were identified according to the World International Patent Classification (WIPC) using the USPTO's Energy Sustainable Technology (EST) cross-reference table. The reason for using the number of patent applications rather than the patents granted here is that patent applications take less time and better reflect cities' current innovation dynamics and enthusiasm than patents granted.

(2) Resource allocation (*DIS*). It uses the degree of resource mismatch to measure the allocation efficiency of capital and labor factors in cities. Referring to Chen and Hu [67], we classified resource mismatch into two kinds, i.e., capital mismatch (DIS_K) and labor mismatch (DIS_L):

$$\tau_{ki} = \frac{1}{1 + DIS_{ki}}; \tau_{li} = \frac{1}{1 + DIS_{Li}} \tag{9}$$

where τ_{ki} and τ_{li} are to be absolute distortion coefficients, referring to Cui et al. [68], using the factor relative distortion coefficients $\hat{\tau_{ki}}$ and $\hat{\tau_{li}}$.

$$\hat{\tau_{ki}} = \frac{K_i/K}{S_i\beta_{ki}/\beta_k}; \hat{\tau_{li}} = \frac{L_i/L}{S_i\beta_{li}/\beta_l} \tag{10}$$

where K and L represent the capital and labor factor; $S_i = \frac{y_i}{Y}$, which is the proportion of the output in i to total output; β denotes the elasticity of the factor output. Taking the capital factor as an example, $\beta_k = \sum_{i=1}^{N} S_i\beta_{ki}$, where K_i/K indicates the actual ratio of capital volume in region i to total capital volume, $S_i\beta_{ki}/\beta_k$ indicates that the effective allocation of capital is the theoretical ratio of capital volume in region i to the total capital volume, and the ratio of the two can reflect the degree of capital mismatch. If $\hat{\tau_{ki}}$ is greater than 1, it indicates the over-allocation of capital; conversely, if it is less than 1, it means capital is under-allocated. Similarly, the distortion index of the labor factor can be obtained. The factor output elasticity β_{ki} and β_{li} is estimated using the Solow allowance residual method. They are assuming a constant payoff to the scale of the production function $Y_{it} = AK_{it}^{\beta_k}L_{it}^{1-\beta_k}$. Both sides of the logarithm are taken simultaneously, and individual and time effects are added: $\ln\left(\frac{Y_{it}}{L_{it}}\right) = lnA + \beta_{ki}ln(K_{it}/L_{it}) + u_i + \delta_t + \varepsilon_{it}$. Each city's GDP serves as a proxy for output, and the number of employees is represented as labor input; the fixed capital stock in each region stands for capital input (using the perpetual inventory method). The depreciation of fixed assets is set at 9.6% [69]. The capital mismatch and labor mismatch indices are obtained after substitution. To keep the regression direction consistent, the absolute value of the resource mismatch index is taken, and an immense value indicates a less-efficient resource allocation.

4.2.4. Control Variables

Controlling the main factors affecting CO_2 emissions and reducing errors caused by omissions is necessary. So, this article refers to the relevant research [6,23], selecting the following control variables: (1) Energy intensity (*ENE*): this study uses urban electricity consumption to convert to standard coal consumption divided by regional GDP; (2) Financial development (*FIN*): it adopts deposits balance at the end of the year from financial institutions divided by regional GDP; (3) Economic development (*GDP*): this study uses the logarithm of real GDP per capita in each city to indicate it; (4) Government intervention (*GOV*): this study utilizes general financial budget expenditures divided by the general budget revenue; (5) Average temperature (*TEM*): the research period's average yearly temperature for each city; (6) Precipitation (*PRE*): the research period's average precipitation for each city; (7) Average relative humidity (*HUM*): the research period's average relative humidity for each city. The results of the descriptive statistics for the variables are presented in Table 2.

Table 2. Descriptive statistics.

Variables	Meaning	Obs	Mean	SD	P25	Median	P75
$LnCO_2$	CO_2 emissions	3250	3.2566	0.9267	2.6697	3.3015	3.8725
PCO_2	Per capita CO_2 emissions	3250	0.1152	0.1724	0.0364	0.0684	0.1265
URB	NTU	3250	0.1266	0.1065	0.0681	0.0881	0.1389
ENE	Energy intensity	3250	0.1735	0.1674	0.0958	0.1331	0.1934
FIN	Financial development	3250	1.3852	0.6932	0.9590	1.2462	1.6208
GDP	Economic development	3250	10.5657	0.6834	10.0923	10.5234	11.0220
GOV	Government intervention	3250	2.7919	1.7956	1.5675	2.2455	3.3985
TEM	Average temperature	3250	14.6843	5.1310	11.3777	15.6651	17.8721
PRE	Precipitation	3250	1070.9110	564.2507	599.3931	982.3388	1478.0506
HUM	Average relative humidity	3250	69.4842	9.5419	62.9871	72.0671	77.2291
GIN_1	Green invention innovation	3250	4.1148	1.8263	2.7726	3.9703	5.2730
GIN_2	Green technological innovation	3250	5.0417	1.7343	3.7842	4.9698	6.1696
DIS_L	Labor mismatch	3250	1.1914	1.4029	0.4110	0.8567	1.4327
DIS_K	Capital mismatch	3250	0.3779	0.3997	0.1480	0.2998	0.4813

4.2.5. Data Source

The data from 250 cities in China are from 2008 to 2020. Due to the severe lack of some indicators in some places, these are not included areas, such as Macau, Hong Kong, Tibet, Xinjiang, and Taiwan. The data come from the *China Statistical Yearbook*, *China City Statistical Yearbook*, *China Urban Construction Statistical Yearbook*, Carbon Emission Accounts & Datasets (CEADs) (https://ceads.net/) (accessed on 12 April 2023), and *Statistical Yearbooks for each provinces and cities in China*. Missing data are filled in by the moving average method. All value variables are converted with the price index, and the investment-related index is converted with a fixed asset price index. The GDP data are converted with the GDP flat reduction index. At the same time, logarithmic processing of relevant variables is required to make each variable at the same level and reduce the impact of different variances.

4.3. Descriptions of NTU and CO_2 Emissions

To portray the evolution of NTU and urban CO_2 emissions during 2008–2020, ArcGIS was used to draw 250 prefecture cities' NTU and the actual CO_2 emissions in 2008 and 2020.

Figure 3 shows the annual CO_2 emissions of 2008 and 2020 of 250 sample cities. The CO_2 emissions are significantly higher in the northern cities. In 2008, CO_2 emissions from northeastern cities were mainly in the range of 0–120 Mt, those of central-north cities were mainly in the range of 20–120 Mt, and those of central-south cities were mainly in the lower range of 0–40 Mt. In terms of the urban CO_2 emission regions in 2020, overall urban CO_2 emissions have always shown a significant increase over the past thirteen years. CO_2 emissions in southeastern cities remained at the 2008 level, but CO_2 emissions in some cities in the northeast have increased, such as Hulunbuir, Bayannur, Ordos, Yulin, and Changchun. In contrast, some cities in the southeastern region have decreased CO_2 emissions, such as Qingyuan, Hangzhou, Jiangmen, and Dongguan. CO_2 emissions in some cities in the central region also declined significantly. Overall, CO_2 emissions in cities in 2020 still show the pattern of northeast > central > southeast.

Figure 4 shows the combined scores of NTU from 250 cities in 2008 and 2020. The China cities' level in 2020 increased dramatically compared to 2008. The NTU level in Shanghai, Chongqing, and Guangzhou was in the high-level range of the country in 2008 and 2020. From Figures 3 and 4, it can be observed that the levels of NTU and CO_2 emissions show a specific correlation, with regions with high levels of NTU showing a lower trend of CO_2 emissions. In contrast, regions with lower levels of NTU show a higher trend of CO_2 emissions.

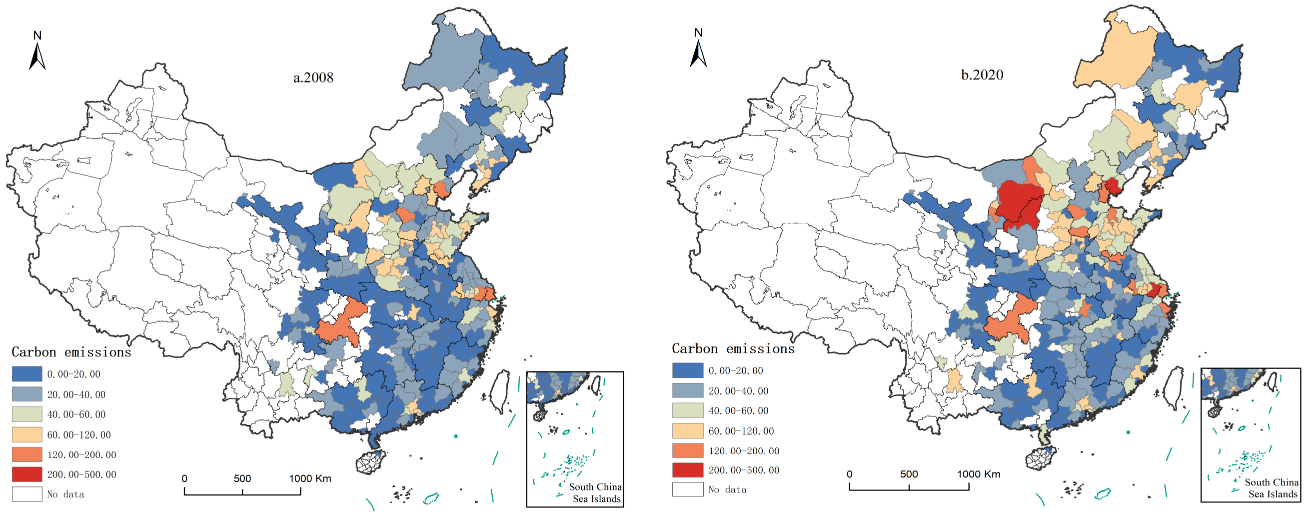

Figure 3. Urban CO_2 emissions in China in 2008 and 2020.

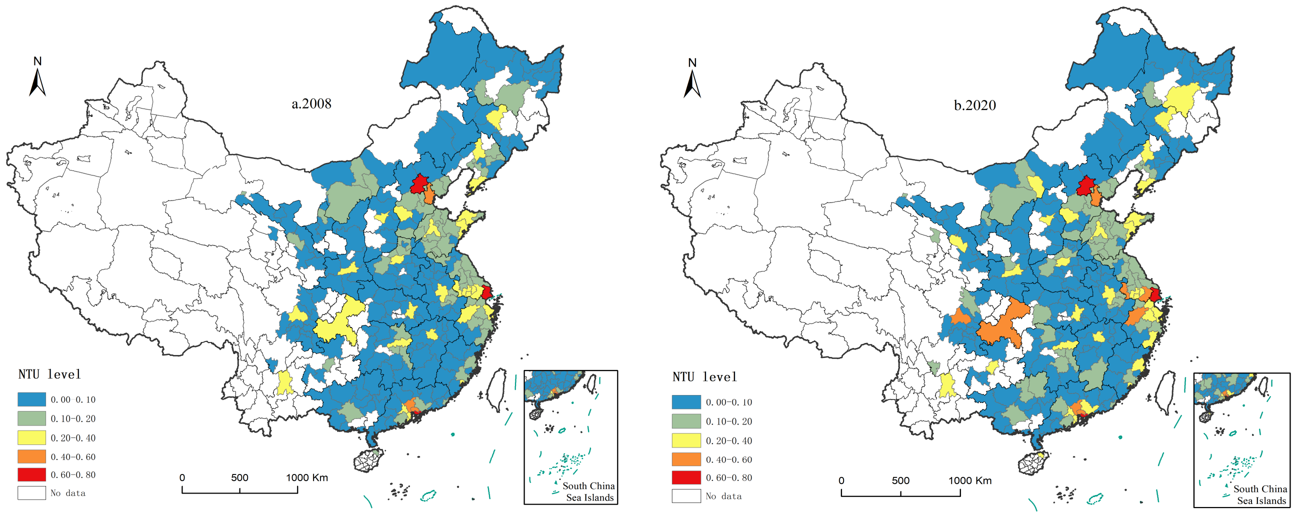

Figure 4. NTU level in China in 2008 and 2020.

5. Results

5.1. Benchmark Regression Results

Table 3 provides the estimation results of the baseline model for the effect of NTU on urban CO_2 emissions. Column (1) shows that NTU greatly decreases when no control variables are added, which indicates that CO_2 emissions are reduced as the NTU increases. Secondly, after adding control variables such as energy intensity and financial development in Columns (2)–(4), it can be observed that NTU has a significantly negative influence on urban CO_2 emissions, with an impact coefficient of -0.9339, which is remarkable at 1%. This means that NTU can dramatically decrease CO_2 emissions. Thus, the H1 of this study is initially verified.

Table 3. Baseline regression results of the effect of NTU on urban CO_2 emissions.

Variable	(1) $lnCO_2$	(2) $lnCO_2$	(3) $lnCO_2$	(4) $lnCO_2$
URB	−0.7857 ***	−0.8047 ***	−0.8721 ***	−0.9339 ***
	(−2.5998)	(−2.6528)	(−2.8241)	(−3.0164)
ENE		−0.2894 ***	−0.2849 ***	−0.3124 ***
		(−3.9724)	(−3.8620)	(−4.1848)
FIN		−0.0227 **	−0.0205 **	−0.0177 *
		(−2.2708)	(−1.9815)	(−1.7023)
GDP			0.0402	0.0122
			(0.3858)	(0.1146)
GOV			−0.0063	−0.0066
			(−1.1931)	(−1.2563)
TEM				0.0155
				(1.2162)
PRE				−0.0000
				(−1.4538)
HUM				0.0055 **
				(2.5666)
Constant	3.1196 ***	3.2326 ***	2.8528 ***	2.5792 **
	(79.7613)	(70.3470)	(2.7315)	(2.3484)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3250	3250	3250	3250
R^2	0.2102	0.2160	0.2164	0.2183

Note: $lnCO_2$ represents the logarithmic value of urban carbon emissions, and URB represents NTU. No control variable is added in Column (1), and other control variables are gradually introduced in Columns (2)–(4). The fixed effects of city and year are controlled in all regressions. t-values are in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Further, we explored the selected control variables' role in urban CO_2 emissions. The influence coefficient of energy intensity on urban CO_2 emissions is −0.3124; it is significant at a 1% statistical level, indicating that with the improvement of energy efficiency, it will be more beneficial to accelerate the reduction in urban CO_2 emissions. The influence resulting from financial development is −0.0177, which is significant at a 10% statistical level, probably because China's improved financial market and more efficient the capital allocation will help reduce urban carbon emissions. The influence coefficient of economic conditions on CO_2 emissions is positive but not significant. The coefficient of government intervention in CO_2 emissions is negative but not significant. Although government interventions such as environmental regulations are conducive to reducing urban CO_2 emissions, many aspects could be further improved. For example, in non-state enterprises, the more government intervention, the less carbon information is disclosed. The coefficient of the average temperature on CO_2 emissions is positive. Due to the rapid development of Chinese industry, the high-carbon characteristics of energy consumption put tremendous pressure on greenhouse gas emission reduction. Additionally, the increased CO_2 emissions will also cause a rise in average temperature.

5.2. Robustness Tests

5.2.1. Replacement of Dependent Variable

With the increase in China's socio-economic volume and technological advancement, the reduction in CO_2 emissions should be reflected in the reduction in per capita CO_2 emissions. So, the regression of replacing CO_2 emissions in the baseline regression with per capita CO_2 emissions is reported in Column (1) of Table 4. Observing these coefficients, NTU still plays an inhibitory role in CO_2 emissions, and the coefficient of NTU in this regression is −1.3014, which is significant at 1%. The regression results support the baseline regression coefficient result, indicating that the results in baseline regression are credible.

Table 4. Robustness test results.

Variable	(1) $lnPCO_2$	(2) $lnCO_2$	(3) $lnCO_2$	(4) $lnCO_2$	(5) $lnCO_2$
URB	−1.3014 ***		−1.5546 ***	−0.9917 ***	−0.9878 ***
	(−4.1173)		(−3.0738)	(−3.0286)	(−3.2194)
URB2		−0.0372 ***			
		(−3.6556)			
Constant	−1.3179	2.6633 **	6.1265 ***	2.9379 ***	4.4182 ***
	(−1.1754)	(2.4310)	(3.8122)	(2.6370)	(3.7544)
Control variables	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3250	3237	2326	3198	3250
R^2	0.1552	0.2189	0.1857	0.2207	0.2253

Note: Column (1) of this table shows that per capita CO_2 emissions are used as a substitute variable for the robustness test. Column (2) shows the NTU composite index calculated by the principal component method. Column (3) shows the robustness test after eliminating low-carbon pilot cities. Column (4) in the table shows the robustness test after excluding first-tier cities. Column (5) in the table shows the robustness after reducing the tail of continuous variables by 1%. Other information is the same as in Table 3. **, and *** denote significance at 5%, and 1%, respectively.

5.2.2. Replacement of Independent Variable

In this section, we use the principal component method for dimensionality reduction analysis and recalculate the total score of NTU. Column (2) in Table 4 reports the regression results; moreover, it can be found that the influence coefficient of NTU on CO_2 emissions is −0.0372 and is significant at the level of 1%, indicating that NTU can promote a decline in urban CO_2 emissions, which reconfirms the conclusion in the baseline regression.

5.2.3. Elimination of Low-Carbon Pilot Cities

The low-carbon pilot city policy was first released in July 2010 in China, which listed eight cities and five provinces, including Guangdong, Liaoning, Hubei, etc. The second batch was identified in November 2012 and the third batch in January 2017. To exclude the influence of these policies, we removed cities in the pilot policies mentioned above from this study and then conducted robustness tests. The results of the test reported in Column (3) of Table 4 show that the influence coefficient of NTU on CO_2 emissions is −1.5546, significant at 1%, further verifying the accuracy of the study's baseline regression findings.

5.2.4. Excluding First-Tier Cities

NTU across China shows significant regional heterogeneity and imbalance. The first-tier cities with superior economic strength are Beijing, Shanghai, Guangzhou, and Shenzhen. The baseline regression model was re-estimated after excluding the above first-tier cities. The findings in the fourth column of Table 4 show that the influence coefficient of NTU on carbon dioxide emissions is −0.9917, and the significance is 1%, which further proves that NTU is helpful to reduce carbon dioxide emissions.

5.2.5. Excluding Extreme Values

In this study, the continuous variables may be subject to errors in surveys and records, or data anomalies in particular years, making some of the sample data appear as extreme outliers, and thus causing the regression coefficient results to deviate from the actual values. Therefore, to exclude the effect of above situation on the baseline regression results, the first and last 1% of the continuous variables in this study were intercepted and re-regressed separately. The findings in the last column of Table 4 indicate that the influence coefficient of NTU on CO_2 emissions is −0.9878, which is significant at 1%. This further confirms that even after excluding possible extreme values, the estimation results are still reliable.

5.2.6. Instrumental Variable Test

In the baseline regression, the control variables related to CO_2 emissions were controlled as much as possible, with the addition of the time and regional fixed effects. However, there might still be potential omitted variables and other endogeneity problems. Thus, referring to Chen et al. [70], we adopted the lag period of dependent variable NTU as the tool variable in this paper. Specifically, on the one hand, one-phase lagging NTU has no effect on the city's carbon emissions in this period. On the other hand, the level of NTU lagging one phase has an incentive effect on the city's future development, which satisfies the prerequisites for the use of instrumental variables. Table 5 reports regression for both stages after using the instrumental variables. The instrumental variable test was conducted for the first-stage regression, showing that the F-test and LM-test statistics are greater than 10, which satisfies the requirement of this means. The first-stage regression coefficients indicate that NTU with a lag of one phase can significantly affect the NTU of the city. Meanwhile, excluding endogenous factors, the NTU's influence on the CO_2 emissions coefficient is -1.4701, significant at the 5% level, confirming that the baseline regression results are credible.

Table 5. Robustness test results by instrumental variables.

Variable	(1) URB	(2) $\ln CO_2$
l_URB	0.4839 ***	
	(27.7453)	
URB		−1.4701 **
		(−2.2103)
Constant	−0.1754 ***	
	(−2.6940)	
Cragg–Donald Wald F statistic	769.802	
Anderson canon. corr. LM statistic	604.706	
Control variables	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
N	3000	3000
R^2	0.3882	0.1645

Note: The lagged NTU was further used as the instrumental variable for robustness tests. Column (1) of the chart indicates the regression result of independent variable CO_2 emissions to instrumental variables, and Column (2) shows the influence of NTU after alleviating endogenous factors by instrumental variables. Other information is the same as in Table 3. **, and *** denote significance at 5%, and 1%, respectively.

5.3. Heterogeneity Analysis

The above provides empirical test evidence that NTU can reduce urban CO_2 emissions. However, do CO_2 emission reduction effects show different characteristics depending on the differences in urban resource endowment, urban function, and environmental quality? In this section, we examine heterogeneity from four perspectives: Resource-Based Cities (RBC)/Non-Resource-Based Cities (NRBC), Old Industrial Cities (OIC)/Non-Old Industrial Cities (NOIC), High-Urbanization-Level Cities (HULC)/Low-Urbanization-Level Cities (LULC), and High-Innovation-Ability Cities (HIAC)/Low-Innovation-Ability Cities (LIAC).

5.3.1. Heterogeneous Effects across RBC and NRBC

According to Li et al. [71], 250 cities were divided into 91 RBC and 159 NRBC in this paper. As described in Columns (1) and (2) of Table 6, NTU suppresses CO_2 emissions for both cities. Specifically, the influence coefficient of NTU on CO_2 emissions of RBC is -2.3502, and it is significant at 5%. The coefficient of NTU on CO_2 emissions of NRBC is -0.9687, and it is significant at 1%. Compared with NRBC, NTU has a stronger effect on RBC. This is mainly because, first, the differences in natural resource endowments lead to differences in their development approaches and urban industrial structures. Second, resource-based industries often do not require high-quality workforces, thus hindering technological innovation. In contrast, the NTU strategy promotes and improves workforce quality, integrating the advantages of resources and improving production efficiency and quality, ultimately reducing CO_2 emission intensity in RBC. Third, compared to RBC, the economy in NRBC develops rapidly and higher requirements are needed for environmental quality; moreover, the implementation of NTU policies has increased public awareness and participation in environmental monitoring.

Table 6. Results of heterogeneity analysis.

Variable	RBC	NRBC	OIC	NOIC
	(1) lnCO_2	**(2) lnCO_2**	**(3) lnCO_2**	**(4) lnCO_2**
URB	−2.3502 **	−0.9687 ***	−3.1873 ***	−1.1942 ***
	(−2.3370)	(−2.9851)	(−3.3210)	(−3.5090)
Constant	9.4545 ***	−2.0336	7.0211 ***	0.1255
	(4.6829)	(−1.4500)	(4.5702)	(0.0818)
N	1183	2067	1066	2184
R^2	0.1785	0.2629	0.1558	0.2781
	HULC	**LULC**	**HIAC**	**LIAC**
	(5) lnCO_2	**(6) lnCO_2**	**(7) lnCO_2**	**(8) lnCO_2**
URB	−0.6359 **	−1.9467 **	−0.6065 **	−0.9871
	(−2.0228)	(−2.4189)	(−2.0891)	(−1.5696)
Constant	3.7359 *	3.0734 **	−2.6789	4.4875 ***
	(1.9018)	(2.2502)	(−1.4056)	(3.3691)
N	923	2327	689	2561
R^2	0.3350	0.2081	0.3274	0.2145
Control variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: The first two columns disclose the impact coefficients of NTU on CO_2 emissions in two types of cities (RBC and NRBC). Columns (3) and (4) show the impact of NTU on CO_2 emissions in two types of cities (NOC and NOIC). Columns (5) and (6) show the impact of NTU on CO_2 emissions in two kinds of cities (HULC and LULC). The last two columns show the results in two kinds of cities (HIAC and LIAC). Other information is the same as in Table 3. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

5.3.2. Heterogeneous Effect across OIC and NOIC

The National Plan for the Adjustment and Transformation of Old Industrial Bases (2013–2022) was formulated in 2013, identifying 120 OIC covering 27 provinces. Accordingly, this section groups a sample of 250 cities into 82 OIC and 168 NOIC to examine heterogeneity due to the different functional positioning of cities. Columns (3) and (4) of Table 6 show the effect of NTU on urban CO_2 emissions after distinguishing whether they are OIC. The influence coefficient of NTU on CO_2 emissions in OIC is −3.1873 and significant at 1%. The coefficient of CO_2 emissions from NTU in NOIC is −1.1942, which is significant at 1%. However, it has a stronger suppressive effect on CO_2 emissions in OIC. The first possible reason for this is that with NTU development, the function of cities to absorb important resources is strengthened, which promotes transformation and upgrading in OIC, thus reducing CO_2 emissions. Second, NTU also proposes higher requirements for the development of OIC, which promotes the OIC to continuously carry out green technology innovation and industrial structure upgrading, thus reducing CO_2 emissions. Finally, because the industrial structure of NOIC is “lighter” and their CO_2 emissions are not high, the suppression of CO_2 emissions from NTU in NOIC is limited.

5.3.3. Heterogeneous Effect across Urbanization Levels

In this part, HULC and LULC cities in the swatch are divided considering the average levels of NTU in the sample cities from 2008 to 2020. The regression results in Columns (5) and (6) of Table 6 demonstrate that the influence coefficient of NTU on CO_2 emissions in LULC is −1.9467, which is significant at 5%. The coefficient of NTU to CO_2 emissions of HULC is −0.6359, and it is significant at 5%. Compared with HULC, NTU has a stronger effect on LULC. This phenomenon may be because LULC are not yet at a high level of development and receive greater support from national policies compared to cities at a HULC, providing favorable conditions for LULC, while government financial resources continue to be concentrated in LULC. On the contrary, cities with high urbanization levels have strong pollution management capacities and lower CO_2 emission levels due to their more developed economies and well-constructed infrastructure, so NTU has no noticeable curbing effect on the CO_2 emissions of such cities.

5.3.4. Heterogeneous Effect across Innovation Levels

This section classifies the sample cities under investigation into HIAC and LIAC based on the average level of INN in the sample cities from 2008 to 2020. The results in the last two columns of Table 6 reveal that for HIAC, the inhibitory effect of NTU on CO_2 emissions is significantly higher than for LIAC. Specifically, the influence coefficient of NTU on CO_2 emissions in HIAC is −0.6065, and it is significant at 5%. In contrast, the regression coefficient of NTU is negative but not significant for LIAC. This study suggests that there are possible reasons for this phenomenon: first, NTU can help HIAC pool high-end enterprises, increase capital investment in R&D, and optimize the production process of low-carbon cities, thus reducing CO_2 emissions; second, in the context of HIAC, NTU can gather innovative talents for urban development, promote knowledge acquisition and diffusion, improve urban economic efficiency, and accelerate green and low-carbon development. Third, traditional high-pollution and high-emission enterprises in LIAC have less incentive to transform their industrial structures into advanced and rationalized ones. Thus, NTU has limited CO_2 emission reduction effects in LIAC.

5.4. Mechanism Analysis

Given the previous theoretical hypotheses, this study suggests that NTU may affect CO_2 emissions through technological innovation and the mitigation of resource mismatches. Therefore, the mechanism needs to be verified empirically. The findings are reported in Table 7. Column (1) of the table shows that the influence coefficient of NTU on GIN_1 is 1.6469, significant at 5%. The second column of the table shows that the influence coefficient on GIN_2 is 1.1526, which is significant at 5%. Moreover, urban innovation can accelerate the green transformation of cities and the upgrading of low-carbon process technologies by improving energy efficiency. Further, this study verifies that NTU can promote the optimization of resource allocation. The mismatch of urban capital and labor factor resources is indicated in the last two columns, with regression coefficients of −0.9735 and −0.2766, significant at least at the level of 10%, which reveals that NTU can significantly improve the cities' resource allocation. Improving the efficiency of resource allocation is a "win-win" measure to achieve economic development and environmental protection simultaneously to enhance the net efficiency of green production and ultimately reduce CO_2 emissions. At this point, H2 and H3 are verified.

5.5. The Spatial Spillover Effects of NTU on Urban CO_2 Emissions

5.5.1. Spatial Correlation Test

After examining the mechanism analysis, NTU's possible spatial spillover effect on urban carbon emissions was further analyzed by a spatial econometric mode. When applying the spatial econometric model, it is vital to first examine whether NTU and urban CO_2 emissions are spatially correlated in space. Scholars often test this relationship between cities by using Moran's I index. Table 8 reports the Global Moran's I index of NTU and urban CO_2 emissions, revealing that the NTU and CO_2 emissions index for all years is notably positive, demonstrating an obvious positive spatial correlation between NTU and CO_2.

Table 7. Test results for the mechanism analysis.

Variable	GIN_1	GIN_2	DIS_L	DIS_K
URB	1.6469 **	1.1526 **	−0.9735 ***	−0.2766 *
	(2.4040)	(2.1501)	(−2.6316)	(−1.8050)
Constant	−27.3507 ***	1.7216 ***	−1.5794	0.1656 *
	(−11.2550)	(3.6089)	(−1.2036)	(1.8177)
Control variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3250	3250	3250	3250
R^2	0.7857	0.8540	0.0785	0.1453

Note: Column (1) of the chart confirms the influence of NTU on GIN_1. The second column shows the coefficient of NTU on GIN_2. Column (3) of this table shows the influence of NTU on DIS_l. The last column of the chart shows NTU's influence on DIS_k. Other information is shown in Table 3. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 8. Global Moran's I index of NTU and urban CO_2 emissions from 2008 to 2020.

Year	NTU					
	W_1		W_2		W_3	
	I	*p*-Value	I	*p*-Value	I	*p*-Value
2008	0.046	0.000	0.234	0.000	0.415	0.000
2009	0.044	0.000	0.226	0.000	0.414	0.000
2010	0.043	0.000	0.225	0.000	0.402	0.000
2011	0.045	0.000	0.235	0.000	0.430	0.000
2012	0.046	0.000	0.237	0.000	0.429	0.000
2013	0.053	0.000	0.277	0.000	0.434	0.000
2014	0.047	0.000	0.237	0.000	0.434	0.000
2015	0.044	0.000	0.232	0.000	0.424	0.000
2016	0.043	0.000	0.224	0.000	0.423	0.000
2017	0.043	0.000	0.225	0.000	0.417	0.000
2018	0.038	0.000	0.201	0.000	0.415	0.000
2019	0.042	0.000	0.220	0.000	0.412	0.000
2020	0.045	0.000	0.239	0.000	0.415	0.000
Year	Urban $lnCO_2$ Emissions					
	W_1		W_2		W_3	
	I	*p*-Value	I	*p*-Value	I	*p*-Value
2008	0.066	0.000	0.271	0.000	0.410	0.000
2009	0.061	0.000	0.256	0.000	0.403	0.000
2010	0.063	0.000	0.275	0.000	0.399	0.000
2011	0.060	0.000	0.267	0.000	0.391	0.000
2012	0.061	0.000	0.268	0.000	0.385	0.000
2013	0.060	0.000	0.258	0.000	0.371	0.000
2014	0.064	0.000	0.272	0.000	0.379	0.000
2015	0.067	0.000	0.284	0.000	0.384	0.000
2016	0.071	0.000	0.294	0.000	0.363	0.000
2017	0.071	0.000	0.300	0.000	0.360	0.000
2018	0.067	0.000	0.278	0.000	0.326	0.000
2019	0.068	0.000	0.280	0.000	0.332	0.000
2020	0.068	0.000	0.280	0.000	0.332	0.000

Moran's I index scatterplot was used to observe the spatial relation between NTU and CO_2. Figure 5 shows that most of the urban samples in 2008 and 2020 are in quadrants 1 and 3, and a small number of observed values are in quadrants 2 and 4. The results indicate that the spatial distribution between NTU and urban CO_2 emissions presents a "high-high" and "low-low" agglomeration condition. They present apparent spatial dependence and agglomeration characteristics. However, the point imbalance in the two quadrants indicates that NTU and CO_2 emissions are unevenly distributed in space.

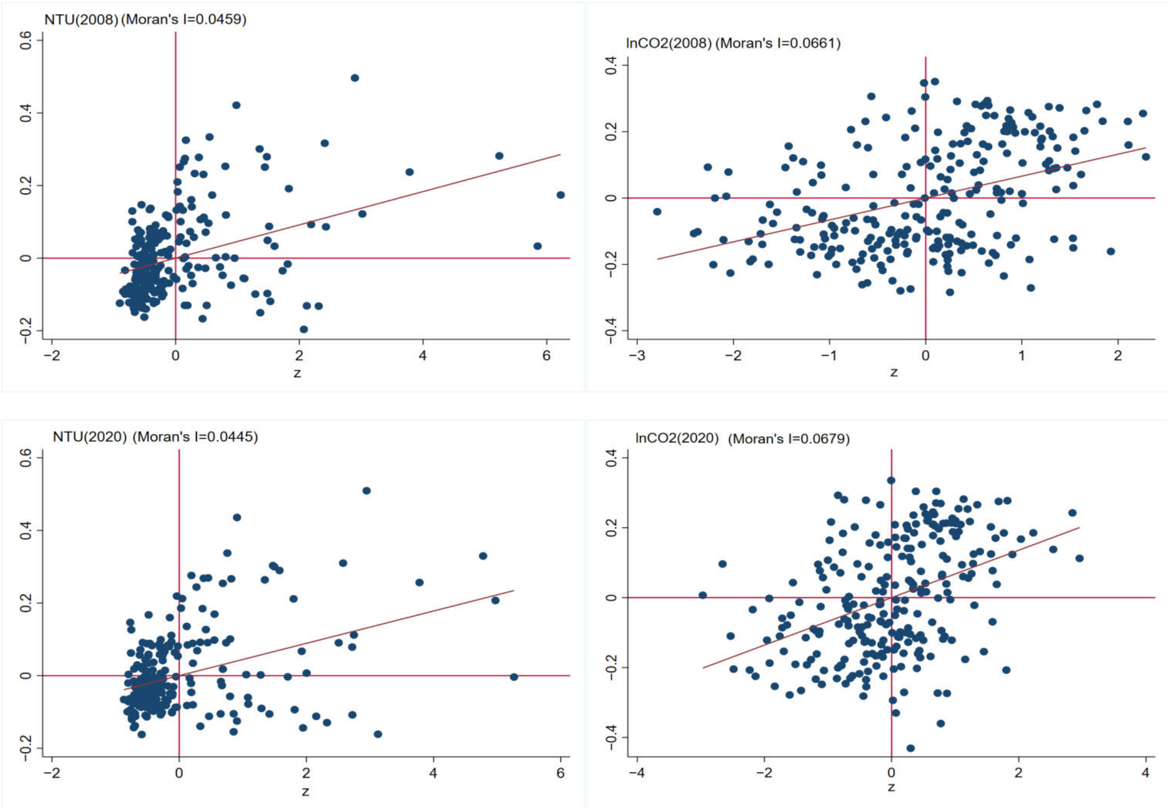

Figure 5. Sample Moran's I index scatterplot of China's NTU and urban CO_2 emissions in 2008 and 2020.

5.5.2. Statistical Testing of Model Selection

The spatial autocorrelation test shows that there is a significant spatial correlation between the two in all years. Therefore, the spatial factors are incorporated into the model to analyze in depth the impact of NTU on CO_2 emissions through a spatial econometric model. The SDM test and estimation results are listed in Table 9.

Table 9. Test results of model selection.

Tests	Statistic	*p*-Value
LM(lag)test	43.851	0.0000
Robust LM(lag)test	7.624	0.0060
LM(error)test	48.639	0.0000
Robust LM(error)test	12.412	0.0000
SDM Hausman test	12.480	0.0857
LR_spatial_lag	70.690	0.0000
LR_spatial_error	71.030	0.0000

From the results of the model test, the LM test and robust LM test of the non-spatial panel model significantly reject the original hypothesis, indicating that spatial panel model considering the spatial effect is more suitable for this study. To select the spatial econometric model, the LR test for spatial lag and the LR test for spatial error were performed on the basis of the geographic distance weight matrix (W_1). The coefficients in Column (2) of Table 9, which have estimated values of 70.69 and 71.03, respectively, and are significant at the 1% level, indicating that the SDM cannot be downgraded to SAR or SEM. So, it can be applied to this study. In this study, three models—SAR, SEM, and SDM—were chosen to simultaneously identify the spatial spillover effects of NTU on CO_2 emissions.

5.5.3. Estimated Results Analysis of the Spatial Econometric Model

The findings for the spatial spillover impact of NTU on urban CO_2 emissions under the W_1 matrix are displayed in Table 10. Looking at the spatial autoregressive coefficients, urban CO_2 emissions have a conspicuous spatial spillover effect.

Table 10. Estimation results of the spatial econometric model.

Variable	**SEM**	**SAR**	**SDM**
	(1) lnCO_2	**(2) lnCO_2**	**(3) lnCO_2**
URB	−0.8051 ***	−0.8750 ***	−0.7130 **
	(−2.7126)	(−2.9725)	(−2.4036)
λ	0.6317 ***		
	(7.2975)		
ρ		0.6250 ***	0.5642 ***
		(7.2288)	(5.8644)
Direct:URB		−0.8703 ***	−0.8059 ***
		(−2.8600)	(−2.6309)
Indirect:URB		−1.6318	−29.4660 **
		(−1.6235)	(−2.3730)
Total:URB		−2.5022 **	−30.2718 **
		(−2.0766)	(−2.4305)
Control variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3250	3250	3250
R^2	0.0031	0.0791	0.0153

Note: Columns (1)–(3) of the table show the coefficient results under SEM, SAR, and SDM. Direct, Indirect, and Total denote the effects of NTU on CO_2 emissions, respectively. Other information is shown in Table 3. **, and *** denote significance at 5%, and 1%, respectively.

The spatial autoregressive coefficient of the double fixed effects model is 0.5642, passing the 1% significance test, demonstrating a remarkable spatial correlation of urban CO_2 emissions, which further verifies that the spatial econometric model is more accurate. NTU significantly reduces urban CO_2 emissions according to the models of SEM, SAR, and SDM. Moreover, they are significant at 5% at least, further confirming the previous baseline regression. Specifically, the influence coefficients of NTU on urban CO_2 emissions are −0.8051, −0.8750, and −0.7130 under the three models. Learning from the regression coefficients in the third column of Table 10, the direct and indirect influences of NTU on urban CO_2 emissions are −0.8059 and −29.4660, respectively. The total effect coefficient is −30.2718, significant at 5%. In summary, the above results suggest that NTU has a spatial spillover effect on urban carbon emissions. So, H4 is verified.

The reason for this phenomenon may be that, on the one hand, as the NTU level increases, the degree of informatization increases correspondingly and improvement of various types of infrastructure construction, which facilitates the overflow of knowledge, technology, and information from neighboring regions. Meanwhile, residents' environmental protection and conscious emission reduction actions can be effectively promoted, creating a good demonstration effect. Further, the fiscal decentralization system and the promotion system of officials are essential driving forces that the government can use to promote the NTU process. Accordingly, the cooperative mechanism of pollution and carbon reduction among neighboring cities will be continuously improved, and CO_2 emission regulation and environmental standards will be enhanced.

This study further verifies the spatial spillover effect of NTU on CO_2 emissions by setting the spatial weight matrix W_2 and W_3. The last two columns of Table 11 report the Spatial Durbin Model (SDM) test results using W_2 and W_3.

Table 11. Replacing the matrix for the robustness test.

Variable	W_1	W_2	W_3
	(1) $lnCO_2$	(2) $lnCO_2$	(3) $lnCO_2$
URB	−0.7130 **	−0.3221	−0.3600
	(−2.4036)	(−1.1026)	(−1.1749)
ρ	0.5642 ***	0.2382 ***	0.1565 ***
	(5.8644)	(9.9748)	(6.7025)
Direct:URB	−0.8059 ***	−0.5268 *	−0.4424
	(−2.6309)	(−1.7535)	(−1.4232)
Indirect:URB	−29.4660 **	−4.6118 ***	−3.0288 ***
	(−2.3730)	(−7.2269)	(−4.4181)
Total:URB	−30.2718 **	−5.1386 ***	−3.4712 ***
	(−2.4305)	(−7.0382)	(−4.8537)
Control variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3250	3250	3250
R^2	0.0153	0.0160	0.0696

Note: Columns (1)–(3) of the table show the coefficient results under W_1, W_2, and W_3, respectively, with Direct, Indirect, and Total representing the same as in Table 10. Other information is shown in Table 3. *, **, and *** denote significance at 5%, and 1%, respectively.

Observing the spatial autoregressive coefficients, we can determine that the spatial autoregressive coefficients of the dual fixed effects model are 0.2382 and 0.1565 under W_2 and W_3, respectively, and they are positive at the significance level of 1%, which means urban CO_2 emissions do correlate spatially. Further decomposition of the NTU's effects on CO_2 emissions into direct, indirect, and total effects can be achieved by using the partial differentiation method of spatial regression. It can be clearly observed that the direct effect of NTU on CO_2 emissions is inhibition, while under the W_2 matrix, the coefficient is −0.5268. The direct effect is not significant under the W_3 matrix; under the W_2 matrix, the indirect effect coefficient of NTU is −4.6118, while under the W_3 matrix, it is −3.0288. In both W_2 or W_3, the total effect is significantly negative at 1%, with coefficients of −5.1386 and −3.4712, respectively, which demonstrates that the spatial spillover effect of NTU on CO_2 emissions has a strong correlation between spatial geography and economic distance.

6. Discussion

This study is based on the essential connotation of NTU. With the entropy method, we constructed an NTU evaluation indicator system from five dimensions, i.e., population, economy, society, space, and ecology, innovatively expanding the perspective of NTU to the dimension of ecological urbanization. On this basis, this paper investigated how NTU affects urban CO_2 emissions and the specific path of its impact. Furthermore, the spatial spillover effect of NTU on CO_2 emissions was examined. The findings show that NTU can significantly reduce urban carbon emissions. By comparative analysis, some studies have found that NTU can increase urban CO_2 emissions [72,73], while others have suggested that there is a nonlinear correlation between them [23,74]. Scholars have reached different conclusions, which may be due to several factors. On the one hand, it demonstrates the intricate connection between CO_2 emissions and urbanization construction. On the other hand, various scholars are constrained by the limitations of scientific and technological conditions and subjective understanding. Different insights give us a more profound experience of this scientific issue. This study's findings help facilitate a low-carbon transition for China's NTU. They can also strongly support global green development, especially for developing countries undergoing rapid urbanization.

Most existing studies ignore the ecological dimension of NTU. Alternatively, the model, policy logic, and path choices of the low-carbon development transition of NTU have been fully explored. However, less literature has conducted an in-depth analysis of how NTU affects CO_2 emissions. So, based on the previous findings, it is not easy to give more targeted countermeasure suggestions. Furthermore, an NTU evaluation index was established in this paper from a multidimensional perspective, using the entropy method to estimate the NTU level in 250 cities in China, expanding and enriching the research content of NTU. Through verification of the two paths of "technological innovation" and "optimizing resource allocation", the internal mechanism of NTU's effect on CO_2 emissions will be more thoroughly examined. In addition, this study also found that in resource-based cities, old industrial areas, and cities with lower urbanization and higher innovation levels, NTU has a much greater impact on reducing CO_2 emissions. NTU can reduce local and neighboring cities' CO_2 emissions, which provides policy inspiration to enhance urban green development in a coordinated manner across regions and within critical areas.

Even though this study clarifies the link between NTU and urban carbon emissions, there are a few limitations. First, research perspectives could be more diverse. Based on the China Carbon Accounting Database (CEADs) and obtaining CO_2 emissions data for 250 cities in China, a macro perspective analyzes how NTU affects urban CO_2 emissions. In future research, the research sample will be expanded to further explore the impact of NTU on urban CO_2 emissions in a worldwide context, broadening the research in this area, e.g., by targeting important international organizations, countries at different stages of development, developing and developed countries, etc. In addition, it needs to be analyzed from a micro perspective, examining how NTU affects urban CO_2 emissions for enterprises, individuals, or households. Second, because the paths through which NTU affects urban carbon emissions are diverse, many factors affect urban development. The extensive changes in social structures and lifestyles triggered by NTU could impact consumption habits and energy consumption structures, and will entail changes in fiscal inputs. This study only empirically verifies that two paths reduce carbon emissions, and there may be other specific paths. Potential factors influencing urbanization will be identified in future research. We will explore the impact of major public emergencies such as COVID-19 on the development of economic and social activities, and thus on urban carbon emissions from both macro and micro perspectives, which may change our previous understanding. Third, NTU is a dynamic and challenging process. Urbanization is a critical path to modernization, and promoting organic coordination among subsystems should also be a focus of future academic research.

7. Conclusions

We examined the influence of NTU on urban CO_2 emissions in 250 Chinese cities from 2008 to 2020 in this study, leading us to draw five conclusions: (1) The level of NTU in China is generally increasing, and the volume of CO_2 emissions has increased slightly. NTU shows trends of being high in the south and low in the north, while the spatial distribution of CO_2 emissions is the opposite. (2) The baseline regression found that NTU can significantly reduce urban CO_2 emissions. This conclusion still holds after a series of robustness tests by changing the dependent variable to CO_2 emission intensity, excluding the low-carbon pilot area, replacing the dependent variable, excluding first-tier cities, and excluding extreme values. (3) The mechanism analysis shows that NTU can reduce CO_2 emissions by improving urban technology innovation and the efficiency of urban resource allocation. (4) NTU's ability to reduce carbon emissions varies by geography. Specifically, the emission reduction function of NTU is more significant for old industrial cities and resource-based cities; meanwhile, NTU plays a prominent role in declining carbon emissions in areas with lower urbanization levels and cities with high innovation levels. (5) Using spatial correlation tests, it was found that NTU and CO_2 emissions locally have a strong positive geographical spillover impact. NTU can reduce CO_2 emissions of native cities and adjacent cities.

The research conclusions have essential reference significance for sustainable development, which can help the government formulate reasonable and efficient regional planning and policy and thus support the high-level development of NTU. The policy recommendations resulting from this research are outlined as follows.

First, NTU development policies ought to be formulated according to local conditions. NTU should depend on the city's resource endowment, the strength of government environmental supervision, and innovation and development capacity; it is important to effectively promote ecological urbanization in non-resource-based cities, improve urban innovation and development in backward areas, and strengthen the local government's environmental supervision. At the same time, a differentiated policies should be formulated according to the characteristics of each city, and consider the positive externalities of the low-carbon effect of NTU.

Second, encouraging urban development in terms of technological innovation and resource optimization is crucial. The local government ought to accelerate the modification of the urban industrial structure and extensively promote clean technology development. Meanwhile, more effective utilization and planning of urban capital, labor, and land resources are required. To boost the economic impacts of urban agglomeration and scale, increasing the utilization efficiency of high-quality urban resources is essential.

Third, it is crucial to strengthen regional joint prevention and control and collaborative governance. In the context of "double carbon", it is essential to establish a cooperation mechanism to form an emission reduction system as soon as possible. Governments should take actions to strengthen the joint environmental enforcement mechanism between regions, build a unified CO_2 emission detection platform, and implement regional CO_2 emissions information sharing and joint early warning.

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