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The Impact of High-Standard Scenic Areas Construction on County-Level Carbon Emissions and Its Spatial Spillover Effects: Evidence from a Quasi-Natural Experiment

Ke Xu [1], Rui Zhang [2,*] and Yun Tong [1]

[1] College of International Tourism and Public Administration, Hainan University, Haikou 570228, China; 20223005701@hainanu.edu.cn (K.X.); tongyun@hainanu.edu.cn (Y.T.)
[2] School of Management, Hubei University of Chinese Medicine, Wuhan 430065, China
* Correspondence: zhang97@hbucm.edu.cn

Abstract: This study investigated for the first time the tourism–carbon emissions nexus based on the destination construction perspective, using the China's national scenic areas (CNSA) construction as a vehicle for concretization. A multi-source county panel dataset of 29,628 samples was constructed. The staggered Difference-in-Differences (DID) model and spatial DID model were further formulated. The findings show that: (1) the CNSA resulted in a 0.1024% reduction in carbon emission intensity (CEI) in treatment counties relative to non-treatment counties, and although the effect exhibits a delay, it persists and intensifies over time; (2) our heterogeneity results indicate that the inhibiting effect is significantly more pronounced in the western, eastern, and county subsamples; and (3) the spatial DID analysis reveals that the CNSA exerts a negative spatial spillover effect on CEI. This work enhances comprehension of the tourism–carbon emissions nexus, with implications for advancing regional carbon emission reduction policy strategies.

Keywords: China's national scenic areas; carbon emissions; spatial DID; multi-source data

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1. Introduction

Climate change, driven by evaluated greenhouse gas concentrations such as carbon dioxide, is exposing humanity to disasters such as rising sea levels, more extreme weather events, and loss of biodiversity [1]. A worldwide consensus now exists to advance emission reduction [2]. Tourism, recognized as an eco-friendly industry due to its lower energy consumption and reduced pollution [3], has been confirmed to effectively mitigate carbon emissions through its industrial substitution effect, environmental regulation effect, and opening-up effect [4]. However, tourism constitutes a substantial source of carbon emissions, representing around 8% of total global emissions [5], and is anticipated to increase by 25% by 2030 compared to 2016 levels[1]. What exactly is the effect of tourism on carbon emissions?

The effect of tourism on carbon emissions has been thoroughly examined and can be categorized into the two main areas: (1) by quantifying tourism carbon emissions and identifying their influencing factors, strategies have been suggested to mitigate these emissions [6,7], thus contributing to regional carbon emission reductions; (2) measuring the effect of tourism on regional total carbon emissions from an externality perspective. Due to the limited availability of statistical data, this type of research predominantly employs indicators such as tourism receipts [8,9], tourist arrivals [10,11], tourism specialization (tourism receipts as a percentage of GDP) [4], and tourism agglomeration (calculated on the basis of tourism receipts and tourist arrivals) [12] as proxy variables for tourism. Variations in study scales, study area, and data have resulted in inconsistent findings about the tourism–carbon emissions nexus. A literature review table (Table 1) is displayed to more effectively identify research gaps better. Table 1 illustrates the following research gaps: (1) Research perspectives require expansion. Tourism revenue primarily represents the income derived from tourists' travel behaviors and related economic activities at tourist destinations, whereas tourist arrivals denote the number of tourists visiting tourist destinations. Both indicators assess the tourism development level by evaluating the requirements and behaviors of tourists, focusing on the tourism subject and medium among the three primary components of tourism, while excluding the tourism object (destination). In other words, the construction and development of destinations have received little attention. (2) Research scales require refinement. Constrained by data availability, established studies predominantly operates at the national or provincial scales. This complicates the identification of small-scale impacts within intricate socio-economic contexts and hinders the formulation of locally tailored carbon reduction strategies. (3) Research contents require enhancement. Additional empirical research is required about the local-neighborhood characteristics of the tourism carbon reduction effect [13], which would facilitate a comprehensive understanding of the tourism–carbon emissions nexus.

Table 1. Literature review table.

Proxy for Tourism	Study Scales	Key Findings		Source
Revenue/arrivals	Countries	Linear	Increase	[8,9,14]
			Decrease	[15,16]
		Non-linear		[17]
Revenue/arrivals	Provinces	Linear	Increase	[10]
		Non-linear		[11]
Tourism agglomerations		Non-linear		[12]
Comprehensive index				[18]
Revenue/arrivals	Cities	Linear	Increase	[19]
			Decrease	[20]
		Non-linear		[21]
Tourism specialization		Linear	Decrease	[4]

The CNSA, led by the State Council, can provide a quasi-natural experiment to address the aforementioned research gaps. After a CNSA is approved, a master plan must be formulated and submitted to the State Council for endorsement within one year, and then developed and executed in strict compliance. Thus, it can be considered a policy for tourism from the standpoint of destinations' construction. Furthermore, as the CNSA primarily consists of coordinate data, it can enhance study scales in a manner that transcends the limitations of statistical data accessibility. Utilizing data from 1646 Chinese counties between 2000 and 2017, we employed staggered DID and spatial DID models to investigate the effect of the CNSA on CEI.

The contributions of this study are as follows: (1) It presents new empirical evidence from a destination construction perspective. This paper utilizes manually gathered data on the CNSA to explore the tourism–carbon emissions nexus from the perspective of policy shocks, in contrast to prior studies that rely on revenue or arrival indicators. On the one hand, it eliminates the problem of relying on a single tourism indicator. On the other hand, the endogeneity problem, potentially arising from bidirectional causality, is addressed. (2) Relying on high-precision remote sensing image data, statistical data, and manually collated policy documents, the research scale is deepened to the county level, which is not addressed by existing studies. A large panel dataset with a sample size of 29,628 was constructed, enhancing the precision and credibility of the results. (3) The tourism–carbon emission nexus is explored more comprehensively from the spatial spillovers perspective, enriching the established findings.

2. Policy Background and Theoretical Analysis

2.1. Policy Background

To promote tourism growth, relevant Chinese departments have consecutively instituted several high-standard scenic area policies. The aim is to attain both conservation of resources and tourism development. The CNSA is the earliest and most authoritative policy among them, and plays a crucial role in modern tourism development due to its exceptional natural conditions and ecological environment. Since 1982, the State Council has announced nine batches of 244 CNSAs. Upon approval of a CNSA, a comprehensive plan must be formulated to address the need for harmony between humankind and nature, coordinated regional development, and holistic economic and social progress. The general plan primarily encompasses the evaluation of scenic resources, protection measures for resources, allocation of significant construction programs, intensity of development and utilization, functional structure and spatial arrangement, scope of prohibitions and restrictions on development, tourist capacity, and related specialized planning. The CNSA is expected to exert economic, social, and environmental effects.

The CNSA was selected to explore the tourism–carbon emissions nexus for the following reasons: (1) The CNSA is the only high-standard scenic area system issued by the State Council, hence possessing authoritative status. (2) The variation in batch creation across different years renders the CNSA an effective quasi-natural experiment. Consequently, the policy effects can be precisely discerned utilizing DID techniques. (3) The CNSA mandates that landscapes must be predominantly in a natural condition or preserve their historical authenticity with no direct correlation to local carbon emissions, which mitigates endogenous disturbance.

2.2. Theoretical Analysis

The CNSA can reduce the CEI of scenic areas and adjacent areas by enacting supportive policies. On the one hand, the CNSA's sustainable attributes and associated policy documents can influence carbon reduction through 'hard' environmental regulation. To efficiently safeguard and rationally use scenic resources, policymakers have formulated and issued relevant regulations and policy documents aimed at directly diminishing the CEI of the CNSA and its surrounding small areas. There are explicit normative requirements for afforestation and tree planting by a CNSA, intending to properly safeguard forest vegetation. Increased vegetation cover correlates with a decreased CEI [22]; the CNSA requires that scenic areas and their surrounding protection zones be free from environmentally harmful facilities and imposes restrictions on the layout and configuration of related infrastructure development. Consequently, carbon emissions resulting from the expansion of tourism-related infrastructure development can be mitigated; regulations on CNSAs stipulate that tourists should not be admitted above the established capacity without restriction. Regulating tourist capacity promotes a reduction in tourism carbon emissions [23]; the Ministry of Housing and Urban-Rural Development of the People's Republic of China mandates annual reports on the formulation and implementation of plans for CNSA regulatory purposes. Moreover, a penalty mechanism has been established for unauthorized development, landscape destruction, and ecological destruction within the CNSA and adjacent conservation zones. Carbon emissions resulting from non-compliance can be effectively mitigated. On the other hand, the CNSA can facilitate CEI reduction through 'soft' environmental regulation, including shaping public attitudes and behavior. With its unique natural landscape and deep cultural heritage, the CNSA can attract public attention in environment issues, hence indirectly contributing to the reduction in CEI within the CNSA and adjacent county unit [24]. Given China's strong commitment to ecological civilization and sustainable development, the 'soft' environmental regulation is even more magnified [25].

The CNSA can diminish the CEI of its respective county unit by facilitating the change and enhancement of the industrial structure. Firstly, as a high-standard scenic area, the CNSA substantially influences the local tourism economy [26], which in turn raises the prices of local factors of production such as labor and land, thus compressing the space for industrial development. Secondly, the CNSA can expand the tourism industry chain by promoting the development of traditional service industries such as accommodation and catering, thus increasing the proportion of tertiary industries. Finally, the CNSA can increase the proportion of tertiary industry in its location by releasing investment decision-making signals. Destinations are commodities with a variety of attributes that cannot be directly observed [27], which makes it difficult for tourism enterprises to make accurate judgments about the destination investment's value. Counties with a CNSA have the advantages of unique landscape resources, strong policy support, high market demand, and high-quality brand image, which usually have higher investment value. Therefore, the CNSA can address the information asymmetry in investment decision-making to a certain extent. According to signaling theory[2], a CNSA can be seen as a signal for investment decisions. Tourism enterprises (signal receivers) receive the signal and provide feedback, ultimately opting to enter counties with a CNSA and establishing tourism industry clusters. This can augment the share of tertiary sector, ultimately facilitating a drop in the CEI [29]. Consequently, the first hypothesis is proposed.

Hypothesis 1. *The CNSA can reduce CEI.*

Due to the enhanced accessibility of neighboring counties, scenic areas in these regions possess the natural advantage of attracting tourists and benefiting from the experience of the CNSA. CNSAs, as the most authoritative high-standard scenic areas, can significantly stimulate the growth of associated industries in the neighboring counties, which mostly accounts for the spatial spillover characteristics of its negative effect on CEI. Specifically, the CNSA, as an investment decision signal, can stimulate the development of tourism reception facilities, support facilities, and related industries in the neighboring counties, ultimately creating a tourism industry cluster that can reduce the CEI of these counties. Furthermore, the spatial spillover effects of the CNSA on CEI can also be realized through the spillover of carbon emissions [30]. Thus, the second hypothesis is established.

Hypothesis 2. *The CNSA can reduce CEI in neighboring counties through spatial spillover effects.*

The analysis framework is displayed in Figure 1.

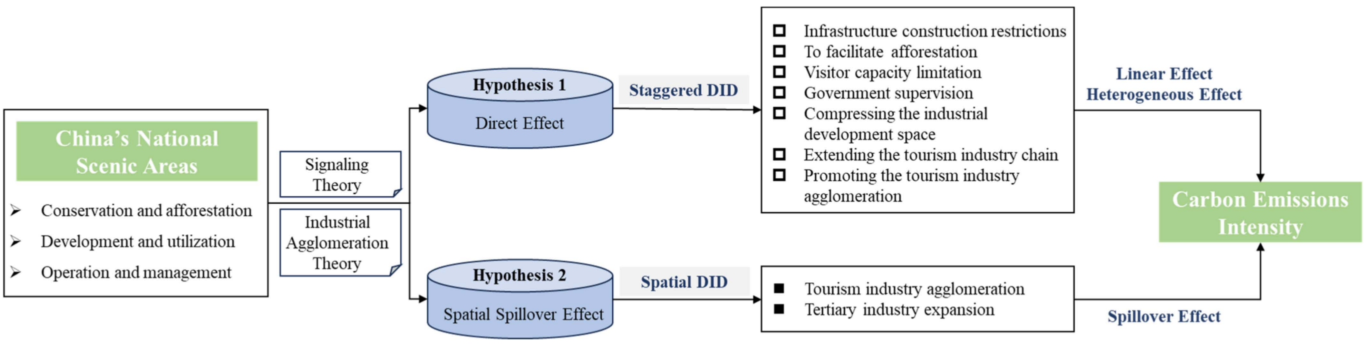

Figure 1. Analysis framework.

3. Methodology

3.1. Models Specification

3.1.1. Staggered DID Model

The State Council adopts a batch approach to construct the CNSA, rendering it a quasi-natural experiment. A staggered DID model was employed to explore the effect of the CNSA on CEI, accounting for variations in both time and area dimensions. The specification is as follows:

$$\ln Y_{i,t} = \alpha_0 + \beta Scenery_{it} + \alpha \ln Z_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where $Y_{i,t}$ is the dependent variable for county i and year t. We select CEI to characterize county-level carbon emissions. The dummy variable $Scenery_{it}$ represents the independent variable. β means the net effect of the CNSA on CEI. Z_{it} denotes control variables. μ_i, γ_t, and ε_i denote the county fixed effect, year fixed effect, and random perturbation terms, respectively.

3.1.2. Spatial DID Model

1. Model specification

Carbon emissions exhibit a characteristic transboundary geographic impact [1]. Meanwhile, the CNSA in neighboring counties exerts a demonstrative effect on local CNSAs. In other words, spatial spillovers may exist among the counties with a CNSA and those without, which does not satisfy the basic assumption that different individuals are affected by the policy independently. The traditional DID model fails to consider the migration decision of policy externalities, while the spatial Durbin model can capture it. The spatial DID model relaxes the assumption and is able to examine both local and neighboring policy effects. Accordingly, we referred to Yu and Zhang [31] to explore the effect of the CNSA on CEI with spatial DID model. The formula is as follows:

$$\ln Y_{i,t} = \rho W \ln Y_{i,t} + \beta_1 \ln Scenery_{it} + \beta_2 Z_{it} + \theta_1 W \ln Scenery_{it} + \theta_2 W \ln Z_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where W denotes the spatial matrix. ρ represents the spatial spillover effect of CEI. β_1 represents the effect of the CNSA on CEI. θ_1 captures the effect of the CNSA in neighboring counties on local CEI, while β_2 and θ_2 denote the effect of local control variables on local CEI and the effect of neighboring control variables on local CEI, respectively. Other symbols have same meaning as in Equation (1).

2. Spatial weight matrix construction

The construction of a spatial weight matrix may often be categorized into two types: one based on geographical location information (neighborhood and distance relations) and the other on socio-economic factors. The former is more intuitive and satisfies the assumption of exogeneity of the spatial weight matrix. The latter possesses significant economic significance, but it does not satisfy the assumption of exogeneity. Thus, in reality, the spatial weight matrix is mostly constructed using geographical location information [32].

① According to the first law of geography, entities are interconnected and exhibit stronger relationships with proximate entities [33]. Therefore, the most intuitive neighborhoods should be prioritized initially. This study investigated the effect of local CNSAs on the CEI of neighboring county units, referring to [34]. A queen neighborhood spatial weight matrix (W0–1) was constructed, comprising an n × n 0–1 matrix with zero diagonal elements. 0 signifies that counties are non-adjacent, while 1 denotes that counties are adjacent.

② The adjacency matrix allocates identical weight to all neighboring county units, disregarding the actual distance. In actuality, as the geographical distance among units expands, the spatial spillover effects diminish. This study employs the inverse geographic distance among county units, where proximity correlates with effect strength, as the foundation for the spatial weight matrix, integrating it with higher-order neighborhoods to construct the K-nearest neighborhood spatial weight matrix (Wk) [35,36]. It is constructed in the following manner:

County i has four neighboring county units, with the spatial weight of these neighboring counties being the inverse of the geographic distance, whereas the spatial weight of all other counties is zero.

$$W_{ij}^{k} = \begin{cases} 0, i = j \\ 0, i = j, j \notin nbd(\dot{\Pi})_k \\ \frac{1}{d_{ij}}, i \neq j, j \notin nbd\left(\dot{\Pi}\right)_k \end{cases} \tag{3}$$

where d_{ij} denotes the Euclidean distance calculated from the geographic center of mass coordinates of county i and j. $nbd(i)$ is the neighboring county of county i.

In addition, considering the sensitivity of the spatial measures results to the construction of spatial weight matrices [37], we established k values of 3, 5, and 6 for robustness testing.

3.2. Variable Definitions

1. Dependent variable

The county-level carbon emission is measured by CEI, calculated as the ratio of total carbon emissions to the GDP [38].

2. Independent variable

The dummy variable $Scenery_{it}$ is defined as follows: if county i has a CNSA in year t, then $Scenery_{it}$= 1, otherwise $Scenery_{it}$ = 0. It should be noted that the first batch of CNSAs was constructed in 1982. The study period is constrained by data availability, spanning from 2000 to 2017. The inclusion of counties that constructed a CNSA prior to 2000 as experimental groups may influence the conclusions, which were excluded.

The spatial distribution of CNSAs and the CEI are shown in Figure 2.

3. Control variables

Considering the various factors that can affect CEI, the following county-level control variables have been added: Economic development level, Industrial structure, Population density, Urbanization, Temperatures, Energy intensity, Government intervention, and Vegetation cover.

Economic development level (*Eco*). Eco is a crucial determinant influencing the CEI. GDP per capita serves as a proxy for Eco [39]. A crude model of economic development would lead to energy consumption, thus producing carbon emissions [40]. Meanwhile, when the economic development level rises, infrastructure gradually improves and energy efficiency increases, which is beneficial to carbon emission reduction.

Industrial structure (*Ind*) is measured by the proportion of secondary industry in GDP [41]. The secondary sector is the primary contributor of carbon emissions.

Population density (*Pop*). The ratio of population to administration areas serves as a proxy for population density. Population density can affect carbon emissions through scale and agglomeration effects [42], which is a significant determinant of CEI.

Urbanization (*Urb*) is proxied by the proportion of built-up land area to the administration area. Urb is a key driver of CEI. The modernization of lives during urbanization results in increased energy consumption, thereby contributing to emissions [42]. However, enhanced urbanization can serve as an effective means to improve resource efficiency [43], thus facilitating emission reductions.

Temperatures (*Temp*) is measured by the average annual temperature. Increasing temperatures result in a heightened need for air conditioning, thus elevating carbon emissions [44].

Energy intensity (*Ene*) is captured by the energy use per GDP. Energy intensity is an expression of energy efficiency, where elevated levels signify increased carbon emissions per unit of energy consumed. Enhancements in energy efficiency can facilitate the substitution of fossil fuels with renewable and cleaner energy sources, thereby optimizing the energy structure, which is a crucial method for mitigating carbon emissions [45]. Therefore, the coefficient is anticipated to exhibit a positive sign. Tripathy et al. [46] demonstrated a linear relationship between the nighttime lighting index and energy consumption. Given the data availability at the county level, we refer to Tong et al. [4] and adopt nighttime lighting data as a proxy indicator for energy consumption.

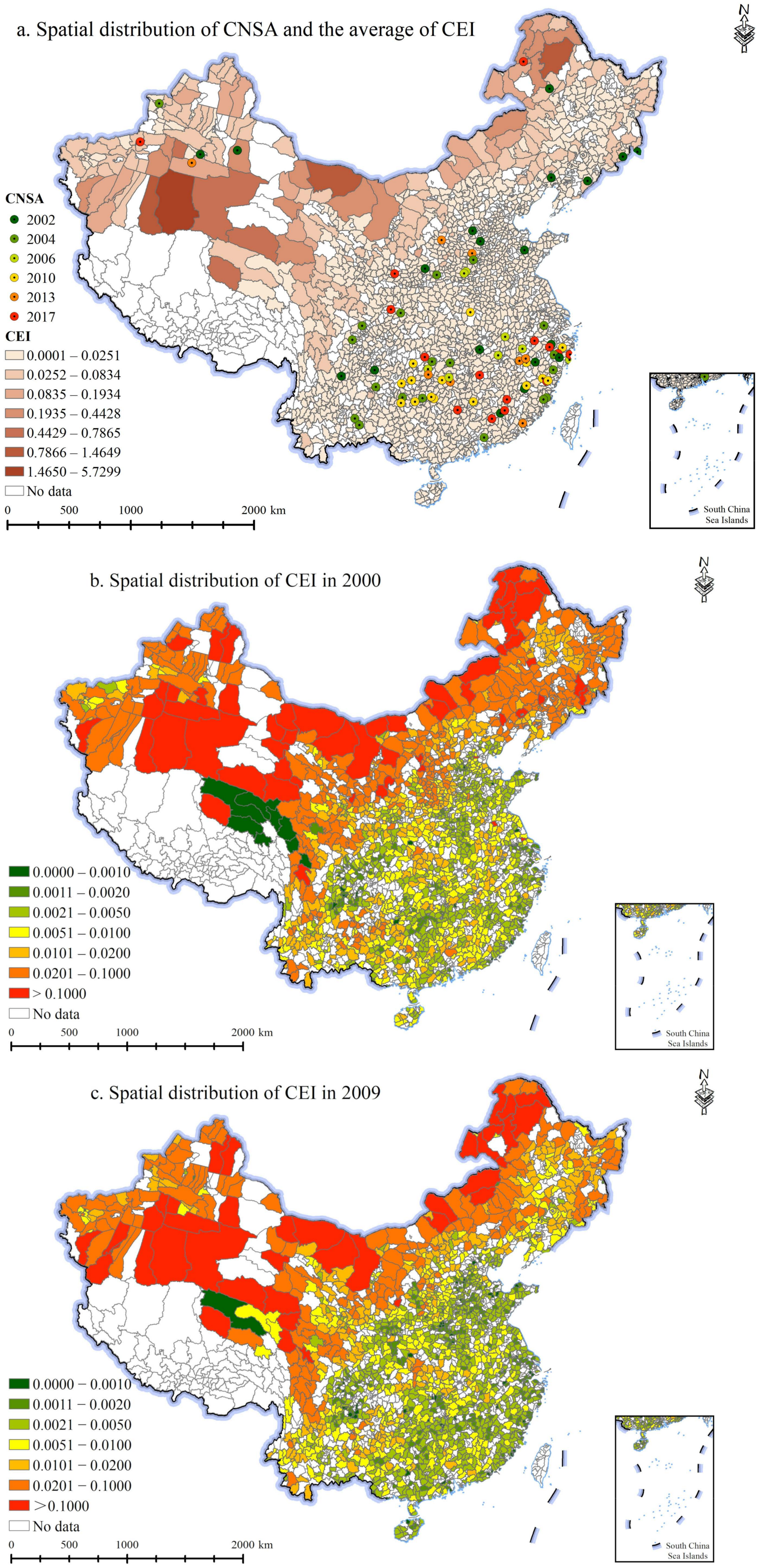

Figure 2. *Cont.*

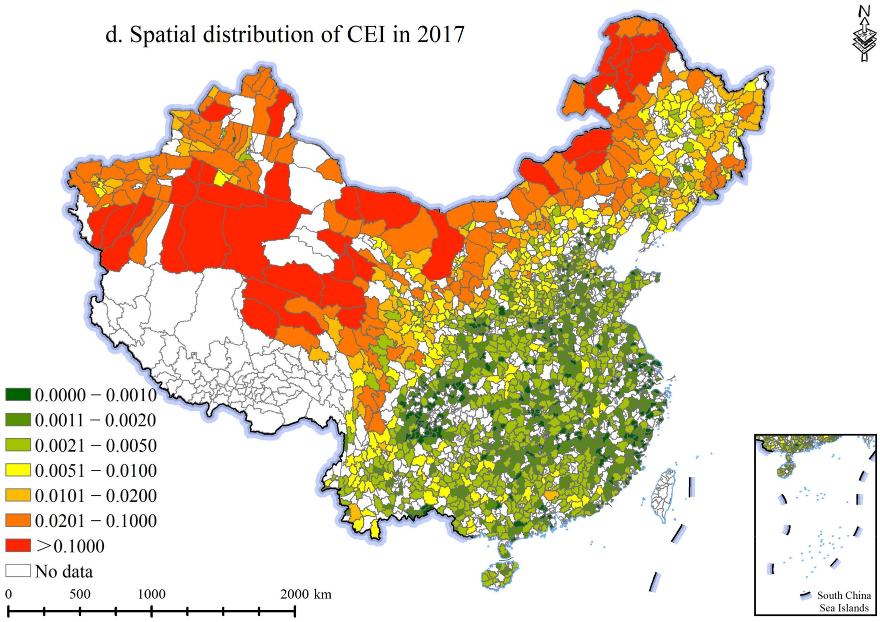

Figure 2. Spatial distribution of CNSAs and the CEI. (**a**) Spatial distribution of CNSAs and the average of CEI. (**b**) Spatial distribution of CEI in 2000. (**c**) Spatial distribution of CEI in 2009. (**d**) Spatial distribution of CEI in 2017.

Government intervention (*Gov*). Public budget expenditure as a share of regional GDP is used as a proxy for Gov [47], which can provide the macro-control on carbon emissions.

Vegetation cover (*Veg*) is defined as the Normalized Difference Vegetation Index (NDVI). NDVI serves as an indicator of surface vegetation, which can reduce pollution concentrations by mitigating airborne dust and enhancing deposition, absorption, and tropospheric pollutants [45]. Consequently, enhancing vegetation cover is a viable way to decrease emissions.

Table 2 displays the descriptive statistics. To avoid heteroscedasticity, variables were taken logarithmically.

Table 2. Descriptive statistics.

Variables	Observations	Mean	S.D.	Min.	Max.	VIF
ln*CEI*	29,628	−5.2515	1.3335	−18.4554	2.2379	-
Scenery	29,628	0.0284	0.1660	0.0000	1.0000	1.01
ln*Eco*	29,628	1.9243	1.3927	−3.8137	9.5429	3.58
ln*Ind*	29,628	−0.9856	0.4657	−4.8842	0.5130	1.68
ln*Pop*	29,628	−2.6061	2.2388	−14.0491	3.3557	5.27
ln*Urb*	29,628	−1.5638	0.2473	−3.5165	−0.5726	2.46
ln*Temp*	29,628	2.4053	0.7379	−5.8493	3.3923	1.94
ln*Ene*	29,628	−3.2324	1.9461	−12.1356	3.0994	2.96
ln*Gov*	29,628	−1.8117	0.7554	−4.7303	1.6923	1.56
ln*Veg*	29,628	−0.3814	0.3503	−2.8968	−0.1078	2.04

3.3. Data Sources

The original data for the explanatory variables were obtained from Chen et al. [48]. The PSO-BP algorithm was employed to integrate the DMSP/OLS and NPP/VIIRS data. The total carbon emissions were calculated accordingly.

The core explanatory variable was manually collated from the Notice on the List of National Scenic Areas issued by the State Council.

As for the control variables, the raw data of Eco came from Chen et al. [49] and the Socioeconomic Data and Applications Center (https://sedac.ciesin.columbia.edu/data/

set/gpw-v4-population-count-rev11, accessed on 9 October 2024). The raw data of Pop were obtained from the Socioeconomic Data and Applications Center (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11, accessed on 9 October 2024). The raw data of Urb, Ene and Veg were available at the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 9 October 2024). The original data of Temp were obtained from the National Data Center for Meteorological Sciences (http://data.cma.cn/, accessed on 9 October 2024). The raw data of other variables came from the China Statistical Yearbook (County-level) (2001–2018), and missing values were filled using linear interpolation method.

4. Results

4.1. Baseline Results

Table 3 displays the baseline estimates. Autocorrelation due to disturbance terms in the county and year dimensions may result in the underestimation of standard errors in panel data. Thus, we adhered to Moshiriana et al. [50] and clustered the regression standard errors within the county-year dimension. Columns (1)–(5) incrementally add a variety of control variables while accounting for county fixed effect (FE) and year FE. Upon controlling for variables that may influence CEI, it is evident that the CNSA continues to inhibit CEI. Accordingly, H1 is established.

Table 3. Baseline regression.

	(1) lnCEI	(2) lnCEI	(3) lnCEI	(4) lnCEI	(5) lnCEI
Scenery	−0.0559 *** (0.0169)	−0.0801 *** (0.0129)	−0.0772 *** (0.0134)	−0.0983 *** (0.0134)	−0.1024 *** (0.0138)
ln*Eco*		−0.8976 *** (0.0113)	−0.8722 *** (0.0111)	−0.8965 *** (0.0117)	−0.8696 *** (0.0127)
ln*Ind*		0.2603 *** (0.0243)	0.2405 *** (0.0236)	0.2003 *** (0.0234)	0.2231 *** (0.0254)
ln*Pop*			1.0633 *** (0.1766)	1.1047 *** (0.1772)	1.1436 *** (0.1817)
ln*Urb*			−2.3622 *** (0.3120)	−2.6186 *** (0.3504)	−2.5343 *** (0.3534)
ln*Temp*				−0.0461 * (0.0250)	−0.0453 * (0.0251)
ln*Ene*				0.0891 *** (0.0068)	0.0871 *** (0.0068)
ln*Gov*					0.1254 *** (0.0235)
ln*Veg*					−0.0267 (0.0549)
_constant	−5.2499 *** (0.0029)	−3.2672 *** (0.0416)	−4.2585 *** (0.4982)	−4.1452 *** (0.5470)	−3.7325 *** (0.5930)
Observations	29,628	29,628	29,628	29,628	29,628
R^2	0.8639	0.8947	0.8967	0.8982	0.8986
County FE	√	√	√	√	√
Year FE	√	√	√	√	√

Note: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. S.D. values are given in parentheses. The same below.

4.2. Parallel Trend Test

The parallel trends in CEI among counties with a CNSA and those without a CNSA are a prerequisite for the validity of staggered DID estimates. That is, prior to the CNSA construction, the CEI of the counties with a CNSA and those without show a similar trend.

Referring to Jacobson et al. [51], an event study approach was employed to test the parallel trend assumption. The specific econometric model is presented below:

$$\ln Y_{it} = \alpha_0 + \sum_{t=-6}^{6} \delta_t D_{it} + \alpha \ln Z_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (4)$$

Among them, D_{it} is a dummy variable for the CNSA, with its value determined by m_i, which represents the year in which county i constructs the CNSA. If $t\text{-}m_i \geq 0$, then $D_{it} = 1$, otherwise $D_{it} = 0$. All other variables remain consistent with those in Equation (1). We focus on δ_t, which reflects the difference in CEI among counties with a CNSA and those without a CNSA in year t. Following Tong and Zhang [52], the first period preceding the implementation of a CNSA serves as the reference period. Figure 3 portrays the coefficients across the relative years of a CNSA. The coefficient δ_t is insignificant prior to CNSA construction, indicating that the parallel trend test was passed. The significance of δ_t commencing from t = 2 implies that the CNSA has a delay in reducing CEI. The potential explanation is that once a CNSA is approved, the coordinated preparation and implementation of the plan requires time.

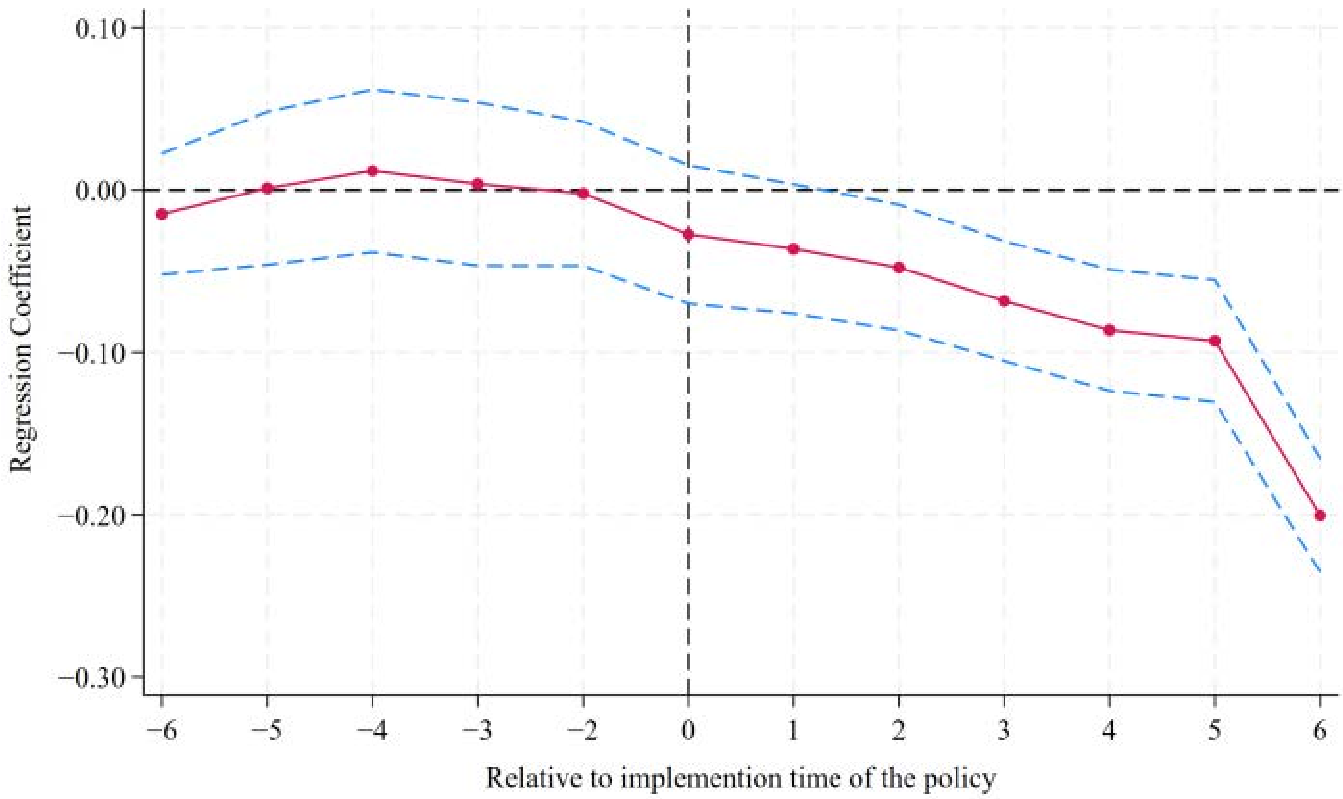

Figure 3. Parallel trend test.

4.3. Robustness Tests

The baseline results indicate that the CNSA significantly inhibits CEI. To exclude confounding effects, we conducted robustness tests, including a placebo test, replacing the dependent variable, excluding outliers, excluding other relevant policy interferences, PSM-DID estimation, and endogeneity treatment.

4.3.1. Placebo Test

The baseline results may be affected by unobservable omitted variables. To address this problem, we referred to Cai et al. [53] and performed a placebo test by replacing the experimental counties. Specifically, eighty-four[3] counties were randomly generated as false treatment units, while the remaining counties served as false control units. We then repeated the regression with CEI as the explanatory variable for 500 times. Figure 4 graphs the estimated coefficients, which are predominantly clustered around 0 and conform to a normal distribution. The true estimate of baseline results is −0.1024, significantly lower than the pseudo estimates. Overall, the baseline result is robust.

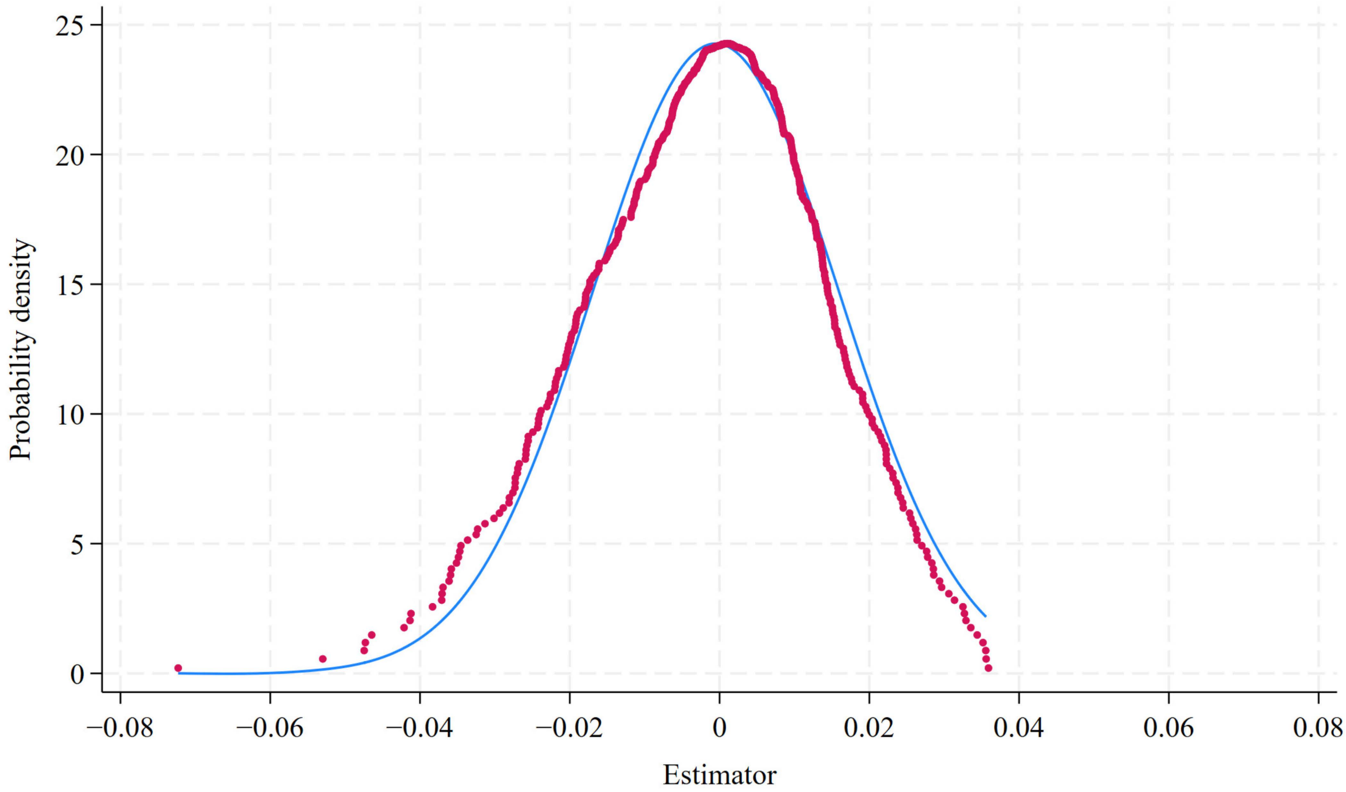

Figure 4. Placebo test.

4.3.2. Replacing Variable

Referring to Peng et al. [54], the total carbon emissions was set as the explanatory variable. Table 4 column (1) indicates that *Scenery* coefficients were significantly adverse, implying that the baseline result is robust.

Table 4. Robustness test results.

	(1) Replacing Dependent Variable	(2) Excluding Outliers	(3) Excluding Outlier	(4) Excluding Smart Pilot Interference	(5) Excluding 5ATA Interference	(6) Cross-Sectional PSM-DID Estimation	(7) Year-by-Year PSM-DID Estimation	(8) IV-2SLS
Scenery	−0.1024 *** (0.0138)	−0.0866 *** (0.0110)	−0.0843 *** (0.0116)	−0.1068 *** (0.0139)	−0.1009 *** (0.0137)	−0.1043 *** (0.0313)	−0.0894 *** (0.0295)	−0.1453 *** (0.0528)
Smart				−0.0772 *** (0.0070)				
5ATA					−0.0633 *** (0.0147)			
_constant	2.3902 *** (0.5930)	−4.0038 *** (0.8041)	−3.6550 *** (0.6787)	−3.6468 *** (0.5804)	−3.6989 *** (0.5928)	−4.9826 *** (1.0359)	−5.6449 *** (0.7971)	
Anderson canon. corr LM								9031.660 ***
Cragg–Donald Wald F								$1.3 \times 10^{0.4}$ {16.38}
Controls	√	√	√	√	√	√	√	√
Observations	29,628	29,628	29,628	29,628	29,628	29,300	27,093	29,628
R^2	0.8961	0.9656	0.9633	0.8988	0.8987	0.3807	0.4329	0.3358
County FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√

Note: Stock-Yogo weak ID test critical value (10% maximal IV size) is given in brace.

4.3.3. Excluding Outliers

To exclude the interference of outliers, we excluded 2% and 5% of the sample points from both ends of lnCEI and subsequently re-regressed. The results are reported in columns (2) and (3) of Table 4. As displayed, the baseline results are robust.

4.3.4. Excluding Other Relevant Policy Interferences

Further, we conducted regressions to eliminate the effect of the following relevant policy interferences: (1) Smart pilot cities (districts and counties) policy. Shu et al. [55] found that the policy is capable of diminishing emissions. Therefore, the dummy variable Smart was established to indicate if a county is a pilot smart city (district or county) in the current year; if so, Smart = 1, otherwise Smart = 0. The results are displayed in Table 4 column (4). (2) 5A-level tourist attractions (5ATA). A dummy variable 5ATA was conducted to ascertain the presence of 5ATA(s) in a county; if present, 5ATA = 1, else 5ATA = 0. Subsequently, 5ATA was added in the baseline regression, with results displayed in Table 4 column (5). The findings reported in columns (4) and (5) of Table 4 are consistent with those in Table 3, indicating that the CNSA effectively reduces the CEI.

4.3.5. PSM-DID Estimation

Following Liu et al. [56], we utilized cross-sectional and year-to-year PSM-DID models to mitigate endogeneity problems arising from sample selection bias. The results are reported in columns (6) and (7) of Table 4. The *Scenery* coefficients are -0.1043 and -0.0894, both of which are significant, corroborating the baseline results.

4.3.6. Endogeneity Treatment

Our baseline results may be biased because to endogeneity issues associated with *Scenery*. An IV is designed to address this issue by extreme difference in altitude. A bigger disparity in altitude correlates with an abundance of natural resources for tourism, which satisfies the correlation condition. Furthermore, altitude is a natural geographic variable that does not influence CEI, thus satisfying the exogeneity condition. Given that extreme difference in altitude consists of cross-sectional data, we follow Nunn and Qian [57] in constructing an interaction term between extreme difference in altitude and year. The IV-2SLS results are shown in columns (8) of Table 4, which demonstrates the robustness of the baseline results. In addition, Anderson canon. corr LM and Cragg–Donald Wald F statistics indicate that there is neither insufficient nor weak identification.

4.4. Heterogeneity Analysis

The counties have significant differences in location conditions and administrative constraints, which leads to differences in the effect of the CNSA on CEI.

4.4.1. Location Conditions Heterogeneity Analysis

Referring to Wu et al. [58], the sample was divided into eastern, central, and western regions based on locational conditions. Columns (1) to (3) of Table 5 report the location conditions' heterogeneity analysis results. The *Scenery* coefficients for both the east and west are significant, with the *Scenery* coefficient for the west being less than that for the east. Conversely, the west, characterized by a diminished carbon locking effect, has responded more swiftly to the CNSA. Therefore, the counties in this region can more quickly exert the inhibiting effect of the CNSA on CEI.

Table 5. Heterogeneity analysis results.

	(1) East	(2) Central	(3) West	(4) Counties	(5) Municipal Districts and County-Level Cities
Scenery	−0.0356 ***	0.0126	−0.1469 ***	−0.1186 ***	−0.0112
	(0.0113)	(0.0111)	(0.0400)	(0.0170)	(0.0183)
_constant	−4.2242 ***	−5.9213 ***	1.5367	−1.9336 *	−4.4372 ***
	(0.3041)	(0.2441)	(1.4936)	(1.0378)	(0.1927)
Controls	√	√	√	√	√
Observations	7866	11,070	10,692	23,184	6444
R^2	0.9893	0.9873	0.8314	0.8798	0.9902
County FE	√	√	√	√	√
Year FE	√	√	√	√	√

4.4.2. Management System Heterogeneity Analysis

In China's administrative hierarchy, counties, municipal districts, and county-level cities hold the same rank. Municipal districts and county-level cities typically possess enhanced administrative and financial authority. Hence, the counties are divided into one sub-sample, while the others are allocated to another. The management system heterogeneity analysis results are reported in columns (4) to (5) of Table 5. The inhibiting effect of the CNSA on CEI is significant in certain counties, while it is not significant in others.

4.5. Spatial Spillover Effects

The spatial DID estimation results are displayed in Table 6. The *Scenery* coefficients are negative at the 5% significance level under W0-1 and Wk, revealing that the CNSA can reduce CEI. In terms of the spatial lag term, the W × *Scenery* coefficient is negative at a non-significant level under W0–1, whereas it is negative at the 10% significance level under Wk. Consequently, it may be first assessed that the CNSA's inhibitory effect on CEI has spatial spillover features.

Table 6. Spatial analysis.

	(1) W0−1	(2) Wk
Scenery	−0.0537 **	−0.0549 **
	(0.0238)	(0.0230)
W × *Scenery*	−0.0594	−0.0812 *
	(0.0430)	(0.0432)
LR_direct	−0.0676 **	−0.0745 ***
	(0.0265)	(0.0260)
LR_indirect	−0.1687 **	−0.2325 **
	(0.0845)	(0.0915)
LR_total	−0.2363 **	−0.3070 ***
	(0.0984)	(0.1056)
Controls	√	√
rho	0.5348 ***	0.5644 ***
	(0.0056)	(0.0051)
Observations	29,628	29,628
R^2	0.3213	0.3528
County FE	√	√
Year FE	√	√

Lesage and Pace [59] argued that relying solely on point estimates to test for spatial spillovers results in bias. The regression coefficients reflect the effect of the explanatory variable on the outcome variable in the traditional panel econometric model. However, it includes feedback effects subsequent to considering the spatial spillover effect. The spatial lag term coefficient cannot completely quantify the effect of the CNSA on CEI. Hence, we present the results of the direct and indirect effect derived from decomposition analysis using partial derivatives, as illustrated in Table 6. For the direct effect, the *Scenery* coefficient is significantly negative. For the indirect effect, under W0–1 and Wk, the CNSA may cause a decrease in CEI of approximately −0.1687 and −0.2325, respectively. Therefore, H2 is valid.

The robustness test results were obtained by substituting the estimation model or the spatial weight matrix [60,61], thereby affirming the robustness of the spatial analysis results.

5. Discussion

5.1. The Effect of the CNSA on CEI Is Negative, Which Persists and Intensifies over Time

This result is similar to the findings of Huang et al. [25]. They utilized a multiperiod Difference-in-Differences model to investigate the causal relationship between China's high-standard scenic areas' (Prototype-zone of National Ecotourism Attractions, PNEA) certification and carbon emissions. The result in this study can be explained by the symbiotic relationship among CNSAs and CNSA-located counties. First, the benefit symbiosis. High-standard scenic areas can facilitate tourism economy [62], stimulate the development of tourism-related industries, and consequently optimize the industrial structure. The beneficiaries of the CNSA extend beyond its confines to encompass the entire tourism destination (county). Second, the environment symbiosis. Environmental monitoring and education are important components in the establishment of the CNSA. On the one hand, the CNSA can safeguard the local environment by raising public awareness; however, due to the diffuse nature of carbon emissions, geographical proximity delineates the environmental symbiosis among CNSAs and the CNSA-located counties. As a result, the negative effect of the CNSA on CEI is prominent.

The dynamic character of the gradual enhancement of the effect is related to the adjustment of industrial structure. Industrial restructuring is an extensive and intricate process. The establishment of CNSAs can effectively expand the tourism industry chain, thus optimizing the industrial structure and reducing CEI. Over time, the industrial structure has undergone substantial transformation, with an increasing proportion of tourism and related sectors. Concurrently, as technology advances and the market evolves, CEI will be further diminished. In conclusion, the negative effect of the CNSA on regional total CEI is even more magnified.

5.2. The Negative Effect of the CNSA on CEI Is Significantly More Evident in Western and Eastern Regions

This result is different from the results of Zhang and Zhang [19]. They used 313 Chinese cities' panel data to explore the effect of tourism on carbon emissions, revealing that tourism revenue and tourist arrivals positively influence carbon emissions, with significant effects shown in the eastern and central regions, while the western region exhibited insignificant results. The difference can be explained by the different proxy indicators and the study scales. In addition, Paramati et al. [8] identified an inverted U-shaped relationship between tourism and carbon emissions, corroborating our findings. The results of this study can be explained by economic development. The level of economic development in the western, central, and eastern regions gradually increases. In the initial phase of economic development, the requisite infrastructure construction and tourism activities linked to the founding of the CNSA can result in heightened carbon emissions. However, in the long term, as the economy grows and living standards improve, there will be heightened demands for the quality of CNSA establishment. Due to stringent environmental restrictions and technological advancements, the creation of the CNSA will surpass the inflection point of carbon emissions. Consequently, when the amount of economic development rises, an inverted U-shaped correlation emerges between the CNSA and carbon emissions.

5.3. The Negative Effect of the CNSA on CEI Is Not Significant in the Municipal District and County-Level City Subsamples

This study is the first to investigate the tourism–carbon emissions nexus at county level based on the perspective of management system heterogeneity, while existing studies have paid much attention to location or other heterogeneities. Examining the effect of the CNSA on CEI from the management system heterogeneity's perspective helps enhance the accurate development of policies. Regarding administrative responsibilities, counties and county-level cities, despite being at the same governmental tier, have distinct functions; counties concentrate on rural areas, whereas county-level cities prioritize urban development, placing greater emphasis on economic and social advancement. Municipal districts, as components of the urban area, are interconnected with comprehensive city development and exhibit a superior level of economic and social advancement as well as infrastructure. Therefore, for the conclusion of this study, one explanation is that municipal districts generally function as centers of robust economic growth, characterized by sophisticated industrial frameworks and established environmental governance systems, thereby diminishing the inhibitory impact. The county-level cities prioritized economic development, emphasizing industrial growth and urbanization over tourism.

5.4. The Negative Effect of the CNSA on CEI Has a Spatial Spillover Characteristic

This conclusion is consistent with Shan and Ren [63] but is different from the findings of Zhou et al. [64]. Zhou et al. [64] examined the impact of tourism clusters on direct household carbon emissions using data from 30 provinces and determined that the geographical spillover effect was insignificant. An excessively large study size typically encompasses more confounding variables, which may diminish the spillover effects. The findings in this research can be elucidated through the lens of signaling theory. The CNSA serves as a crucial conduit for regional tourism integration, facilitating the movement of tourism resources among counties. This promotes the transmission of investment decision-making signals to adjacent counties, thereby generating spatial spillovers of the carbon emission reduction effect through the agglomeration of the tourism industry.

6. Conclusions and Implications

6.1. Conclusions

Existing exploration on the tourism–carbon emissions nexus is mostly based on the perspective of tourists, using indicators such as tourism income or tourist arrivals, but lack the exploration from the destination construction perspective. This study considers the CNSA across different counties and years as a quasi-experiment. We conducted staggered DID and spatial DID estimations to explore the effect of the CNSA on CEI. Using a county-level panel dataset of 29,628 samples based on multi-source data from 2000 to 2017, we reveal that the CNSA decreases CEI in treatment counties by 10.24% relative to non-treatment counties following the CNSA construction. This conclusion is validated upon the completion of robustness tests. Moreover, the negative effect has a certain delay, but persists and intensifies over time. Furthermore, the negative effect is particularly evident in the western, eastern, and county subsamples. Lastly, the results indicate that the effect of the CNSA on CEI exhibits a spillover characteristic, facilitated by indirect effects.

6.2. Policy Recommendations

The findings have several policy implications. First, policymakers should consistently enhance the management framework of the CNSA and develop tailored methods for various categories of CNSA to amplify its reducing impact. For CNSAs, predominantly characterized by natural landscapes, it is imperative to enhance ecological conservation and restoration, as well as to develop and maintain beautiful regions in accordance with ecological carrying capacity, thereby ensuring a superior ecological environment. For CNSAs, characterized by predominantly humanistic landscapes, it is essential to establish comprehensive laws and regulations for the protection of these landscapes. In this context, a thorough exploration of the cultural significance of scenic sites is necessary, alongside the development of innovative tourism products focused on history and culture, to enhance the tourism industry chain and ultimately diminish such regions' carbon emission intensity.

Second, the heterogeneous emission reduction policies should be developed based on regional development differences. In the eastern counties, increased efforts are necessary to advance and invest in low-carbon technology. In the western counties, low-carbon tourism routes can be established by prioritizing the preservation of the natural environment and biodiversity, while also considering local geological structure and climatic characteristics. The planning and CNSA construction in central counties and municipal districts must adhere rigorously to system standards, thereby mitigating the carbon lock effect and promoting industrial structure optimization. County-level cities must strengthen the role of tourism to increase publicity efforts, thereby maximizing the brand value of the CNSA and mitigating its negative effect of the CNSA on the CEI.

Third, the integration of regional co-operation should be strengthened, and the role of radiation driven by the CNSA should be developed. In our spatial DID analysis, the CNSA can decrease CEI. As such, the spillover effects should be fully exploited. The spillover effects should be thoroughly utilized. Adjacent regions can cultivate a low-carbon tourism economy by leveraging CNSA resources, including the development of low-carbon tourism products, the innovation of low-carbon tourism services, and the enhancement of low-carbon tourism promotion. Consequently, the regional tourism industry chain can be expanded, facilitating the development of low-carbon tourism clusters. Furthermore, the spillover impact can be enhanced by establishing interoperability among tourism transport systems in adjacent counties and collaboratively developing tourism-related sectors, thereby maximizing the radiative influence of counties with a CNSA.

6.3. Limitations

There are also some limitations. First, the endogeneity test confirms the robustness of this study. However, this study assumed that a CNSA required afforestation and tree planting, and restricted the layout and configuration of related infrastructure development. In other words, it implied the effect operates through environmental regulations, which should be included as a control variable in the analysis. Limited by data availability, environmental regulation—a variable to be included in the empirical analysis framework—cannot be quantified. Therefore, further attempts to refine the research design using richer data collection methods are needed. Second, the geographical boundaries of the inhibiting effect of the CNSA on CEI can be further clarified, as the coordinated preparation and implementation of the plan is geographically limited. Third, the effect of other top-level tourist attractions on CEI can be explored. The CNSA takes resource protection as its main goal, while other similar top-level tourist attractions, such as 5A-level scenic spots, emphasize the creation of high-quality scenic spots and highlight economic and social benefits. Last, the impact of the CNSA on CEI can be quantified from a mechanism perspective in the future with mediation effects models or structural equation models.

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Notes

[1] https://www.unwto.org/sustainable-development/climate-action (accessed on 9 October 2024).

[2] Signaling theory is an explanation framework to understand the way stakeholders negotiate information problems to assist them in making decisions and ultimately achieve goals [28], and is often applied to solve information asymmetry problems.

[3] Since the number of counties with a CNSA in the study period was 84, 84 counties were sampled in the placebo test for consistency of numbers.

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