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Impact of the Urban-Rural Income Disparity on Carbon Emission Efficiency Based on a Dual Perspective of Consumption Level and Structure

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Abstract: Utilizing Chinese provincial panel data from 2006–2019, this paper applies the super-efficient epsilon-based measure (EBM) model including non-desired output to measure carbon emission efficiency (CE) and analyze spatio-temporal characteristics of CE, in which social fixed asset investment, energy consumption and urban employment per unit are used as input indicators and regional GDP and CO2 emissions are used as output indicators. Additionally, we use the spatial Durbin model to explore the impact of urban-rural income disparity (URID) on carbon emission efficiency and its spatial spillover effect and explore indirect mechanisms of consumption level and consumption structure on CE using mediating effect test. The results showed that: (1) The national CE level generally declined between 2006–2012 and fluctuated upward from 2013–2019. The trend of regional CE showed "high in the east and low in the west". (2) The "inverted U" model accurately reflects the relationship between national CE and URID, with a "U" shaped association in the central, western, and northeastern regions, and a positive correlation with consumption level and consumption structure. (3) There is a significant mediating effect of consumption level and structure in the mechanism of URID in regulating CE. Local governments should adopt local policies, take measures to narrow URID and CLD, advocate low-carbon and environmentally friendly living for residents, and promote the upgrading of consumption structure to boost carbon emission efficiency.

Keywords: urban-rural income gap; carbon emission efficiency; resident consumption; the super-efficient (EBM) model; spatial spillover effect

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1. Introduction

Since the 1920s, income and wealth distribution disparity in global economies has typically gone through a phase of aggravation, improvement, and further worsening [1]. China is typical of the urban-rural dichotomy, with the URID causing more than 65% of the income disparity overall [2]. As of 2019, URID ratio in was China 3.20, and URID is still floating at a high level [3]. Meanwhile, there are disparities in consumption preferences and consumption structure between urban and rural residents [4]. By 2020, China's per capita income and consumption will both be around twice as high as they were in 2010 [5]. The fact that the gap between the rich and the poor has widened dramatically is due to the rapid economic development. In-depth investigations are needed to understand how China may accomplish high-quality economic growth, which entails maximizing economic benefits as well as unifying and optimizing economic, social, and environmental benefits. In the past decade, China has become the top emitter of CO_2, and the high concentration of CO_2 has aggravated the greenhouse effect, which will inevitably affect the sustainable growth of ecological economy [6–8]. Due to the urgency of environmental protection, China proposed in 2015 "reducing CO_2 emission intensity per unit of gross domestic product (*GDP*) by 60–65% by 2030 compared to 2005". As a developing country, the balance between economic development and low carbon goals is crucial to the future development of China.

CE indicates the ability to maximize economic benefits with fewer resources, and less expense and environmental cost. Reduced carbon emissions mean improved carbon efficiency with constant inputs and outputs [9]. Currently, there is no consensus among scholars on the definition of CE, but it is widely accepted that CE considers both environmental costs and economic output [10]. Based on the existing literature, the study defines CE as the level of regional economic growth under the carbon emission restriction, with CO_2 emissions as the non-desired output. In theoretical studies, income disparity is considered to be an important factor affecting CO_2 emissions, the direction of which is uncertain [11]. It has been shown that the effect of income disparity on CO_2 emissions is negative, i.e., a rise in income disparity contributes to a reduction in carbon emissions [12,13]. In contrast, Baloch et al. (2020) and Hao et al. (2016) found that a reduction in income disparity is beneficial for carbon reduction [14,15]. According to Sager (2019) and Chen et al. (2020), income equality in developing countries is beneficial to reduce CO_2 emissions, while it has a weak effect on carbon emissions in developed countries, confirming that there may be stage heterogeneity in the effect of income disparity on carbon emissions depending on the differences in economic growth [16,17]. In addition, it has been argued that there are disparities in consumption structures among income groups, i.e., changes in the share of different types of consumer goods will have an impact on carbon emissions [18,19]. The 2020 Emissions Gap Report investigates the consumption patterns of the population and suggests that upgrading the consumption structure plays a decisive role in enabling China to achieve its carbon reduction targets on schedule [20]. Therefore, studying CO_2 emissions from both income and consumption perspectives is of great theoretical and practical significance in achieving the goal of carbon peaking and carbon neutrality.

Firstly, when the literature has examined the relationship between income disparity and CO_2 emissions, it has mostly chosen carbon emissions or carbon emission intensity [21,22]. CE measures carbon emissions from the perspective of production efficiency, and the promotion of CE can more accurately reflect the meaning of balancing environmental protection and economic development [23,24]. Second, scholars do not consider spatial spillover effects as much when studying URID and carbon emissions. Liu et al. (2023) confirmed the existence of significant spatial agglomeration characteristics between URID in China [25]. The study by Zhang and Hao (2022) reflects that it is necessary to consider the spatial spillover effect when analyzing the effects of income disparity and economic agglomeration on carbon emissions [22]. Therefore, it is necessary to consider the spatial spillover effect when studying the mechanism of urban-rural income disparity on CE. In light of this, this study examined the influence mechanism of URID on CE and the spatial spillover effect. It also investigated the indirect mechanism of consumption level and consumption structure in the influence of URID on CE. The contributions are as follows: (1) At present, studies on the impact mechanism of carbon emission reduction rarely consider both income and consumption factors. This study complements existing research by investigating the impact of URID on CE from the standpoint of consumption level and consumption structure. (2) The adoption of CE is more relevant to sustainable development goals than the existing carbon emission and carbon intensity indicators frequently used in the literature. (3) This study explores the transmission mechanism of URID, consumption level, and consumption structure affecting CE with the mediating effect model to provide scientific evidence for the decision-making of provinces and cities. The remainder of the study is structured as follows. Section 2 gives a theoretical analysis, a review of the pertinent literature, and the research hypothesis. Section 3 discusses the methodology, variables chosen, and data sources for this work. Section 4 discusses the spatio-temporal characteristics of CE and the findings of explanatory model regressions and robustness tests. Section 5 expands on the issue of indirect mechanisms of action and heterogeneity analysis. The results and policy suggestions are presented in Section 6.

2. Theoretical Analysis and Research Hypotheses

2.1. Urban-Rural Income Disparity and Carbon Emission Efficiency

URID influences carbon emission efficiency in two ways: on the one hand, because of the diminishing marginal propensity to pollute by income, higher-income groups have a lower marginal propensity to pollute [26]. In China, urban residents generally have higher incomes than rural residents, and when URID expands, as urban residents pay more attention to environmental quality, when they accumulate more wealth, more people choose green lifestyles and CE improves. On the other hand, due to the widening of the URID, urban-rural inhabitants and native governments will change their environmental preferences. Farmers are more concerned with their income than environmental issues, resulting in the establishment of industries in rural regions with lower environmental thresholds, and high carbon emission firms leading to a decrease in CE. It is clear that the URID possesses both beneficial effects and detrimental effects on CE; however, the degree of these effects at various phases of economic growth is uncertain. As a result, the following hypothesis is proposed.

Hypothesis 1. *URID and carbon emission efficiency have a non-linear connection.*

2.2. URID, Consumption Levels, and CE

Income disparity influences consumption level and hence CE by modulating the incentive to consume and conserve. On one hand, income disparity impacts CE through consumption propensity. If the rich's proclivity to emit is not greater than the poor's, the diminishing propensity to consume determines that a narrowing of the income gap (i.e., transfer of income from rich to poor) will enhance population consumption level. Production of consumer goods required by the population, such as food, clothing, housing, and transportation, will consume large amounts of energy, and higher energy usage leads to greater carbon emissions [27]. Income disparity, on the other hand, influences carbon emissions through the desire to save. According to Veblen (2017), people are willing to demonstrate their social position through consumption; however, Knight et al. (2017) concluded that a widening income gap reduces the willingness of consumers to expend [28,29]. As a result, the following hypothesis is proposed.

Hypothesis 2. *Consumption level serves as an intermediary between URID and carbon emission efficiency.*

2.3. URID, Consumption Structure, and CE

Previous research has indicated that an unbalanced income composition weakened residents' preference for air quality, and widening income gap leads to a higher proportion of consumption of carbon-intensive products, which is not advantageous to carbon emission reduction [30,31]. Conversely, a narrower income disparity will result in a more environmentally friendly consumption structure [32]. Current research indicates that consumption composition affects CE. Yuan et al. (2015) argue that the escalation of consumption structure is not conducive to improving CE [33], and Zhou and Lin (2019) believed that the upgrading of consumption structure represents a decrease in the proportion of consumer spending on clothing, food, housing and transportation [34]. The decrease in the share of consumer goods in clothing, food, housing, and transport, which mainly comes from the industrial sector with high CO_2 emissions, contributes to the improvement of CE.

Hypothesis 3. *The association between URID and carbon emission efficiency is mediated by the consumption structure.*

In conclusion, the theoretical framework is shown in Figure 1.

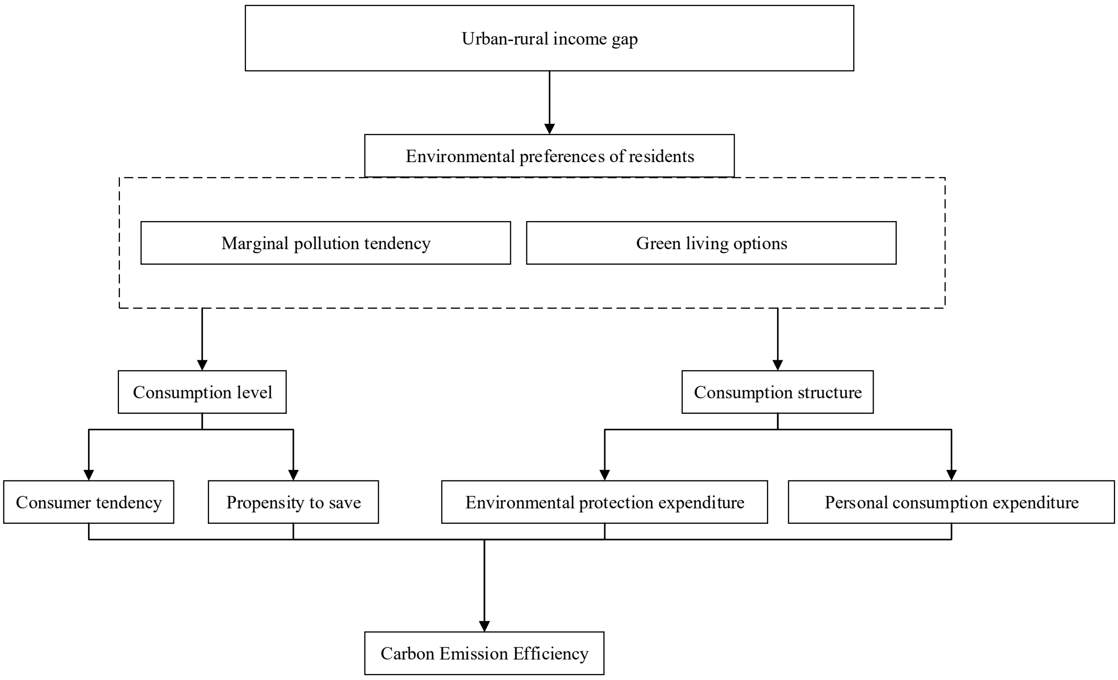

Figure 1. Theoretical framework.

3. Methods and Data

3.1. Research Methodology

3.1.1. Spatial Autocorrelation Model

Firstly, we examine the spatial correlation of CE by Moran index (Moran′ s I). When the spatial correlation of CE is significant, we construct a spatial econometric model to analyze the spatial spillover effect of URID on CE. Global Moran index and local Moran index are shown in Equations (1) and (2).

$$I_G = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(CE_i - \overline{CE}\right)\left(CE_j - \overline{CE}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}\left(CE_i - \overline{CE}\right)^2} \tag{1}$$

$$I_L = \frac{\left(CE_i - \overline{CE}\right)}{\sum_{i=1}^{n}\left(CE_i - \overline{CE}\right)}\sum_{j=1,j\neq i}^{n} W_{ij}\left(CE_j - \overline{CE}\right) \tag{2}$$

In Equations (1) and (2), CE_i and Y_j represent CE values of the regions *i* and *j*, respectively. *n* is the number of regions. W_{ij} is the spatial weight matrix.

3.1.2. Spatial Econometric Models

Some scholars believe that the income gap and carbon emission intensity have a "U" shaped relationship 22. Therefore, this paper adds URID and its squared term to the spatial econometric model to verify whether Hypothesis 1 stands. Equation (3) was built in conjunction with the theoretical analysis of this paper to explore the correlation between urban-rural wealth disparity and CE from the perspective of consumption level and consumption structure. To simplify the computation, the logarithm is usually taken for both sides in empirical analysis:

$$\begin{aligned}
&\ln CE_{it} = \rho_0 \sum_{i=1}^{n} w_{ij} CE_{jt} + \alpha_0 + \alpha_1 \ln URID_{it} + \alpha_2 (\ln URID_{it})^2 + \rho_1 \sum_{i=1}^{n} w_{ij} URID_{jt} \\
&+\alpha_3 \ln CLD_{it} + \rho_2 \sum_{i=1}^{n} w_{ij} CLD_{jt} + \alpha_4 \ln CSD_{it} + \rho_3 \sum_{i=1}^{n} w_{ij} CSD_{jt} + \\
&\alpha_5 X_{it} + \rho_4 \sum_{i=1}^{n} X_{jt} + \sigma_t + \varepsilon_{it}
\end{aligned} \tag{3}$$

In Equation (3), i = 1, 2, 3 … 30 represent 30 provinces in China. Relevant data were lacking for Tibet, Hong Kong, Macau, and Taiwan; hence, these regions were not discussed. t = 1, 2, 3…14 represent time variables from 2006–2019, CE_{it}, $URID_{it}$, CLD_{it}, and CSD_{it}, represent carbon emission efficiency, urban-rural income disparity, consumption level difference, and consumption structure difference, respectively. X represents a collection of control variables that includes regional GDP; α_0 is a constant term; α_{1-4}, ρ_{1-4}, and φ are estimated coefficients, and; ε_{it} is a random disturbance term. A binary adjacency matrix was utilized to represent the spatial panel weighting matrix w_{ij}; ρ_0 represents the spatial autoregressive coefficients; X_{it} means a collection of control variables for province i in year t; σ_t represents time-fixed effects.

3.1.3. Intermediate Effects Test Model

To examine whether URID affects CE through consumption level and consumption structure, the following mediation model is constructed in conjunction with Equations (4)–(6) [35].

$$\begin{aligned}
&\ln CE_{it} = \pi_0 \sum_{i=1}^{n} w_{ij} CE_{jt} + \beta_0 + \beta_1 \ln URID_{it} + \beta_2 (\ln URID_{it})^2 + \pi_1 \sum_{i=1}^{n} w_{ij} URID_{jt} + \\
&\beta_3 X_{it} + \pi_2 \sum_{i=1}^{n} w_{ij} X_{jt} + \mu_t + u_{it}
\end{aligned} \tag{4}$$

$$\begin{aligned}
&\ln CLD_{it} = \theta_0 \sum_{i=1}^{n} w_{ij} CLD_{jt} + \delta_0 + \delta_1 \ln URID_{it} + \delta_2 (\ln URID_{it})^2 + \theta_1 \sum_{i=1}^{n} w_{ij} URID_{jt} \\
&+\delta_3 X_{it} + \theta_2 \sum_{i=1}^{n} w_{ij} X_{jt} + \tau_t + v_{it}
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\ln CSD_{it} = \lambda_0 \sum_{i=1}^{n} w_{ij} CSD_{jt} + \omega_0 + \omega_1 \ln URID_{it} + \omega_2 (\ln URID_{it})^2 + \lambda_1 \sum_{i=1}^{n} w_{ij} URID_{jt} \\
&+\omega_3 X_{it} + \lambda_2 \sum_{i=1}^{n} w_{ij} X_{jt} + o_t + \kappa_{it}
\end{aligned} \tag{6}$$

The following steps confirmed this: (1) we examined the significance of the coefficients β_1 and β_2 to be estimated in Equation (5) and conducted the second step of the test whether at least one of β_1 and β_2 was significant; (2) we evaluated the significance of the coefficients to be estimated, δ_1 and δ_2, and ω_1 and ω_2, and performed the third step of the test if at least one of δ_1 and δ_2 or at least one of ω_1 and ω_2 was significant; and (3) the significance of the coefficients to be estimated, α_3 and α_4, was examined, and if one of the coefficients was significant it indicated a partial mediation effect, otherwise it indicated a full mediation effect.

3.2. Variables and Data

(1) Carbon emission efficiency was the explained variable (CE). To improve the accuracy of the calculation results, this study CE used Super-EBM model with non-desired

outputs [36]. To avoid the drawbacks of the radial and non-radial models, this paper adopted the super-efficient EBM model, as Equation (7).

$$r^* = \min \frac{\gamma - v_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{i0}}}{v + v_y \sum_{k=1}^{s} \frac{w_k^+ s_k^+}{y_{k0}}}$$
$$s.t. \begin{cases} \sum_{j=1}^{n} c_j x_{ij} + s_i^- = \gamma x_{i0} & (i = 1, 2, \ldots \mathrm{m}) \\ \sum_{j=1}^{n} c_j y_{kj} - s_k^+ = v y_{k0} & (k = 1, 2, \ldots \mathrm{s}) \\ c_j \geq 0, \sum c = 1,\ s_i^-, s_k^+ \geq 0 \end{cases} \tag{7}$$

In Equation (7), r^* denotes the carbon emission efficiency; n means the number of decision-making cells; the input and desired output are denoted by x and y; c represents the relative weight of units; γ and v denote the planning parameters of the radial part; and ${s_i}^-$ and ${s_k}^+$ denote the slack of the i-th input and k-th desired output, whose weights are denoted ${w_i}^-$ and ${w_k}^+$. ν is a parameter that ranges from 0–1 and represents the relevance of the non-radial element. In this study, the three input indicators were social fixed asset investment, energy consumption, and the number of employees per urban unit (10,000 people) in 30 provinces in China from 2006–2019. The expected output indicator was the gross regional product (billion yuan) and the non-expected output was carbon emissions (million tons).

(2) The explanatory variable is urban-rural income disparity (*URID*). In Equation (8), the Theil index was used to measure URID, which included demographic changes as well as total urban and rural income:

$$URID_{it} = \sum_{j=1}^{2} \left(\frac{c_{ij,t}}{c_{i,t}} \right) \ln \left(\frac{c_{ij,t}}{c_{i,t}} / \frac{r_{ij,t}}{r_{i,t}} \right) \tag{8}$$

In Equation (8), j = 1, 2 refer to cities and villages; r_{ij} represents the population of cities and villages i; r_i denotes the number of people in area i; c_{ij} denotes total income in the cities and villages i; and c_i denotes the total income in area i.

Urban-rural income ratio. The Theil index was replaced by this in the robustness test, which was calculated by dividing the per capita disposable revenue of farmers by that of urban dwellers. The net income of farmers becomes the disposable income of farmers after 2013, and both were referred to as the statistical indicator in this study due to the small difference between the two indicators and the same change trend [37].

(3) Consumption level differences (*CLD*) and consumption structure differences (*CSD*) were the mediating variables. In Equation (9), the Gini Index (*Gini*) of per capita consumer expenditure of city dwellers and farmers was used to measure the disparity in consumption levels.

$$CLD_{it} = \frac{1}{2n^2 \overline{D}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| D_i - D_j \right| \tag{9}$$

In Equation (9), representing the mean values of household per capita consumption expenditure, D_i and D_j are the per capita consumption expenditures of households i and j, respectively. Gini coefficients of urban and rural consumption levels for Chinese provinces were calculated using the total consumption expenditure per capita of urban households and that of rural households.

Consumption structure differences (*CSD*). Consumption structure differences are measured using the Theil index of urban-rural population consumption structure. Drawing on previous studies [38], this study measured the consumption structure by comparing the ratios of four developmental enjoyment consumption items: household equipment and services; cultural, educational and recreational; health care; and other goods and services to the total expenditure of people, using the subdivisional data of the eight categories of consumption expenditure per capita of city dwellers and farmers in provinces published and population size of city dwellers and farmers in the statistical yearbook to make specific measurements.

$$CSD_{it} = \sum_{i=1}^{n} \frac{s_{ij,t}}{s_{i,t}} \ln \frac{s_{ij,t}}{s_{i,t}} \quad (10)$$

In Equation (10), s_{ij} represents the proportion of enjoyment-based consumption expenditure of urban or rural residents in region i; j is the same as Equation (8); s_i is the proportion of enjoyment-based consumption expenditure in region i.

(4) Control variables. To prevent the omission of important explanatory variables from generating endogeneity problems, the study also selected several control variables affecting CE, for instance, economic growth, industrial structure, degree of external openness, energy structure, and environmental regulation.

Economic growth (*PGDP*). Economic growth significantly affects carbon emissions [39]. In this study, the gross regional product per capita (10,000 yuan/person) was chosen to represent economic growth and was taken in its logarithmic form. To ensure comparability of data, the nominal *GDP* for each year was converted to comparable price data for the base period of 2006.

Industrial structure (*IS*). Changes in the relative weight of industries influence the carbon emissions intensity [40]. As a result, the proportion of the added value of the tertiary industry to regional *GDP* was chosen to indicate industrial structure.

Openness to foreign investment (*OP*). The amount of foreign direct investment has been proven to influence CO_2 emission efficiency [41]. The degree of openness to the outside world is represented by the amount of actual foreign capital utilized divided by the value of regional GDP.

Energy structure (*ES*). Optimization of the energy structure greatly reduces carbon emissions, and the value of thermal power generation divided by overall power generation was utilized to describe energy structure, based on previous studies [42,43].

Environmental regulation (*ER*). Regions with higher income disparities have significantly lower spending on environmental policies, and increasing environmental regulation can help reduce carbon emission intensity [44]. This indicator was expressed as a *GDP*-to-industrial-pollution-control ratio.

This study covered 30 Chinese provinces from 2006–2019 (note: due to missing data, the study excluded Tibet, Hong Kong, Macau, and Taiwan). Data for each indicator were derived from the China Statistical Yearbook (2007–2020), the China Energy Statistical Yearbook (2007–2020), and previous years' statistical yearbooks published by provinces. Table 1 displays the main descriptive information for each indicator.

Table 1. Descriptive statistics of variables.

Variable Name	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Carbon efficiency	420	2.76	0.19	0.38	4.60
Urban-rural income gap	420	2.58	0.49	1.85	3.72
Consumption level differences	420	0.40	0.07	0.23	0.60
Consumption structure differences	420	1.13	0.16	0.85	1.65
Economic growth	420	20,822.67	13,283.68	6267.32	66,464.64
Industrial structure	420	0.10	284.97	0.29	0.84
Degree of external openness	420	0.95	1.09	0.05	5.85
Energy structure	420	0.74	0.23	0.06	1
Environmental regulation	420	0.15	0.13	0.01	0.87

4. Results and Analyses

4.1. Spatial and Temporal Characteristics of CE

4.1.1. National Carbon Emission Efficiency

Based on the input-output index system constructed in this study, the CE of 30 provinces, municipalities, and autonomous regions from 2006–2019 was measured by MAXDEA. The results are shown in Table 2. Taking 2006, 2010, 2015, and 2019 as examples, the spatial distribution of CE in China was plotted using Arcgis, as shown in Figure 2.

Table 2. CE of 30 Chinese provinces in 2006, 2010, 2015, and 2019.

Province	2006	2010	2015	2019	Mean	Standard Deviation
Beijing	1.02	1.11	1.21	1.23	1.16	0.08
Tianjin	0.76	0.77	0.78	0.88	0.78	0.04
Hebei	0.64	0.66	0.88	0.81	0.78	0.14
Shanxi	0.62	0.49	0.60	0.73	0.59	0.06
Inner Mongolia	0.57	0.58	0.70	0.69	0.63	0.06
Liaoning	0.56	0.58	0.68	1.01	0.69	0.17
Jilin	0.55	0.56	0.67	0.76	0.62	0.07
Heilongjiang	0.69	0.52	0.70	0.87	0.66	0.09
Shanghai	0.81	1.05	1.19	1.10	1.06	0.12
Jiangsu	1.00	1.00	0.77	0.87	0.90	0.11
Zhejiang	0.91	0.84	0.87	1.00	0.87	0.04
Anhui	0.61	0.61	0.61	0.57	0.60	0.02
Fujian	0.83	0.74	0.69	0.69	0.73	0.05
Jiangxi	0.70	0.70	0.59	0.61	0.65	0.05
Shandong	0.73	0.73	1.00	1.01	0.86	0.13
Henan	0.60	0.59	0.62	0.72	0.62	0.04
Hubei	0.63	0.57	0.62	0.65	0.60	0.03
Hunan	0.66	0.62	0.73	0.71	0.68	0.05
Guangdong	1.12	1.05	0.94	0.84	0.99	0.09
Guangxi	0.68	0.63	0.65	0.63	0.65	0.02
Hainan	0.77	0.64	0.55	0.60	0.60	0.06
Chongqing	0.63	0.61	0.64	0.61	0.61	0.03
Sichuan	0.60	0.62	0.65	0.65	0.63	0.03
Guizhou	0.49	0.38	0.41	0.38	0.42	0.03
Yunnan	0.49	0.47	0.55	0.62	0.51	0.04
Shaanxi	0.54	0.49	0.48	0.53	0.50	0.02
Gansu	0.55	0.42	0.46	0.50	0.48	0.03
Qinghai	0.49	0.46	0.53	0.49	0.49	0.03
Ningxia	0.49	0.46	0.53	0.49	0.49	0.03
Xinjiang	0.50	0.43	0.47	0.46	0.47	0.02
National	0.68	0.65	0.69	0.72	0.68	0.03

CE in 30 Chinese provinces was spatially imbalanced, i.e., efficient in the east but inefficient in the west (Figure 2). In 2006, Beijing, Jiangsu and Guangdong in the eastern region had higher CE, while Guizhou, Yunnan, Qinghai, Ningxia and Xinjiang in the west have lower CE. The CE of nine provinces in the central and northeastern regions are between 0.55 and 0.69. In 2019, CE was efficient in Beijing, Shanghai, Shandong, and Guangdong in the east, and in Liaoning in the northeast, and two additional provinces had carbon efficiency >1 compared to that in 2006.

The national mean of CE from 2006–2019 was 0.68. Except for Shandong and Heilongjiang, The remaining provinces were less efficient in CO_2 emissions than the national mean value, indicating that CE can be improved. At the provincial level, except Beijing (1.16) and Shanghai (1.06), no other provinces achieved a carbon emission efficiency of 1. Guizhou (0.42), Xinjiang (0.47), and Gansu (0.48) had the lower CE. CE of Liaoning fluctuated the most, with a standard deviation of 0.17; it increased from 0.56 in 2006 to 1.01 in 2019. The degrees of variation in CE in Hebei and Shandong followed closely behind, with a steady fluctuation trend. Jiangsu had more significant variations, although the trend of the oscillations was downward, from 1.00 in 2006 to 0.87 in 2019. From 2006–2019, four provinces (Anhui, Guangxi, Shaanxi, and Xinjiang) showed relatively moderate variations in carbon emission efficiency, with a standard deviation of 0.02. Overall, the CE of China ranged from 0.60–0.70.

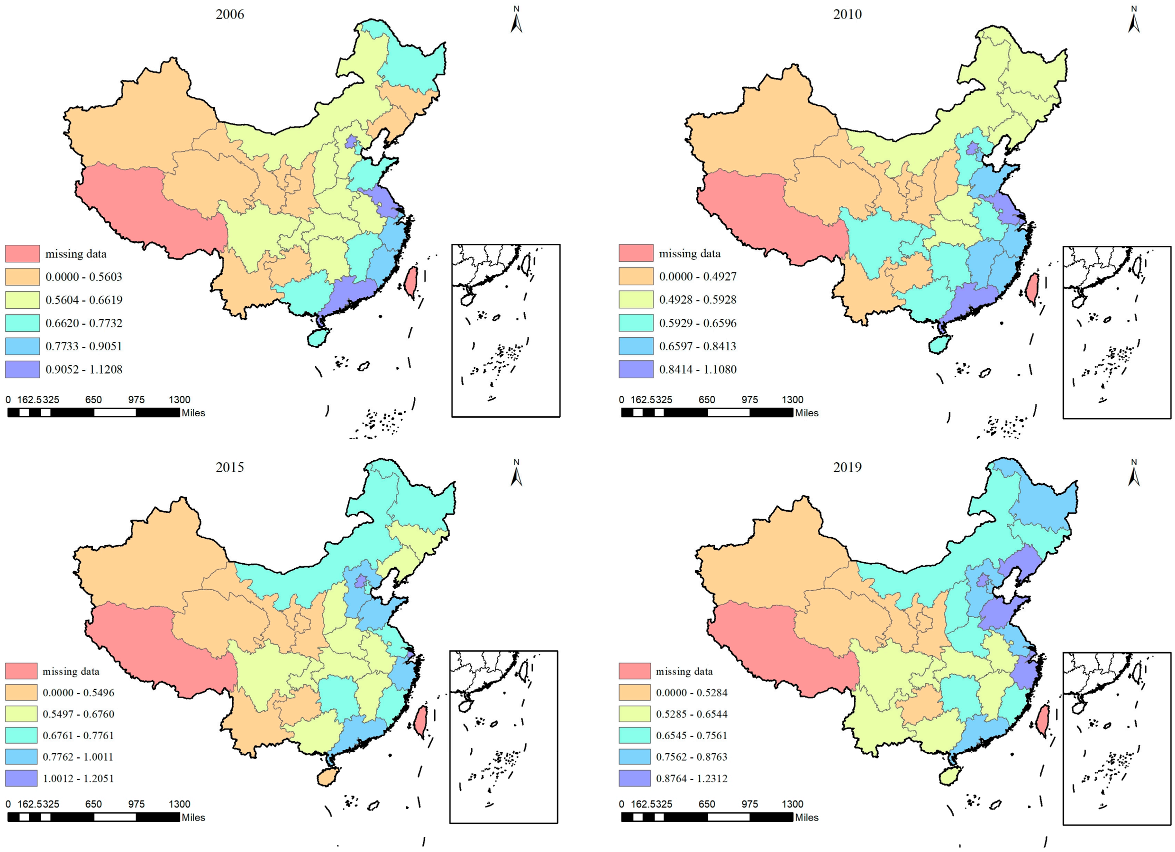

Figure 2. Spatial distributions of CE in China in 2006, 2010, 2015, and 2019.

4.1.2. Spatial and Temporal Characteristics of Regional CE

China was classified into eastern, central, western, and northeastern regions, and the mean values of carbon emission were calculated and plotted in Figures 3 and 4. As shown in Figure 3, the CE of the eastern area was always highest, whereas that of the western region was the lowest and differed substantially from that of the eastern region. The northeast was less efficient than the Central in 2006 and 2010, and the opposite was true in 2015 and 2019.

As shown in Figure 4, CE varied significantly among regions. Except for the northeast region, all regions followed the national carbon efficiency trend over time. From 2006–2012, the CE of the eastern region was generally steady. During the study period, CE peaked at 0.91 in 2013; it decreased in 2014 and then steadily increased until 2019. Overall, The eastern was more efficient than the national average and most efficient in China.

Throughout the study period, CE in the central region was continuously lower than the mean. From 2006–2013, the central region was more efficient than the northeast. Carbon emission efficiency in the central region changed from 2013–2019, during which time exhibited a “U” shape.

CE in the west was 0.55 in 2006, and had a declining trend from 2006–2012, reaching its lowest point (0.49) in 2012. The CE subsequently remained steady at approximately 0.55 from 2013–2019, which was usually lower than the mean.

CE of the northeast decreased steadily from 2006–2010 and showed a fluctuating increasing trend after 2010. CE of other regions and the national average decreased in 2013, whereas that of the northeast region increased. After 2013, the CE of the northeast gradually surpassed the central region and the mean.

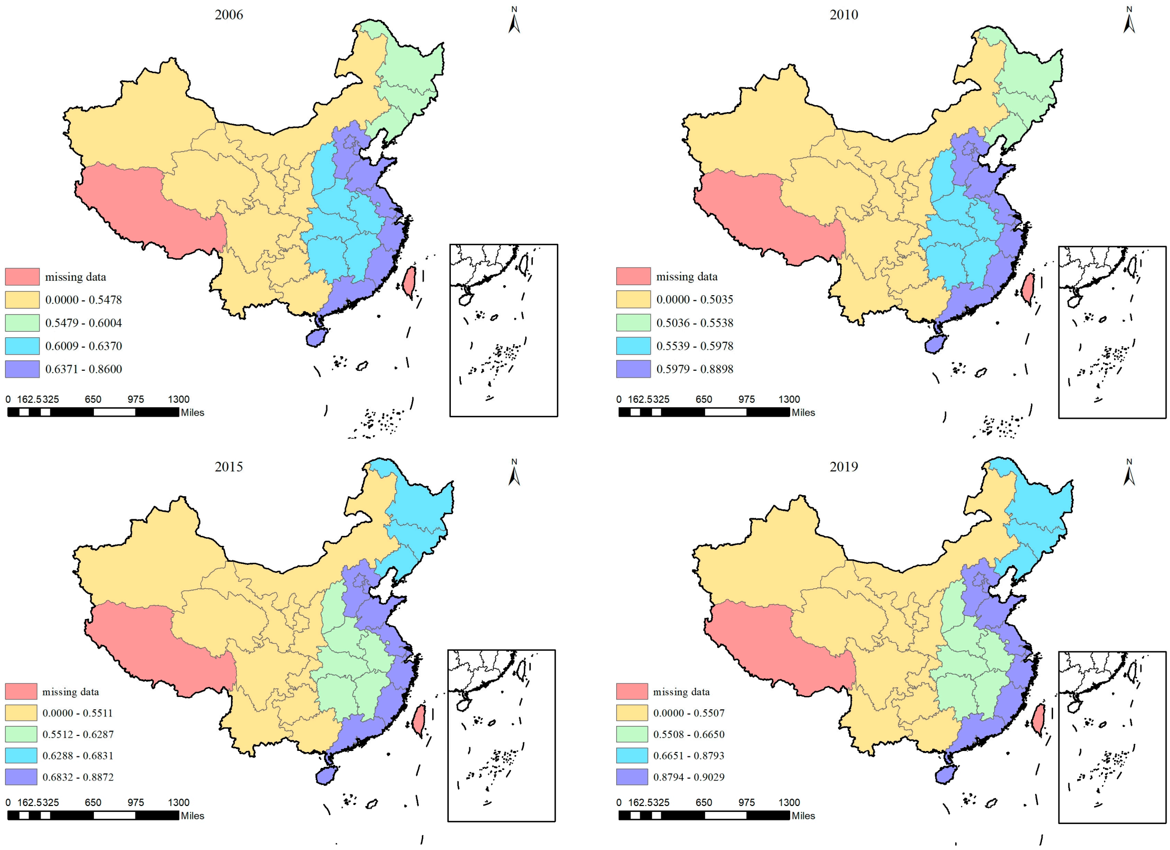

Figure 3. Spatial distributions of CE in regions in 2006, 2010, 2015, and 2019.

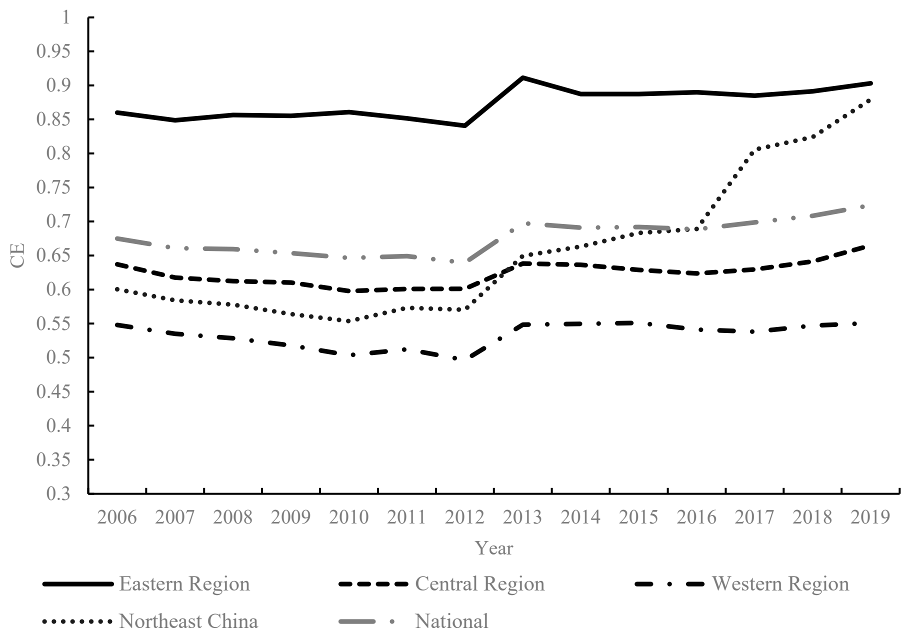

Figure 4. Trends in mean carbon efficiency in the regions and nationally from 2006–2019.

4.2. Spatial Autocorrelation Test

CE of provinces was examined for spatial autocorrelation, and Moran's *I* index from 2006–2019 was calculated with Stata 16.0 software. As shown in Table 3, Moran's *I* index was significantly positive, showing that CE of Chinese provinces had a significant spatial association.

Table 3. Global Moran's *I* index of CE.

Year	Moran's I Index	Z-Value	*p*-Value	Year	Moran's I Index	Z-Value	*p*-Value
2006	0.397 ***	3.941	0.000	2013	0.349 ***	3.489	0.000
2007	0.398 ***	3.974	0.000	2014	0.288 ***	2.980	0.001
2008	0.413 ***	4.065	0.000	2015	0.267 **	2.782	0.003
2009	0.404 ***	3.978	0.000	2016	0.278 **	2.888	0.002
2010	0.387 ***	3.836	0.000	2017	0.333 ***	3.356	0.000
2011	0.313 ***	3.211	0.001	2018	0.332 ***	3.319	0.000
2012	0.308 ***	3.152	0.001	2019	0.326 ***	3.251	0.001

***, ** and * represent $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively.

4.3. Model Selection Test

In this paper, the variables are tested by Stata 16.0 software for model testing, and the results show that the LM test passes the significance test at the 1% level and the spatial econometric study is selected; the Hausman test is significant at the 5% level and the fixed effect is selected; the LR test results are all significant at the 1% level, indicating that the SDM (spatial Durbin), model does not degenerate into a SAR (spatial lag) model or SEM (spatial error) model, the Wald test results are significant at the 1% level, and finally the SDM model with period fixed effects is determined to explore the impact of urban-rural income disparity on carbon emission efficiency at the national level. The specific test results are shown in Table 4.

Table 4. Model selection correlation test results.

Inspection Type	(1) Coefficient	Variable	(2) W* Coefficient
LM test	SEM model	15.765 ***	Rejection
	SAR model	18.207 ***	
Hausman test	Random effects	32.010 **	Fixed effects
Wald test	SAR model can be simplified to SDM model	20.91 ***	Rejection
	SEM model can be simplified to SDM model	25.60 ***	
LR test	SDM model degraded to SEM model	110.17 ***	Rejection
	SDM model degraded to SAR model	109.07 ***	

W* coefficients are spatial lagged terms for each variable. *** $p < 0.01$, ** $p < 0.05$.

4.4. Regression Results Analysis

CE of 30 provinces was geographically connected in China. Stata 16.0 software was used to calculate the results of the spatial Durbin model (SDM), and the SDM model with period-fixed effects was used to study the impact of URID on CE at the national level. The results are presented in Table 5. The R^2 value was 0.729, indicating that the model was well-fitting.

The coefficients of URID and its quadratic term were 1.340 and -0.670, indicating an inverted "U"-shaped link between URID and carbon emission efficiency, and supporting Hypothesis 1.

The consumption level difference coefficient is 0.045, meaning that the greater the consumption level difference, the more efficient the carbon emissions. This is because an increase in the consumption level difference reduces the consumption of high-carbon emitting commodities as rural dwellers save more of their income to protect themselves against unknown threats.

The consumption structure variation coefficient was 0.251. The amount of disposable items used by city dwellers and farmers has reduced as the household consumption structure in China has changed, while changes in consumption structure have led to changes in energy usage efficiency, indirectly boosting efficiency.

Table 5. Spatial Durbin model (SDM) regression results.

Variable	(1) Coefficient	(2) W* Coefficient	Variable	(1) Coefficient	(2) W* Coefficient
URID	1.340 *** (0.00)	−0.835 ** (0.04)	*OP*	−0.043 *** (0.00)	0.167 *** (0.00)
URID^2	−0.670 *** (0.00)	0.245 ** (0.03)	*ES*	−0.050 *** (0.00)	0.303 *** (0.00)
CLD	0.045 *** (0.00)	−0.258 ** (0.02)	*ER*	0.056 *** (0.00)	0.054 *** (0.00)
CSD	0.251 *** (0.00)	0.373 *** (0.00)	ρ	0.203 *** (0.00)	
PGDP	0.275 *** (0.00)	−0.365 *** (0.00)	R^2	0.729	
IS	0.144 * (0.08)	0.888 *** (0.00)			

W* coefficients are spatial lagged terms for each variable. the *p*-values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The positive coefficient indicated that CE has improved with economic growth, as provinces and municipalities advocate for high-quality economic development and the traditional economy is gradually transitioning to a low-carbon economy. At the same time, China has stepped up its efforts in environmental protection.

The coefficient of the industrial structure was positive. The majority of tertiary industries are labor and capital-intensive, with low resource and energy consumption levels, and increasing their share can reduce total carbon emissions. Green industries with low carbon emissions have developed rapidly, and the industrial structure has been optimized, which is beneficial to improve efficiency.

The coefficient for openness to foreign investment was negative, indicating that an increase in the actual amount utilized reduces CE. This may be because certain provinces allowed foreign investment with low or no green requirements, and CO_2 was transferred to other regions, causing a decrease in total efficiency.

The energy structure coefficient was negative. Electricity consumption, major end-use energy consumption in China, was dominated by thermal power generation, which is dominated by coal. It indicates that the more thermal power generation, the more CO_2 is generated, resulting in the detriment of CE.

The environmental regulation coefficient was positive. Environmental regulation encourages businesses to increase their investment in industrial pollution management, increasing their production costs. To maximize revenues, businesses choose to implement cleaner manufacturing methods that minimize environmental management inputs. Simultaneously, greener manufacturing processes assist in CO_2 reduction and enhance CE.

4.5. Decomposition of Direct and Indirect Effects

When ρ does not satisfy the condition of being significantly 0, the meaning of the SDM regression coefficient changes. The regression coefficients do not indicate the influence of the spatial lag term. As a result, further assessment of the direct, indirect, and total impacts is necessary. The direct effect is the effects of the various factors on CE in the province, and the consequent change in neighboring provinces is the indirect effect. This paper analyzed the influence of explanatory variables on CE by decomposing their direct, indirect, and total effects, and the results are displayed in Table 6.

Table 6. Direct, indirect, and total effects of factors influencing CE.

Variable	Direct Effects	Indirect Effects	Total Effect
URID	1.325 *** (0.00)	−0.667 (0.42)	0.658 *** (0.00)
$URID^2$	−0.672 *** (0.00)	0.120 (0.75)	−0.552 *** (0.0)
CLD	0.039 * (0.08)	−0.291 ** (0.01)	−0.252 ** (0.02)
CSD	0.270 *** (0.00)	0.503 *** (0.00)	0.773 *** (0.00)
PGDP	0.259 *** (0.00)	−0.375 * (0.07)	0.116 (0.20)
IS	0.194 (0.12)	1.105 *** (0.00)	1.299 *** (0.00)
OP	−0.035 *** (0.00)	0.192 *** (0.00)	0.157 *** (0.00)
ES	−0.036 ** (0.03)	0.354 *** (0.00)	0.318 *** (0.00)
ER	0.053 *** (0.00)	0.052 * (0.07)	0.001 (0.90)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The direct effect of the urban-rural income disparity (*URID*) quadratic term was −0.672, implying an inverted "U"-shaped curve between urban-rural revenue disparity and CE in the province; whereas, the indirect effect was insignificant, indicating that the impact of URID on neighboring areas was weak.

The indirect effect of consumption level difference (*CLD*) was −0.291, suggesting that increasing the CLD of the province would result in a decrease in CE in neighboring regions. The indirect effect of consumption structure difference (*CSD*) was 0.503, which was greater than 0.270, indicating that the more the consumption structure tends towards enjoyable consumption, the more the CE of the province and neighboring regions can be improved.

GDP per capita (*PGDP*) had a direct effect coefficient of 0.259 and an indirect effect coefficient of −0.375. This means that an increase in *PGDP* will increase the CE of the province while decreasing the CE of neighboring provinces. The indirect coefficient for industrial structure (*IS*) was 1.105, suggesting that raising the percentage of tertiary sector value added will boost the CE of neighboring regions. The direct effect of openness to foreign investment (*OP*) and energy structure (*ES*) was negative, whereas the indirect effect was positive, implying that greater openness to foreign investment and a greater share of thermal power generation will result in a decrease in CE in the province and an increase in CE in neighboring provinces. The direct and indirect effects of *ER* were both positive, meaning that greater investment in *ER* will increase the CE of the province and neighborhoods.

4.6. Endogeneity and Robustness Tests

The paper uses the one-period lagged terms of the explained variables as instrumental variables and endogeneity treatment of the variable. The result is shown in Table 7. To test the robustness of the regression results, the core explanatory variables were replaced and the core explanatory variables were lagged by one period. The results are displayed in Table 8 (columns two and three), demonstrating that the findings of the study are robust. The results are displayed in Table 8 (columns four and five), which showed a lagged effect of urban-rural income disparity on CE, with a significant inverted "U" shape.

Table 7. Endogeneity tests.

Variable	(1) Coefficient	(2) W* Coefficient	Variable	(1) Coefficient	(2) W* Coefficient
URID	1.355 * (0.07)	−0.148 *** (0.00)	*OP*	0.028 * (0.09)	0.032 * (0.08)
URID^2	−2.666 *** (0.00)	1.178 *** (0.00)	*ES*	−0.097 *** (0.00)	0.009 * (0.08)
CLD	0.147 *** (0.00)	−0.132 * (0.08)	*ER*	0.022 ** (0.02)	0.033 ** (0.02)
CSD	0.076 * (0.08)	0.259 *** (0.00)	ρ	0.511 *** (0.00)	
PGDP	0.634 ** (0.03)	−0.158 * (0.06)	R^2	0.614	
IS	0.164 * (0.08)	0.473 ** (0.05)			

W* coefficients are spatial lagged terms for each variable. the *p*-values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8. Robustness tests.

Variable	Replacement of Core Explanatory Variables		Core Explanatory Variables Lagged by One Period	
	Coefficient	W* Coefficient	Coefficient	W* Coefficient
URID	0. 023 * (0.09)	−0.006 * (0.06)	0.017 * (0.07)	−0.007 ** (0.03)
URID^2	−0.003 * (0.06)	0.002 ** (0.03)	−0.002 *** (0.00)	0.003 * (0.08)
CLD	0.036 * (0.07)	−0.346 *** (0.01)	0. 035 * (0.09)	−0.336 *** (0.00)
CSD	0.286 *** (0.00)	0.385 *** (0.00)	0.274 *** (0.00)	0.353 *** (0.00)
PGDP	0.306 *** (0.00)	−0.262 *** (0.00)	0.308 *** (0.00)	−0.260 *** (0.00)
IS	0.048 * (0.08)	0.334 *** (0.00)	0.058 * (0.08)	−0.310 * (0.06)
OP	−0.038 *** (0.00)	0.183 *** (0.00)	−0.038 *** (0.00)	0.179 *** (0.00)
ES	−0.053 *** (0.00)	0.302 *** (0.00)	−0.053 *** (0.00)	0.304 *** (0.00)
ER	0.064 *** (0.00)	0.045 ** (0.03)	0.065 *** (0.00)	−0.044 ** (0.03)
ρ	0.163 ** (0.01)		0.177 *** (0.01)	
R^2	0.775		0.775	

W* coefficients are spatial lagged terms for each variable. the *p*-values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Further Analysis

5.1. Testing the Mediating Effect of Consumption Level and Consumption Structure

According to the mediating effect model, whether consumption levels difference and consumption structure differences play an indirect role in the influence of URID on carbon emission efficiency was investigated. Tables 9 and 10 present the empirical findings.

Table 9. Test results for differences in consumption levels.

Variables	CE	CLD	CE
URID	0.134 *** (1.46)	0.211 *** (4.91)	0.283 *** (0.00)
URID^2	−0.108 *** (−0.80)	−0.0177 ** (−2.74)	−0.044 *** (0.00)
CLD			0.229 *** (0.00)

*** $p < 0.01$, ** $p < 0.05$.

Table 10. Test results for differences in consumption structure.

Variables	CE	CSD	CE
URID	0.142 *** (1.50)	0.287 ** (2.25)	0.283 *** (0.00)
URID^2	−0.083 *** (−0.59)	0.019 ** (0.10)	−0.044 *** (0.00)
CSD			−0.142 ** (−1.94)

*** $p < 0.01$, ** $p < 0.05$.

To begin, as shown in Tables 9 and 10, the coefficients of both the URID and its quadratic term pass the 1% significance test, suggesting that the URID and CE have an aggregate effect. Second, if both the URID and its quadratic term are significantly non-zero, then consumption level and consumption structure are thought to have a mediating influence. Meanwhile, the results show that the coefficient of the quadratic term of URID is significantly negative, indicating that there is an inverted "U" shaped curve between the URID, consumption level difference, and consumption structure difference. Finally, the coefficient of URID and its quadratic coefficient, the coefficient of consumption level difference, and the coefficient of consumption structure difference are all significant, indicating that consumption level and consumption structure have a partial mediating effect, and Hypotheses 2 and 3 are both valid.

5.2. Test for Heterogeneity

Chinese provinces vary dramatically in terms of geography, city size and resource endowment. Therefore, this paper uses the division criteria published by the National Bureau of Statistics to divide the country into eastern, central, western and northeastern regions to analyze the heterogeneous impact of URID on CE. From the results of the Moran's I index, LM test, Hausman test, Wald test and LR test, it is clear that all should choose an SDM model with fixed effects for estimation; Table 11 displays the results in various areas. The quadratic coefficient of URID is positive in the central, western, and northeastern regions, and the relationship between URID and CE is "U" shaped. The coefficient of consumption structure disparity is negative in the eastern, western, and northeastern regions, and an increase in consumption structure disparity will result in a drop in CE. The greater the consumption level difference in the center region, the greater the CE. The coefficient of consumption structure difference is negative in the eastern and western regions, and the consumption structure difference is negatively related to carbon emission efficiency, whereas the relationship is reversed in the central and northeastern regions. The link between *GDP* per capita and CE is negative in the west. The relationship between industrial structure and CE is negative in the eastern, central, and western regions, but positive in the northeastern region. The greater the openness to foreign investment in all four regions, the lower the CE. Only in the east does the direction of influence of energy structure and environmental regulation on CE differ from other regions.

Table 11. The effect of regional URID on carbon emission efficiency.

Variables	Eastern Region	Central Region	Western Region	Northeast Region
URID	1.167 *	−0.819 **	−1.913 ***	−10.513 ***
	(0.08)	(0.03)	(0.00)	(0.00)
$URID^2$	−0.459 **	0.100 **	0.696 **	7.370 ***
	(0.04)	(0.03)	(0.02)	(0.00)
CLD	−0.041 ***	0.528 ***	−0.028	−0.753 ***
	(0.00)	(0.00)	(0.11)	(0.00)
CSD	−0.010 ***	0.167 ***	−0.222 ***	1.480 ***
	(0.00)	(0.01)	(0.00)	(0.00)
PGDP	4.248 ***	0.170 **	−0.826 *	5.656 ***
	(0.00)	(0.04)	(0.09)	(0.00)
IS	−0.047 **	−0.101	−0.268 ***	2.327 ***
	(0.04)	(0.46)	(0.00)	(0.00)
OP	−0.041 ***	−0.025 *	−0.028	−0.423 ***
	(0.00)	(0.09)	(0.14)	(0.00)
ES	0.302 ***	−0.075	−0.034 ***	−3.870 ***
	(0.00)	(0.11)	(0.00)	(0.00)
ER	0.004	−0.213 ***	−0.015	−0.157 ***
	(0.18)	(0.00)	(0.20)	(0.00)
ρ	−0.297 ***	−0.447 ***	−0.708 ***	−0.214 *
	(0.00)	(0.00)	(0.00)	(0.08)
R^2	0.663	0.617	0.681	0.551
Moran's I index	7.004 ***	3.740 ***	14.199 ***	2.562 ***
LM test(SAR)	51.709 ***	9.014 ***	166.476 ***	0.709 *
LM test(SEM)	6.812 ***	7.409 ***	153.916 ***	1.542 *
Hausman test	54.322 ***	19.031 ***	45.653 ***	20.458 ***
Wald test(SAR)	373.44 ***	253.12 ***	28.67 ***	12.64 *
Wald test(SEM)	395.99 ***	895.98 ***	18.18 ***	12.59 *
LR test(SAR)	52.22 ***	60.66 ***	185.88 ***	51.14 ***
LR test(SEM)	50.67 ***	58.18 ***	199.39 ***	48.69 ***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Conclusions and Policy Implications

6.1. Research Findings

Based on the perspectives of consumption level and structure, this study investigated the relationship between URID and CE based on panel data from 30 provinces from 2006–2019 to measure and analyze the CE of provinces. We also analyzed its spatial and temporal characteristics using the super-efficient EBM model and applied the SDM model in light of the spatial spillover effect to investigate the effect and mechanism of URID on carbon emission efficiency and construct a mediating effect model to test the indirect role of consumption level and consumption structure. The following conclusions were obtained.

(1) Carbon emission efficiency measurements for provinces in China revealed considerable spatial disparities, with a characteristic of efficiency in the east but inefficient in the west, fluctuating and undulating in the rest of the region. From 2006–2012, national carbon emission efficiency exhibited an overall decreasing trend, followed by a fluctuating increase from 2013–2019.

(2) In China, the inverted "U" curve more accurately describes the relationship between the urban-rural income gap and CE. The consumption level and structure difference coefficients were all positive, showing that they had a positive influence on CE. Furthermore, the effect of urban-rural income disparity on the CE of neighboring provinces is non-significant. Widening differences in consumption levels in one region will lead to lower CE in neighboring provinces and cities.

(3) Consumption level and structure both had a somewhat mediating function in the transmission mechanism of the URID, which influenced CE. The association between URID and CE was "U"-shaped in the central, western, and northeastern regions. In

all three regions except the central region, CLD expansion impedes carbon efficiency improvements. The wider the consumption structure difference between urban and rural residents, the higher CE in central and northeastern regions, and the lower the CE in eastern and western regions.

6.2. Policy Implications

This study offers the following policy implications.

(1) Provinces should increase exchanges and collaboration with neighboring provinces and municipalities on carbon emission governance. Advantage should be taken of the spatial spillover effect of CE. Inter-provincial synergy in emission reduction should be promoted by capitalizing on regional advantages, strengthening cooperation in environmental governance and scientific and technological innovation, and improving carbon emission efficiency by driving improvements in production methods with technological progress. Because carbon emission efficiency varied by province, each province should consider its particular resource endowment and stage of economic growth when defining carbon emission control objectives and developing a strategy to enhance CE depending on the local conditions. Provinces and cities with high CE should increase investment in low-carbon technology research and focus on developing new high-tech industries; on the other hand, provinces with low CE, for instance, Qinghai, Ningxia, and Xinjiang, should eliminate backward production capacity as soon as possible and optimize their industrial structure.

(2) Income distribution should be improved while encouraging green and low-carbon consumption. In response to the large urban-rural income disparity, the government can narrow the gap by deepening income distribution reform, increasing financial assistance to rural areas, and promoting income growth among farmers. Significantly, due to the economic growth driven by strategic plans for rural revitalization (2018–2022), rural carbon emissions are growing rapidly, and localities should take measures to address the problem [45]. The government can also accelerate urbanization, ensure coordinated resource allocation between cities and villages, encourage synergistic growth of urban and rural consumption, and raise the consumption level of residents. The balanced growth of urban and rural consumption economies has resulted in increased environmental awareness among inhabitants and a green transformation of the consumption structure. The reduction of URID increased consumption, and the promotion of upgrading of consumption structure are all ways that provinces might improve their CE, which is a win-win development for the economy and environment.

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