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The Carbon Dioxide Emissions Differences Impacts Between Urban and Rural Areas

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ABSTRACT

In China, the patterns of carbon emissions exhibit a clear divergence between urban and rural areas. While cities experience a surge in carbon emissions, rural regions maintain more stable levels, albeit with modest increases. These contrasting trends contribute to widening inter-provincial disparities in urban areas, whereas rural inequalities remain relatively unchanged. Over time, the overall inequality in carbon emissions across the country has undergone distinct phases, transitioning from a period of escalation to gradual reduction, eventually reaching a point of stabilization. Market-driven factors, alongside governmental actions, are crucial in shaping this inequality, with urban and rural areas responding differently to policy interventions. The digital economy has emerged as a pivotal force in mitigating disparities, producing significant positive spillover effects across regions. The relationship between economic development and carbon emissions inequality follows a U-shaped pattern, indicating that early stages of growth might aggravate inequality before improvement occurs. On the other hand, while optimizing industrial structures can address urban-rural disparities, the spatial spillover impact of these changes remains limited. Governmental efforts to regulate carbon emissions have been less effective in reducing inequality and, in some cases, may inadvertently contribute to further divergence. Meanwhile, openness to international markets has a more beneficial influence, whereas the role of population density in this dynamic proves to be multifaceted and difficult to predict.

KEYWORDS

Urban emission; Rural population; Digital economy

1. INTRODUCTION

In recent decades, global warming has emerged as a critical issue with far-reaching effects on the environment, economy, and society [1]. Since the 1980s, the acceleration of global warming has led to severe environmental impacts, including glacier melting, rising sea levels, more frequent extreme weather events, and significant losses in biodiversity. Data from the World Meteorological Organization indicates that in 2022, the global average temperature was approximately 1.15°C above pre-industrial levels [3]. Additionally, NASA's report reveals that the global mean surface temperature in 2022 matched that of 2015, marking it as the fifth hottest year on record with temperatures around 1.11°C above the late 19th-century average. Initially, the greenhouse effect was not universally accepted as the primary driver of global warming. However, subsequent research has solidified the understanding that greenhouse gases, particularly carbon dioxide and methane, are significant contributors to this phenomenon [4]. In response to this pressing issue, the international community has launched several initiatives aimed at curbing greenhouse gas emissions. Key agreements such as the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement have been established to foster global cooperation and mitigate the effects of climate change.

Even with global climate agreements in place, the issue of greenhouse gas emissions remains critical, particularly in nations undergoing rapid. Data from the International Energy Agency reveals that energy-related emissions reached a historic high of 41.3 billion tons of carbon dioxide equivalent in 2022. The majority of these emissions, 89%, are derived from carbon dioxide produced through energy use and industrial activities. The impact of this increase is not uniform across all regions. In China, a prominent contributor to global emissions, there is a noticeable difference in carbon output between urban and rural areas. This urban-rural emissions gap illustrates the broader implications of China's rapid economic and urban growth, which challenges both national policies and international climate objectives.

Achieving the "dual carbon" goals—reducing emissions and enhancing carbon sequestration—requires a focus on emissions reduction as a foundational element [5]. In China, urban and rural areas exhibit notable disparities in economic development, resource distribution, and infrastructure. These differences extend to consumption patterns, where structural variances between urban and rural regions are particularly stark. As urbanization advances and consumer spending rises, significant shifts in the lifestyles of urban and rural populations lead to increased energy demands.

To effectively address carbon emissions linked to consumer behavior and facilitate a shift towards low-carbon consumption, a thorough analysis of consumption-related carbon emissions in China is essential. This analysis should include an assessment of current carbon emissions from urban and rural consumption, an evaluation of the disparities in these emissions, and an investigation into the factors influencing these inequalities. Developing targeted interventions to promote low-carbon consumption and assess the ecological value of urban versus rural areas is crucial.

This paper aims to explore the carbon emissions associated with the consumption activities of urban and rural residents in China through several dimensions. Initially, it quantifies CO2 emissions from direct energy use by urban and rural households at the provincial level using the IPCC calculation method. Subsequently, the paper examines the evolving patterns of these emissions through kernel density estimation. It further analyzes regional variations in carbon emissions between urban and rural areas across China's eight major regions using the Theil Index to measure inequality. Finally, it investigates the factors affecting the disparity in carbon emissions between urban and rural residents using provincial-level panel data, discussing potential spatial spillover effects.

2. RELATED WROK

In China, the lack of official agencies providing direct carbon dioxide emission data necessitates alternative methods for assessing carbon emission intensity. Various techniques are employed to measure carbon emissions in both urban and rural settings, including chemical mass balance and inventory methods, eddy covariance and micrometeorological approaches, as well as remote sensing and geospatial technologies. Chemical mass balance and inventory methods have been utilized in several studies. For instance, Blanchard et al. [6] applied this method along with the U.S. EPA’s National Emission Inventory to pinpoint sources of particulate and gaseous emissions in different areas. [7] adopted a consumption-based perspective, linking urban development's climate impacts to global emissions. Additionally, [7] employed an inventory approach to compile and summarize CO2 emissions and sequestrations within urban environments. Eddy covariance and micrometeorological methods have also been applied. [8] validated urban carbon emission models through direct eddy-covariance flux measurements. [9] used continuous CO2 flux measurements with the eddy covariance method to assess emissions in urban areas, while [10] addressed the challenges associated with eddy covariance CO2 flux measurements in urban settings and proposed various solutions. In the realm of remote sensing and geospatial technologies, [11] utilized texture classification of Landsat-TM satellite imagery to estimate CO2 emissions related to urban land use and activities.

Accurate measurement of carbon dioxide emissions is crucial for understanding the characteristics and determinants of carbon emission inequality. Research at global and national scales has shown varying patterns of carbon emission inequality. [12] identified disparities in carbon emissions among countries due to differences in per capita income, noting a modest reduction in inequality from 1971 to 1999. [13] explored the effects of urban expansion, industrialization, trade, and economic development on emissions across multiple levels, from national to household scales. At a more localized level, [14] examined spatial carbon inequality within China's Yangtze River Economic Belt, attributing it primarily to economic factors, industrial composition, and final demand structures. [15] documented a decreasing trend in per capita industrial carbon emissions inequality within the Pearl River Delta urban agglomeration, highlighting industrial energy intensity as a significant factor. Regarding the interplay between income inequality and carbon emissions, [16] observed that higher income inequality in the United States initially increased emissions but eventually led to reductions in the long term. [17] found that in OECD and high-income non-OECD countries, increased income inequality generally led to reduced emissions, though this effect was minimal in low-income non-OECD countries. [18] both reported that greater income inequality was associated with environmental degradation and higher carbon emissions. In terms of spatial spillover effects, [20] found positive spatial correlations in carbon emissions across Chinese provinces, with population growth and economic urbanization being key determinants of regional emission levels. [19] highlighted significant spatial spillover effects in carbon emissions, particularly pronounced in Western China compared to the Eastern and Central regions. [21] pointed out that factors such as urbanization, technology, wealth, and population density have varying spatial impacts on carbon emissions across different regions i Existing research indicates that although studies on carbon emission intensity have seen a steady rise each year, there remains significant potential for further exploration in this area. Firstly, much of the current research has concentrated on emissions from the industrial sector, while comparatively little attention has been given to household emissions, particularly those arising from domestic energy consumption. With ongoing urbanization and rising living standards in both urban and rural areas, emissions from household energy use have become increasingly relevant and should not be ignored. Secondly, the limited research on household energy consumption has often focused on specific regions or rural households. More comprehensive studies that analyze both urban and rural households across China, utilizing a unified measurement approach and consistent analytical framework, are necessary. Finally, there is a shortage of systematic and thorough investigations into the current patterns and dynamics of urban and rural carbon emissions in China. Few researchers have examined the spatial spillover effects of the factors driving carbon emission inequality between urban and rural residents, leaving an important gap in understanding this issue in China.

3. METHOD

3.1. Urban and Rural Residents' Carbon Emission Calculation

In 2006, the Intergovernmental Panel on Climate Change (IPCC) introduced a set of methodologies and guidelines aimed at estimating and reporting greenhouse gas emissions. The IPCC approach emphasizes emissions from three key areas: fossil fuel combustion, industrial processes and product use, and agricultural activities [22]. Carbon emissions are calculated using the following formula:

$$CO2 = \sum_{I=1}^{N} E_I \times ncv_I \times CEF_I \times OF_I \times \frac{11}{3} \quad (1)$$

Where, I is the energy categories, and the E_I represents its consumption. NCV_I refers to the net calorific value, representing the average lower heating value of the energy source. CEF_I stands for the carbon emission factor per unit of heating value, while OF_I refers to the carbon oxidation factor.

The constants 11 and 3 represent the molecular weights of carbon dioxide and carbon, respectively, and are used to convert carbon emissions into equivalent carbon dioxide emissions.

3.1.1. The density of kernel analysis

The kernel density estimation (KDE) technique is a robust non-parametric method used for estimating the probability density function of a random variable. By applying a smooth kernel function around individual data points, it generates a continuous estimate of the data's distribution. This approach is particularly valuable for analyzing the changing patterns of carbon emissions at various levels, including national, urban, and rural scales. Unlike traditional methods, KDE does not require any assumptions about the data's underlying distribution, allowing for a flexible and unbiased analysis of emission trends across different regions. The method offers a more intuitive and detailed visualization of both the spatial and temporal evolution of carbon emissions, aiding researchers and decision-makers in evaluating and comparing the effectiveness of carbon reduction policies across regions. Additionally, KDE is especially useful in identifying multimodal distributions and skewed data, which is critical for comprehending complex emission behaviors. The formula used for this analysis is presented as follows:

$$f(x) = \frac{1}{NH} \sum_{i=1}^{N} (\frac{x - x_i}{H}) \tag{2}$$

In Equation 2, $f(x)$ indicates the density estimate at the location x. The variable N represents the number of samples available, and x_i refers to each specific data point. The parameter H (where $H > 0$) determines the extent of the kernel function's influence. The kernel function $f(x)$ is a non-negative function that sums to one and is employed to smooth out data surrounding each observation.

The choice of kernel function and bandwidth H is crucial for accurate kernel density estimation. Commonly used kernel functions include Gaussian, uniform, and triangular types. The selection of H greatly affects the density estimate's smoothness. Equation 3 provides the formula to determine the optimal value for H:

$$H = \left(\frac{4}{3N}\right)^{\frac{1}{5}} = 1.6N^{0.2} \tag{3}$$

3.1.2. Econometric analysis

Global Spatial Autocorrelation: In order to comprehensively analyze the spatial autocorrelation of urban-rural carbon emission inequality and its contributing factors, this study employs the Global Moran's Index. This statistical tool measures the degree of clustering or dispersion in the spatial distribution of carbon emission inequality across various regions. The calculation of the Global Moran's Index is described by the following formula:

$$I = \frac{N}{\sum_{I=1}^{N} \sum_{J=1}^{N} W_{i,j}} \times \frac{1}{W_{i,j}} \tag{4}$$

Where $W_{i,j}$ is the spatial relations between I and J. In the analysis of urban and rural carbon emissions and their influencing factors, the Global Moran's Index is employed to quantify spatial autocorrelation. This tool is instrumental in detecting the spatial clustering of carbon emissions and examining how these clusters vary across different geographical regions. By providing a spatial perspective, it enhances our understanding of urban-rural carbon emission disparities and facilitates more effective policy responses. Spatial Durbin Model (SDM): To further investigate the determinants of urban-rural carbon emission inequality and their spatial spillover effects, this study applies the Spatial Durbin Model (SDM) within a spatio-temporal framework. The SDM not only captures the spatial lag of the dependent variable but also incorporates the spatial lag of explanatory variables. This dual consideration allows the model to account for spatial dependencies and the spillover effects of these factors, providing a more comprehensive analysis of spatial relationships (Han and Yang, 2020). The foundational equation for the SDM is given in Equation 5:

$$y_{it} = \rho W y_{it} + \beta X_{it} + W X_{it} \gamma \quad (5)$$

The Spatial Durbin Model (SDM) is applied in this analysis to capture both the direct and spillover effects of factors influencing urban-rural carbon emission inequality (URC). The model employs different spatial weight matrices, including geographic distance, contiguity, and inverse distance matrices, to ensure robustness and mitigate potential errors in the spatial weight matrix setting. The spatial autoregressive coefficient reflects the degree of spatial dependency, while the direct and spillover effects are represented by respective coefficient vectors. The analysis includes a range of explanatory variables related to both market and government factors. Market-level variables include the digital economy (measured through information development, internet penetration, and digital transactions), economic development (represented by per capita GDP), and industrial structure (captured through the ratio of tertiary to secondary industry output). To account for non-linear effects, the analysis incorporates a quadratic term for economic development. Government-level factors include environmental regulation, measured by the ratio of industrial pollution control investment to industrial added value, and government intervention, represented by fiscal expenditure as a percentage of regional GDP. Additionally, the study examines the effects of foreign direct investment, using the total value of imports and exports as a measure, and population density, calculated as the total population divided by the region's administrative area. These variables allow for a comprehensive analysis of how market dynamics and government policies influence carbon emission inequality across different regions in China which is shown as Table 1.

Table 1. Descriptive statistics

Variable	Obs	Mean	SD	Min	Median	Max
URC	510	0.07	0.09	0.00	0.05	0.55
DDT	510	0.13	0.145	0.00	0.09	0.819
AGDP	510	1.20	0.780	0.33	0.93	4.80
IS	510	1.11	0.642	0.50	0.93	5.29
GI	510	0.23	0.09	0.08	0.20	0.64
ER	510	0	0.004	0.00	0.03	0.031
FI	510	0.330	0.354	0.08	0.139	1.72
PP	510	455.612	668.9	7.51	292.14	3925.87

3.2. Dynamic Emissions Changes

This paper analyzes the dynamic evolution of national, urban, and rural carbon emissions, focusing on the trends in national residential carbon emissions from 2005 to 2021, as illustrated in Figure 1. The kernel density analysis shown in Figure 1A highlights the overall shift in the distribution of carbon emissions during the study period. The center of the density function moves rightward, indicating a clear increase in national average residential carbon emissions over time.

In 2005, the distribution was more concentrated with a unimodal pattern, but by 2021, the distribution had broadened significantly. The peak density in 2021 [24] is lower than in previous years, despite a rightward shift, signifying increased variability in emissions. While fewer residents fall into high-emission categories, the overall emissions have grown, and the range has expanded, signaling wider provincial disparities. The evolving distribution in Figure 1 reflects changes in energy consumption patterns, economic development, and improved living standards across provinces, which have led to diverse lifestyle impacts and rising carbon emission intensities. This visualization underscores the need to address regional inequalities in carbon emissions as part of broader national carbon reduction efforts.

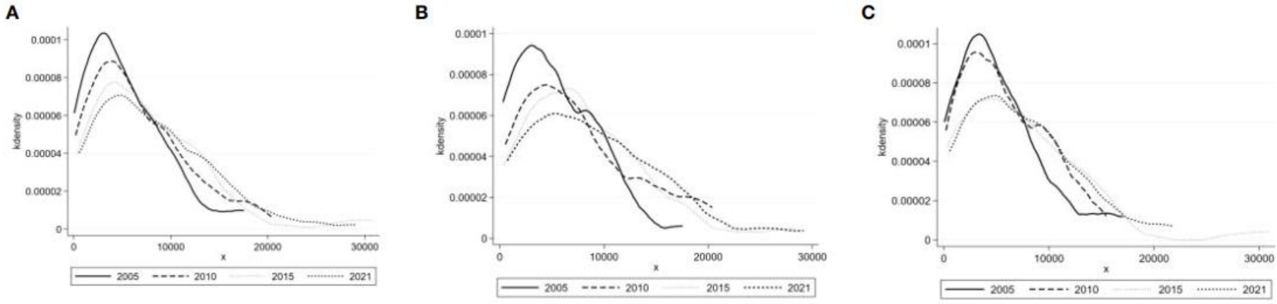

Figure 1. The results of carbon emissions

Figure 1B illustrates the temporal changes in urban residential carbon emissions. Over the study period, the center of the density function shifts rightward, indicating an overall rise in emissions. The peak shows fluctuations but remains relatively stable, while the range of emissions expands. From 2005 to 2010, the curve’s shape remains consistent with a rightward shift and a slight decrease in peak height, suggesting increased urban carbon emission intensity and a widening provincial disparity. By 2015, the density function evolves from a unimodal shape to a smoother distribution, with an expanded range, reflecting further growth in emission intensity and a continued provincial gap. In 2021, the density function shifts significantly rightward, displaying a lower peak and substantial multimodality, indicating a pronounced increase in average urban carbon emissions and a notable expansion of the provincial gap.

Figure 1C depicts the trend in rural residential carbon emissions. The analysis shows a slight rightward shift in the density function center, with a decrease in peak height and an expanding range. Compared to 2005, the 2010 data shows a minor increase in rural emissions and no significant change in the provincial gap. By 2015, the rightward shift of the center continues [25], with a smoother peak and ongoing range expansion, suggesting a slight rise in emission intensity and a possible widening of the provincial gap. In 2021, the density function exhibits minimal changes in the center, a further decrease in peak height, and a maintained expansion of the range with some multimodality. This implies that rural emission intensity may have stabilized or slightly decreased, with the provincial gap remaining steady or slightly increasing over the study period.

3.3. The Regional Difference of Carbon Emission

Figure 2 illustrates the temporal dynamics of the national carbon emissions as measured by the Theil Index. The data reveal a notable decrease in the Theil Index from 0.1056 in 2005 to 0.0598 in 2021, indicating a progressive reduction in the overall variance of carbon emission intensity across the nation. Region-specific analyses demonstrate varying trends. The Northeast region experienced a significant increase in the Theil Index, rising from 0.0099 in 2005 to 0.0621 in 2021. This increase suggests an intensification of carbon emission disparity within this region over the study period. Conversely, coastal regions, including the Northeastern Coastal, Northern Coastal, and Southern Coastal areas, exhibited relatively stable Theil Index values, indicating consistent levels of emission intensity disparity. The Northwest and Southwest regions displayed some fluctuations; however, the overall trend remained stable. More pronounced fluctuations were observed in the Yangtze River Midstream and Yellow River Midstream regions. Notably, the Yellow River Midstream region saw an increase in its Theil Index from 0.0757 in 2005 to 0.0854 in 2021, reflecting a widening disparity in carbon emission intensity.

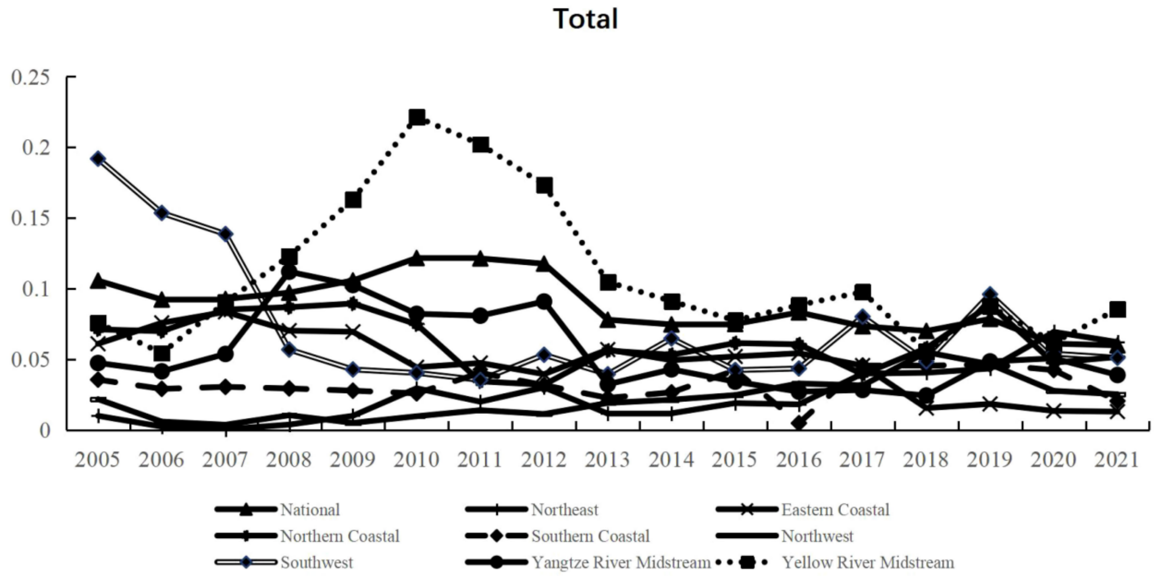

Figure 2. The dynamic trends of carbon emissions

Figure 3 provides an analysis of urban carbon emissions, revealing that the national Theil Index decreased from 0.177 in 2005 to 0.1124 in 2021. This reduction indicates a decrease in the variance of urban carbon emission intensity across the country. In particular, the Northeast region exhibited a substantial rise in the Theil Index, increasing from 0.0007 in 2005 to 0.1214 in 2021. This trend indicates a growing imbalance in urban carbon emission intensity in the Northeast. Coastal regions, such as the Northeastern Coastal, Northern Coastal, and Southern Coastal areas, displayed only minor fluctuations in their Theil Index values, suggesting relatively stable differences in emission intensity. The Northwest and Southwest regions also experienced some variability, though without significant overall changes. The Yangtze River Midstream and Yellow River Midstream regions experienced more significant variations in their Theil Index values [27]. In particular, the Yellow River Midstream region showed a notably higher index from 2008 to 2011 compared to other regions, indicating an increasing disparity in urban carbon emission intensity during this period.

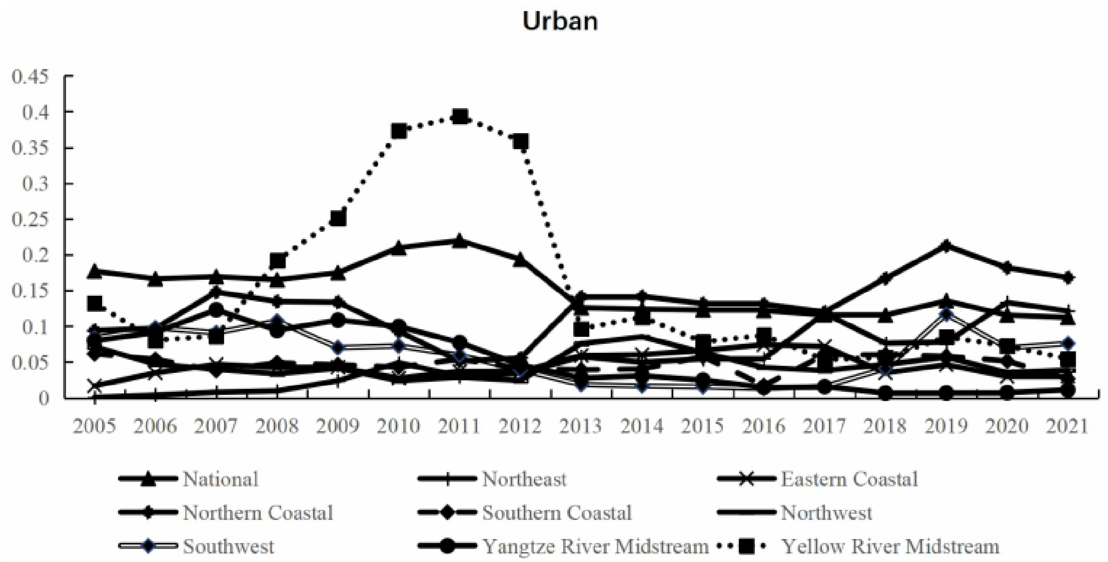

Figure 3. The dynamic distribution of urban carbon emissions

Figure 4 illustrates the trends in rural carbon emissions as measured by the Theil Index. The national Theil Index decreased from 0.2275 in 2005 to 0.1136 in 2021, indicating a significant reduction in the variance of rural carbon emission intensity across China. This trend reflects a movement toward greater uniformity in rural carbon emissions over the study period. In the Northeast region, the Theil

Index also decreased, from 0.165 in 2005 to 0.0427 in 2021, signifying a reduction in the disparity of rural carbon emissions within this region. Coastal regions, including the Northeastern Coastal, Northern Coastal, and Southern Coastal areas, exhibited substantial fluctuations in their Theil Index values. However, these fluctuations did not reveal a clear long-term trend, suggesting that variations in agricultural production methods and energy consumption patterns contribute to the diversity observed in these areas. The Northwest and Southwest regions experienced relatively minor changes in their Theil Index, indicating that the differences in rural carbon emission intensity are relatively stable in these regions. The Theil Index values for the Yangtze River Midstream and Yellow River Midstream regions exhibited more complex patterns. Specifically, the Yangtze River Midstream region displayed fluctuating indices from 2005 to 2021, while the Yellow River Midstream region showed a notable downward trend starting from 2008. This downward trend, particularly evident from 2008 onwards, reflects significant structural changes in agricultural production and energy consumption in the Yellow River Midstream area.

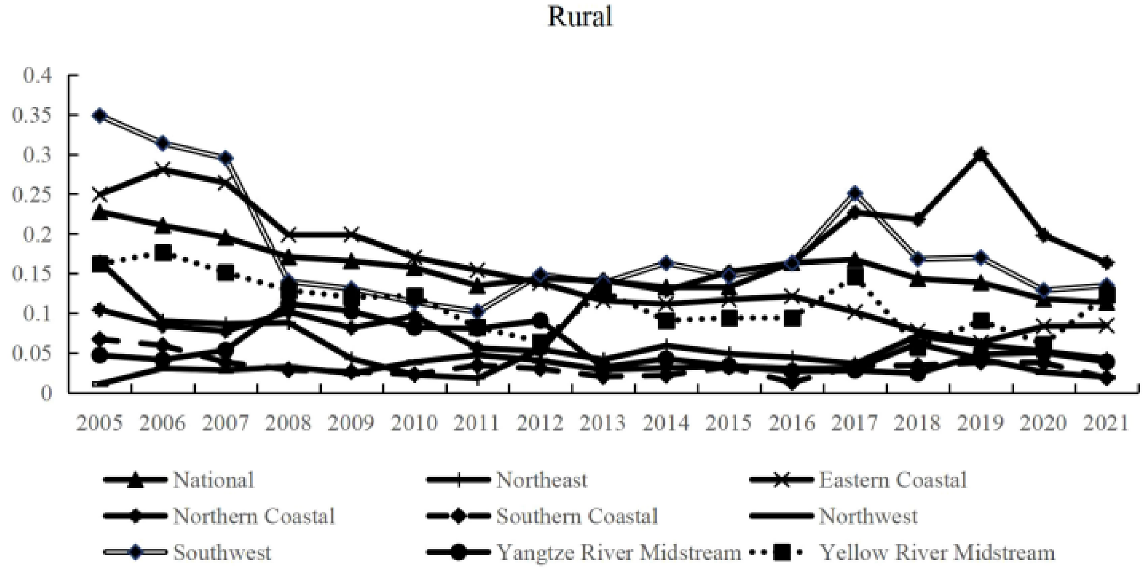

Figure 4. The dynamic distribution of urban rural emissions

3.4. The Impact of Uneven Urban and Rural CO2 Emissions

Before delving into the inequality of urban-rural carbon emissions and the factors influencing it, this study performed a global spatial autocorrelation test for these variables. The results are summarized in Table 2 and visualized in Figure 5, which presents the Moran scatterplot for urban-rural carbon emission inequality in 2018. The analysis revealed that Moran's I for urban-rural carbon emission inequality generally passed the significance test across most years, showing an upward trend despite some fluctuations. This indicates that high-inequality regions were often adjacent to other high-inequality areas, while low-inequality regions tended to be close to other low-inequality areas throughout the study period. In 2010, Moran's I for the digital economy showed a significant positive value, highlighting a notable positive spatial correlation between digital economy development and urban-rural carbon emission inequality. This correlation was particularly strong in that year. Conversely, the Moran's I for economic development consistently showed a significant positive value across all years, indicating a stable positive spatial clustering between economic growth and urban-rural carbon emission inequality. The Moran's I for industrial structure demonstrated negative values in some years, suggesting a potentially dispersed spatial distribution for this factor. Government intervention and foreign direct investment also passed the significance test in most years, reflecting significant spatial clustering effects for these variables. The Moran's I for industrial concentration was significant in all years, indicating a strong and stable spatial correlation effect on urban-rural carbon emission inequality. However, Moran's I for population density was not significant in most years, suggesting that the spatial relationship between population density and urban-rural carbon emission inequality is less pronounced.

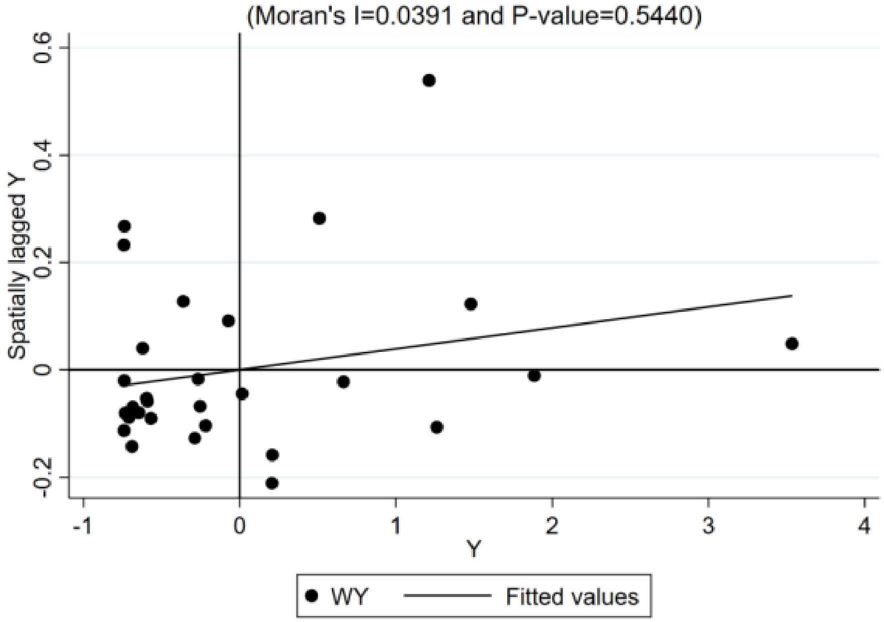

Figure 5. The dynamic distribution of urban rural emissions

Table 2. Descriptive statistics

Year	URC	DT	AGDP	IS	ER	GI	FI	PP	
2005	0.038	0.008	0.112	-0.066	-0.035	0.118	-0.002	-0.015	
2010	0.054	0.079	0.118	-0.047	0.041	0.148	0.009	-0.023	
2015	-0.02	0.012	0.100	-0.060	0.034	0.138	0.017	-0.023	
2020	0.104	-0.036	0.044	-0.036	0.014	0.140	0.001	-0.020	
2023	0.082	0.119	0.120	0.137	0.2335	0.2339	0.043	-0.021	

In summary, Table 2 and Figure 5 reveal significant spatial autocorrelation between urban-rural carbon emission inequality and its influencing factors in China, with distinct characteristics observed in different years. These findings suggest that policy formulation should account for the spatial clustering characteristics of these factors and their impact on urban-rural carbon emission inequality through spatial relationships.

In examining urban-rural carbon emission inequality and its influencing factors, this study utilized multiple spatial weight matrices, including geographic distance, economic distance, and adjacency matrices, to conduct an extensive spatial econometric analysis.

The methodology involved several key steps:

Initial Estimation: An Ordinary Least Squares (OLS) estimation was first performed on a model that did not account for spatial effects. This preliminary analysis provided the basis for deriving the Lagrange Multiplier (LM) and its robust statistics (R-LM), which helped in determining whether a Spatial Autoregressive (SAR) model or a Spatial Error Model (SEM) was appropriate.

Spatial Effects Testing: If the LM test indicated the presence of spatial effects, the study followed Elhorst’s (2014) recommendation by applying the Spatial Durbin Model (SDM) directly. The SDM was chosen for its general applicability in spatial econometrics.

Fixed Effects Evaluation: The Likelihood Ratio (LR) test was then used to assess whether to include Spatial Fixed Effects (SFE) or Temporal Fixed Effects (TFE) in the SDM.

Fixed vs. Random Effects: The Hausman test was employed to decide between fixed effects and random effects in the SDM framework.

Model Simplification: Finally, the Wald and LR tests were conducted to determine whether the SDM could be simplified to a SAR or SEM model.

The results indicated that the dynamic Spatial Durbin Model with dual fixed effects was the most suitable for spatial econometric estimation in this study. To validate the fit of the SDM, Wald and LR tests were performed. The P-values for the Wald space lag test, LR space lag test, Wald space error test, and LR space error test were all significantly below the 1% level, confirming the superior fit of the SDM model.

Additionally, the regression coefficients of the SDM model did not conform to the transformation hypothesis, suggesting that the SDM model could not be effectively reduced to either a SAR or SEM model. Consequently, the study selected the SDM model as the most appropriate analytical approach for assessing urban-rural carbon emission inequality and its determinants.

3.5. Analysis of the Spatial Spillover Effects of Various Factors

This study provides an in-depth analysis of the factors influencing urban-rural carbon emission inequality, using the estimation results from Table 3 to assess direct, indirect (spatial spillover), and total effects. The analysis employs various spatial matrices, including geographic, economic, and spatial adjacency matrices. The direct effects of economic development on urban-rural carbon emission inequality are negative across all spatial matrices, with values of -0.100 in the geographic matrix, -0.224 in the economic matrix, and -0.126 in the spatial adjacency matrix, all significant at the 5% level. This indicates that economic development generally reduces the disparity in carbon emissions between urban and rural areas. However, the quadratic term for economic development is positive in all models, revealing a U-shaped relationship where, after a certain level of economic growth, inequality may increase. The direct effects of industrial structure are consistently negative across all spatial matrices and significant at least at the 5% level in the geographic and economic matrices, suggesting that changes in industrial structure contribute to reducing carbon emission inequality. Despite this, the indirect effects of industrial structure are not significant in any of the models, indicating that spatial spillovers from industrial structure do not significantly impact urban-rural carbon emission inequality. Government intervention shows no significant direct effects in any of the models, suggesting that it does not have a substantial direct impact on carbon emission inequality between urban and rural areas. Conversely, environmental regulation has positive direct effects significant at the 10% level in the economic matrix, suggesting that stricter regulations might, in some cases, increase urban-rural carbon emission inequality. The degree of openness exhibits negative and significant direct effects at the 5% level in the spatial adjacency matrix, implying that increased openness can help reduce carbon emission inequality between urban and rural areas. Meanwhile, population density has positive direct effects significant at the 5% level in the geographic matrix, indicating that higher population density may directly contribute to increased inequality. However, the indirect effects of population density are negative and significant at the 1% level in the spatial adjacency matrix, suggesting that although higher population density may increase local inequality, it could reduce inequality in neighboring regions through spatial spillover effects. Overall, these findings underscore the complex interplay of factors affecting urban-rural carbon emission inequality and highlight the need for nuanced policy measures that consider both direct impacts and spatial spillovers.

Table 3. Direct and indirect effects.

Variable	Geographic distance			Economic distance			Gographical proximity		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
DT	-0.050	-0.204	-0.254	-0.042	0.179	0.137	-0.021	-0.166	-0.187
	(0.020)	(0.091)	(0.085)	(0.020)	(0.056)	(0.063)	(0.021)	(0.039)	(0.035)
AGDP	-0.100	-0.521	-0.621	-0.224	-0.149	-0.372	-0.126	-0.316	-0.441
	(0.051)	(0.181)	(0.164)	(0.044)	(0.096)	(0.090)	(0.050)	(0.094)	(0.084)
AGDP2	0.062	0.160	0.222	0.064	0.060	0.124	0.061	0.101	0.163
	(0.008)	(0.034)	(0.033)	(0.007)	(0.020)	(0.020)	(0.008)	(0.018)	(0.018)
IS	-0.036	0.056	0.020	-0.036	0.103	0.067	-0.037	0.028	-0.010
	(0.013)	(0.072)	(0.075)	(0.013)	(0.034)	(0.036)	(0.014)	(0.038)	(0.044)
GI	0.132	-0.811**	-0.679*	-0.012	-0.249	-0.261	0.023	-0.179	-0.157
	(0.086)	(0.407)	(0.375)	(0.079)	(0.167)	(0.183)	(0.087)	(0.145)	(0.139)
ER	0.900	-2.505	-1.605	1.413	-1.759	-0.346	0.953	-0.870	0.083
	(0.781)	(4.192)	(4.198)	(0.827)	(2.053)	(2.144)	(0.783)	(1.922)	(2.127)
FI	-0.031	-0.098	-0.129	-0.035	-0.002	-0.038	-0.057	-0.078*	-0.134
	(0.027)	(0.133)	(0.143)	(0.029)	(0.070)	(0.071)	(0.028)	(0.045)	(0.061)
PP	0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

4. CONCLUSION

This paper utilizes the IPCC methodology to assess urban and rural carbon emissions across Chinese provinces from 2005 to 2021. By employing kernel density estimation and the Theil Index, the study examines regional disparities and temporal changes in carbon emissions. Key findings are:

Dynamic Trends: From 2005 to 2021, national, urban, and rural carbon emissions displayed notable differences. National urban carbon emission density generally increased, with a shift in the center of the density function and a widening inter-provincial gap. Urban areas saw a rightward shift and fluctuating peak, indicating growing carbon emission intensity. Rural areas showed slight rightward movement and a decreasing peak, reflecting relative stability but increasing inter-provincial differences.

Phases of Inequality: Urban-rural carbon emission inequality in China experienced three phases: rise, decline, and stabilization. The Theil Index rose rapidly from 2005 to 2010, then declined annually from 2017. Urban inequality increased from 2005 to 2010, while rural inequality decreased significantly from 2005 to 2008. Regional variations included an increasing trend in the Northeast, a decreasing trend in Eastern and Southern Coastal regions, low but fluctuating inequality in the Northwest, and a downward trend in the Southwest and Yangtze River Midstream regions. The Yellow River Midstream region experienced considerable fluctuations.

Influencing Factors: Market factors such as digital economy development directly and significantly reduce urban-rural carbon emission inequality, with notable spatial spillover effects. Economic development shows a U-shaped relationship with inequality, and optimizing industrial structure helps reduce inequality but lacks significant spillover effects. Government intervention has an insignificant direct impact, while stronger environmental regulations may increase inequality in some cases. Openness reduces inequality, while higher population density may increase local inequality but potentially decrease it in neighboring areas.

The findings suggest that effective policies should leverage the benefits of digital economy growth and address the complexities of openness and population density to manage urban-rural carbon emission inequality. Prioritizing digital infrastructure investment and fostering innovation can help reduce emissions and improve efficiency across regions

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