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Relationship between Urbanization and Carbon Emission Efficiency - Based on Super-Efficient SBM Model and Semi-Parametric Modeling

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ABSTRACT

The This paper aims to explore the relationship between urbanization and carbon emission efficiency in China. By employing the super-efficient SBM model and semiparametric regression model, the study examines data from 30 provinces in China spanning the period from 2008 to 2019. Additionally, the analysis distinguishes between coastal and non-coastal regions to account for geographical variations. The findings reveal that: (1) there is no inverted " U " curve relationship between urbanization and carbon emission efficiency; (2) in coastal areas, urbanization is negatively associated with carbon emission efficiency; (3) population concentration positively affects carbon emission efficiency to a certain extent; (4) an increase in per capita income inhibits carbon emission efficiency; (5) the rapid development of the tertiary industry also hampers carbon emission efficiency. Finally, based on the study's conclusions, policy recommendations are proposed.

Keywords: Urbanization; Carboon emissions; Semi-parametric model; Regional difference

INTRODUCTION

The release of the Sixth Assessment Report by the United Nations Intergovernmental Panel on Climate Change (IPCC) emphasizes the role of human activities in greenhouse gas emissions and the urgent need for reducing emissions to mitigate global warming. The adoption of green economic development and low-carbon lifestyles has become a global consensus. As the world's largest CO2 emitter, China faces challenges such as an unbalanced industrial structure, high energy intensity, and limited technological innovation[1]. In response, China has issued the Action Plan for Peak Carbon by 2030, which sets ambitious targets for increasing the proportion of non-fossil energy consumption and reducing carbon emissions.

Scholars worldwide have been actively researching ways to reduce carbon emissions and enhance emission efficiency. For example, Wang et al. investigated the impact of transportation charging policies on reducing motor vehicle usage and consequent carbon dioxide emissions[2]. Zhang et al. examined the distribution efficiency of carbon emissions in different provinces in China, suggesting that the adoption of advanced technologies can contribute to carbon emission reductions, and provinces can devise suitable strategies based on their economic characteristics [3]. Bartholomeu et al. found that improving road conditions in Brazil can enhance energy efficiency, reduce reliance on fossil fuels, and subsequently lead to reductions in carbon dioxide emissions [4].

Urbanization is a global phenomenon characterized by the rapid increase in the proportion of urban population. According to Yu et al., the proportion of urban population rose from 33% in 1950 to 55% in 2018 [5]. China's urbanization process has been gradual, initially slow and then experienced rapid growth. In 2012, China released the 2012 China's New Urbanization Report, which identified six stages of development, with the period from 1992 to the present characterized by rapid urbanization .Zhang et al. found that in 1978, the proportion of China's urban population to the total population reached 17.92%, and by 2012, it had reached 52.6%, indicating significant progress. However, China's urbanization level still lags behind that of developed countries [6]. Recognizing the importance of the relationship between urbanization and ecological efficiency, China has issued the "14th Five-Year Plan" for the implementation of new urbanization. With China's urbanization rate surpassing 64.7%, the focus has shifted to internal development and the creation of livable cities with enhanced public service facilities. Furthermore, the plan emphasizes the need for ecological restoration, environmental protection, and the promotion of low-carbon production and lifestyles. Rehman et al. found that energy consumption plays a significant role in China's carbon emissions [7]. Zhang et al. also determined a unidirectional long-term causality between energy consumption and carbon emissions [8]. It is evident that as urbanization continues to advance, China's energy consumption, particularly the utilization of fossil fuels, remains high, making it a primary driver of carbon dioxide emissions.

The Environmental Kuznets Curve (EKC) has been a topic of interest among scholars studying the relationship between economic development and environmental pollution. The core idea of the EKC suggests an inverted "U" curve relationship, indicating that as economies develop, environmental degradation initially worsens, but eventually improves as the economy reaches a certain level of development. However, research findings on the existence of the EKC and its applicability to specific countries have been mixed. For instance, a study conducted in China and India revealed a long-term relationship between variables and found that urbanization, real GDP, and natural gas had a positive impact on carbon emissions in both countries, but did not find evidence of an EKC [9]. Another study by Kwakwa, using time-series data, observed that income and income squared had statistically significant positive and negative effects on CO2 emissions, respectively, suggesting the absence of an EKC [10]. Similarly, Zhang analyzed the factors influencing carbon emissions in five Central Asian countries and found that urbanization had a positive effect on carbon emissions, but did not find evidence of an inverted "U" relationship, indicating no support for the EKC hypothesis [11].

To address the challenge of achieving energy-saving and emission reduction goals without compromising economic development, many scholars have shifted their focus to improving carbon emission efficiency. Measurement of total factor productivity (TFP) can be approached using various methods, including the traditional accounting method, stochastic frontier analysis (SFA), and data envelopment analysis (DEA).For instance, Zhu utilized the DEA model to measure carbon emission efficiency [12]. Qu et al. incorporated uncertainties and multiple risks into a robust DEA model to analyze carbon emission efficiency in China [13]. Zhao et al. employed a three-stage data envelopment analysis model to investigate carbon emission efficiency, revealing a slow but increasing trend in China's overall carbon emission efficiency [14]. Wang et al. conducted a stochastic frontier analysis (SFA) to evaluate the eco-efficiency of cities in China, finding regional disparities with higher eco-efficiency observed in eastern cities [15].Building upon these methods, this paper adopts the super-efficient SBM model to measure carbon emission efficiency, addressing biases associated with input-output perspectives and radial selection bias commonly observed in traditional DEA models. Additionally, a semiparametric model is constructed using data from 30 provinces in China spanning the period from 2008 to 2019 to explore the relationship between urbanization and carbon emissions. Given the significant spatial heterogeneity in China, the study considers the differential impacts of urbanization on carbon emission efficiency in coastal and inland cities. The objective of this paper is to gain insights into the relationship between urbanization and carbon emission efficiency in China. Moreover, the study aims to propose region-specific recommendations for energy-saving and emission reduction strategies to enhance carbon emission efficiency.

The rest of the paper is organized into the following five sections. Section 2 briefly reviews the literature; Section 3 the model and methodology; Section 4 the empirical results; and Section 5 draws conclusions and policy recommendations.

LITERATURE REVIEW

Literature review on urbanization and CO2 emissions

The impact of urbanization on the environment has garnered significant attention from scholars, as the influx of rural populations to cities can have profound effects on urban environments. Numerous studies have explored the relationship between urbanization and carbon dioxide emissions, yielding compelling findings. At the national level, Shahbaz et al. investigated the relationship between carbon emissions and urbanization in Malaysia using the bayer-hank cointegration method within the STIRPAT framework. The study revealed a "U" curve relationship, indicating that carbon dioxide emissions initially decrease with the development of urbanization, but then increase after reaching a certain threshold [16]. Similarly, Behera et al. employed the Pedroni cointegration method to study the relationship in 17 countries across South and Southeast Asia, categorizing them into high-income, middle-income, and low-income groups. The findings indicated a cointegration relationship between urbanization, energy consumption, foreign direct investment, and carbon dioxide emissions in middle-income countries, with the significance of each factor varying based on income level [17].Sun et al. explored the factors influencing carbon emission efficiency in China using the stochastic frontier model. The study revealed an inverted "U" curve relationship between urbanization level and carbon emission efficiency. In the early stages, carbon emission efficiency and urbanization level showed a positive association, but after surpassing a certain threshold, they began moving in opposite directions [18]. Similarly, Shah et al. employed the Johnson cointegration and vector error correction model to analyze the factors influencing carbon emissions in Pakistan. The results indicated a dynamic "U" shaped relationship between urbanization and carbon emissions [19].The above studies contribute to our understanding of the relationship between urbanization and carbon emissions, revealing both direct and nuanced associations. These findings underscore the importance of considering the specific context and income levels when studying the urbanization-emissions relationship.

Literature Review on Population and CO2 Emissions

The impact of population size on the environment is another crucial aspect that scholars consider when studying environmental issues. Understanding the relationship between population and carbon emissions provides insights into the role of demographic factors in environmental challenges.Anser et al. examined the population size of SAARC (South Asian Association for Regional Cooperation) member countries and found a positive relationship with carbon emissions. The study revealed that larger populations in these countries corresponded to increased carbon emissions per capita [20].

Guo et al. analyzed the relationship between demographic structure and carbon emissions using the logarithmic mean split exponential model. Their findings indicated that the scale effect of population was significantly higher in the eastern region compared to the central and western regions. The study also demonstrated that changes in population, as well as population size, were associated with an increase in carbon dioxide emissions [21].Liddle's work summarized the impact of demographic factors on carbon emissions. The article noted a relationship between higher population density and emission levels, highlighting the role of population in influencing emissions [22].These studies emphasize the importance of considering population size and demographic factors when examining environmental issues, particularly in relation to carbon emissions. Such insights contribute to a comprehensive understanding of the complex interplay between population dynamics and environmental sustainability.

Literature review on energy and CO2 emissions

The use of energy, particularly fossil fuels, is a significant factor contributing to the increase in carbon dioxide emissions. In response to the global warming issue, many countries have implemented policies aimed at reducing carbon dioxide emissions. Consequently, scholars from various countries have conducted extensive research in this area.Ahmed et al. examined carbon emissions in Indonesia and found that both energy intensity and economic growth have a positive impact on carbon dioxide emissions. The study highlighted the complex relationship between energy use, economic factors, and carbon emissions [23].Al-mulali et al. investigated the long-term relationship between urbanization, energy consumption, and carbon emissions in seven regions using the fully modified ordinary least squares (FMOLS) method. The results revealed that in 84% of the regions, there is a long-term positive correlation between the variables, indicating that urbanization and energy consumption contribute to carbon emissions. However, in the remaining 16% of regions, the relationship is mixed, suggesting the presence of other influencing factors [24].Wu et al. utilized the U-Kaya formula to analyze the factors influencing carbon dioxide emissions in China. The findings indicated that as the urbanization rate, energy carbon emission coefficient, and energy intensity increase, the carbon emissions of cities also rise. This underscores the influence of urbanization and energy-related factors on carbon emissions [25].Together, these studies highlight the significance of energy-related variables, such as energy intensity, consumption, and carbon emission coefficient, in understanding and addressing carbon dioxide emissions. They contribute to our understanding of the intricate relationship between energy use, urbanization, and carbon emissions.

Literature review on economic development and CO2 emissions

Economic development plays a crucial role in shaping income levels and industrial structures, leading to a significant impact on carbon dioxide emissions. Numerous studies have explored the relationship between economic development and carbon emissions, revealing diverse findings.

Begum et al. employed the ARDL method to analyze the factors influencing carbon emissions in Malaysia. The study found that GDP per capita had different effects on carbon dioxide emissions per capita during different periods. In the early period, there was a negative relationship between per capita carbon dioxide emissions and per capita GDP, while in the late period, a positive relationship emerged. Furthermore, in the long run, economic growth was found to have a negative impact on carbon emissions in Malaysia [26].Shanthini et al. investigated the long-term relationship between GDP per capita and carbon emissions per capita in Australia. Their findings revealed a positive relationship, indicating that as GDP per capita increases, so do carbon emissions per capita [27].Wang et al., through empirical analysis, found that the proportion of the tertiary industry and GDP per capita could effectively inhibit carbon emission intensity. This implies that as the tertiary sector grows and income levels increase, carbon emission intensity decreases [28].Considering the existing literature, very few studies have examined the relationship between carbon emission efficiency and urbanization. Most studies have focused on analyzing changes in carbon emissions itself, while neglecting the correlation between urbanization and carbon emission efficiency. Therefore, this study utilizes the super-efficient SBM model to analyze panel data from 30 provinces in China between 2008 and 2019, with a specific focus on calculating carbon emission efficiency. Based on these calculations, the study further explores the relationship between urbanization and carbon emission efficiency. By investigating the correlation between urbanization and carbon emission efficiency, this research adds valuable insights to the existing literature. The utilization of panel data from multiple provinces in China enhances the robustness and generalizability of the findings.

This paper makes three contributions to the existing body of research:

Utilization of the super-efficient SBM model: This study employs the super-efficient SBM model to measure carbon emission efficiency. The results obtained from this model provide valuable information for decision-makers, enabling them to better manage and optimize the evaluated entities. The measurement of carbon emission efficiency serves as an indicator of a country's green economy level and offers guidance for the development of sustainable and environmentally friendly practices.

Application of nonparametric models: Few studies have utilized nonparametric models to examine the relationship between carbon emissions and urbanization. In this paper, a nonparametric model is constructed based on the STIRPAT framework to identify the nonlinear relationship between urbanization and carbon emission efficiency. By uncovering this relationship, the study provides insights and recommendations for promoting future environmentally friendly development.

Analysis of regional differences: Given the distinct variations in resources, culture, and economic development across different regions in China, this paper divides the 30 provinces and cities into coastal and inland areas. Through a comparative analysis, the study explores the differences between these regions and proposes corresponding suggestions.

This regional perspective enhances the understanding of the complexities of carbon emission efficiency within China, facilitating targeted strategies and policies.

MODELS AND METHODS

Super-efficient SBM model

To address the limitations of the traditional radial DEA model in measuring inefficiency and its bias towards input and output perspectives, the Tone-proposed model is employed in this study. The model incorporates the non-expected output SBM (Slack-Based Measure) model, which allows for a more comprehensive assessment of efficiency [29].In the context of measuring carbon emission efficiency in China, the study considers the 30 provinces and cities as decision-making units. Each decision-making unit comprises specific input indicators, desired outputs, and non-desired outputs. To account for these considerations, the SBM model incorporating desired outputs is formulated as follows:

$$\theta^* = \min_{\lambda,s^-,s^+} \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}^t}}{1+\frac{1}{q+h}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{ro}^t}+\sum_{k=1}^{h}\frac{s_k^-}{b_{ko}^t}\right)}$$

$$s.t.\, x_{io}^t = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t x_{ij}^t + s_i^- \qquad i = 1,2,\dots,m;$$

$$y_{ro}^t = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t y_{rj}^t - s_r^+ \qquad r = 1,2,\dots,q;$$

$$b_{ko}^t = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t b_{kj}^t + s_k^- \qquad k = 1,2,\dots,h;$$

$$\lambda_j \geq 0(\forall j), s_i^- \geq 0(\forall i), s_r^+ \geq 0(\forall r), s_k \geq 0(\forall k)$$

By adopting this SBM model, which includes desired outputs, the study aims to provide a more accurate and comprehensive evaluation of the carbon emission efficiency of the different provinces and cities in China. i represents the number of input variables. s_i^- represents the slack variable of the input, indicating input redundancy. r represents the number of output variables. s_r^+ is a slack variable for output, indicating that the desired output is insufficent. k represents the number of non-desired output variables. s_k^- slack variable for non-desired outputs, indicating excess non-desired outputs. λ indicates weight. a represents the decreasing function of each slack variable, measured in this paper as carbon emission efficiency. It can be found from Eq, When and only when s_i^-、s_r^+、s_k^- are both 0, $\theta^* = 1$,which shows that the function is efficient at this point and an optimal solution is obtained. If $\theta^*<1$, it means that at least one of the slack variables is not equal to 0 and there is a loss in the efficiency of the decision unit, which makes it necessary to improve the inputs and outputs. Tone combines the super-efficient DEA with the SBM model to propose the super-efficient SBM model, which is utilized in this paper to measure carbon emission efficiency.The super-efficient SBM model relaxes the restriction that the carbon emission efficiency must be equal to 1, allowing for further comparisons among multiple decision-making units, even when they are all efficient simultaneously. The model is set up as follows:

$$\theta^* = \min_{\lambda,s^-,s^+} \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}^t}}{1-\frac{1}{q+h}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{ro}^t}+\sum_{k=1}^{h}\frac{s_k^-}{b_{ko}^t}\right)}$$

$$s.t.\, x_{io}^t \geq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t x_{ij}^t - s_i^- \qquad i = 1,2,\dots,m;$$

$$y_{ro}^t \leq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t y_{rj}^t + s_r^+ \qquad r = 1,2,\dots,q;$$

$$b_{ko}^t \geq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j^t b_{kj}^t - s_k^- \qquad k = 1,2,\dots,h;$$

$$\lambda_j \geq 0(\forall j), s_i^- \geq 0(\forall i), s_r^+ \geq 0(\forall r), s_k \geq 0(\forall k)$$

The paper adopts the super-efficiency SBM-DEA model to measure carbon emission efficiency. Table 1 outlines the inputs and outputs required for this measurement.The input indicators in this model include capital input, labor input, and energy input. The desired output is per capita GDP of each region, while the non-desired output is carbon dioxide emissions of each region [30-32].Specifically, the labor force is measured by the number of urban employed population in each region. Capital input is measured by the amount of investment in fixed assets of the entire society for the given year, usually calculated using the perpetual inventory method at the national level. The energy indicator is measured by total energy consumption.As for the output indicators, the desired output is measured by the gross domestic product (GDP) of each region. The non-desired output, namely CO_2 emissions, is based on the research of other scholars and is selected as the measurement indicator [33, 34].To calculate CO_2 emissions, the paper refers to the 2007 IPCC Fourth Assessment Report, which identifies fossil fuel combustion as the main source of greenhouse gas (GHG) increase. Therefore, CO_2 emissions are determined based on end-use energy consumption data from previous years in each province. The calculation method follows the IPCC Guidelines for National Greenhouse Gas Emission Inventories. The formula is expressed as follows:

$$C_{it} = \sum E_{ijt} \times \eta_j (i = 30, j = 1,2, \ldots, 9)$$

C_{it} represents the total carbon emissions of province i in year t. Meanwhile, E_{ijt} refers to the consumption of the jth type of energy in province i in year t. To convert the original statistics of energy consumption into standard statistics for measuring carbon emissions, the carbon emission coefficient η_j for each energy type is considered. Based on the China Energy Statistical Yearbook, final energy consumption is categorized into nine types:Raw coal、Coke、Crude oil、Gasoline、Diesel fuel、Kerosene、Fuel oil、Natural gas、Electricity.

Table 1 Input–output index system of carbon emission efficiency

Indicator system	Type of indicator	Name of indicator
Input indicators	Capital Inputs	Capital stock by region (billions of dollars)
	Labor Inputs	Urban employed population by region (10,000 people)
	Energy inputs	Total energy consumption by region (tons of standard coal)
Output indicators	Desired outputs	GDP per capita in each region (yuan/person)
	Undesired outputs	CO_2 emissions by region (tons)

Semi-parametric models

The IPAT model was initially proposed in the 1970s by American ecologist Ehrlich et al. [35]. The model considers three key factors: population size §, affluence (A), and technology level (T), and their non-proportional impact on the ecological environment. The IPAT model formulates the relationship between these determinants as follows:

$$I = P * A * T$$

Indeed, scholars have recognized certain limitations of the original IPAT model. One of the assumptions in the IPAT model is the uniform elasticity of ecological factors in response to population, affluence, and technology. This assumption prevents a direct examination of the individual impacts of these factors on the environment. Furthermore, relying solely on these three factors may be considered incomplete and insufficient for explaining environmental factors. As a response to these limitations, numerous scholars have proposed an extended version of the IPAT model, called the STRIPAT model, which takes into account additional factors. The extended model is formulated as follows:

$$I = \alpha P^b A^c T^d e$$

The coefficients b, c, and d represent the respective impacts of population size, affluence, and technology level on the environmental impact. The coefficient a represents the coefficient of the model. Lastly, e represents the error term of the model, accounting for unexplained variation or measurement errors. By obtaining the natural logarithm of both sides, it is possible to transform the original model to a log-linear form. This transformation allows for easier interpretation and analysis of the relationships between the variables, as it linearizes the relationship between them.

$$lnI = lna + b * lnP + c * lnA + d * lnT + lne$$

The advantage of the STRIPAT model is its flexibility to incorporate new control variables that can contribute to the analysis of ecological impact. In this paper, the focus is on studying the impact of urbanization on carbon emission efficiency. Building upon previous research, the paper selects five indicators (population density, per capita disposable income, energy intensity, the proportion of the tertiary industry in GDP, and urbanization) to establish the model [36-38]. Since few studies have explored the nonparametric relationship between urbanization and carbon emission efficiency, the paper aims to establish a nonparametric model within the framework of the STRIPAT model. The objective is to test whether there exists an Environmental Kuznets Curve (EKC) relationship between urbanization and carbon emission efficiency. The model is formulated as follows:

$$lnCS_{it} = lna_i + \beta_1 lnPI_{it} + \beta_2 lnIncome_{it} + \beta_3 lnEI_{it} + \beta_4 lnTI_{it} + f(UR_{it}) + \varepsilon_{it}$$

In this model, the variables and their respective definitions are as follows: CS_{it}: Carbon emission efficiency of the ith province at time t. PI_{it} : Population density of the ith province at time t. $Income_{it}$: Disposable income of urban residents of the ith province at time t. TI_{it}: Share of the tertiary industry in GDP of the ith province at time t. EI_{it}: Energy intensity of the ith province at time t.

The model allows for the potential nonlinear relationship between urbanization and carbon emission efficiency. As a result, the functional form f(·) that captures this relationship is left unspecified. This nonparametric approach allows for greater flexibility in assessing the potential nonlinear pattern between urbanization and carbon emission efficiency. By not imposing a specific functional form on the relationship between urbanization and carbon emission efficiency, your study aims to explore the potential nonlinear association between these variables. This approach provides the opportunity to capture a wide range of possible relationships that exist in the data without making any specific assumptions about the functional form.

EMPIRICAL RESULTS

Data sources and descriptive statistics

In this paper, panel data from 30 provinces in China for the period 2008 to 2019 was collected and used for empirical analysis. The data used in this study was obtained from the 《China Statistical Yearbook》 and 《Energy Statistical Yearbook》. Table 2 presents the results of the statistical analysis using the panel data. This table provides descriptive statistics such as means, standard deviations, and potentially other relevant measures for the variables included in the analysis. The data reveals that the average level of urbanization in China stands at 56.393% [39]. It is important to note that China's urbanization process has been characterized by both its rapid speed and immense scale.

Table 2 Descriptive statistics

Variable	Definition	Mean	Min	Max
CS	Carbon Emission Efficiency	0.758	0.383	1.36
Income	Per capita urban disposable income （Yuan）	26936.483	10969.41	73848.513
PI	Population density （People per square kilometer）	457.423	7.674	3829.874
EI	Energy intensity （tce/10k）	0.876	0.208	2.94
UR	Urbanization （%）	56.393	29.11	89.6
TI	Tertiary sector to GDP ratio （%）	44.749	28.615	83.521

Figure 1 illustrates China's average carbon emission efficiency during the period of 2018-2019. The figure shows that in the initial period, China's carbon emission efficiency remained relatively stable. However, in 2012, there was a noticeable increase in carbon emission efficiency. This change can be attributed to the Chinese government's implementation of the "Outline of the Twelfth Five-Year Plan for the Development of the National Economy and Social Society" and its efforts to raise awareness of climate change across society. In order to promote low-carbon production and consumption and regulate the certification of low-carbon products, the government introduced the Interim Measures for the Administration of Low-Carbon Product Certification. These measures played a significant role in gradually increasing carbon emission efficiency starting from 2013. In the latter part of the period under consideration, carbon emission efficiency remained stable.

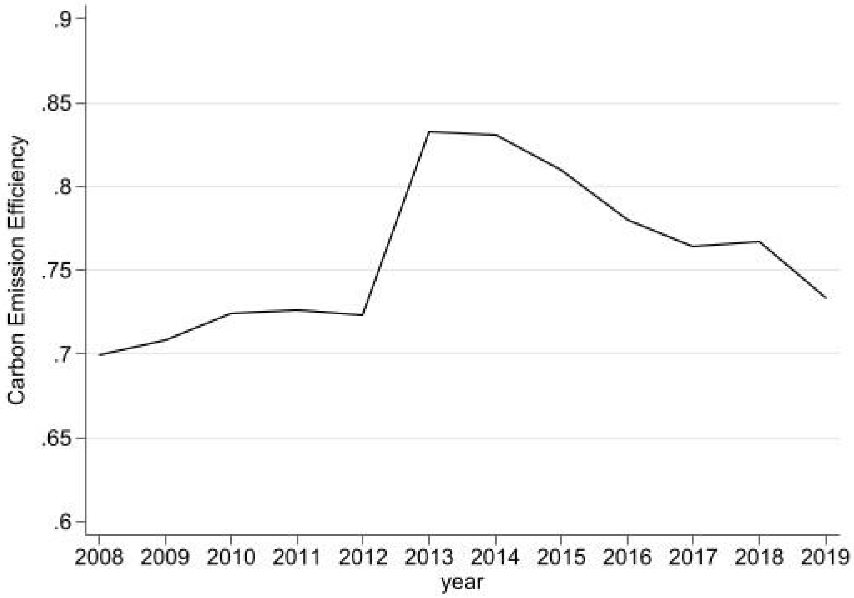

Fig 1 Average Carbon Emission Efficiency by Region in the Country

China is indeed a resource-rich country with diverse regional characteristics that can have significant impacts on carbon emissions, urbanization, and other related factors. Recognizing the importance of these regional effects, this paper analyzes both coastal cities and inland cities to provide a comprehensive understanding of the topic.

Figure 2 presents a comparison between the average carbon emission efficiency of coastal cities and inland cities. Generally, it is observed that coastal cities exhibit higher carbon emission efficiency levels compared to inland cities. Additionally, the general trend of carbon emission efficiency is similar for both coastal and inland cities. This finding suggests that coastal cities, which are often more developed and economically vibrant, tend to have greater emphasis on environmental concerns and adopt more efficient practices in terms of carbon emissions. Inland cities, on the other hand, may face different challenges and exhibit relatively lower levels of carbon emission efficiency.

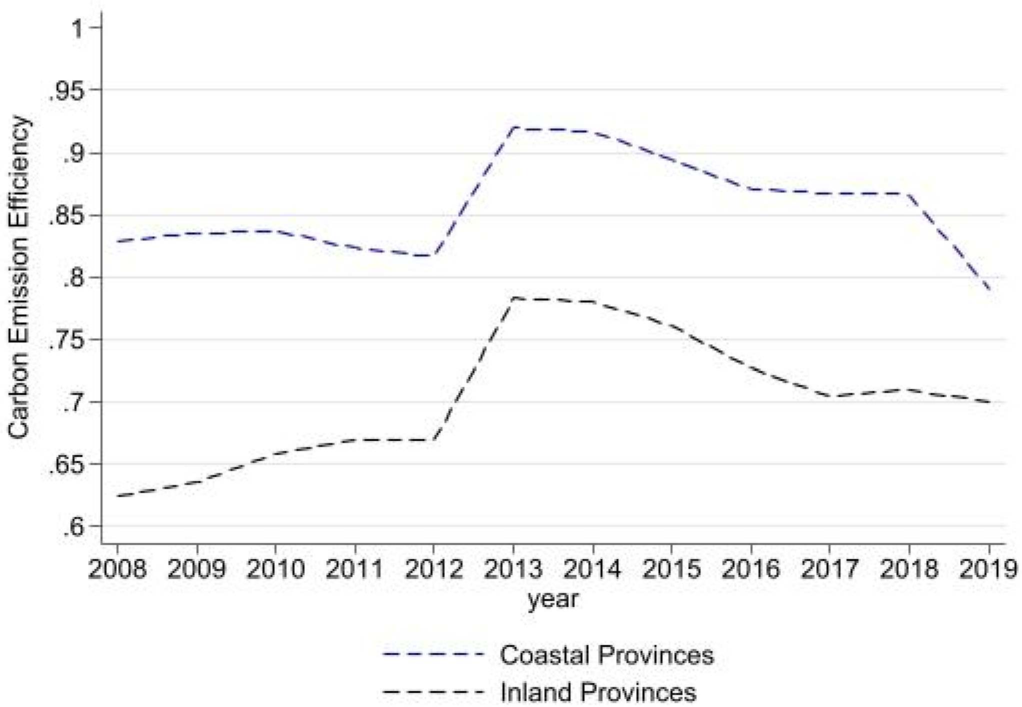

Fig 2 Average Carbon Emission Efficiency of Coastal and Inland Cities

UNIT ROOT TEST

In order to address the issue of pseudo-regression and ensure the validity of the panel data analysis, it is crucial to test the panel data for unit roots. In this paper, Fisher's test is utilized for this purpose. Fisher's test involves testing each individual unit and then combining the resulting p-values using a "Fisher Type" statistic[40]. Choi proposed four ways to combine these p-values: p for the inverse chi-square transform, z for the inverse logistic transform, l* for the modified inverse chi-square transform, and pm for the modified inverse logistic transform.

Table 3 presents the results of the Fisher's test for each variable using the different integration methods. It is noteworthy that all the variables exhibit significance across the various methods employed. Therefore, it can be concluded that the variables are smooth and do not suffer from the problem of pseudo-regression.

Table 3 Unit root test

Variables	P	Z	L*	Pm	Smoothness analysis
lnCS	101.8496 (0.0006)	-3.2110 (0.0007)	-3.1051 (0.0011)	3.8203 (0.0001)	stable
LnEI	85.6486- (0.0165)	-1.9854 (0.0235)	-1.9851 (0.0245)	2.3414 (0.0096)	stable
lnTI	124.0217 (p<0.0001)	-5.5227 (p<0.0001)	-5.4055 (p<0.0001)	5.8444 (p<0.0001)	stable
lnIncome	119.0902 (p<0.0001)	-4.7123 (p<0.0001)	-4.5613 (p<0.0001)	5.3942 (p<0.0001)	stable
lnUR	96.8178 (0.0018)	-2.5991 (0.0047)	-2.5141 (0.0065)	3.3610 (0.0004)	stable
lnPI	109.1582 (0.0001)	-3.7886 (0.0001)	-3.7442 (0.0001)	4.4875 (p<0.0001)	stable

Multicollinearity test

In general, cross-sectional data is more prone to multicollinearity. Panel data can be considered as a combination of time series and cross-sectional data, so it is necessary to test panel data for multicollinearity. The presence of multicollinearity in the model can lead to an increase in the variance and covariance of the parameter estimates, potentially causing the regression coefficients to fail significance tests. Multicollinearity can be tested using the variance inflation factor (VIF) method. The basic idea is to treat each explanatory variable as the dependent variable and perform auxiliary regressions with the remaining explanatory variables. The resulting coefficients indicate the relationship between the variable of interest and the other independent variables. The VIF is then calculated as the reciprocal of the tolerance, which is 1 minus the R-squared value from each auxiliary regression.

$$Var(\widehat{\beta}_i) = \frac{\sigma^2}{\sum {x_i}^2} \cdot \frac{1}{1 - R_i^2} = \frac{\sigma^2}{\sum {x_i}^2} \cdot VIF_i$$

where $\mathrm{VIF_i}$is the variance expansion factor of $\mathrm{X_i}$,

$$VIF_j = \frac{1}{1 - R_j^2}$$

Experience has demonstrated that a VIF value of less than 10 suggests the absence of multicollinearity between the explanatory variables and the other variables. As shown in Table 4, the results indicate that there is no multicollinearity among the variables used in our analysis.

Table 4 Multiple covariance test

Variable	VIF	1/VIF
lnIncome	4.33	0.231046
lnEI	3.00	0.333421
lnUR	2.76	0.362511
lnTI	2.69	0.372210
lnPI	2.06	0.484850
Mean VIF	2.97	

DISCUSSION

This study utilizes panel data from 30 provinces and cities in China to construct an empirical model. Few research studies have explored the relationship between urbanization and carbon emission efficiency using non-parametric models. Therefore, to investigate whether the relationship between urbanization and carbon emission efficiency adheres to the Environmental Kuznets Curve (EKC) assumptions, a semi-parametric model is employed for regression analysis.

The first column of Table 5 presents the results of estimating the control variables within the framework of the semi-parametric panel model, considering the EKC assumptions for the relationship between urbanization and CO_2 emission efficiency at the national level. The estimate for the elasticity of carbon emission efficiency with respect to energy intensity is significantly negative. This implies that a 1% increase in energy intensity leads to a 0.387% decrease in carbon emission efficiency. Considering that China predominantly relies on fossil energy, which emits substantial amounts of carbon dioxide, this finding is consistent with previous studies, such as Naqvi et al. [41].Additionally, the results reveal that the elasticity of carbon emission efficiency with respect to population density is significant at the 1% level. This implies that a 1% increase in population density is associated with a 0.033% rise in carbon emission efficiency. This finding could be attributed to the “crowding effect” caused by population concentration. However, at the current stage, the “crowding effect” does not appear to be excessive. Wang et al. [42] discovered that population density can improve air quality by reducing per capita carbon footprint. In high-density areas, individuals are more likely to walk, which contributes to improved air quality. Furthermore, the benefits of high population density and increased carbon emission efficiency can be attributed to the scale effect of cities. In other words, as density increases, infrastructure consumption decreases due to increased resource sharing. This can contribute to improved carbon emission efficiency. The variable representing affluence, specifically disposable income per capita, is also found to be highly significant. A 1% increase in disposable income per capita results in a 0.133% decrease in carbon emission efficiency. In daily life, people’s lifestyles and habits significantly influence carbon emissions, particularly influenced by their income level. With China’s economic development, disposable income has increased, leading to changes in people’s lifestyles. Hao et al. [43]discovered a “U” curve relationship between per capita income and per capita carbon emissions. In the early stages of development, carbon emissions decrease with increasing per capita income, but in later stages, carbon emissions increase as per capita income continues to rise. As China is currently the world’s second-largest economy, with ongoing economic growth and increasing income levels, the rise in per capita disposable income is likely to result in a decline in carbon emission efficiency. Furthermore, for every 1% increase in the share of the tertiary industry, carbon emission efficiency decreases by 0.259%. Kwok et al. [44] found that reducing the size of the secondary industry and emphasizing the development of the tertiary industry in China could lead to a reduction in carbon emissions. This emphasizes the importance of promoting the development of the tertiary industry and optimizing and upgrading its practices to effectively reduce carbon emissions. China should focus on the structural effects of industries, balance the development of different sectors, and promote environmentally friendly development.

Table 5 Estimation results: CO_2 emissions efficience model for the entire sample, 2008–2019.

	model1	model2	model3
lnEI	-0.387***	-0.467***	-0.369***
	[0.0178]	[0.0309]	[0.0192]
lnPI	0.0330***	0.262***	0.0176
	[0.0095]	[0.0207]	[0.0090]
lnIncome	-0.133***	-0.238***	-0.0525
	[0.0385]	[0.0529]	[0.0442]
lnTI	-0.259***	-0.259**	-0.373***
	[0.0699]	[0.0933]	[0.0997]
N	360	132	228
adj.R-sq	0.662	0.7177	0.6991
AIC	-491.4	-269.5	-330.5
BIC	-475.9	-258	-316.8
Standard errors in brackets			
* p<0.05,**p<0.01,***p<0.001			

Figure 3 illustrates the fitted relationship between urbanization and carbon emission efficiency using a semi-parametric model. It is clear from the figure that there is no evident Environmental Kuznets Curve (EKC) pattern between urbanization and carbon emission efficiency. However, it shows that as urbanization progresses, China’s carbon emission efficiency has been consistently increasing. During the early stage of urbanization, China’s economic level is relatively low, and there may be limitations in technological capabilities and innovation. Furthermore, the development of green initiatives has not yet reached a significant scale, resulting in lower carbon emission efficiency. However, as China enters the later stages of urbanization, improvements in infrastructure, economic development, and industrial structure upgrading are observed. This new approach to urbanization places greater emphasis on environmental benefits rather than solely economic benefits. As a result, carbon emission efficiency can be enhanced.

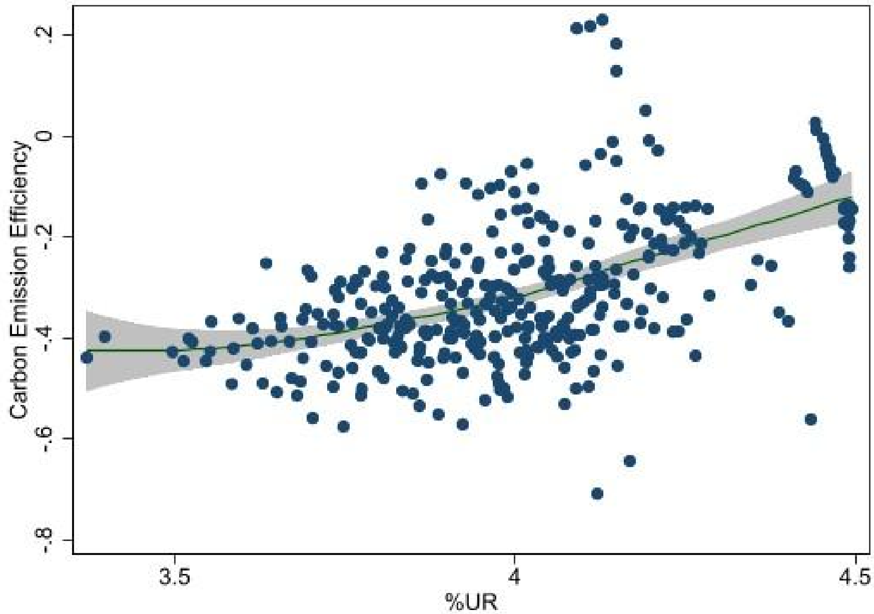

Fig. 3. Partial fit of the urbanisation and CO2 emissions efficiency nexus. Note: Points on the graph are estimated partial residuals for carbon emissions. The maroon curve represents fitted values for adjusted effects of other explanatory variables in the model, and 95% confidence bands are indicated by shading.

The second and third columns of Table 5 present the results of estimating the control variables in the semiparametric panel model for both coastal and inland provinces' municipalized-CO2 emission efficiencies. The coefficient representing the elasticity of carbon emission efficiency with respect to energy intensity is highly significant at the 1% level. The negative coefficient suggests that a 1% increase in energy intensity leads to a 0.467% decrease in carbon emission efficiency for coastal provinces. Most of the enterprises in these provinces still heavily rely on fossil fuels, and the survey data indicates that energy intensity has increased to some extent over time, resulting in a decline in carbon emission efficiency. Similarly, for inland provinces, the elasticity of carbon emission efficiency to energy intensity is also highly significant at the 1% level, but with a positive coefficient. This implies that for every 1% increase in energy intensity, the carbon emission efficiency decreases by 0.369%. Recognizing the importance of energy conservation and emission reduction, China has prioritized the development of clean and renewable energy sources to replace traditional fossil fuels. Many inland provinces have established clean energy bases to promote the adoption of renewable energy, such as photovoltaic and wind energy.

In coastal provinces, the elasticity of the carbon emission coefficient to population density is significant, whereas it is not significant in inland provinces. This can be attributed to the faster economic development of coastal cities and the combined effect of factors like transportation and climate, which attract more people to migrate to these areas for better opportunities. As urbanization progresses, a "Matthew effect" is gradually formed, leading to an increase in population inflow, which in turn contributes to the rise in carbon emission efficiency.

Regarding the elasticity of the carbon emission coefficient to per capita disposable income in coastal areas, it is estimated to be -0.238, indicating a significant negative impact. This suggests that a 1% increase in per capita disposable income leads to a 0.238% decrease in carbon emission efficiency. However, the per capita disposable income does not have a statistically significant effect in inland cities. This difference can be explained by the fact that coastal cities have developed economies with larger industrial sectors and higher per capita incomes. With the increase in per capita disposable income, consumption patterns change, shifting from basic necessities like clothing and food to higher consumption categories such as travel and housing. This change in consumption patterns subsequently leads to increased energy consumption. China's rising Engel's coefficient, which measures the proportion of income spent on food, supports this trend.

The ratio of the tertiary industry to GDP has a significant negative effect on the carbon emission coefficients in both coastal and inland areas. Comparing the coefficients, it is observed that the tertiary industry ratio has a greater impact on inland areas. The development of the tertiary industry has a profound influence on technological progress, labor productivity, and the market economy of a country. Continuous improvement and expansion of this sector lead to increased technical efficiency, effectively promoting resource recycling and reducing pollutant emissions.

In Figure 4, which illustrates the relationship between urbanization and carbon emission efficiency in coastal provinces using a semi-parametric model, no inverted "U" curve relationship between urbanization and carbon emission efficiency is found. It is evident that carbon emission efficiency gradually decreases with the progression of urbanization. Coastal cities experience relatively fast economic development, but the negative impact of economic development on urbanization prevents the appearance of a scale effect on carbon emissions [45].

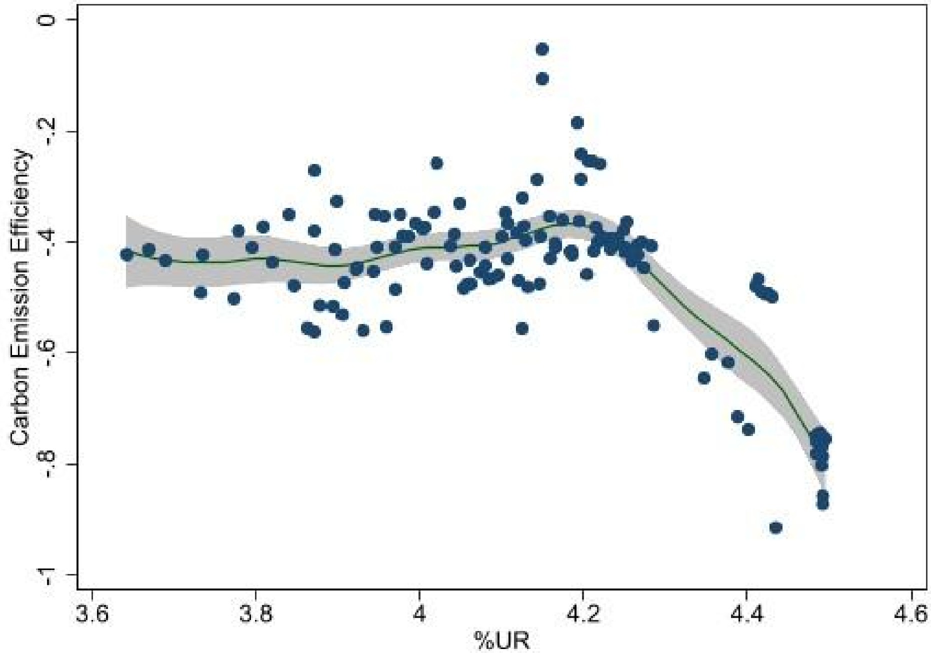

Fig. 4. Partial fit of the urbanisation and CO2 emissions nexus in coastal provinces. Note: Points on the graph are estimated partial residuals for carbon emissions. The maroon curve representsfitted values for adjusted effects of other explanatory variables in the model, and 95% confidence bands are indicated by shading.

Figure 5 presents the relationship between urbanization and carbon emission efficiency in inland provinces using a semiparametric model. The fitted curves in the figure reveal no evidence of an Environmental Kuznets Curve (EKC) relationship between urbanization and carbon emission efficiency. Mehmood et al. also found that urbanization reduces carbon emissions in China [46]. From a macro perspective, urbanization promotes economic growth to a certain extent, accelerates the flow of labor, capital, and technology, and increases productivity. It also impacts industrial structure, encouraging enterprise development. Moreover, urbanization influences residents' lifestyles, employment, education, healthcare, and overall quality of life. Positive and sustainable urbanization can effectively avoid excessive exploitation of land resources and reduce waste. Currently, China advocates "green urbanization," aiming to integrate energy conservation and emission reduction into urban development through ecological construction. Consequently, carbon emission efficiency improves in later stages of urbanization.

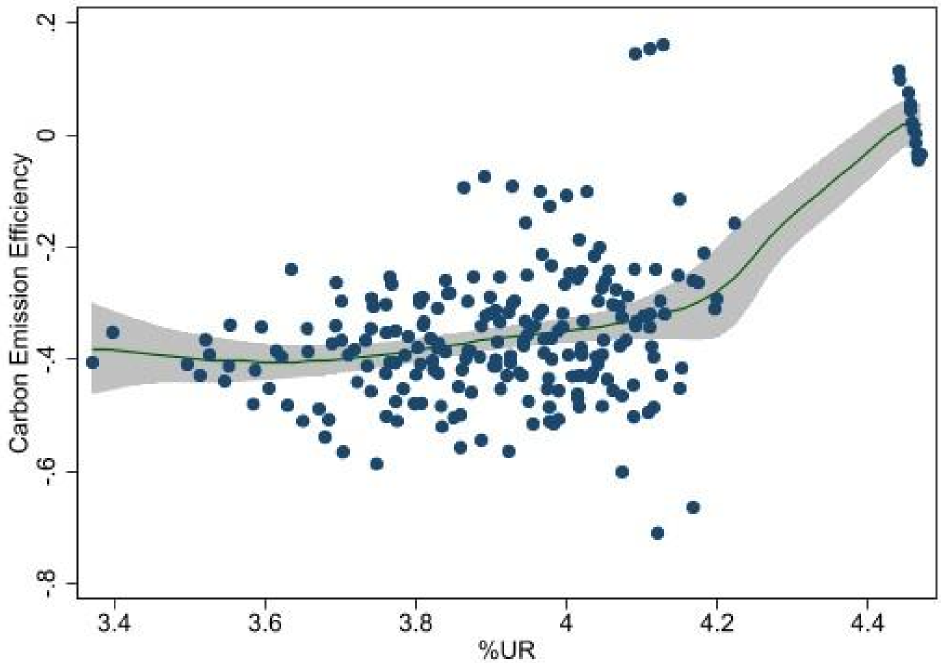

Fig.5. Partial fit of the urbanisation and CO2 emissions nexus in Iand provinces. Note: Points on the graph are estimated partial residuals for carbon emissions. The maroon curve represents fitted values for adjusted effects of other explanatory variables in the model, and 95% confidence bands are indicated by shading.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper adopts the super-efficient SBM model to measure the carbon emission efficiency of each province in China and analyze the impact of urbanization on China's carbon emission efficiency. The results indicate the following:

1. China's overall carbon emission efficiency is relatively low, and on average, coastal cities exhibit higher carbon emission efficiency compared to inland cities.

2. The semi-parametric study demonstrates that China's overall carbon emission efficiency increases with the level of urbanization. However, the carbon emission efficiency of coastal areas decreases as urbanization progresses. In contrast, the carbon emission efficiency of inland areas initially changes smoothly with the level of urbanization and then rises sharply in the later stages.

3. Energy intensity has a significant negative impact on carbon emission efficiency, with coastal cities showing a higher impact than inland cities. Population density has a significant positive impact on carbon emission efficiency, while per capita income has a significant negative impact. However, neither of these factors has a significant impact on carbon emission efficiency in inland cities. The proportion of the tertiary industry in GDP has a negative impact on carbon emission efficiency, with a more significant effect observed in inland cities.

Based on the conclusions drawn in this paper, the following recommendations are proposed:

1. Energy Perspective: Given the significant impact of energy intensity on carbon emission efficiency, it is crucial for each province to actively develop and establish clean energy bases. Encouraging the development and utilization of clean energy sources while reducing reliance on fossil fuels is essential.

2. Population Perspective: Both population density and per capita income play a role in carbon emission efficiency. Cities should implement policies to attract more talents, which can help disperse the population effectively. Additionally, investing in infrastructure to promote shared usage can contribute to improved carbon emission efficiency.

3. Urbanization Perspective: Urbanization has a noteworthy impact on carbon emission efficiency. Considering the significant pressure on China to reduce carbon emissions, it is vital to actively pursue the development of a green economy. While prioritizing the speed of urbanization, equal emphasis should be placed on the quality of urban development.

4. Industrial Structure Perspective: The industrial structure should be adjusted reasonably to enhance carbon emission efficiency. With the rapid growth of China's tertiary industry, it is important to guide technological innovation, promote innovative and green development. Different regions, according to their unique development characteristics, should embrace a green-oriented approach and make appropriate adjustments to their industrial structures to achieve emission reduction goals.

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